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E-Forum, Winter 2014

The CAS *E-Forum,* Winter 2014

The Winter 2014 Edition of the CAS *E-Forum* is a cooperative effort between the CAS *E-Forum* Committee and various other CAS committees, task forces, or working parties.

This *E-Forum* contains Report 7 of the CAS Risk-Based Capital Dependencies and Calibration Working Party (Reports 1 and 2 are posted in *E-Forum* Winter 2012-Volume 1; reports 3 and 4 in *E-Forum* Fall 2012-Volume 2; report 5 in *E-Forum* Summer 2012; and Report 6 in *E-Forum* Fall 2013).

This *E-Forum* also features a report commissioned by the CAS Committee on Valuation Finance & Investments (VFIC) on actuarial housing values. Also included are seven papers submitted in response to call for essays titled, "Climate Change: Impact on the Insurance Industry," which was conducted by the CAS Climate Change Committee.

In addition, this *E-Forum* contains three independent research papers.

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Risk-Based Capital (RBC) Reserve Risk Charges – Improvements to Current Calibration Method

Report 7 of the CAS Risk-based Capital (RBC) Research Working Parties

Issued by the RBC Dependencies and Calibration Working Party (DCWP)

Abstract: The purpose of this paper is to describe the results of research on methods to improve the Current Calibration Method (CCM) for reserve risk charges for use in the NAIC RBC Formula. The paper shows how it is possible to construct risk charges that might be both more reflective of underlying risk and more stable over time than the CCM.

This paper shows the extent to which calibration of reserve risk charges is affected by issues identified, but not measured, in prior research – reserve size by line of business (**LOB-size), pooling, and movement over time**. The paper also identifies and measures the extent to which risk charges are affected by (a) the **"minor line"** effect, which appears to distort risk charges for specialty lines of business (LOBs), and (b) the effect of data **maturity**.

This is one of several papers being issued by the Risk-based Capital (RBC) Dependencies and Calibration Working Party. The approach to calibrating reserve risk charges described in this paper is analogous to the calibration approach for premium risk described in DCWP Report 6.

Keywords. Risk-Based Capital, Capital Requirements, underwriting risk, reserve risk, premium risk, Analyzing/Quantifying Risks, Assess/Prioritizing Risks, Integrating Risks.

1. Introduction

1.1 Background and Purpose

The NAIC RBC Formula ("Formula") has six main risk categories, R0 – R5. The underwriting risk is represented into two of these categories, R4 and R5, reserve risk and written premium risk, respectively. This paper relates to the reserve risk portion of R4.[1]

For each Schedule P line of business (LOB), reserve risk is determined using an "Industry Loss and Expense %"on PR016 Line 4, a value applicable to all companies. We refer to this as the Reserve Risk Factor (RRF). It is also sometimes referred to as the reserve risk charge.

For each LOB the reserve risk charge is produced using the RRF, LOB net loss reserves,[2] and adjustments for investment income, differences between the company reserve development and industry reserve development, and the company proportion of loss

[1] In the application of the RBC formula a portion of Reinsurance Credit Risk is combined with Reserve Risk to produce a charge called R4. This paper discusses the Reserve Risk component of that combined R4.

[2] Loss and all loss adjustment expenses reserves net of reinsurance, Schedule P part 1 column 24.

sensitive contracts.

This paper provides a framework for deriving the RRFs by LOB.

1.2 Terminology, Assumed Reader Background, and Disclaimer

This paper assumes the reader is generally familiar with the property/casualty RBC formula.[3]

In this paper, references to "we" and "our" refer to the principal authors of this paper. "The working party" and "DCWP" refer to the CAS RBC Dependencies and Calibration Working Party.

The analysis and opinions expressed in this report are solely those of the authors, the Working Party members, and in particular are not those of the members' employers, the Casualty Actuarial Society, or the American Academy of Actuaries.

DCWP makes no recommendations to the NAIC or any other body. DCWP material is for the information of CAS members, policy makers, actuaries, and others who might make recommendations regarding the future of the property/casualty RBC formula. In particular, we expect that the material will be used by the American Academy of Actuaries RBC Committee.

In Section 3 we define a "baseline filtering" approach to selecting data for use in our analysis. The purpose of the baseline is to simplify comparison among a number of analyses; it is not presented as a recommendation.

This paper is one of a series of articles prepared under the direction of the CAS RBC Dependency and Calibration Working Party.

Special terms and acronyms are defined in the Glossary.

1.3 Prior Research

The RRFs in the Formula were first set in 1993.[4] Research reports on the RRFs and comparable reserve risk charges were most recently prepared by the American Academy of

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[3] For a more detailed description of the formula and its initial basis, see Feldblum, Sholom, NAIC Property/Casualty Insurance Company Risk-Based Capital Requirements, Proceedings of the Casualty Actuarial Society, 1996 and NAIC, Risk-Based Capital Forecasting & Instructions, Property Casualty, 2010.

[4] Academy (2007)

Actuaries (Academy) in 2007[5] with updates in 2009[6] and 2010[7], and by the Underwriting Risk Working Party (URWP) of the Casualty Actuarial society (CAS) in 2012.[8] In this paper we refer to the method described in the 2007 Academy Report as the "Current Calibration Method" (CCM).

This paper describes new research addressing a number of the issues raised by those prior papers, particularly those identified by URWP, as follows:

1. The current data sources — the most recently available confidential company RBC filings for short-tailed lines of business and the most recently available Schedule P for long-tailed lines of business —yield too few observations for stable estimates of RBC factors from one calibration cycle to the next. Additional data sources should be investigated.
2. Filtering eliminates a significant amount of company experience from the Current Calibration Method. For many lines of business the majority of the companies in the industry are eliminated; for two lines, all companies are eliminated. New ways to filter out questionable data should be investigated. Possible alternatives are discussed in the report. [9]

URWP identified potential improvements to the Current Calibration Method that could be researched within the framework of the current RBC formula (including the following):

Data

1. Filtering strategies.

2. Additional or extended (number of years) data sources.

3. Improved treatment of data from pooled companies.

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[5] Academy (2007)
[6] Academy(2009)
[7] Academy (2010)
[8] CAS *E-Forum*, URWP report, Winter 2012
[9] CAS *E-Forum*, URWP report, Winter 2012– page 2

4. Analysis of the extent to which alternative filtering is affected by run-off and startup companies, and including procedures mitigate that effect, if any. [10]

1.4 Working Party Approach

To address the opportunities for improvements identified by that prior research, DCWP proceeded as described below.

1. Using information provided by the NAIC we compiled the Schedule P information necessary to construct reserve runoff ratios from 14 Annual Statements (1997-2010) from all individual companies and DCWP-defined pools,[11] for long-tailed LOBs and 14 RBC filings (1997-2010) from all individual companies and DCWP-defined pools for short-tailed LOBs. The data produces up to 22[12] reserve runoff ratios. By comparison, CCM uses only one Annual Statement with a maximum of 9[13] reserve runoff ratios. In both the method described here and in the CCM "reserve" means the reserve for loss and defense and cost containment expenses (DCCE).[14]
2. The reserve runoff ratio is described in more detail in Appendix H.
3. We applied less restrictive approaches to filtering data, and thereby retained more data for analysis.

In this DCWP research we continued to apply the CCM framework of measuring the RRF as the 87.5th percentile of observed reserve runoff ratios across companies and initial reserve dates.

The intended time horizon for risk charge assessment, as is the case for the CCM, is the

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[10] CAS *E-Forum*, URWP report, Winter 2012,– page 26
[11] Details in DCWP Premium Risk, Report 6, Appendix G
[12] There is runoff data for 22 initial reserve dates, 1988 to 2009. As the most recent annual statement for this research is 2010, there is an initial reserve, but there is no runoff on initial reserves for initial reserve date 2010.
[13] In the 2010 Annual Statement, for example, there is runoff data for initial reserve dates 2001 to 2009. There is also runoff data in the "Prior" Annual Statement row, but the initial reserve value in that row is the reserve for AY 2000 and prior at December 2001, rather than December 2000. Therefore, the initial reserve for runoff from December 2000 needs data from the 2009 Annual Statement.
[14] The RRFs are applied to unpaid loss and loss expenses reserves including the adjusting and other expenses (A&O). The RRFs are calibrated based on loss and DCCE only, as Schedule P runoff is provided for loss and DCCE only.

claim runoff time period. The data can be used for one-year or other time horizons, but that was not explored by the working party.

1.5 Findings

The main findings from this research are the following, organized by section in this paper:

Section 2 – RRFs calibrated based on the CCM (using 9 initial reserve dates from a single Annual Statement) vary, often widely, from Annual Statement to Annual Statement. This variation seems to be driven by the underwriting cycle and other industry-wide effects. Longer-term data appears necessary to achieve stable indicated RRFs.

Section 3 – We identified certain data points as "minor lines" data points if the Net Earned Premium (NEP) for the LOB for all accident years (AYs) combined represents less than 5% of the company's total premium for that LOB for all AYs combined. For certain specialty LOBs the indicated RRFs excluding the minor lines data points are significantly lower, and more relevant, than the RRFs based on all data points. For those LOBs, failure to exclude the minor lines data points appears to result in RRFs that are not representative of risk for data points representing the bulk of the industry LOB reserves.

Section 3 – Pooling can distort the RRFs. The distortion can be at least partially removed.

Section 3 – We define a baseline filtering approach to selecting data for use in our analysis. This baseline is not a recommendation. Rather, it is a practical way to evaluate a variety of alternatives. This baseline is the starting point for the analyses described in Sections 4-8.

Section 4 – Looking at all 22 initial reserve dates and the 'even-year/odd-year' test suggests that the 22-year data set will produce RRFs that are more stable than the CCM across calibrations from year-to-year.

Section 5 – We demonstrate that indicated RRFs vary with LOB-size; i.e., net loss and

DCCE reserve, size by LOB.[15] To the extent that the RBC formula is not intended to have risk charges that vary by LOB-size, we identify two approaches to treating that issue in the context of the RBC Formula: RRFs based on the median LOB-size and RRFs based on LOB-size above a threshold. There may be other suitable approaches.

Section 6 – RRFs are affected by the maturity of the data to an extent that varies by LOB.

Section 7 – For most LOBs, RRFs are lowest for data points from companies with the longest experience period, 20 or more AYs of Net Earned Premium (NEP) > 0.

While maturity adjustments are not included in the baseline that we used for comparative purposes, it would be reasonable to include them in a final RBC calibration.

2. RRFs Based on CCM

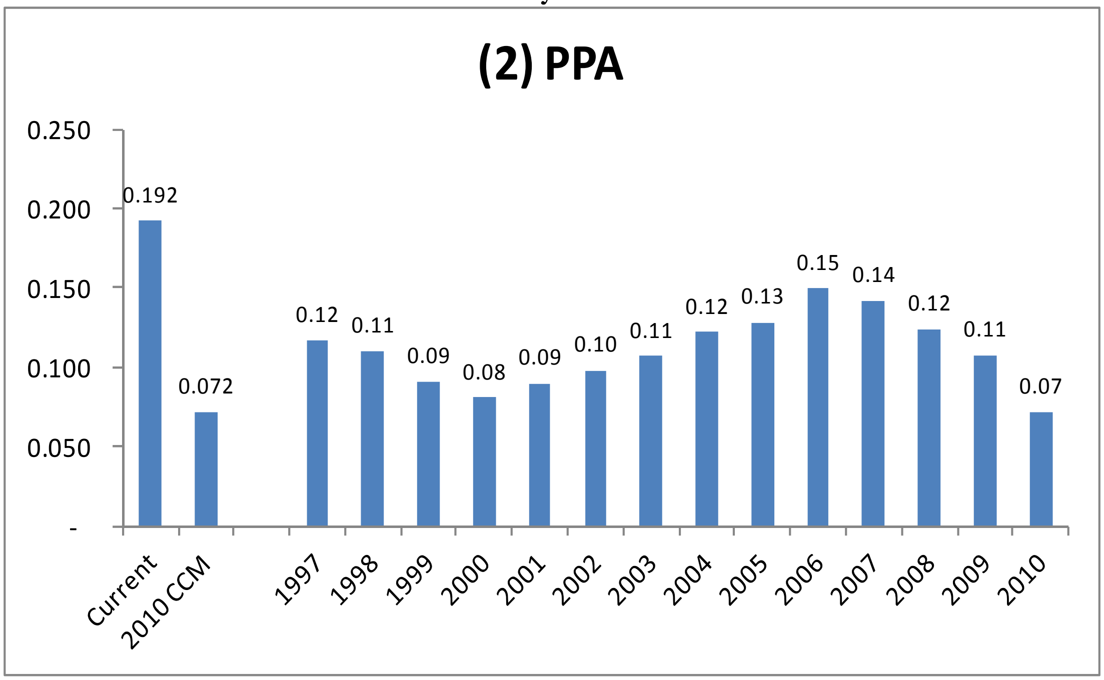
In 2011, the URWP observed that CCM indicated RRFs, based on data from a single Annual Statement, vary widely from year to year and recommended that more data be used in determining the risk charges. In this section we provide a more detailed illustration of the year-to-year variability exhibited by the RRFs indicated by the CCM.

The RRFs indicated by the CCM are based on the empirical 87.5th percentile of the 9 years of reserve development data from all companies at a single Annual Statement date, with filtering described in section 3.2.1.

Table 2.1 shows these values as would be determined from successive Annual Statements from 1997 to 2010, for the Private Passenger Auto (PPA) LOB.

[15] We use the term LOB-size to clearly distinguish between the reserve size of the company and the reserve size for the LOB.

Table 2.1
PPA – CCM RRFs by Annual Statement Year



For this LOB, the RRF varies from 0.07 to 0.15 over the 14 years shown: a swing of eight percentage points RRF with an apparent cycle in the values.

For comparative purposes, the current RRF in the 2010 Formula, 0.192, is shown at the left side of the table. This is the "Industry Loss and Expense %" appearing in Line 04 of 2010 RBC report PR016. The RRF indicated using the CCM and 2010 Annual Statement data, 0.072, is also shown on the left side of the chart. The actual factors were updated over the 2008-2010 period, based on the CCM but subject to limitations ("caps") in year-over-year movements. The caps were ±15% in each of 2008 and 2009, and ±5% in 2010.[16]

Table 2.2 shows the indicated RRFs for workers compensation. Here we see a swing of 24 percentage points of runoff ratio, from 0.10 related to experience in 2000 Annual Statements to 0.34 related to experience in 2008 Annual Statements. The values also show a pattern over time typical of the underwriting cycle.

[16] URWP, page 5

Table 2.2
WC – CCM RRFs by Annual Statement Year

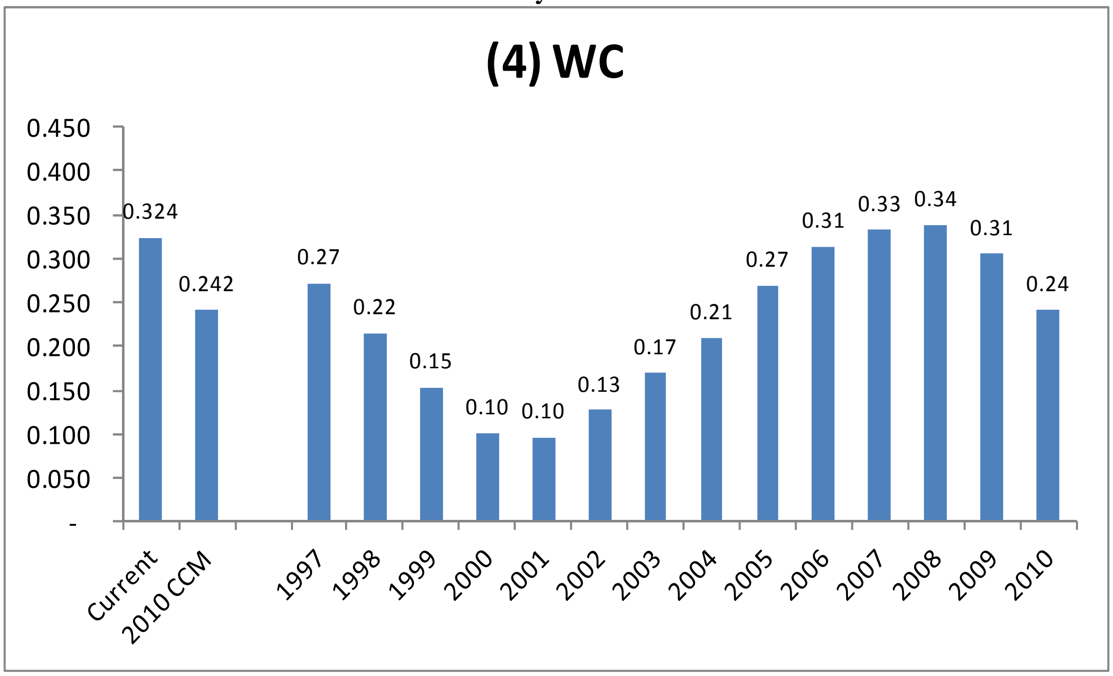
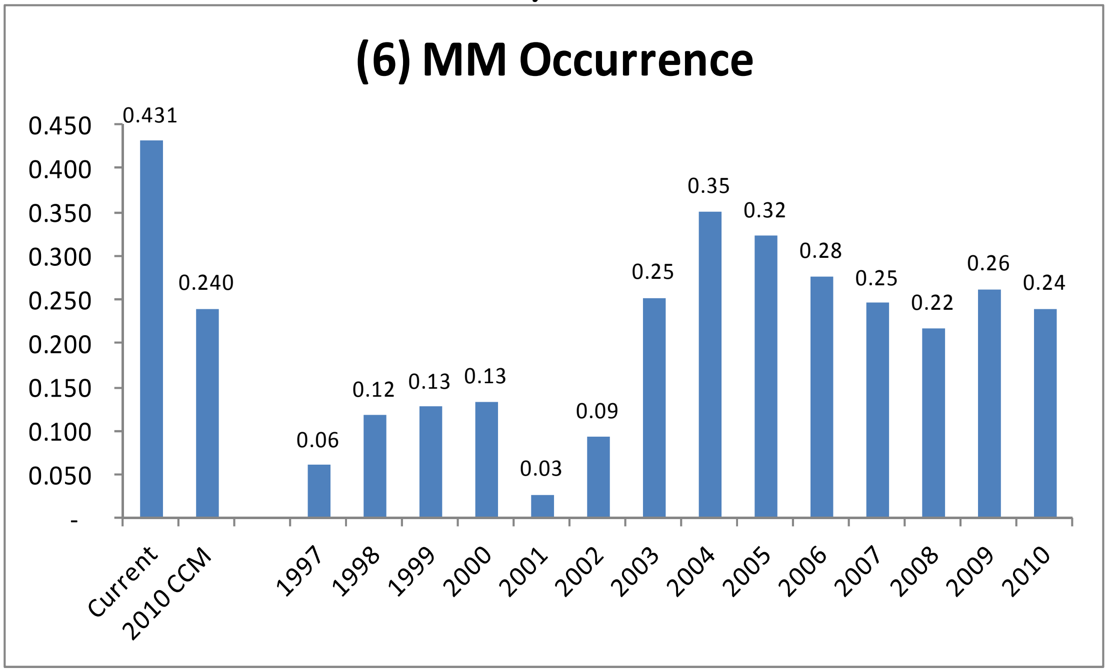


Table 2.3 shows the RRFs for the Medical Professional Liability (MM) – Occurrence LOB. Here the swing is 32 runoff ratio percentage points, from 0.03 to 0.35, from Annual Statement year 2001 to Annual Statement year 2004.

Table 2.3
MM Occ. – CCM RRFs by Annual Statement Year



Similar year-by-year RRF graphs for all LOBs[17] are shown in Appendix A.

It seems clear that the CCM approach of using the most recent Annual Statement will not produce stable RRF indications.

3. Data and Filtering

3.1 Data

Using information provided by the NAIC we compiled Schedule P – Part 2 and Part 3 information from 14 Annual Statements (1997-2010)[18] from all individual companies and DWCP-defined group pools (pools). That provides over 200,000 data points, covering 22 initial reserve dates many of them developed to 9 years maturity. The CCM uses only one Annual Statement with a maximum of 9 initial reserve dates and only one initial reserve date

[17] Appendices A-C and E-F do not include LOBs (14) Financial and Mortgage or (19) Warranty as the number of data points for these LOBs is very limited (see Appendix D and G-Part 2 for data point counts).
[18] For companies that did not file a statement in 2010 or companies that did not begin filing statement until after 1997, there were fewer than 14 Annual Statements.

at 9 years maturity.

Each data point is an initial reserve date-LOB, for a single company or pool, at the latest available maturity. For each data point we have the following information:

- Loss and DCCE reserves at the initial reserve date (initial reserve)
- Reserve runoff at the latest available maturity
- Runoff ratio – the ratio (2)/ (1)
- Age at the latest maturity: 12 months (initial reserve), 24 months (12 months after initial reserve), etc.
- The data point LOB premium and LOB reserve amounts as percentages of all-line premium and all-line reserves, to identify minor lines described under Section 3.2.2.

3.2 Filtering Methodologies

We use the term "filtering" to describe the manner in which we treat data features that might affect the indicated RRFs, such as data errors, LOB-size, maturity of loss experience, etc. In the sections below we discuss the CCM filtering and DCWP filtering approaches.

3.2.1 CCM Filtering

CCM uses data from only one Annual Statement for the calibration. In the CCM all data associated with a LOB for a company is removed if, for the ten years of data included in the latest Annual Statement the company "fails" any of the following tests:

- The company has negative paid values in any AY at any reserve date; or
- The company has negative reserves in any AY at any reserve date (used -$5K to account for rounding errors of Part 2 less Part 3 data); or
- The company has negative incurred amounts in any AY at any reserve date; or,
- The company does not have sufficient (10) years of AY data (determined from the premium risk data filtering).

For each remaining company, the reserve runoff ratio is calculated for each LOB and each initial reserve date by dividing incurred loss and DCCE development (reserve movement) by the initial reserve.

Reserve runoff ratios are capped in the range of -100% to +400%.

3.2.2 Alternative Filtering Methods

In this analysis, we use a less restrictive filtering process.

Positive Values Where Expected

All data associated with a LOB for a company is removed if, for the ten years of data included in an Annual Statement, the company "fails" any of the following tests

- The company has negative paid values for all AYs combined at any reserve date; or
- The company has negative reserves for all AYs combined at any reserve date;[19] or
- The company has negative incurred amounts for all AYs combined at any reserve date.

Consistency Between Annual Statements – "Prior" Annual Statement line

In addition, for this analysis we need to match data from one Annual Statement to the next to maximize the use of the "Prior" data row in Schedule P. Therefore, we applied a consistency test as follows:

Test 1: Reserve in Prior line of the first reserve date (Prior_1) is compared to the reserve for the same group of AYs at the same evaluation date from the prior year's statement (Prior_2). As these values should represent the same information at the same evaluation dates, the values should be the same.

As this is not always the case[20] we say the test fails if the difference is greater or equal to 5%. If the Test 1 difference is small enough, the data point is retained. If the Test 1 difference is too large, Test 2 will be performed.

Test 2: Prior_2 is compared to the reserve for the same group of AYs at the same evaluation date from the second prior year's statement. The test fails if the difference is greater or equal to 5%. If Test 2 fails, data point Prior_1 is removed; otherwise Prior_1 is replaced with Prior_2.

Appendix H shows examples of the consistency tests.

[19] We use minus 5 thousand dollars (-5k) as a weaker threshold rather $0 to avoid discarding data due to rounding errors in using differences between Schedule P Part 2 and Schedule P Part 3, each if which is rounded to thousands.

[20] For example, changes in pooling arrangements from year to year might cause the values to be inconsistent.

Test for Outliers

During the analysis, we observed 210 data points with very high runoff ratios ("outliers"). Reviewing the data showed that a significant portion of those outliers appear to have been caused by inconsistent reporting of paid and incurred loss and DCC triangles in Schedule P Part 2 and Part 3, not connected with inconsistencies between statements on the "Prior" line. This outlier problem is worse for short-tailed LOBs, which are from RBC filings, than for long-tailed LOBs, which are from Schedule P. We excluded data points with runoff ratios greater or equal to 500% from our baseline data set.[21] The effect by LOB of this filter is shown in Appendix G Part 1.

In the rest of this section we discuss four other data filtering issues: pooling, minor lines, LOB-size, and years of NEP greater than zero (NEP>0).

Pooling – For companies with intergroup pooling arrangements the Schedule P reserve runoff ratio for each LOB-AY is the same for each pool member; the common reserve runoff ratio is the weighted average reserve runoff for that LOB-AY across all pool members rather than the individual pool member runoff ratio before pooling.

That feature of the data would distort the results of our analysis in that:

- The same reserve runoff ratio would appear multiple times, reducing the apparent variability in the reserve runoff across companies;
- Companies that appear small based on their pooling percentages would show the lower year-to-year variability associated with the larger size of the overall pool rather than the higher year-to-year variability associated with a company of its apparently smaller size.

To mitigate these effects, we would like to combine the separate pool participants into a single group-wide data point for each LOB-initial reserve date. If that were done, the data would reflect the correct variability between companies and the proper data point LOB-size.

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[21] Excluding the data point from the data set has more effect than using the data point and limiting the value assigned to it. Limiting data point values to 500% will have no effect on the 87.5th percentile calculation if the 87.5th percentile level is below 500%. Removing the data point will reduce the 87.5th percentile level by reducing the number of data points above any level. We believe removing the data points is a reasonable adjustment because we believe the data points are erroneous and not an indication an actual high data runoff value.

We use information in the Annual Statements to identify individual companies that appear to be part of a larger pooled entity. There are 3,730 NAIC legal entities in the initial data set. Of these, 2,695 are not part of any pool and 1,035 entities are mapped into 206 DCWP-constructed pooled entities. Thus the total data set includes 3,730 – 1,035 + 206 = 2,901 entities in total.[22] Our approach to identifying relevant pools is discussed in Appendix G of DCWP Report 6, RBC Premium Risk Charges.[23]

<u>LOB-Size</u> – Indicated RRFs vary by LOB-size, and in Section 5 we evaluate RRFs by LOB-size. In the sub sections below, we test the effect on indicated RRFs of excluding a data point if the LOB reserve is below a threshold which varies by LOB. The selected thresholds are listed in at the end of Appendix B.

<u>Minor Line Filtering</u> – In the premium risk charge analysis in DCWP Report 6 we defined minor lines data points (each data point is a specific AY/LOB) as data points for which the AY NEP for the LOB was less than 5% of the AY NEP for all LOBs combined, <u>separately for each AY</u>.

The straightforward analogue for reserves is to define minor lines data points (each data point is a specific initial reserve date/LOB) as data points for which the initial reserve for the LOB is less than 5% of the initial reserve for all LOBs combined, for the same initial reserve date. We refer to this as a 'reserve-based-definition". However, the reserve-based definition is problematic because (a) short tail lines were too often categorized as minor lines because reserves were low, even though premium was significant; and (b) while certain aspects of management attention reflect reserve size, other aspects of management attention would relate to premium size.

Therefore, we also consider a premium-based, definition that uses premium but recognizes that reserves reflect premium for multiple years. In this premium-based definition, a minor lines data point is a data point where the LOB NEP for all AYs combined is less than 5% of the all-lines total NEP for all AYs combined. We refer to this as an "all-year-premium-based definition." With this definition, for a given company, minor lines is a characteristic of all initial reserve date/LOB data points, regardless of the initial

[22] For each LOB, the number of entities is smaller, as not all companies have written business in each LOB.
[23] As described in Appendix G of Report 6, our approach is approximate as it does not necessarily identify all pools and it may combine some LOB/companies that are not actually pooled.

reserve date.

In section 3.3, Sensitivity Testing, we compare the indicated RRFs using (1) data including minor line data points, (2) data excluding minor line data points based on the reserve-based definition and (3) data excluding minor line data points based on the all-year-premium-based definition.

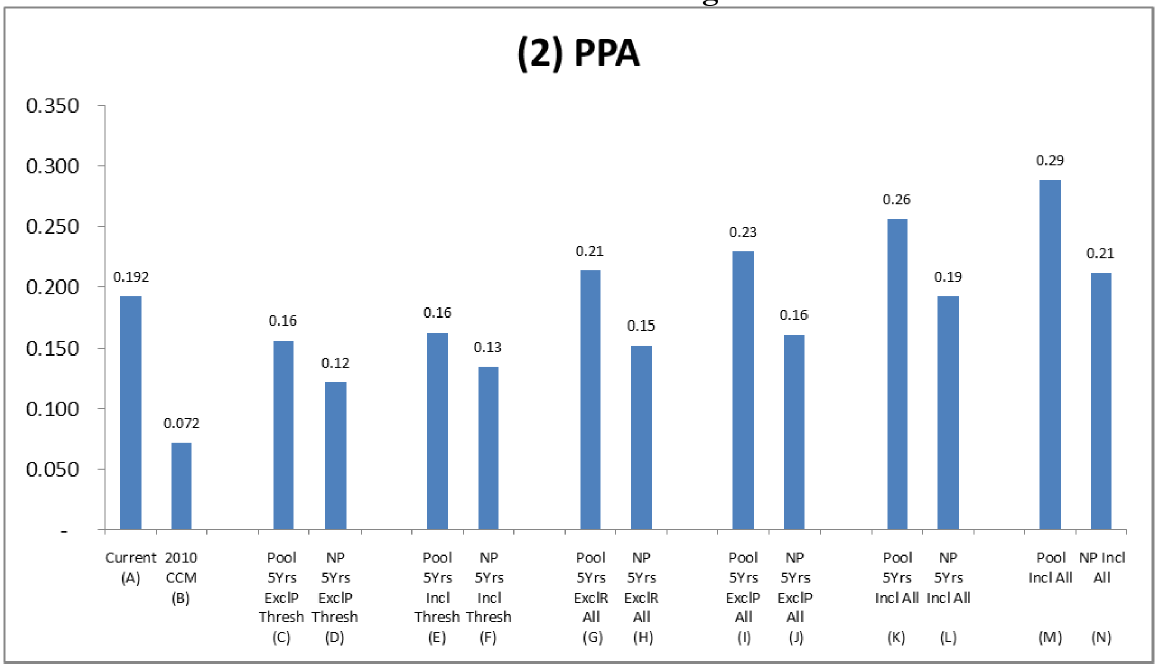
Years NEP>0 - The baseline filtering excludes data from LOBs where the company has had less than five years of positive NEP in that LOB. The five year trigger was selected given that some minimum seemed appropriate, and we wanted to test a criterion that was less strict than the 10 year requirement in the CCM.

3.3 Sensitivity Testing

In this section we describe how we tested the extent to which pooling, minor lines, LOB-size, and years of NEP>0 affect the indicated RRFs.

Table 3.1 shows the results of our filtering sensitivity analysis for the PPA LOB.

Table 3.1
PPA – Effects of Alternative Filtering Methods



The following table explains the legend used in Table 3.1 and will be useful as we discuss the various columns in Table 3.1:

Pool	Pooled data points replace individual company data points, where appropriate
NP	"Un-pooled" data points, using data points before consolidation to reflect pooling arrangements.
5Yrs	Data points from companies/pools with at least five years of premium data
ExclP	Excluding minor line data points – all-year-premium-based definition
ExclR	Excluding minor line data points – reserve-based definition
Incl	Including minor LOB data points
Threshold	LOB-size threshold applied (Thresholds shown at the end of Appendix B)
All	LOB-size threshold not applied

The "Current" and "2010 CCM" values shown in columns A and B at the left of the graph are unchanged from Section 2. We now focus on the pairs of values from right to left.

A comparison of the values in columns M and N at the far right shows the effect on indicated RRFs of pooling adjustments; the "Pool" and "NP" labels designate "Pooling" adjustment applied and "No Pooling" adjustment applied, respectively, with no other filtering. Comparing columns M and N, we see an increase in the indicated RRF using pooled data, from 0.21 to 0.29.

The values in columns K and L show the indicated RRFs excluding data points from companies with less than five years of NEP>0. Comparing columns K and L to M and N, respectively, we observe a decrease in the indicated RRFs by excluding the data points from companies with less than five years of NEP>0; from 0.29 to 0.26 for pooled data and a decrease from 0.21 to 0.19 for unpooled data.

The values in columns G, H, I, and J show the indicated RRFs excluding minor lines filtering based on two definitions of minor lines.

The label "ExclP" used in Columns I and J, indicates that we use the all-year-premium-based minor lines definition; i.e., minor lines data points are excluded if the all-year[24] premium for data point LOB represents less than 5% of the all-year premium for all LOBs combined. The RRFs based on data excluding all-year-premium-based minor lines are shown in Columns I and J, for pooled and unpooled data points respectively. Comparing columns I and J to columns K and L, respectively, we observe a decrease in the indicated RRFs from 0.26 to 0.23 for pooled data and a decrease from 0.19 to 0.16 for unpooled data when minor lines data points are excluded based on premium.

The label "ExclR," in Columns G and H, indicates the use of a reserve-based minor lines definition; i.e., minor lines data points are excluded if the reserve initial reserve for the data point LOB represents less than 5% of the total of the initial reserves for all LOBs combined. The RRF based on data excluding reserve-based minor lines are shown in Column G and H for pooled and unpooled data points respectively. Comparing columns G and H to columns K and L, we observe a decrease in the indicated RRFs from 0.26 to 0.21 for pooled data and a decrease from 0.19 to 0.15 for unpooled data when minor lines data points are excluded based on reserves.

The label "Thresh" in columns C, D E and F indicates the use of the LOB-size threshold.

[24] As discussed in Section 3.2.2, we used the all-year premium rather than a single AY of premium in that the reserve at the initial reserve date represents the risk remaining for all AYs prior to the initial reserve date. We selected all-year premium because of its simplicity. We considered, but did not using more complex premium relationships.

The label "All" in columns G – M indicates that data points of all LOB-sizes are included. Comparing columns E to K and F to L, we again see decreases in the indicated RRFs, from 0.26 to 0.16 and from 0.19 to 0.13.

We observe that the decrease in indicated RRF is larger based on LOB-size threshold than the decrease based on exclusion of minor lines; i.e., that the RRF in Column E is less than the RRF in columns G or I, and similarly for Column F compared with columns H or J. We characterize this as "LOB-size filter is more significant than minor lines filter" for PPA. This general pattern appears in many of the LOBs.

Finally, the values in columns C and D show the indicated RRFs with the 5 year premium requirement, LOB-size, and premium-based minor line filters combined. Comparing columns C and D against the other pooled/not-pooled pairs, there is a further decrease in indicated RRF by applying both the minor line and LOB-size filters.

Table 3.2 displays the filtering sensitivity results for the Homeowners/Farmowners LOB. As with PPA, the Homeowners/Farmowners data shows the following:

- The RRF based on pooled data is higher than the RRF based on unpooled data.
- The RRF excluding minor lines data points is lower than the RRF including minor lines data points.
- The RRF excluding LOB-size below the threshold is lower than the RRF across all LOB-sizes.
- The LOB-size filter is more significant than minor lines filter.

Table 3.2
Homeowners/Farmowners – Effects of Alternative Filtering Methods

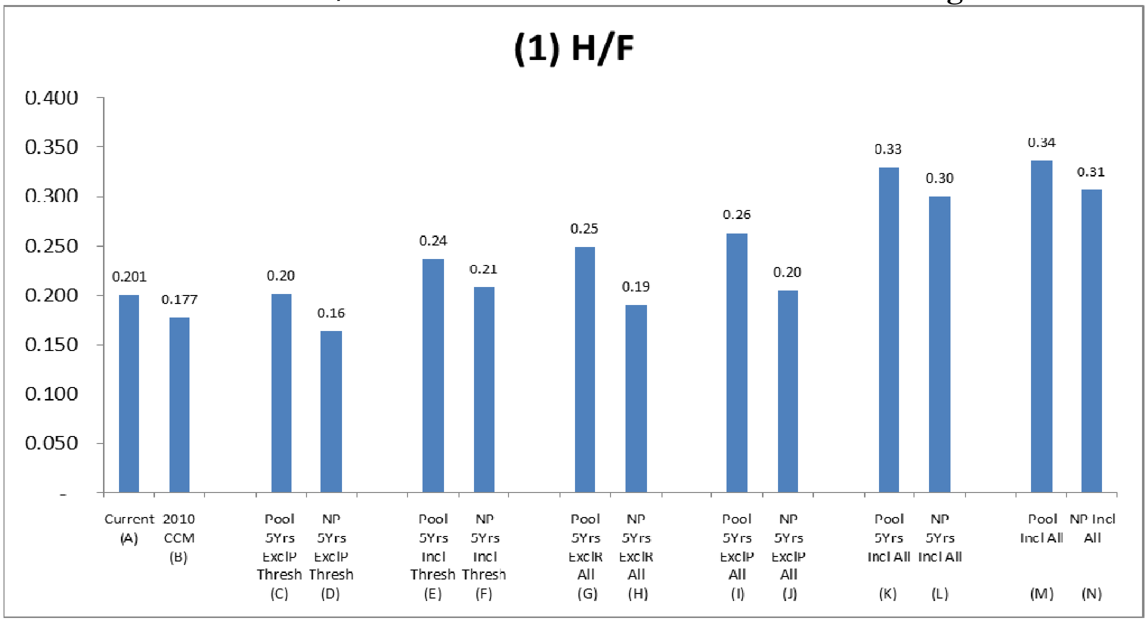
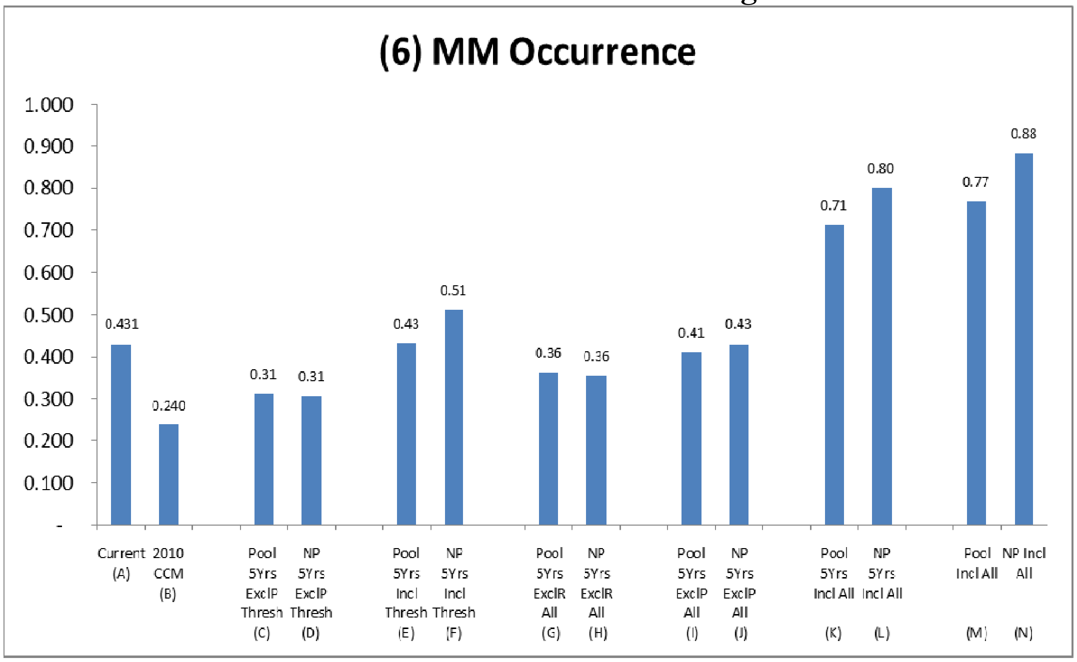


Table 3.3 shows indicated RRFs for the MM – Occurrence LOB with the various filter combinations.

Table 3.3
MM Occ. – Effects of Alternative Filtering Methods

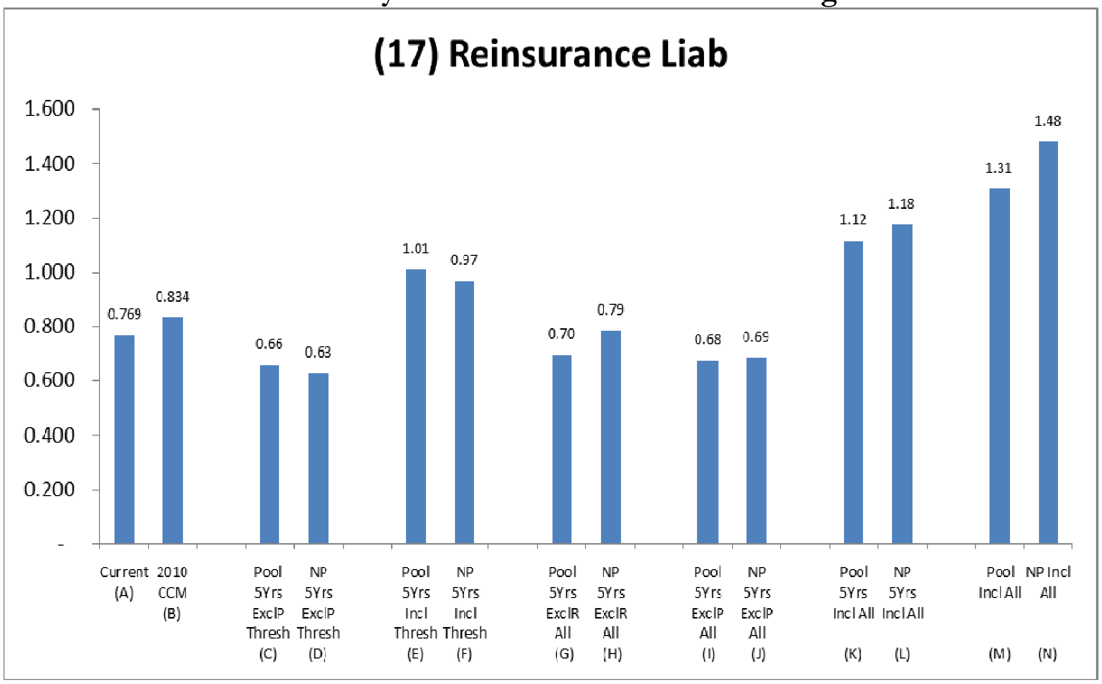


In many respects, the pattern for this MM – Occurrence LOB is similar to the pattern for PPA and Homeowners/Farmowners. However, the pair of columns I and J (or G and H) are lower than the columns E and F, showing that the minor lines filter has a larger effect than the LOB-size filter. This result demonstrates what might be called a "specialist effect," i.e., RRFs are larger for many insurers who write MM – Occurrence coverage but for whom MM – Occurrence is not a significant part of the overall business.

Also, for MM Occurrence, the RRF based on pooled data is lower than the RRF based on data not adjusted for pooling. That is the reverse of the pattern observed for PPA and Homeowners/Farmowners, and most other lines. This indicates that the data points for companies in pools include more of the extreme runoff ratios than data points from companies not in pools. This may relate to the specialist effect, as there may be less pooling for specialist companies.

The pattern of the RRFs for Reinsurance – Liability LOB in Table 3.4 is similar to the pattern of RRFs for MM-OCC. In fact, for Reinsurance – Liability the "specialist" effect is so significant that the minor lines filter alone produces almost the same effect as minor lines plus LOB-size filters; compare columns I and J (or G and H) to columns C and D. Also, as with MM, the unpooled data indicates a higher RRF than the data adjusted for pooling.

Table 3.4
Reinsurance Liability – Effects of Alternative Filtering Methods



Corresponding graphs for all LOBs are shown in Appendix B.

<u>Baseline Filtering</u>

In the following sections, unless otherwise indicated we use data

- on a pooled basis,
- excluding minor lines data points (all-year-premium-based definition),
- excluding data points with LOB-size below the selected LOB-size threshold shown at the end of Appendix B, and
- excluding data points from companies with less than five years NEP for the LOB.

For convenience, we refer to this as the "baseline filtering".

Note that notwithstanding the fact that this analysis relates to reserves, in our further work we use the all-year-premium-based minor line definition. Based on reserves, we observed that short-tail lines tend to become minor lines even for companies where the LOBs are far from minor with respect to premium volume. By using premium for the definition, we include more data and better distinguish minor from non-minor within the short tail lines.

Column C in Tables 3.1-3.5 and Appendix B show the RRFs indicated from baseline filtering for each LOB.

Table 3.5 shows the all-lines number of data points and amount of reserves remaining after each component of the baseline filtering.

Table 3.5
Number of data points and amount of reserve after each step of the baseline filtering
All LOBs Combined

	Reserves ($000,000s)[25]	Data Points
Un-Pooled	8,793,420	229,753
Pooled	8,732,076	128,439
Five year NEP >0	8,702,192	119,509
Excluding Minor LOBs	7,682,622	71,352
Size Threshold	7,678,135	56,127
Outliers[26]	7,676,003	55,917

Appendix G Part 2 shows the proportion of data points and reserve amount by LOB that remain in the data set after filtering, by LOB.

4. Indicated RRF by Initial Reserve Date

In this section we show indicated RRFs by initial reserve date using the baseline filtering. The indicated RRF at each initial reserve date is the 87.5th percentile runoff ratio across data points, after baseline filtering, for all data points with the selected initial reserve date.

Table 4.1 shows these RRF values for the PPA LOB.

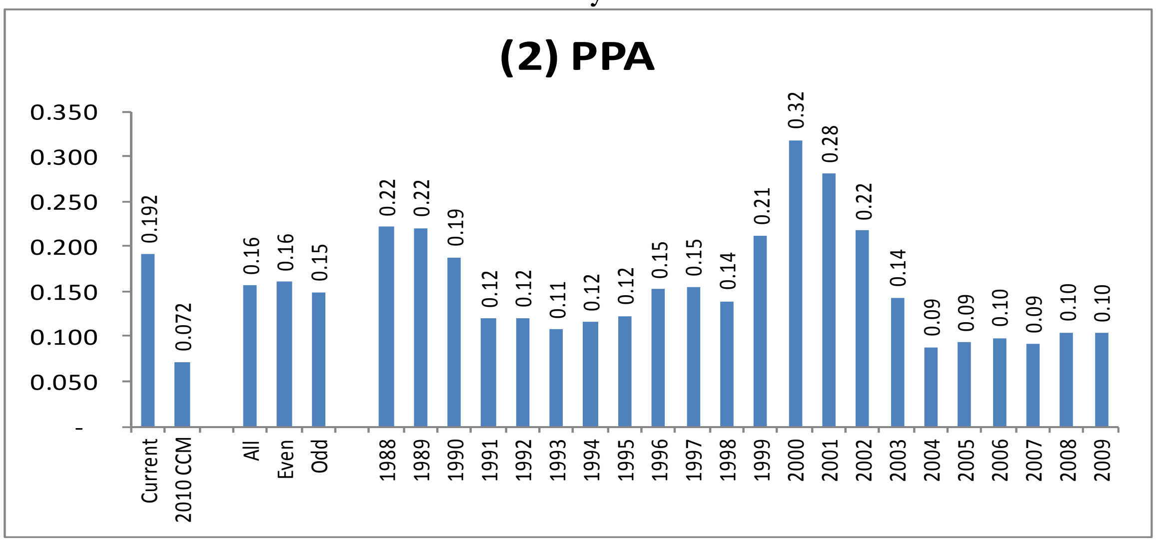
In Table 4.1 the "Current" and "2010 CCM" values on the left side of the chart are

[25] These aggregate reserve amounts are large numbers because they represent the sum of reserves over 23 initial reserve dates. $8.793 million millions (i.e., $ 8.8 trillion) of initial reserves over 23 years is an average initial reserve of about $400 billion, consistent with 2009 initial reserves of approximately $500 billion

[26] After the baseline filtering, there are 159 data points with runoff ratio greater or equal to 500% for 2-year Schedule P lines combined; these 159 points represent reserve amount of 1,011 million, less than 0.1% of the total reserves in the data set. For all 10-year Schedule P lines combined, there are 51 data points with runoff ratio greater or equal to 500%; they represent a reserve amount of 1,122 million.

unchanged from the values in the corresponding graphs in Sections 2 and 3. The column "All" on the left shows the indicated RRF combining all initial reserve dates, again with baseline filtering.[27] The "Odd" and "Even" values represent the results using odd and even initial reserve dates, and give one perspective on whether the results will change significantly if additional years were added to the data set.

Table 4.1
PPA – Indicated RRFs by Initial Reserve Date



Not surprisingly, the individual year-to-year results exhibit more variability than the 10-year average CCM values shown in Section 2. However, the comparison of the "Odd" and "Even" results, 0.16 and 0.15, to the "All" result, 0.16, suggests that the random variation from year-to-year is significantly smoothed over twelve years if spread over sufficient underwriting cycles and other systemic effects.

We also tested variability across every fourth data point (sets of 4 or 5 data points). This is a smaller set, and we expect that the correlation across four years is much less than the correlation between adjacent years. The results of that test, presented at the end of Appendix C, show more variability than the even/odd test, but still much less than the year-to-year variation in the CCM.

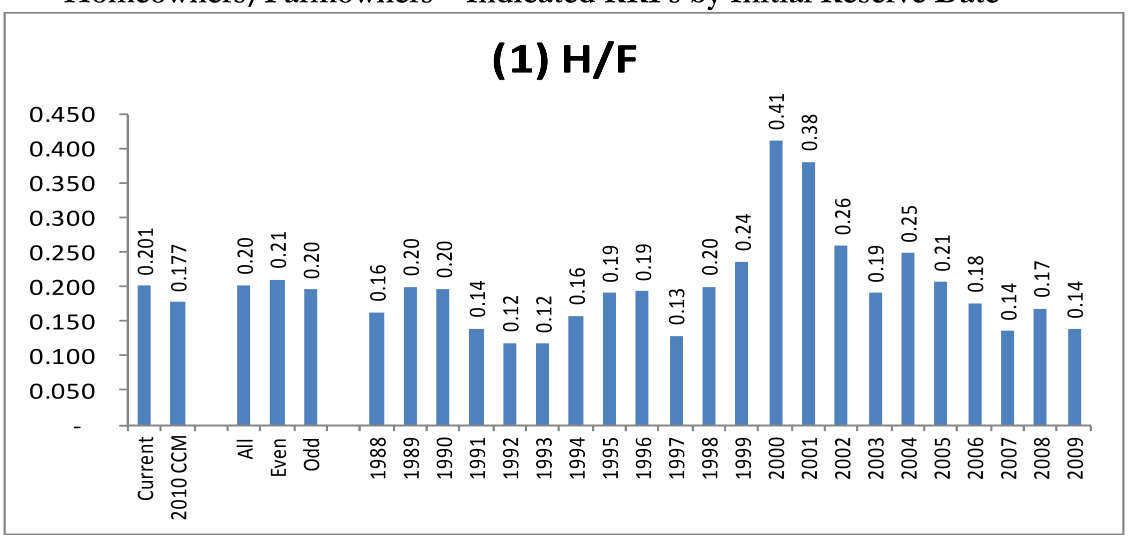
[27] The "all year" indicated RRF is not the average of the year-by-year RRFs. The "all year" RRF is the 87.5th percentile reserve runoff ratio among all reserve runoff ratios, after baseline filtering, regardless of reserve date.

In examining year-by-year data, note that the oldest initial reserve dates shown are 9 years mature, and the more recent years are between one and eight years mature. In Section 6 we observe that for initial reserve dates 1998-2001, RRFs increase with increasing maturity. To the extent that recent year RRFs change with increasing maturity, then the more recent initial reserve date RRFs should be used with caution.[28]

Also note that as RRFs are the 87.5th percentile of runoff ratios in each year, they will vary (a) as average runoff ratio varies and (b) to the extent that variability (e.g., as measured by standard deviation) changes from year to year. We have not studied the components separately.

Table 4.2 shows the indicated RRFs for the Homeowners/Farmowners LOB.

Table 4.2
Homeowners/Farmowners – Indicated RRFs by Initial Reserve Date



In this case the "Odd" and "Even" values are stable, a difference of 0.01 from 0.20 to 0.21. Unlike the situation for PRFs discussed in Report 6, the catastrophe years 1994, 1996 and 2008, which are high for premium risk factors, are not high for RRFs.

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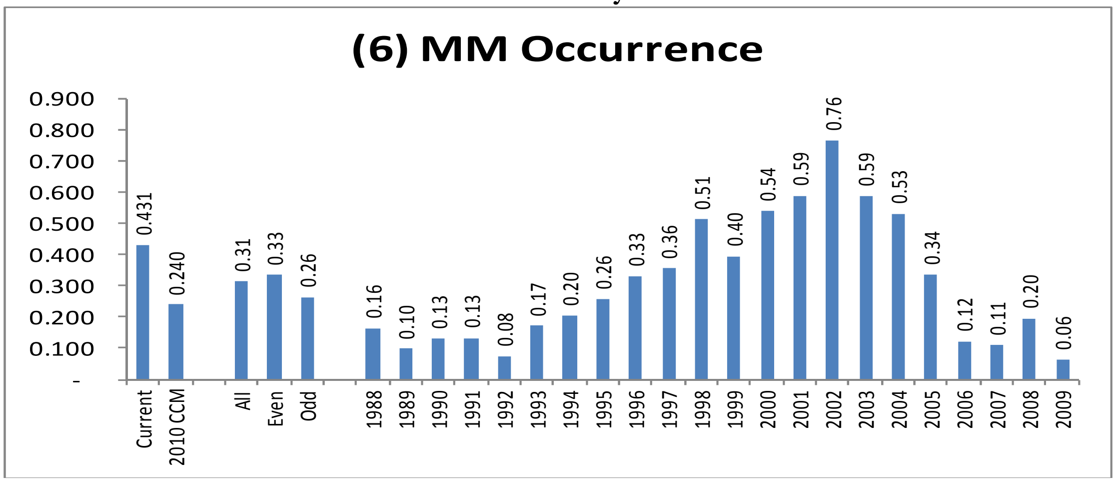
[28] This maturity pattern may not apply for all reserve years. For example reserve years 1998-2001 might have been affected by the adverse side of the underwriting cycle for a LOB like reinsurance. Initial reserve dates on the favorable side cycle might (possibly) develop less unfavorably or even develop favorably. The working party did not test these hypotheses.

Table 4.3 shows the indicated RRFs for the MM – Occurrence LOB.

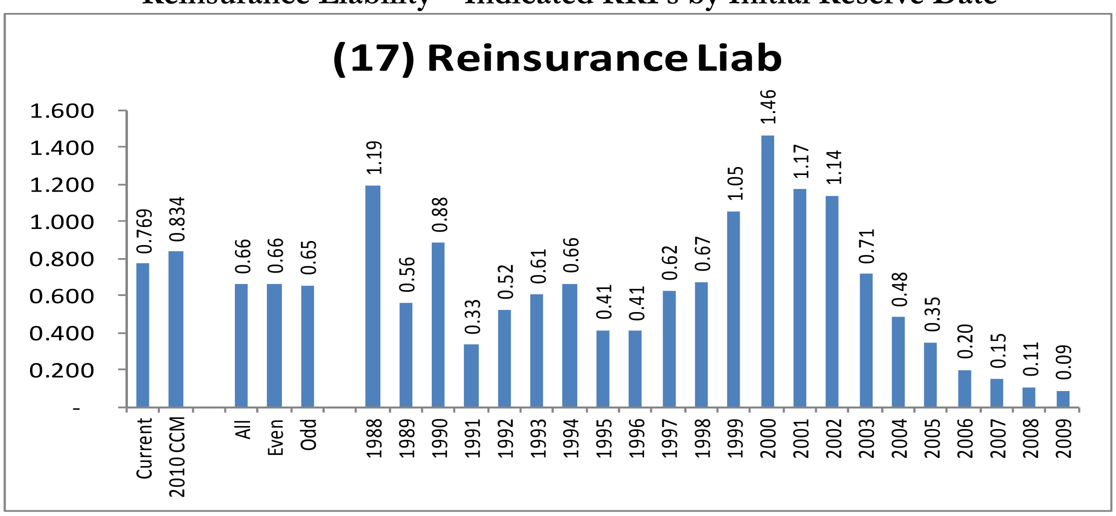
Table 4.3
MM Occ. – Indicated RRFs by Initial Reserve Date



The odd year and even year indicated RRFs vary from 0.26 to 0.33, less variation than in the year-by-year data, but not insignificant relative to the all-year indicated RRF.

Finally, Table 4.4 shows the indicated RRFs for the Reinsurance – Liability LOB.

Table 4.4
Reinsurance Liability – Indicated RRFs by Initial Reserve Date



Again, although the year to year variability is large the odd/even test again indicates the stability resulting from use of additional years of data.

Corresponding graphs for all LOBs are shown in Appendix C.

5. Analysis of LOB-size

In this section we examine the effect of LOB-size on indicated RRF.

To do this, we group LOB results into percentile LOB-size bands and calculate RRFs for the runoff data points in each band.[29] LOB-size bands refer to the LOB-size, regardless of the company size.

Table 5.1 displays the results for the PPA LOB. The row labels in column A refer to the upper-size end of the LOB-size band, so the first row, labeled 15%, refers to data points with reserve amounts in percentiles 0%-15%. The second LOB-size band covers the next 10% of data points, up to the 25th percentile in reserve LOB-size. In the final two rows of the table we show the largest 5% of data points, split between the "95% to largest 100" data points[30] (penultimate row) and the largest 100 data points (final row)

Columns B and C show the lower and upper reserve LOB-sizes corresponding to the percentile levels.

Column D shows the number of data points included in each row.[31]

Column E shows the RRF based on data within the LOB-size band. As expected, we observe in column E that the indicated RRFs are highest in the smallest LOB-size band, and generally decrease in value as we progress through the larger LOB-size bands.

Column F shows the RRF based on all LOB-size bands at or above the LOB-size for that row. For example, the first row in Column F is the RRF for all data points, regardless of LOB-size. The second row in Column F is the indicated RRF for all data points in the top 85% of LOB-sizes; the third row is the indicated PRF for data points in the top 75% of LOB-sizes, and so on. The row called "100%" shows the RRF for the largest 100 data points alone. In this row column E = column F.

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[29] The RRF for a size band is the 87.5th percentile of the runoff ratios for reserve runoff points in the LOB-size band, potentially a small data set.

[30] For some LOBs, the largest 5% of data points constitutes less than 200 data points. For those LOBs, the 'largest l00' means the top 2.5% of data points, even if that is less than 100 data points.
Also, as a single company can have as many as 22 data points, one for each initial reserve year, the top 100 data points might represent only 5 or 6 companies.

[31] The number of data points in Column D is not quite the expected percentage of the total number of points in each cell because, as reserve amounts are rounded to thousand, and multiple years have the same LOB- size when rounded to thousands.

We show the RRF in the 2010 Formula, 19.2%, at the bottom row of the Table.

Table 5.1
PPA – RRFs by LOB-size

(2) PPA					
(A)	(B)	(C)	(D)	(E)	(F)
Size Band	Reserve ($000s)			87.5th Percentile Runoff Ratio	
Endpoint Percentile	from	to	Data Points	all points in band	all points >"from"
15%	0	812	1,351	79.4%	23.0%
25%	812	1,953	903	41.0%	**<u>17.9%</u>**
35%	1,953	4,004	898	31.3%	15.6%
45%	4,004	7,446	901	26.0%	13.9%
55%	7,446	12,522	901	**<u>19.3%</u>**	12.0%
65%	12,522	20,740	901	13.5%	10.2%
75%	20,740	42,864	902	15.7%	9.2%
85%	42,864	105,325	899	8.7%	7.4%
95%	105,325	540,618	901	5.2%	6.2%
largest 100	540,618	3,466,207	351	10.6%	8.0%
100%	3,466,207	17,069,357	100	2.2%	2.2%
	Current Risk Charge Runoff Ratio (PR016, Line 4)				19.2%

There are various ways we might use this information to select the RRF for an RBC formula. One approach is to use the RRF indicated based on data points with LOB-size above a threshold that varies by LOB (threshold approach). The threshold might be selected based on judgment, to maximize the number of data points used while minimizing distortions in the indicated RRF. For the PPA LOB we selected a LOB-size threshold of $1.95 million (Appendix B, PPA, Column C), and Table 3.1 showed that the RRF based on that size threshold is 0.16 (15.6% before rounding).

Alternatively, the threshold might be based on a particular percentile of data points; e.g., excluding the smallest 15% of LOB-size data points. The item marked in bold and underline in the "25%" row of column F indicates the value obtained by setting the threshold to exclude the smallest 15% LOB data points. The RRF based on excluding the smallest 15% LOB-size data points (LOB-size $812,000 or less) is 17.9%.

The second approach is to identify the RRF associated with the median LOB-size, or range of data points around the median LOB-size (median approach). The item marked in bold and underline in column E of the "55%" row, i.e., the value included between the 45th and 55th LOB-size percentiles, is the indicated median value. In Table 5.1 above, we note that the 87.5th percentile reserve runoff ratio for the median LOB-sizes, 19.3%, is quite close to the 19.2% value used in the 2010 RBC Formula for this LOB. This is not the case for all LOBs.

Another approach is to have RRFs vary by LOB-size. Currently, none of the standard formulas vary RRFs in this way; however, Table 5.1 shows that the indicated RRFs for the largest data points (2.2%) is only a fraction as large as the RRF indicated by the median or 15% threshold approaches (19.3% or 17.9%). Thus, using the median or threshold approach to setting RRFs means that the safety margin for the larger data points is higher, perhaps much higher, than the 87.5th percentile.

Table 5.2 displays the results for the Homeowners/Farmowners LOB; the pattern of variation by LOB-size is similar to that of the PPA LOB. The RRFs based on median and threshold approaches are similar, but not as close to each other as they were for PPA. The decrease in RRF from the median to the largest data points, from 27.7% to 5.6%, is a decrease of nearly 80%.

Table 5.2
Homeowners/Farmowners – RRFs by LOB-Size

(1) H/F

(A)	(B)	(C)	(D)	(E)	(F)
Size Band	Reserve ($000s)			87.5th Percentile Runoff Ratio	
Endpoint			Data	all points	all points
Percentile	from	to	Points	in band	>"from"
15%	0	169	1,398	83.3%	26.3%
25%	169	357	926	41.1%	**22.5%**
35%	357	672	931	33.6%	20.1%
45%	672	1,274	927	28.8%	18.0%
55%	1,274	2,500	932	**27.7%**	16.5%
65%	2,500	4,819	927	27.5%	14.2%
75%	4,819	9,742	930	14.2%	11.7%
85%	9,742	19,775	929	8.3%	10.4%
95%	19,775	74,324	930	12.2%	11.5%
largest 100	74,324	521,808	365	11.2%	10.4%
100%	521,808	27,109,142	100	5.6%	5.6%
	Current Risk Charge Runoff Ratio (PR016, Line 4)				20.1%

Table 5.3 displays the results for the MM – Occurrence LOB. The RRFs by LOB-size are more erratic for this line than for the two lines discussed above. The indicated RRFs have a 'local minimum' near the median LOB-size level and have lower values for some of the largest LOB-sizes. This pattern may be due to the relative low number of data points or

differences in types of business (primary vs. excess or institutions vs. health care providers) among the smaller, medium, and larger LOB-sizes.

The RRFs for the median and threshold approaches in Table 5.3, 17.5% and 30.5% respectively, are both lower than the RRF in the 2010 Formula, 43.1%. One factor contributing to this difference is the years of data used. As shown in Table 4.3, the RRFs for MM – Occurrence vary by initial reserve date. The RRF in the 2010 RBC formula may not fully reflect the effects of the more favorable 2006-2009 years included in data underlying Table 5.3.[32]

Another factor contributing to the difference between the RRF in the 2010 Formula and Table 5.3 indicated RRFs may be that data in Table 5.3 excludes minor lines data points while data underlying the RRFs in the 2010 Formula was not adjusted in that way. Table 3.3 showed that excluding minor lines data points has a significant effect on the indicated MM – Occurrence RRF.

[32] While 23 years might be considered a long period, to the extent that the 23 years in this data set, 1988-2010, had more favorable runoff experience than the prior decades, an RBC charge based on the past two decades alone might not be reflective of the long-term future experience.

Table 5.3
MM Occ. – RRFs by LOB-Size

(6) MM Occurrence					
(A)	(B)	(C)	(D)	(E)	(F)
Size Band	Reserve ($000s)			87.5th Percentile Runoff Ratio	
Endpoint			Data	all points	all points
Percentile	from	to	Points	in band	>"from"
15%	0	1,923	183	196.0%	41.1%
25%	1,923	5,289	122	67.8%	**30.5%**
35%	5,289	11,711	123	33.2%	24.8%
45%	11,711	19,746	122	31.4%	23.7%
55%	19,746	37,357	122	**17.5%**	22.5%
65%	37,357	73,248	122	58.4%	24.9%
75%	73,248	113,195	123	40.1%	19.7%
85%	113,195	245,022	122	12.2%	8.7%
95%	245,022	727,276	122	7.6%	7.4%
largest 100	727,276	1,397,205	31	-4.8%	7.1%
100%	1,397,205	3,130,491	31	9.0%	9.0%
	Current Risk Charge Runoff Ratio (PR016, Line 4)				43.1%

Table 5.4 displays the results for the Reinsurance – Liability LOB.

Table 5.4
Reinsurance Liability – RRFs by LOB-Size

(17) Reinsurance Liab					
(A)	(B)	(C)	(D)	(E)	(F)
Size Band	Reserve ($000s)			87.5th Percentile Runoff Ratio	
Endpoint			Data	all points	all points
Percentile	from	to	Points	in band	>"from"
15%	0	3,688	202	114.2%	67.6%
25%	3,688	8,712	135	55.2%	**65.0%**
35%	8,712	18,749	135	78.7%	65.6%
45%	18,749	34,829	135	58.3%	63.3%
55%	34,829	69,801	136	**93.9%**	63.9%
65%	69,801	136,546	135	43.8%	61.2%
75%	136,546	251,973	135	46.4%	65.3%
85%	251,973	582,726	135	68.8%	69.6%
95%	582,726	2,170,556	135	66.4%	70.8%
largest 100	2,170,556	4,502,562	34	122.8%	104.2%
100%	4,502,562	11,516,723	34	4.8%	4.8%
	Current Risk Charge Runoff Ratio (PR016, Line 4)				76.9%

The RRFs for this line generally decline with size, but the pattern is erratic, perhaps due to the small number of data points and/or the long-tail nature and related volatility of the reinsurance-liability LOB.

Corresponding tables for all LOBs are shown in Appendix D.

The tables in Appendix D also include the average, standard deviation, and coefficient of variation of the runoff ratios by LOB-size.

6. Maturity

The DCWP data set includes data points of varying development maturities. The most recent initial reserve date (2009) reflects one year of development. Initial reserve date 2008 reflects two years of development, etc. Initial reserve dates 1988-2001 are the most mature, and reflect reserve development to 9[33] years from the initial reserve date. The CCM and the baseline filtering in this paper treat all data points as equivalent, regardless of the maturity of the data.

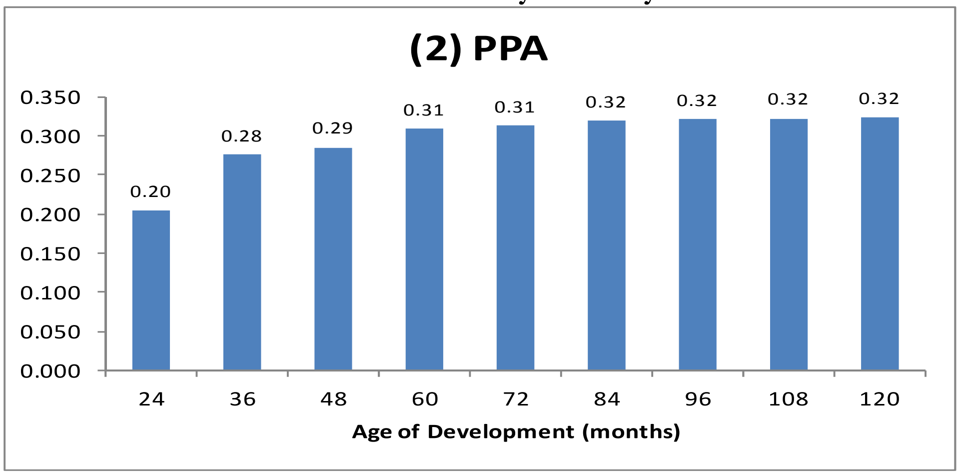
In this section we test whether such equivalent treatment is appropriate. To do so, we examined data from initial reserve dates 1988-2001. These are the initial reserve dates for which we have data points at every maturity from age 24 months to age 120 months. We use the same initial reserve dates for each maturity level to avoid bias that might arise from differences in RRF by initial reserve date shown in Section 4 above.

We calculated RRFs for each maturity level separately using the baseline filtering. The results are discussed below.

Table 6.1 shows the RRFs, for 1988-2001 initial reserve dates combined, grouped by maturity for the PPA LOB.

[33] This applies when 2010 is the most recent Annual Statement. If the most recent Annual Statement is 2009 or prior, then there are fewer runoff ratios at a maturity of 9 years.

Table 6.1
PPA – RRF by Maturity



By 60 months the RRF reaches a value within three percentage points[34] of the ultimate value, reached at 84 months.

Table 6.2 shows the corresponding RRFs for the Homeowners/Farmowners LOB; the pattern is similar to the PPA pattern.

Table 6.2
Homeowners/Farmowners – RRF by Maturity

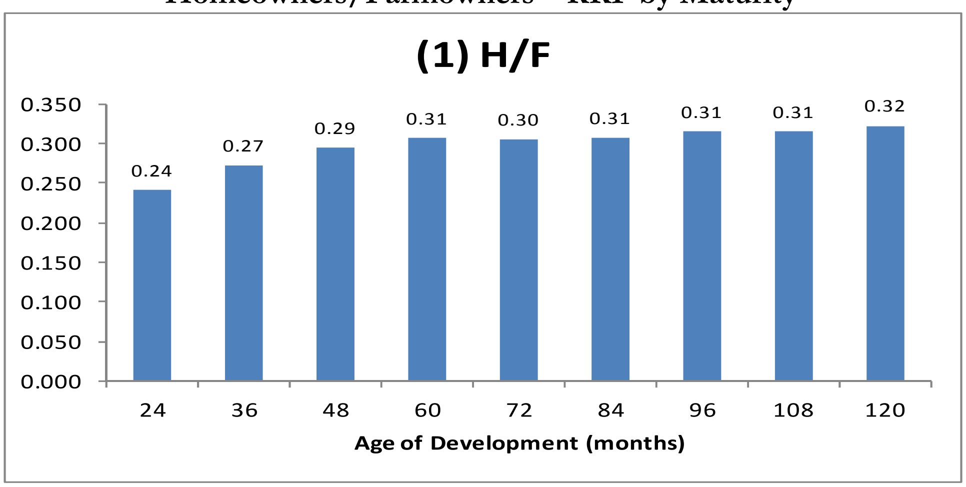
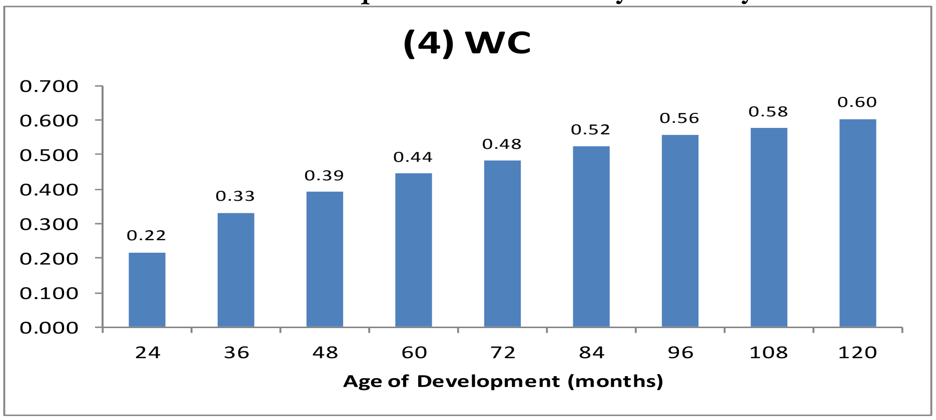


Table 6.3 shows the RRFs grouped by maturity for the workers compensation LOB.

[34] Three percentage points is an arbitrary, but we think reasonable, target for 'mature' for purposes of this paper.

Table 6.3
Workers Compensation – RRF by Maturity



The development period for workers compensation is much longer than for the PPA and Homeowners/Farmowners LOBs.

Some of the development in workers compensation RRF[35] might be due to emergence of tabular reserve. This working party did not analyze that effect.

Table 6.4, below, for the MM – Occurrence LOB shows RRFs that are within 3% of ultimate values by 72 months. Non-tabular reserve, which might appear for medical professional liability lines, does not affect the RRFs because the Schedule P data used in our analysis are gross of non-tabular discount.

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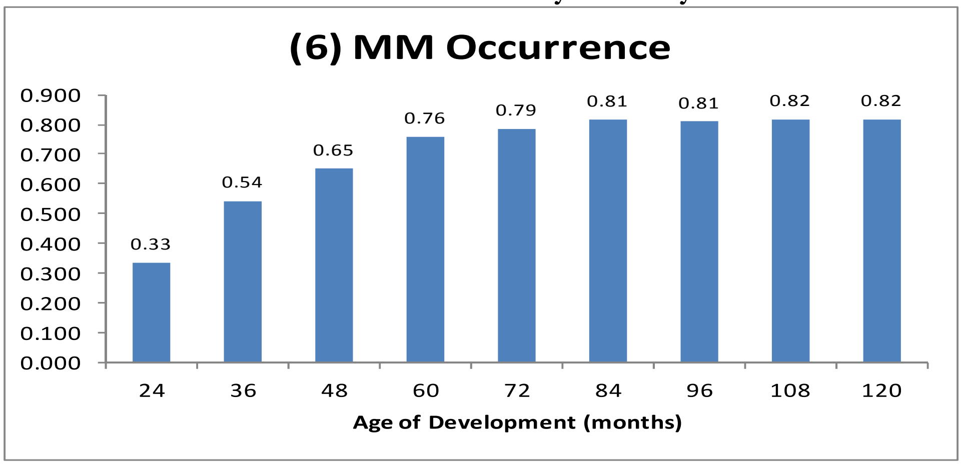
[35] The RRF should be designed with data gross of all interest discount, to the extent possible, in that Investment Income Offset in the RBC formula separately reflects the value of investment income for risk-based capital adequacy purpose.

Table 6.4
MM Occ. – RRF by Maturity



Corresponding tables for all LOBs are shown in Appendix E.

Table 6.5 displays the number of years of maturity required for the RRF to be within three percentage points of the mature RRF for the 1998-2001 initial reserve date experience period.

It is possible that the 1998-2001 time period reflected in Table 6.5 is not typical, at least for some lines, and further research is warranted to examine that. Even given that uncertainty, the simplest way to reflect the maturity issue in calibration of RRFs would be to discard data points that are not sufficiently mature.

A more complex method would be to adjust the RRFs for expected development and use the adjusted data in an all-year RRF calculation. That would require more analysis of the extent to which the RRF 'development' observed for initial reserve dates 1998-2001 is typical.

The working party has not tested the effect of either of the possible maturity adjustments.

Table 6.5
Development Years Needed to Reach Maturity

LOB	Years to Reach Maturity
(1) H/F	4
(2) PPA	5
(3) CA	5
(4) WC	9
(5) CMP	9
(6) MM Occurrence	7
(7) MM CM	8
(8) SL	*
(9) OL	9
(10) Fidelity & Surety	8
(11) Spec Prop *	9
(12) Auto Phys Damage *	9
(13) Other *	*
(15) International	*
(16) Rein Property & Financial	*
(17) Reinsurance Liab	*
(18) Products Liability	9

*The Two-Year LOBs show apparently very long time periods to reach maturity. The reserve risk analysis, unlike the premium risk analysis, requires matching data across Annual Statement years.

For 2-year lines we believe this analysis is not meaningful, as it is too distorted by inconsistent reporting of paid and incurred loss and DCCE triangles in Schedule P Part 2 and Part 3.

7. Years of NEP > 0

The baseline filtering excludes data from LOBs where the company has had less than five years of positive NEP in that LOB. The five year trigger was selected given that some minimum seemed appropriate, and we wanted to test a criterion that was less strict than the 10 year requirement in the CCM.

To test whether the five years was appropriate and evaluate the extent to which RRFs vary by years of NEP, we grouped the data points based on the number of years of positive NEP for the LOB-company/pool and calculated the RRFs for each of the groups.

Table 7.1 shows the reserves and number of data points in each of the NEP>0 year groupings. We see that the 20 and over group is a significant proportion of the total: approximately 90% of the reserves and approximately 62% of the data points. There is relatively little data in the category 0-4 years of NEP>0.[36]

Table 7.1
Reserve and Data Points by Number of Years

	Reserve ($000,000s)					Data Point				
LOB	0-4	5-9	10-19	>=20	Total	0-4	5-9	10-19	>=20	Total
(1) H/F	259	2,710	25,151	239,181	267,300	85	382	1,631	4,992	7,090
(2) PPA	364	3,621	75,989	1,346,589	1,426,562	68	230	1,904	4,625	6,827
(3) CA	128	4,957	29,545	351,104	385,734	27	268	1,322	3,379	4,996
(4) WC	749	26,324	190,318	1,991,671	2,209,062	45	622	2,330	3,384	6,381
(5) CMP	258	2,337	46,048	517,353	565,996	40	203	1,649	3,879	5,771
(6) MM Occurrence	784	1,207	56,234	142,037	200,263	35	81	333	644	1,093
(7) MM CM	78	8,939	29,876	159,837	198,730	19	607	561	1,011	2,198
(8) SL	51	1,156	3,270	32,829	37,306	27	97	339	606	1,069
(9) OL	3,920	6,742	126,499	1,347,227	1,484,389	92	530	1,982	4,688	7,292
(11) Spec Prop	73	992	21,767	75,815	98,647	50	267	1,687	3,481	5,485
(12) Auto Phys Damage	150	244	3,478	54,175	58,048	41	158	1,076	2,186	3,461
(10) Fidelity & Surety	93	16	1,573	10,232	11,914	12	23	320	572	927
(13) Other	913	480	21,201	7,437	30,032	20	75	625	424	1,144
(15) International	7	95	2,047	845	2,993	11	17	40	22	90
(16) Rein Property & Financial	15	1,603	18,404	80,781	100,803	11	89	388	562	1,050
(17) Reinsurance Liab	621	5,212	45,339	532,242	583,415	20	163	424	627	1,234
(18) Products Liability	644	53	4,901	20,282	25,879	38	16	216	350	620
Total	9,106	66,690	701,638	6,909,638	7,687,072	641	3,828	16,827	35,432	56,728
	0%	1%	9%	90%	100%	1%	7%	30%	62%	100%

Tables 7.2 – 7.5 shows the RRFs grouped in bands by "number of years of NEP>0" for the PPA, Homeowners/Farmowners, workers compensation and MM – Occurrence LOBs. In these four cases, and for nearly all lines of business, the RRFs are lowest for the data points in the group with longest NEP>0 for >=20 years, i.e., for the most long-lived companies.

[36] The data points considered here are those that remain after minor and size filters. Those filters will have removed some of the data points in the category of NEP>0 for less than five years. The data set before filtering likely includes more data points with NEP>0 for less than five years.

Table 7.2
PPA – RRF by Number of Years

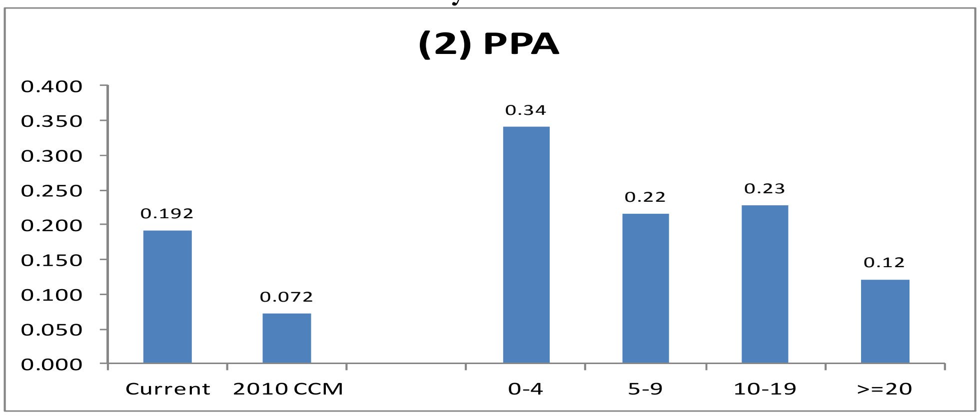


Table 7.3
Homeowners/Farmowners – RRF by Number of Years

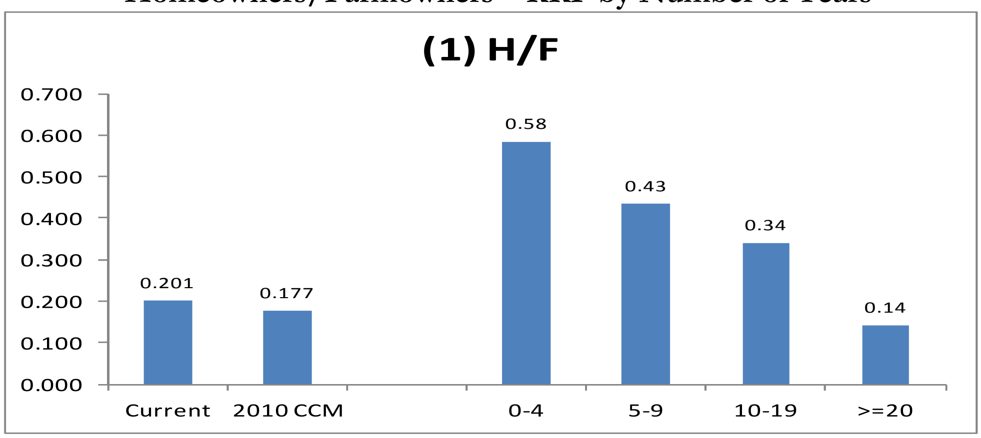


Table 7.4
Workers Compensation – RRF by Number of Years

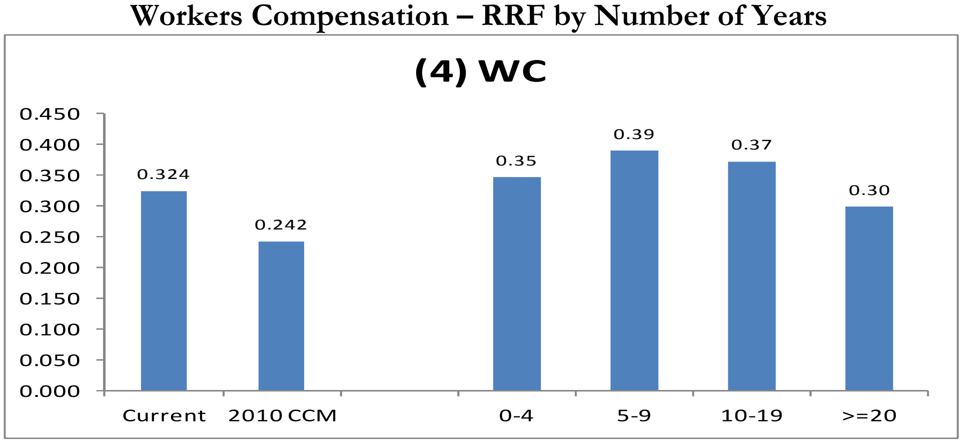
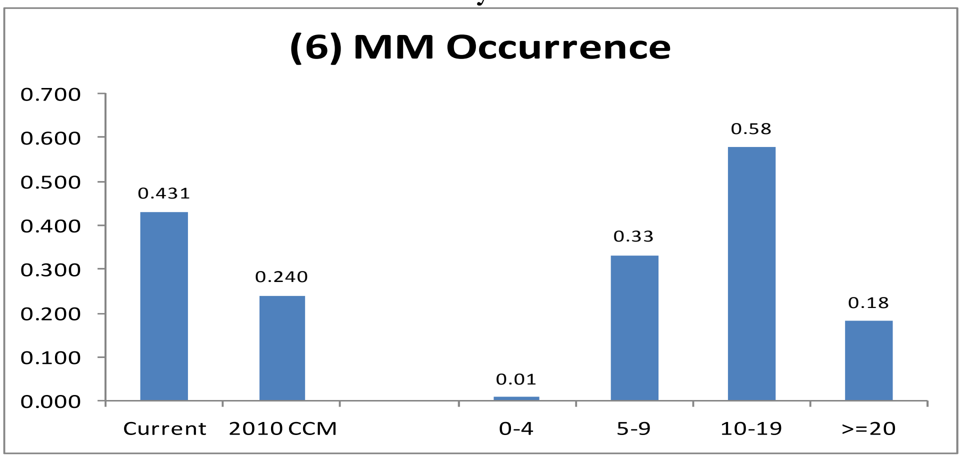


Table 7.5
MM Occ. – RRF by Number of Years



Corresponding tables for all LOBs are shown in Appendix F.

8. Further Research

DCWP is conducting research in the following areas, and reports will be published in due course.

1. Variation in RRFs by type of company; e.g., personal lines, professional reinsurer, etc.
2. Solvency II modeling approach vs. the "empirical approach" used in the research.
3. Comparison of RRFs developed as described in this paper to RRFs obtained by company specific methods such as Mack, stochastic reserving, and the like.

There are a number of other interesting issues, but DCWP is not now conducting research on those areas. These include the following:

A. Issues identified in the report:

4. Effect of maturity for experience periods other than 1998-2001.
5. Effect of workers compensation tabular reserve on observed maturity effect.
6. Interactions between RRF calibration and own-company adjustment and other

aspects of the filtering used in final calibration.

It seems logical that industry average reserve development ratios used in the own company adjustment process should be based on industry average from companies that are consistent with the filtering used to calibrate the RRFs; e.g., excluding minor lines and LOB-size above the size threshold. This report does not examine the impact of that issue, but it may be significant.

7. Investment Income offset – The investment income offset might best be determined considering the years used to calibrate the RRF, as higher interest rates might produce higher reserve runoff ratios and higher RRFs in the past.

8. Risk metrics

    Higher confidence levels, e.g., 90%, 95%... vs. 87.5%

    TVaR vs. VaR vs. Butsic (risk adjusted VaR, DCWP Report 5).

9. Risk metric – Currently it is based on a percentile over all data points all years. Alternatives include percentile determined:

    within years, or

    within companies.

10. Alternative time horizons

9. Authors

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Karen H. Adams, Daniel M. Murphy, Timothy Sweetser, Giuseppe (Franco) LePera

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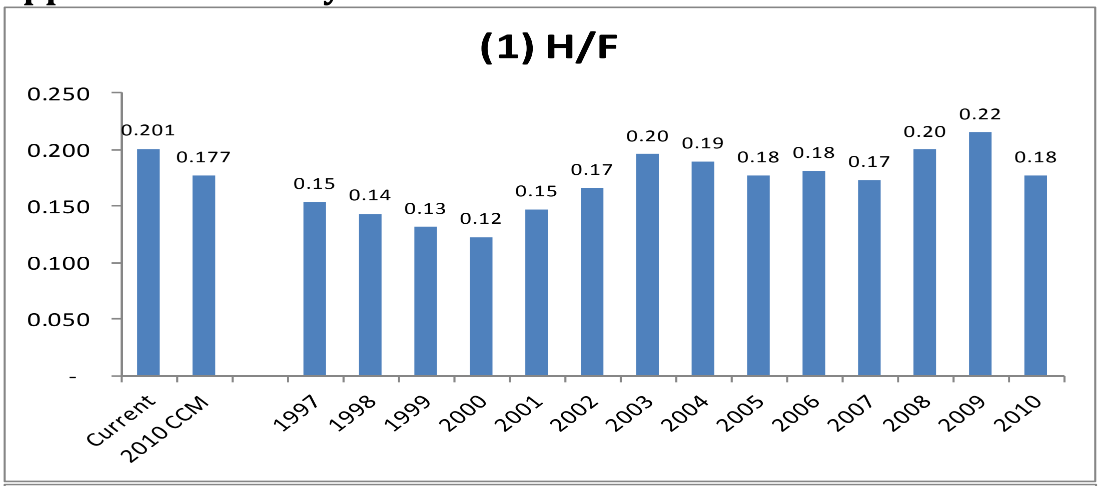
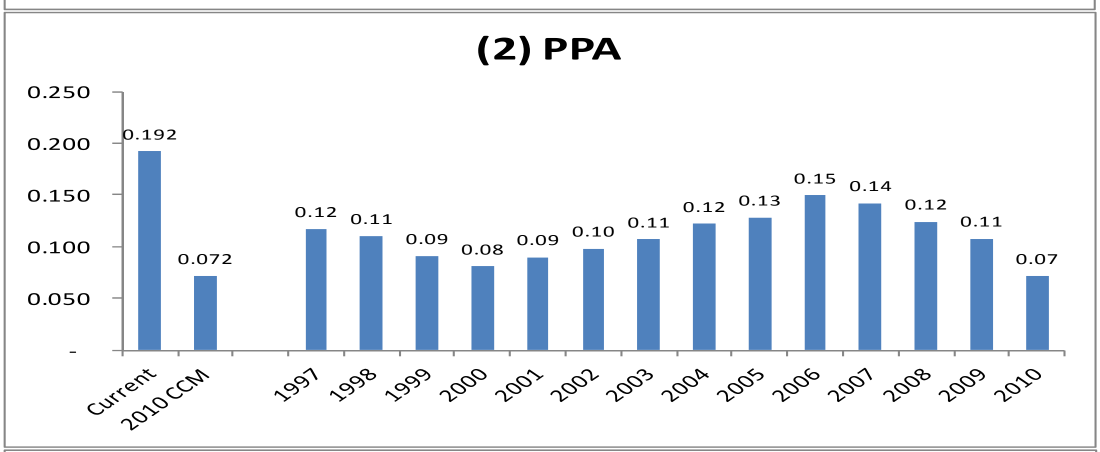
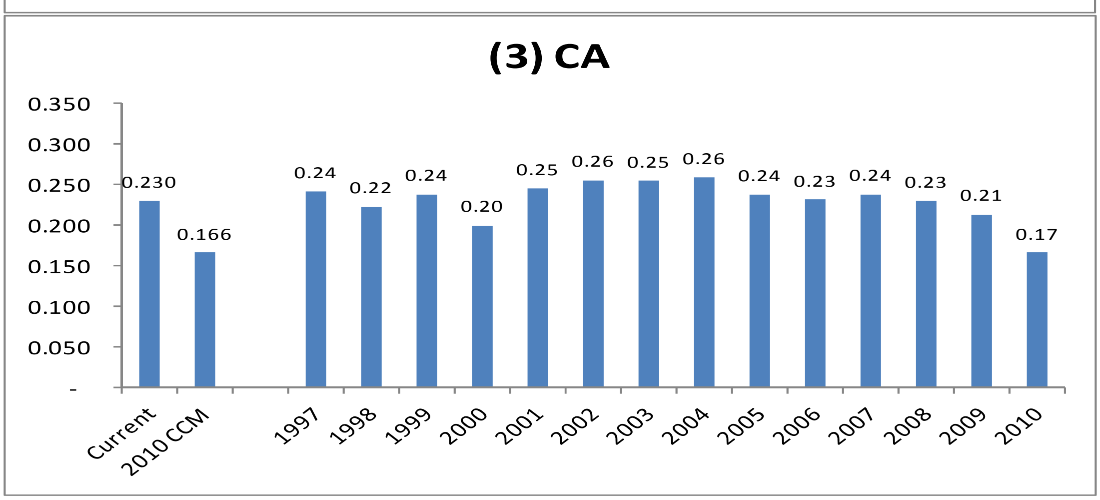
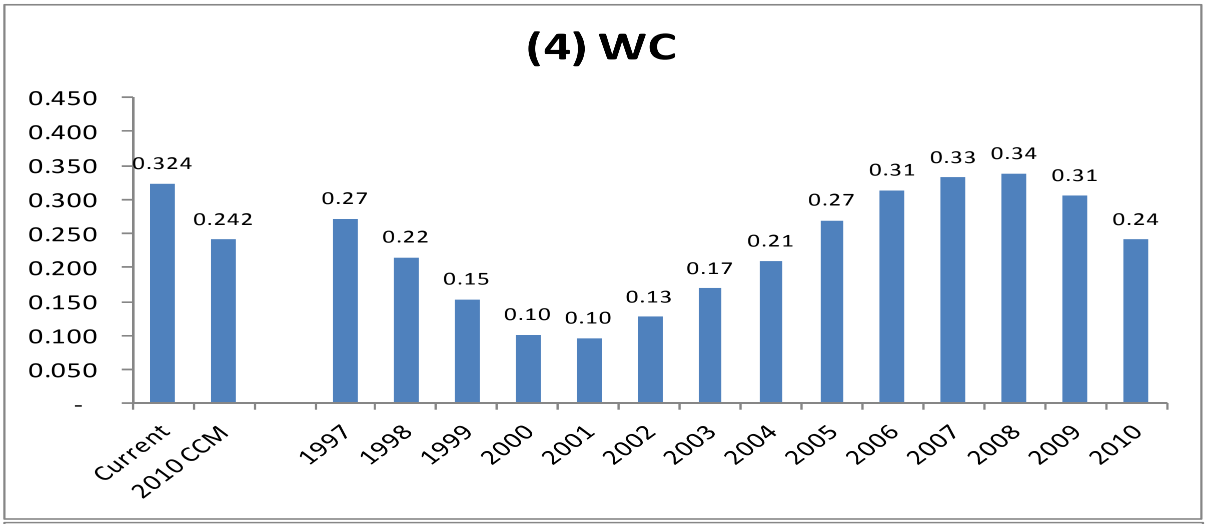
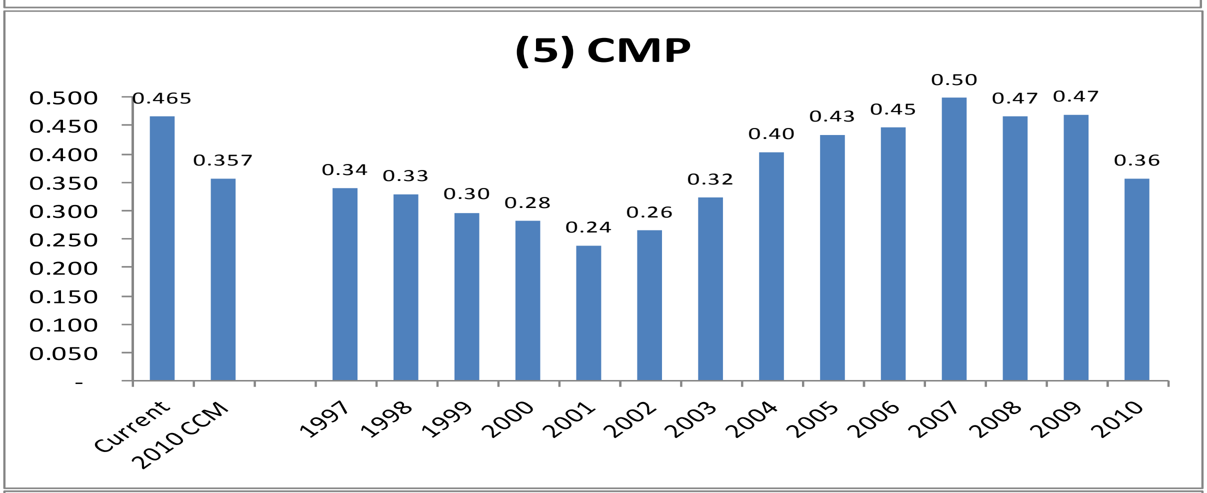
Appendix A –RRF by Annual Statement Year based on CCM

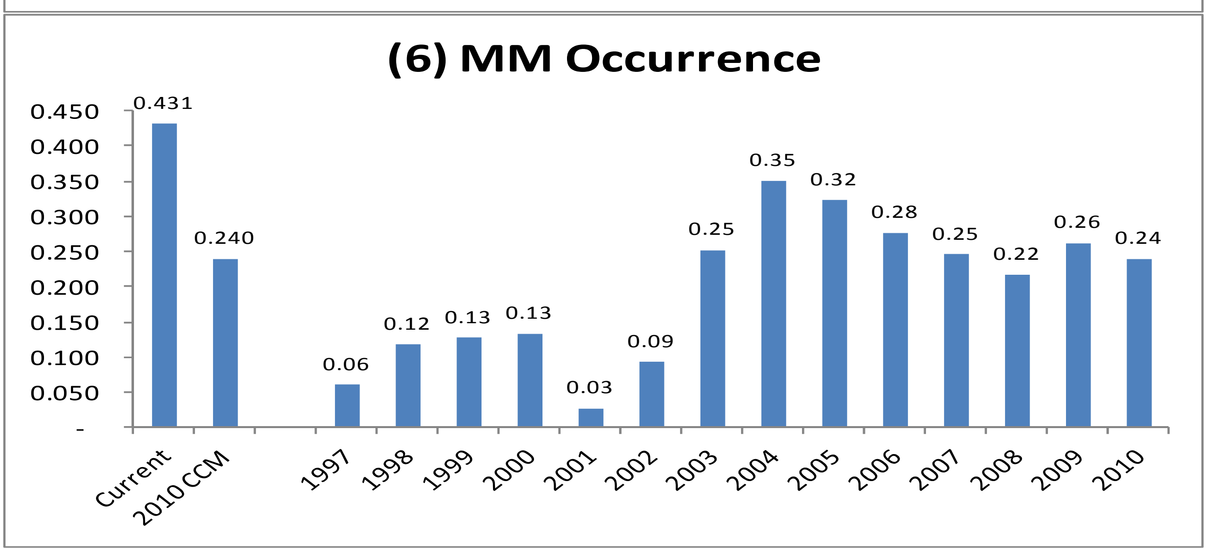




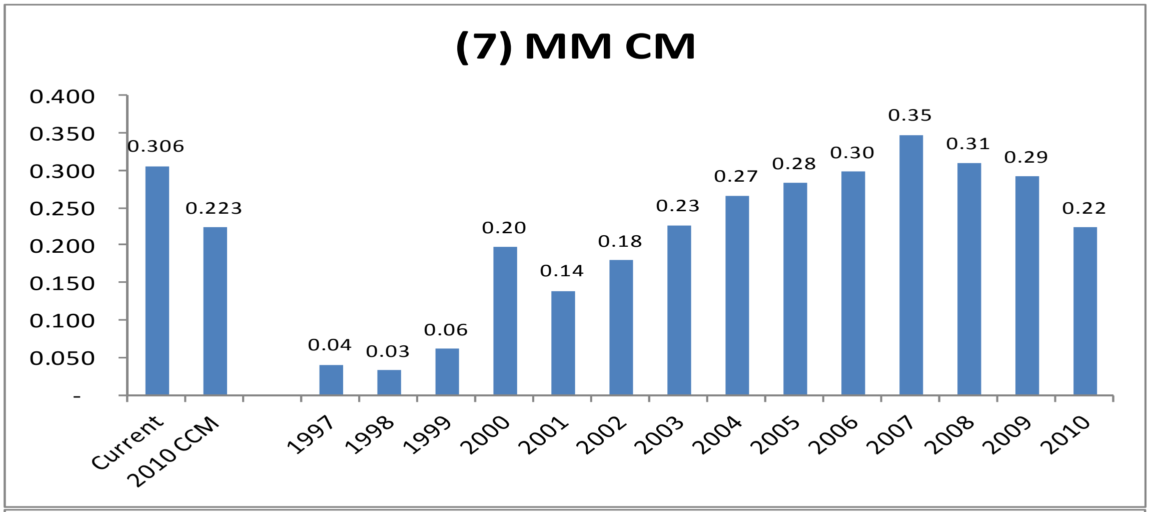


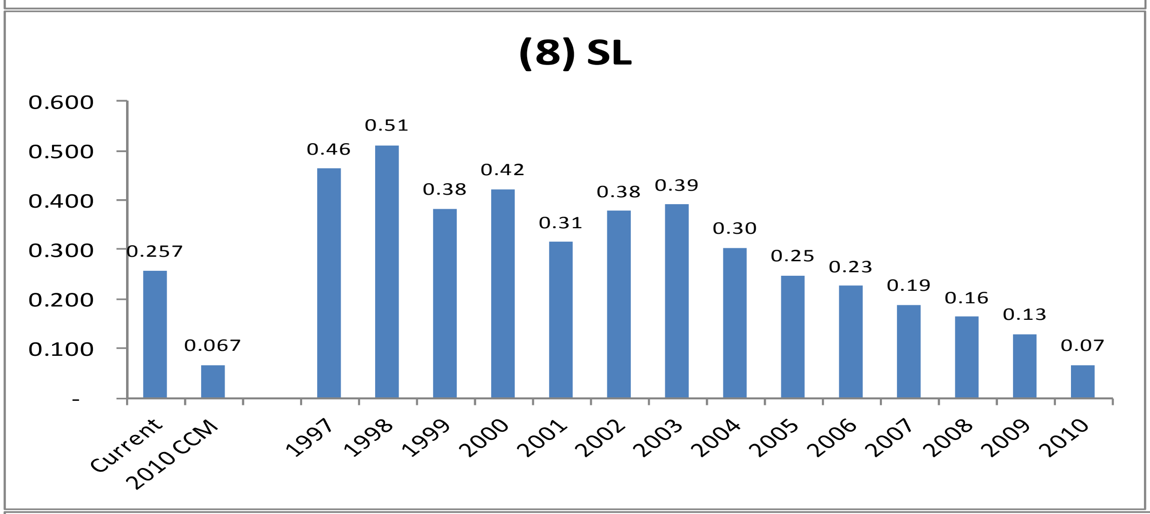

(4) WC
0.450
0.400
0.350
0.300
0.250
0.200
0.150
0.100
0.050
-
0.324
0.242
0.27
0.22
0.15
0.10
0.10
0.13
0.17
0.21
0.27
0.31
0.33
0.34
0.31
0.24
Current
2010 CCM
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010

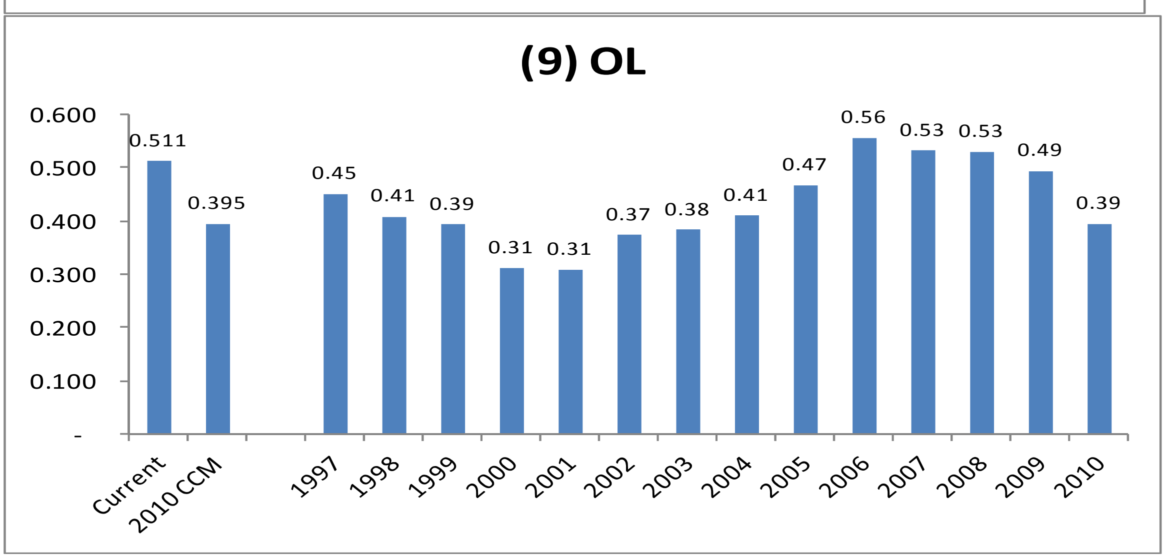

(5) CMP
0.500
0.450
0.400
0.350
0.300
0.250
0.200
0.150
0.100
0.050
-
0.465
0.357
0.34
0.33
0.30
0.28
0.24
0.26
0.32
0.40
0.43
0.45
0.50
0.47
0.47
0.36
Current
2010 CCM
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010


(6) MM Occurrence
0.450
0.400
0.350
0.300
0.250
0.200
0.150
0.100
0.050
-
0.431
0.240
0.06
0.12
0.13
0.13
0.03
0.09
0.25
0.35
0.32
0.28
0.25
0.22
0.26
0.24
Current
2010 CCM
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010

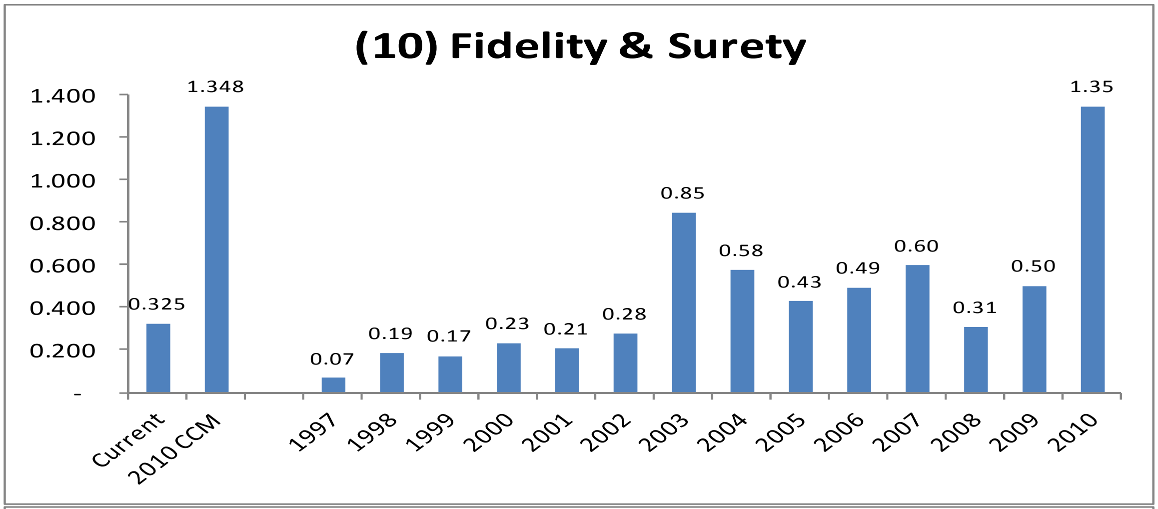
Appendix A – RRF by Annual Statement Year based on CCM

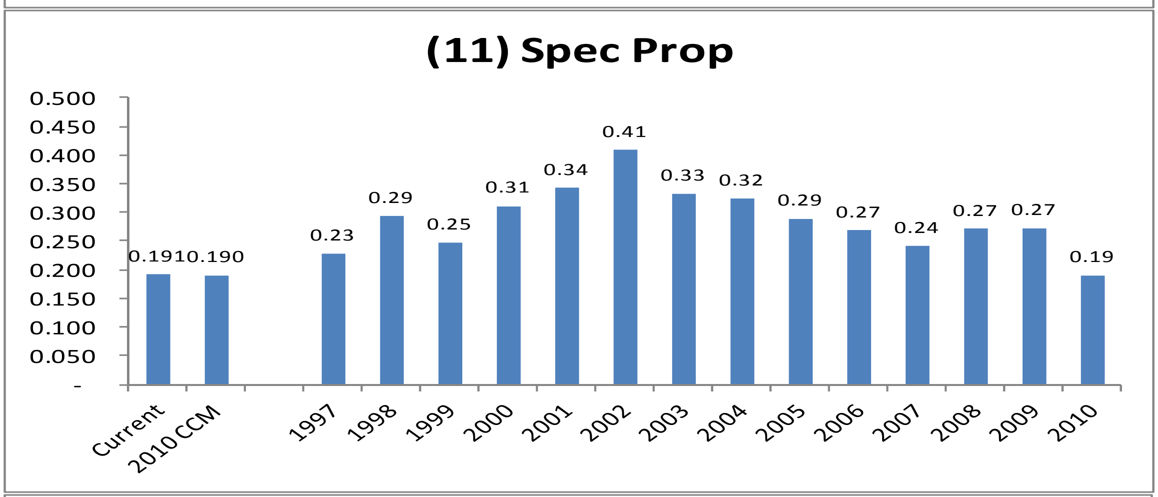


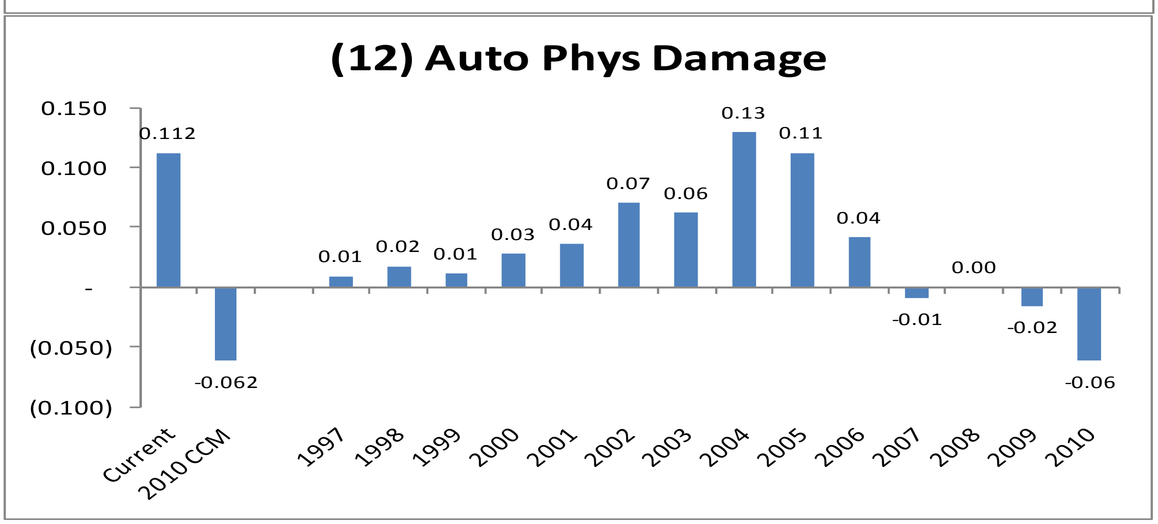


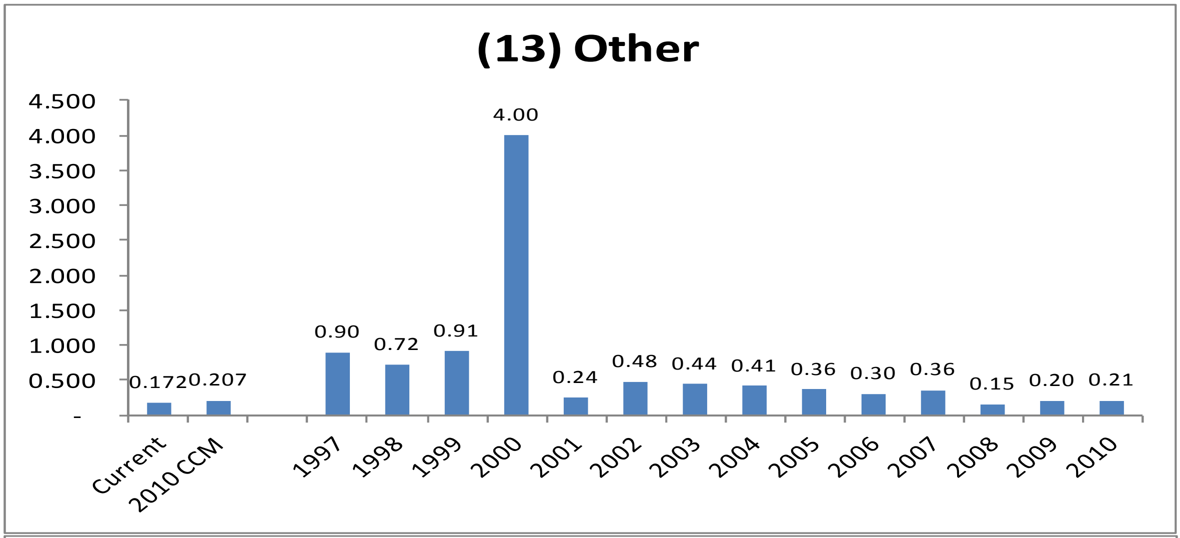


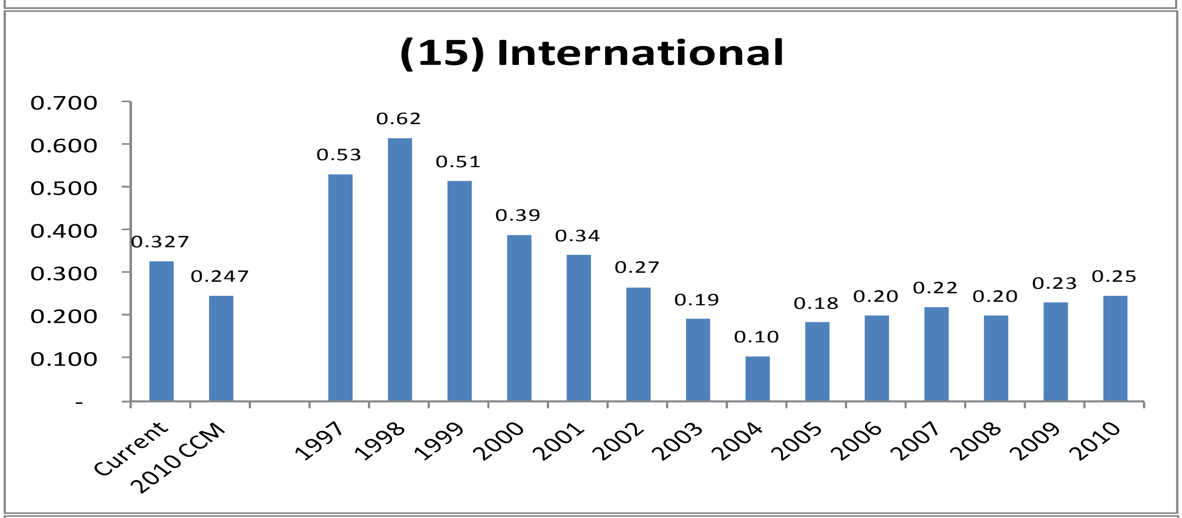
Appendix A – RRF by Annual Statement Year based on CCM

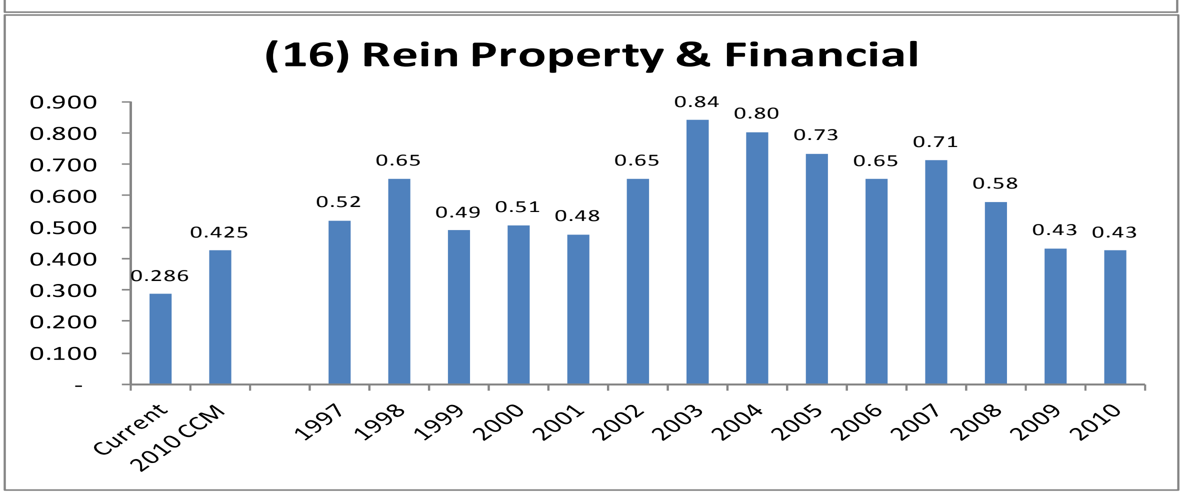


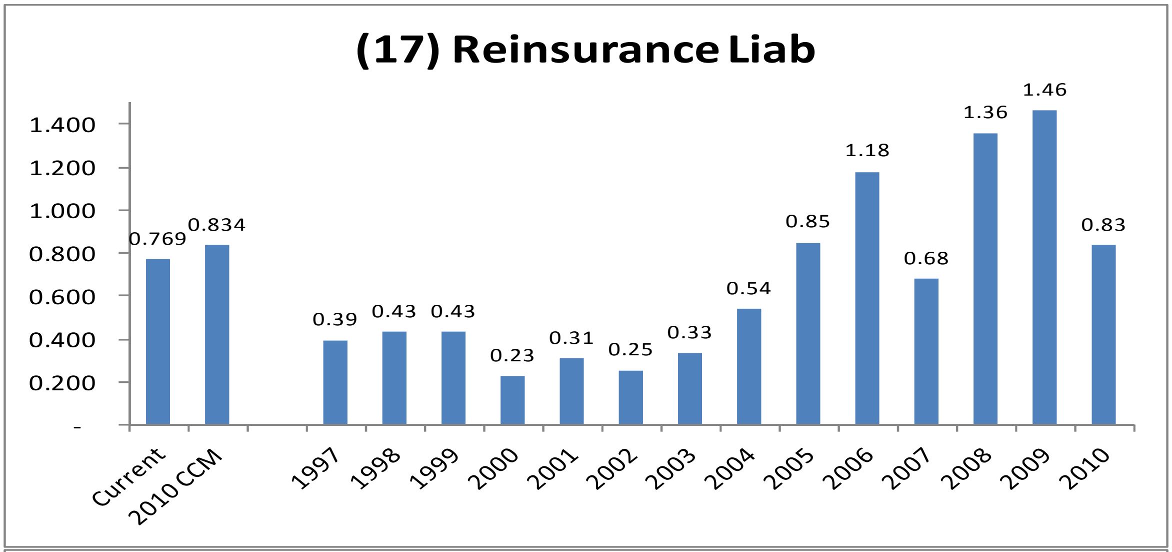


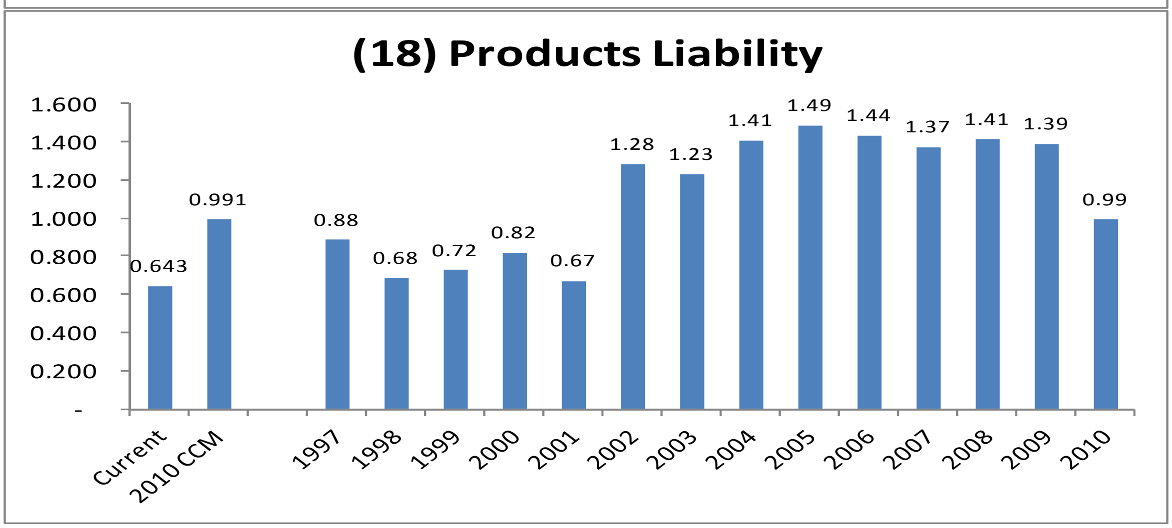



(13) Other
4.500
4.000
3.500
3.000
2.500
2.000
1.500
1.000
0.500
-
0.172
0.207
0.90
0.72
0.91
4.00
0.24
0.48
0.44
0.41
0.36
0.30
0.36
0.15
0.20
0.21
Current
2010 CCM
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010


(15) International
0.700
0.600
0.500
0.400
0.300
0.200
0.100
-
0.327
0.247
0.53
0.62
0.51
0.39
0.34
0.27
0.19
0.10
0.18
0.20
0.22
0.20
0.23
0.25
Current
2010 CCM
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010

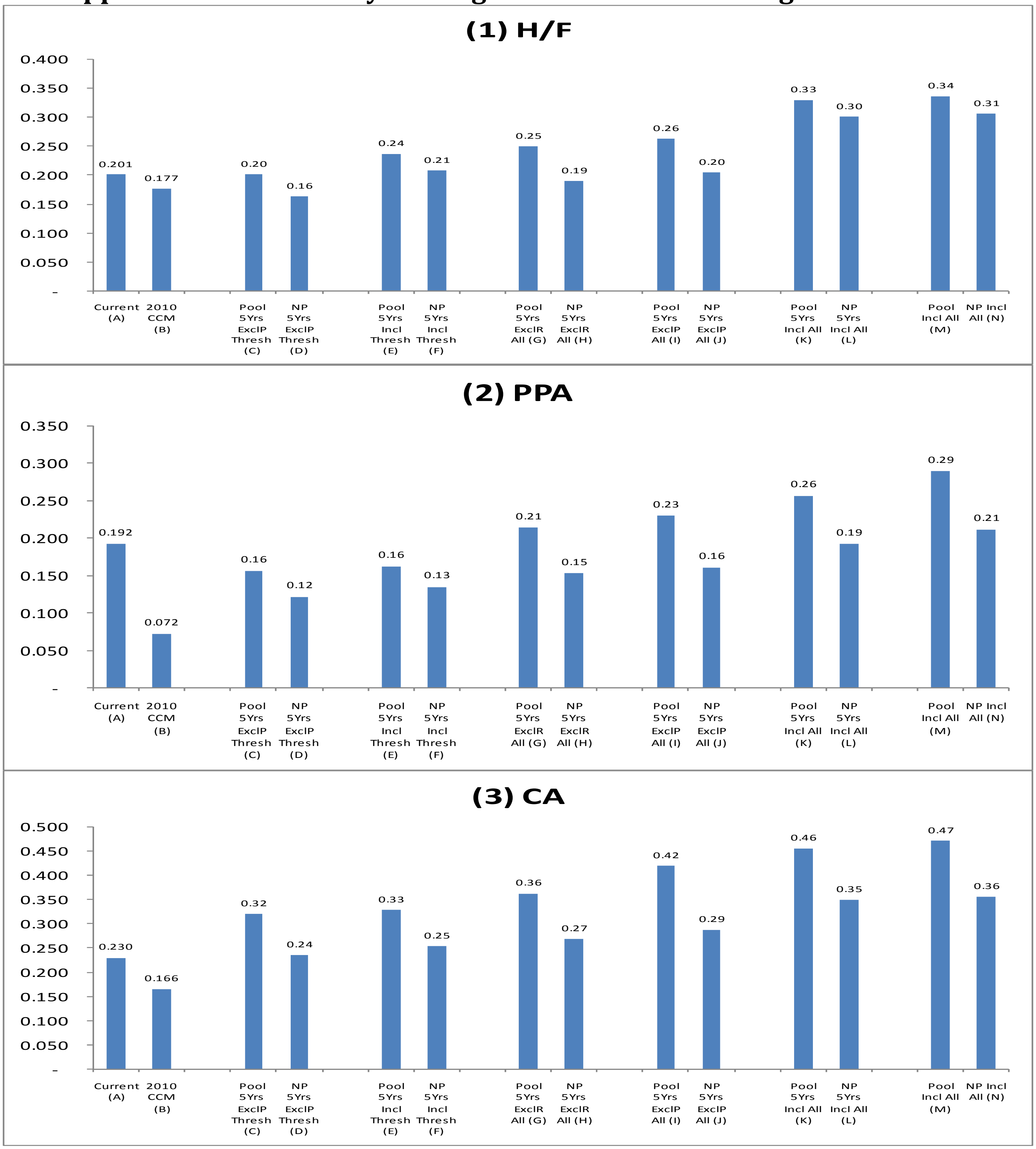

(16) Rein Property & Financial
0.900
0.800
0.700
0.600
0.500
0.400
0.300
0.200
0.100
-
0.286
0.425
0.52
0.65
0.49
0.51
0.48
0.65
0.84
0.80
0.73
0.65
0.71
0.58
0.43
0.43
Current
2010 CCM
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010

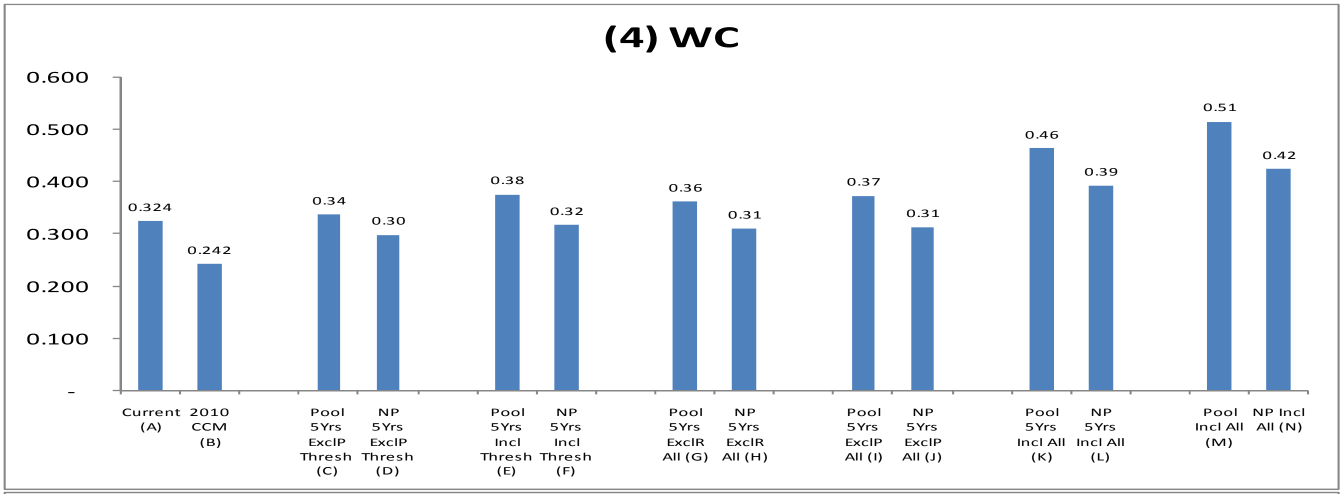


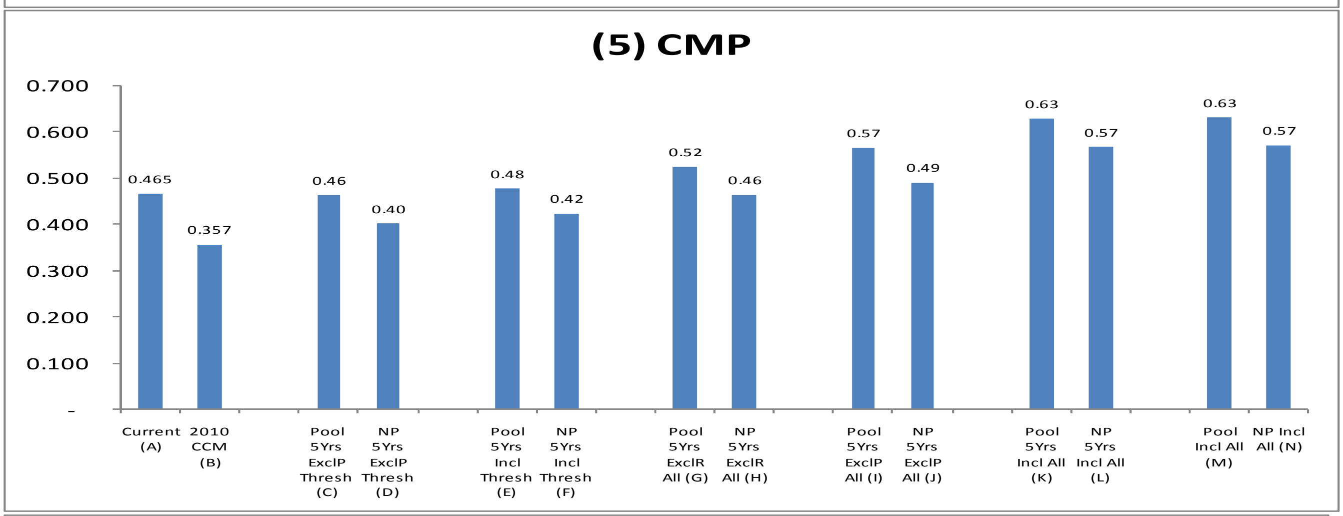


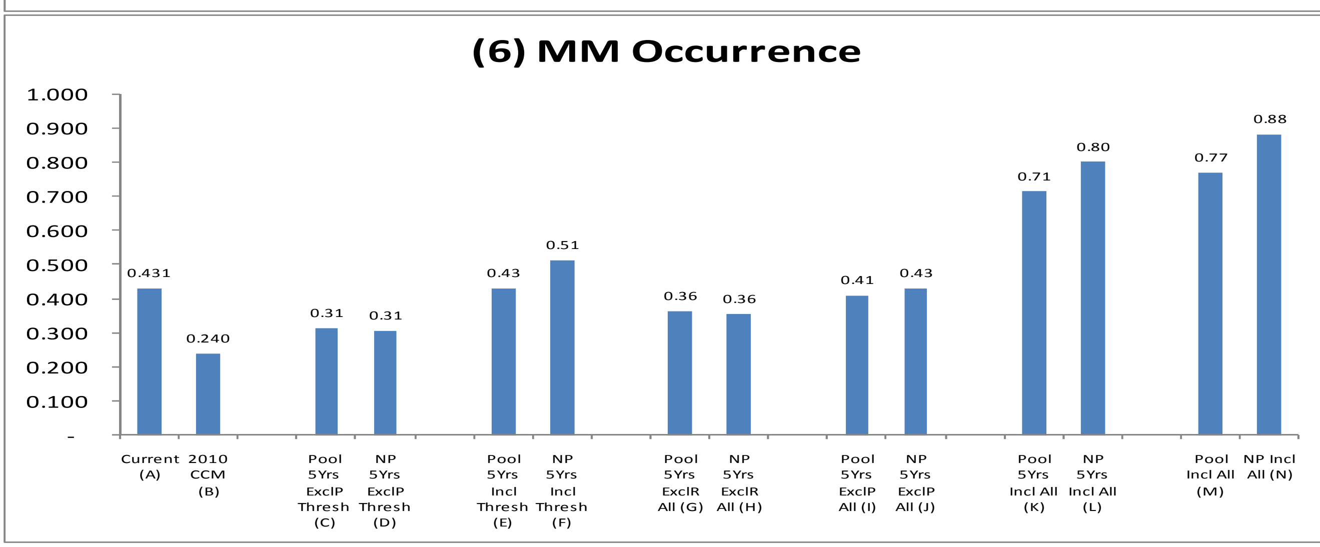
Note: (14) Financial/Mortgage and (19) Warranty are not shown as data for those lines is so new and sparse that charts are not meaningful.

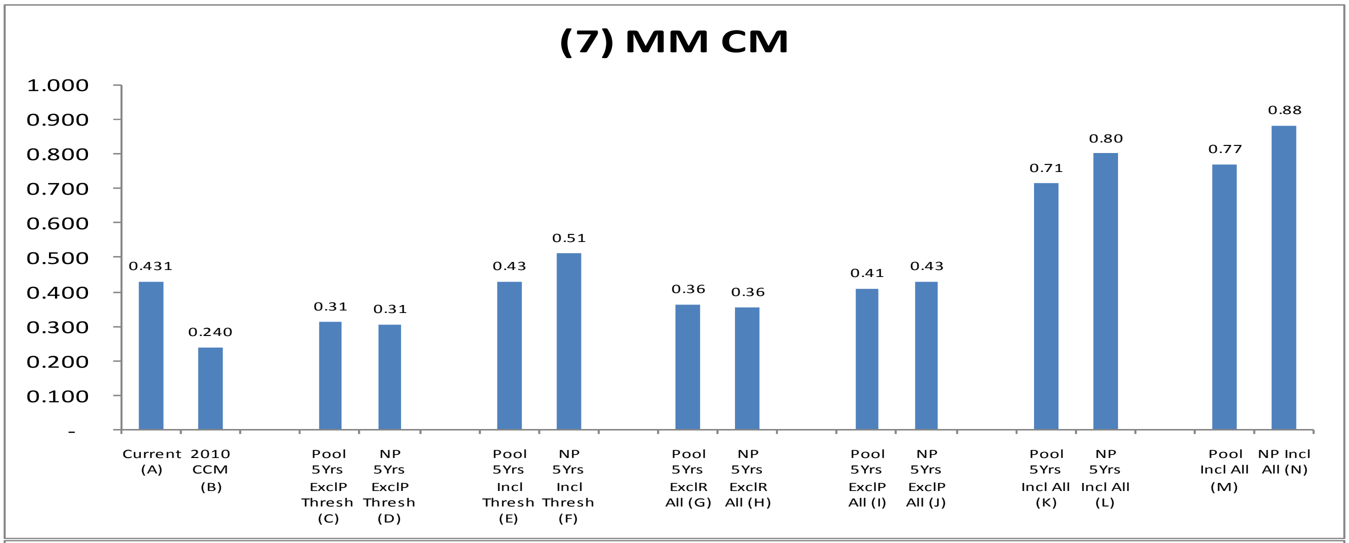
Appendix B – Sensitivity Testing of Alternative Filtering Methods

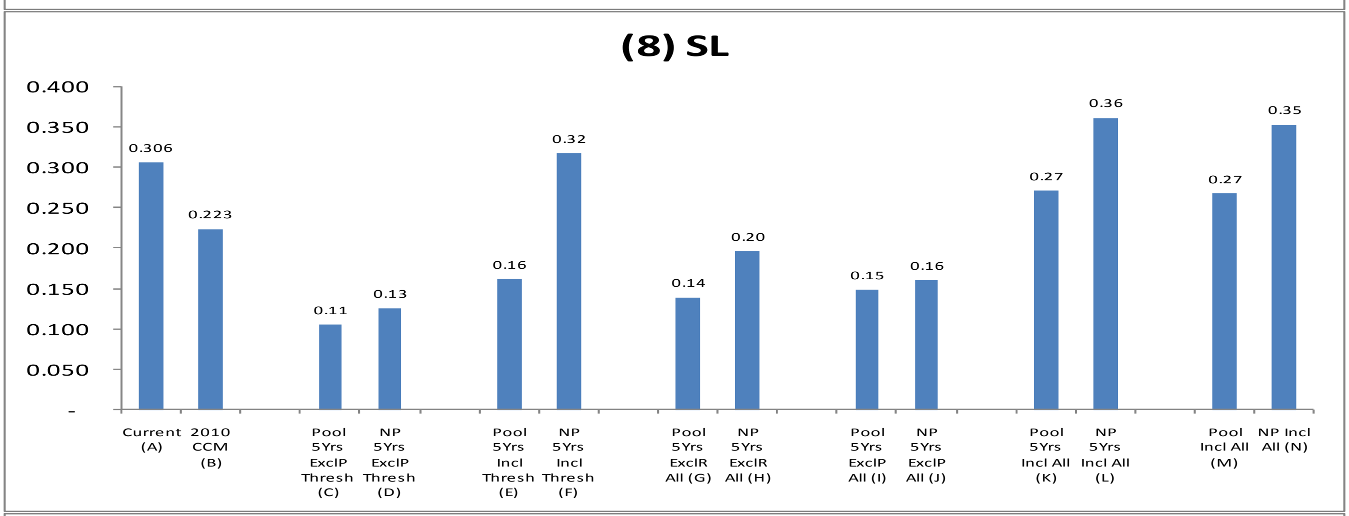



(4) WC
0.600
0.500
0.400
0.300
0.200
0.100
-
0.324
0.242
0.34
0.30
0.38
0.32
0.36
0.31
0.37
0.31
0.46
0.39
0.51
0.42
Current (A)
2010 CCM (B)
Pool 5Yrs ExclP Thresh (C)
NP 5Yrs ExclP Thresh (D)
Pool 5Yrs Incl Thresh (E)
NP 5Yrs Incl Thresh (F)
Pool 5Yrs ExclR All (G)
NP 5Yrs ExclR All (H)
Pool 5Yrs ExclP All (I)
NP 5Yrs ExclP All (J)
Pool 5Yrs Incl All (K)
NP 5Yrs Incl All (L)
Pool Incl All (M)
NP Incl All (N)


(5) CMP
0.700
0.600
0.500
0.400
0.300
0.200
0.100
-
0.465
0.357
0.46
0.40
0.48
0.42
0.52
0.46
0.57
0.49
0.63
0.57
0.63
0.57
Current (A)
2010 CCM (B)
Pool 5Yrs ExclP Thresh (C)
NP 5Yrs ExclP Thresh (D)
Pool 5Yrs Incl Thresh (E)
NP 5Yrs Incl Thresh (F)
Pool 5Yrs ExclR All (G)
NP 5Yrs ExclR All (H)
Pool 5Yrs ExclP All (I)
NP 5Yrs ExclP All (J)
Pool 5Yrs Incl All (K)
NP 5Yrs Incl All (L)
Pool Incl All (M)
NP Incl All (N)


(6) MM Occurrence
1.000
0.900
0.800
0.700
0.600
0.500
0.400
0.300
0.200
0.100
-
0.431
0.240
0.31
0.31
0.43
0.51
0.36
0.36
0.41
0.43
0.71
0.80
0.77
0.88
Current (A)
2010 CCM (B)
Pool 5Yrs ExclP Thresh (C)
NP 5Yrs ExclP Thresh (D)
Pool 5Yrs Incl Thresh (E)
NP 5Yrs Incl Thresh (F)
Pool 5Yrs ExclR All (G)
NP 5Yrs ExclR All (H)
Pool 5Yrs ExclP All (I)
NP 5Yrs ExclP All (J)
Pool 5Yrs Incl All (K)
NP 5Yrs Incl All (L)
Pool Incl All (M)
NP Incl All (N)


(7) MM CM
1.000
0.900
0.800
0.700
0.600
0.500
0.400
0.300
0.200
0.100
-
0.431
0.240
0.31
0.31
0.43
0.51
0.36
0.36
0.41
0.43
0.71
0.80
0.77
0.88
Current (A)
2010 CCM (B)
Pool 5Yrs ExclP Thresh (C)
NP 5Yrs ExclP Thresh (D)
Pool 5Yrs Incl Thresh (E)
NP 5Yrs Incl Thresh (F)
Pool 5Yrs ExclR All (G)
NP 5Yrs ExclR All (H)
Pool 5Yrs ExclP All (I)
NP 5Yrs ExclP All (J)
Pool 5Yrs Incl All (K)
NP 5Yrs Incl All (L)
Pool Incl All (M)
NP Incl All (N)


(8) SL
0.400
0.350
0.300
0.250
0.200
0.150
0.100
0.050
-
0.306
0.223
0.11
0.13
0.16
0.32
0.14
0.20
0.15
0.16
0.27
0.36
0.27
0.35
Current (A)
2010 CCM (B)
Pool 5Yrs ExclP Thresh (C)
NP 5Yrs ExclP Thresh (D)
Pool 5Yrs Incl Thresh (E)
NP 5Yrs Incl Thresh (F)
Pool 5Yrs ExclR All (G)
NP 5Yrs ExclR All (H)
Pool 5Yrs ExclP All (I)
NP 5Yrs ExclP All (J)
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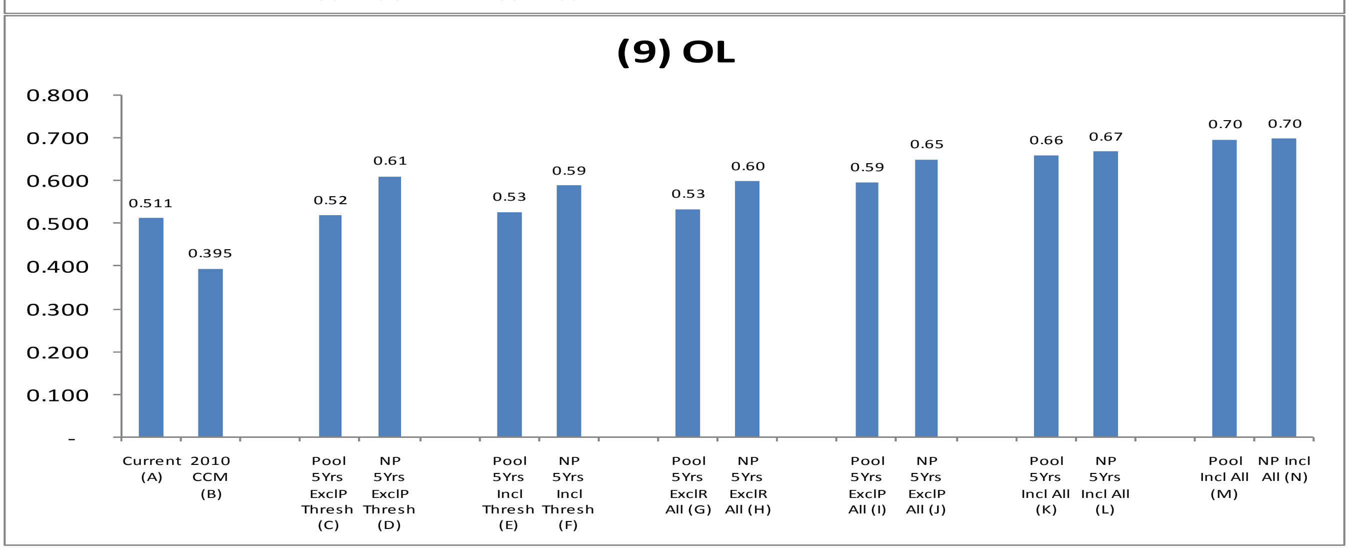
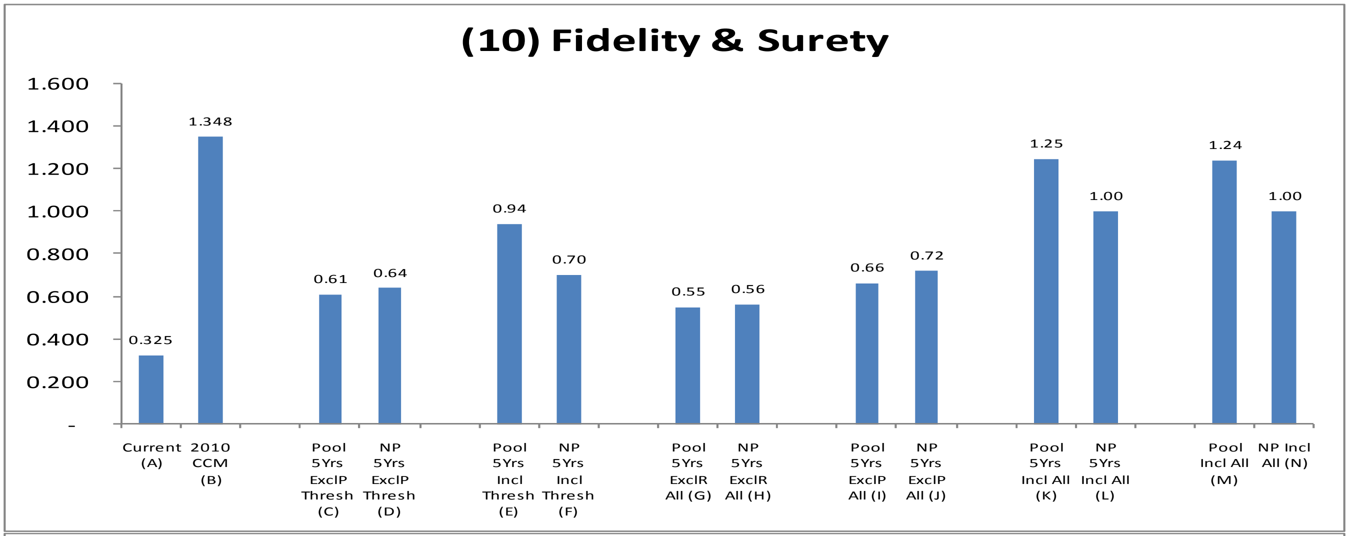
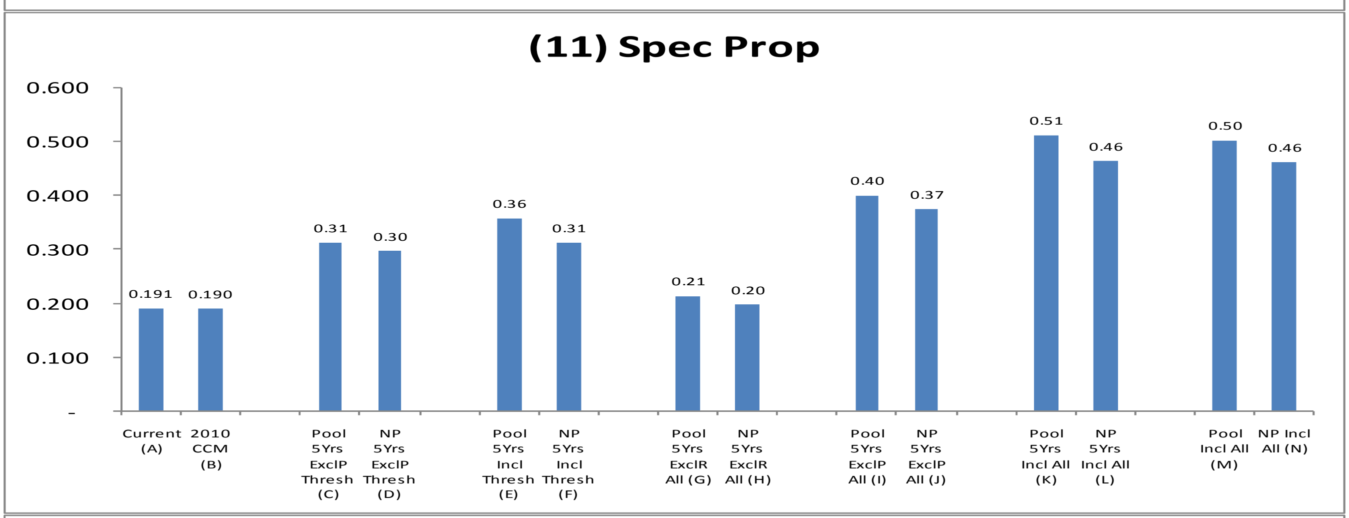
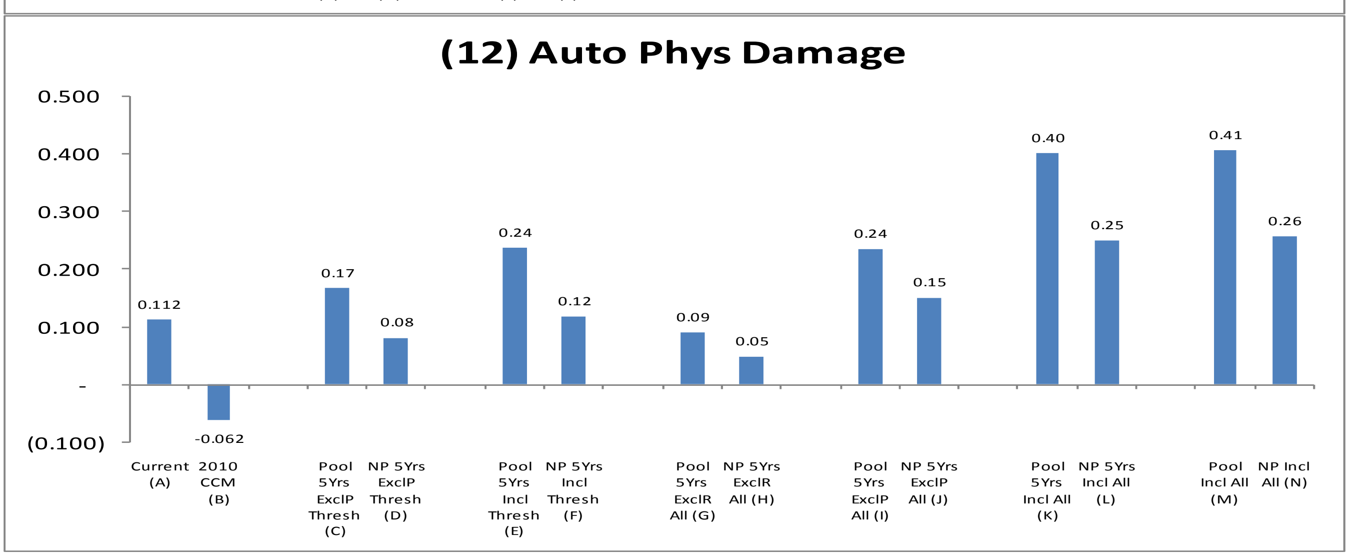
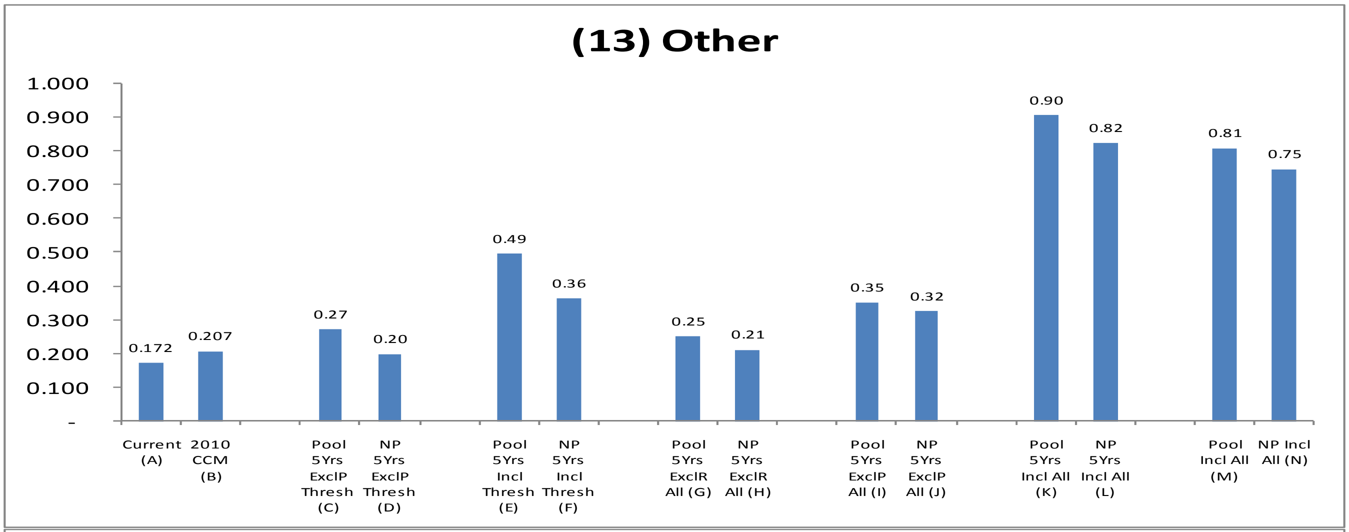
Pool Incl All (M)
NP Incl All (N)

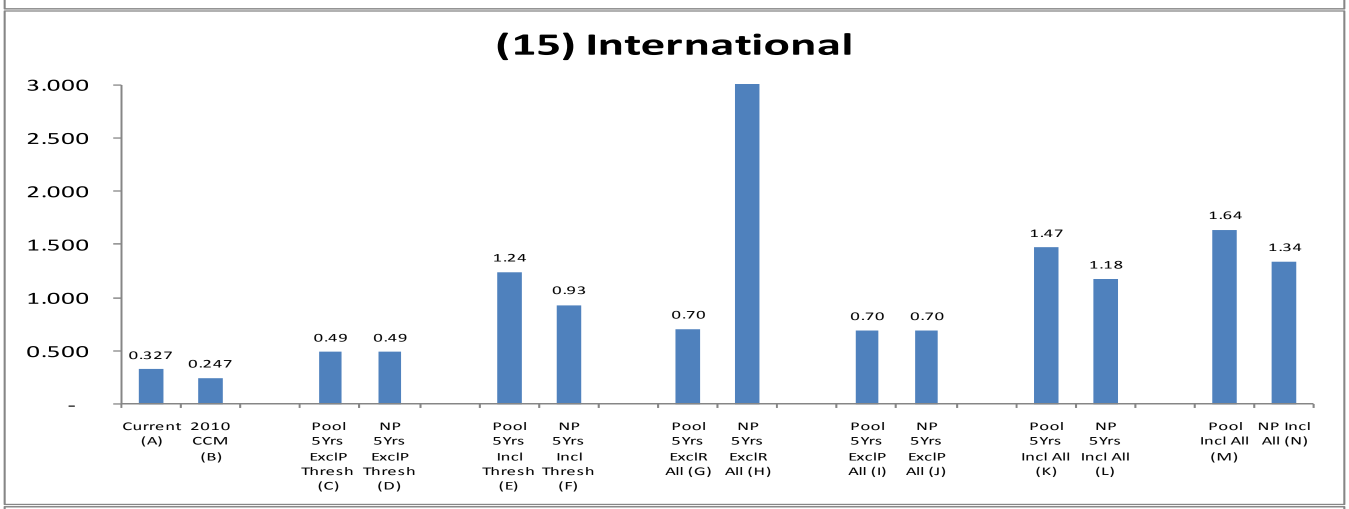

(9) OL
0.800
0.700
0.600
0.500
0.400
0.300
0.200
0.100
-
0.511
0.395
0.52
0.61
0.53
0.59
0.53
0.60
0.59
0.65
0.66
0.67
0.70
0.70
Current (A)
2010 CCM (B)
Pool 5Yrs ExclP Thresh (C)
NP 5Yrs ExclP Thresh (D)
Pool 5Yrs Incl Thresh (E)
NP 5Yrs Incl Thresh (F)
Pool 5Yrs ExclR All (G)
NP 5Yrs ExclR All (H)
Pool 5Yrs ExclP All (I)
NP 5Yrs ExclP All (J)
Pool 5Yrs Incl All (K)
NP 5Yrs Incl All (L)
Pool Incl All (M)
NP Incl All (N)

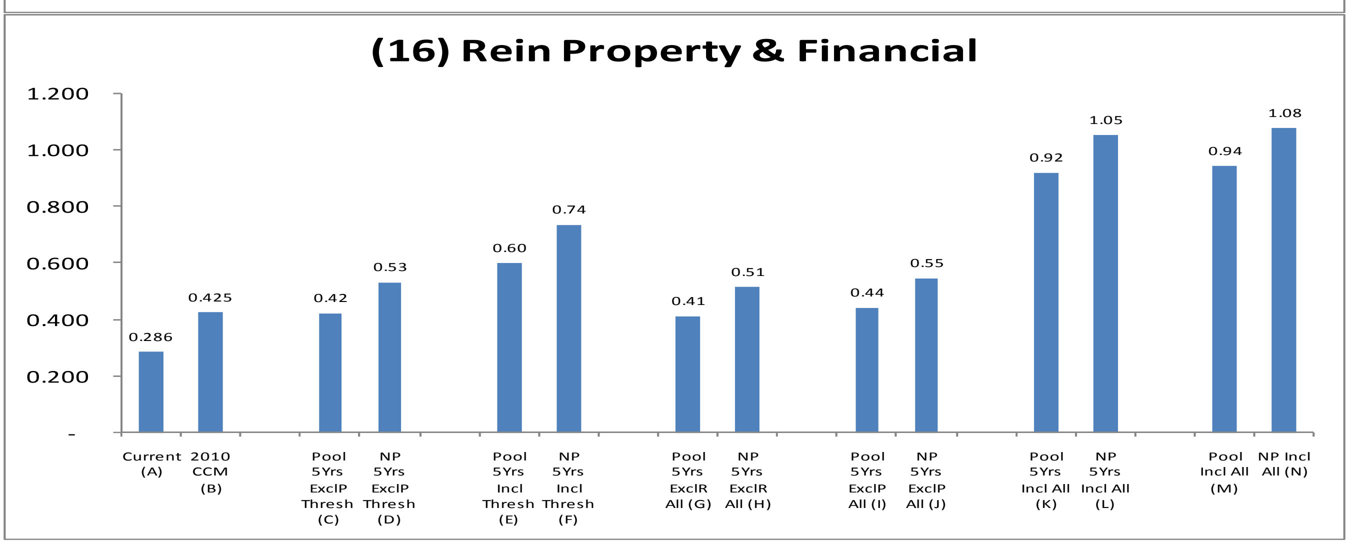

(10) Fidelity & Surety
1.600
1.400
1.200
1.000
0.800
0.600
0.400
0.200
-
0.325
1.348
0.61
0.64
0.94
0.70
0.55
0.56
0.66
0.72
1.25
1.00
1.24
1.00
Current (A)
2010 CCM (B)
Pool 5Yrs ExclP Thresh (C)
NP 5Yrs ExclP Thresh (D)
Pool 5Yrs Incl Thresh (E)
NP 5Yrs Incl Thresh (F)
Pool 5Yrs ExclR All (G)
NP 5Yrs ExclR All (H)
Pool 5Yrs ExclP All (I)
NP 5Yrs ExclP All (J)
Pool 5Yrs Incl All (K)
NP 5Yrs Incl All (L)
Pool Incl All (M)
NP Incl All (N)

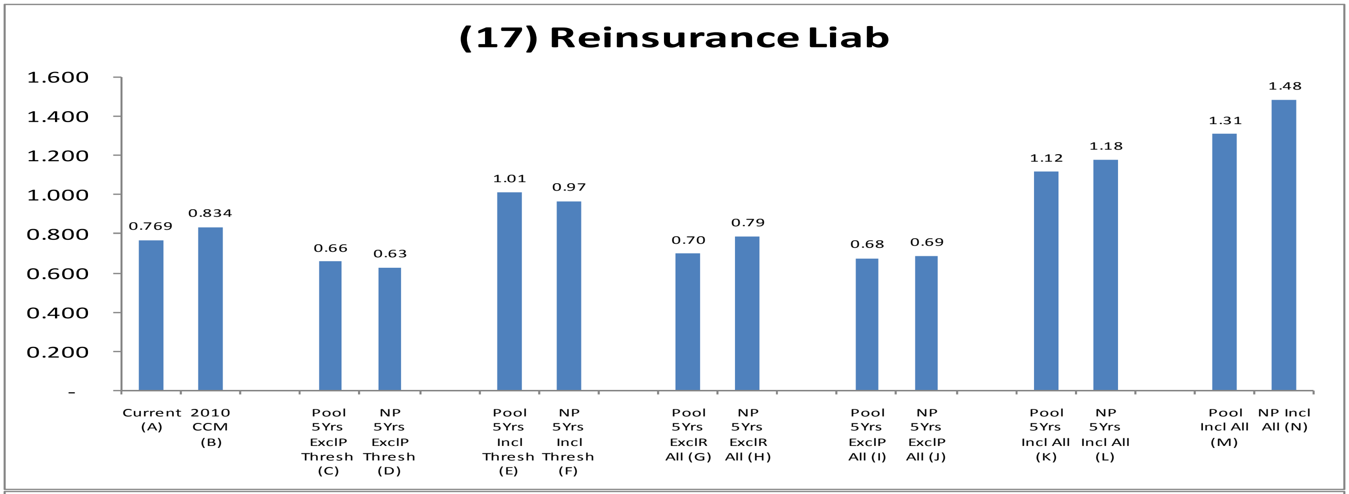

(11) Spec Prop
0.600
0.500
0.400
0.300
0.200
0.100
-
0.191
0.190
0.31
0.30
0.36
0.31
0.21
0.20
0.40
0.37
0.51
0.46
0.50
0.46
Current (A)
2010 CCM (B)
Pool 5Yrs ExclP Thresh (C)
NP 5Yrs ExclP Thresh (D)
Pool 5Yrs Incl Thresh (E)
NP 5Yrs Incl Thresh (F)
Pool 5Yrs ExclR All (G)
NP 5Yrs ExclR All (H)
Pool 5Yrs ExclP All (I)
NP 5Yrs ExclP All (J)
Pool 5Yrs Incl All (K)
NP 5Yrs Incl All (L)
Pool Incl All (M)
NP Incl All (N)

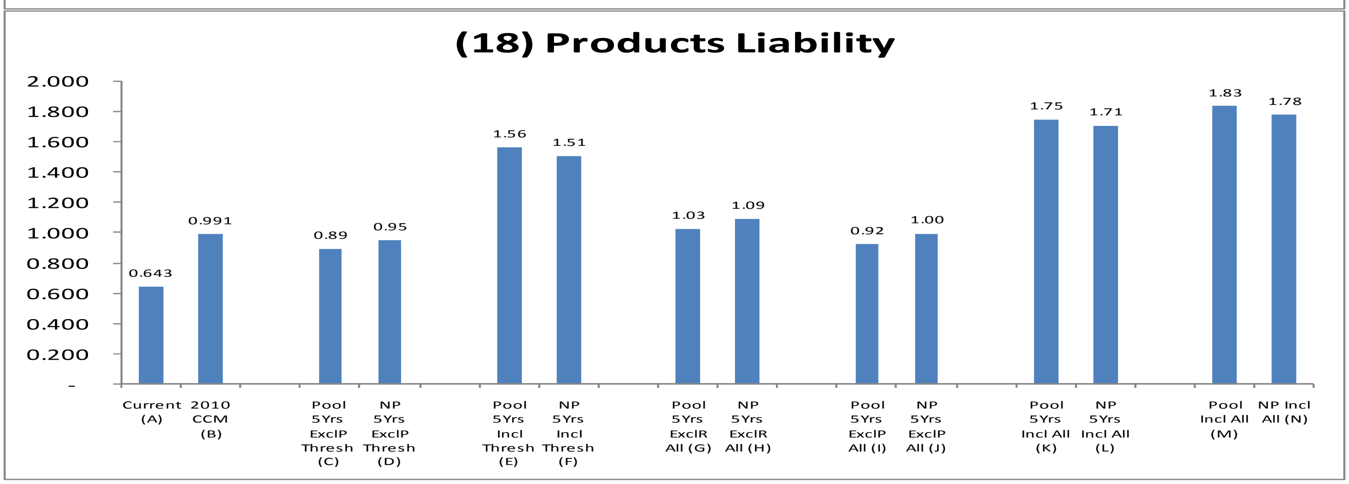

(12) Auto Phys Damage
0.500
0.400
0.300
0.200
0.100
-
(0.100)
0.112
-0.062
0.17
0.08
0.24
0.12
0.09
0.05
0.24
0.15
0.40
0.25
0.41
0.26
Current (A)
2010 CCM (B)
Pool 5Yrs ExclP Thresh (C)
NP 5Yrs ExclP Thresh (D)
Pool 5Yrs Incl Thresh (E)
NP 5Yrs Incl Thresh (F)
Pool 5Yrs ExclR All (G)
NP 5Yrs ExclR All (H)
Pool 5Yrs ExclP All (I)
NP 5Yrs ExclP All (J)
Pool 5Yrs Incl All (K)
NP 5Yrs Incl All (L)
Pool Incl All (M)
NP Incl All (N)


(13) Other
1.000
0.900
0.800
0.700
0.600
0.500
0.400
0.300
0.200
0.100
-
0.172
0.207
0.27
0.20
0.49
0.36
0.25
0.21
0.35
0.32
0.90
0.82
0.81
0.75
Current (A)
2010 CCM (B)
Pool 5Yrs ExclP Thresh (C)
NP 5Yrs ExclP Thresh (D)
Pool 5Yrs Incl Thresh (E)
NP 5Yrs Incl Thresh (F)
Pool 5Yrs ExclR All (G)
NP 5Yrs ExclR All (H)
Pool 5Yrs ExclP All (I)
NP 5Yrs ExclP All (J)
Pool 5Yrs Incl All (K)
NP 5Yrs Incl All (L)
Pool Incl All (M)
NP Incl All (N)


(15) International
3.000
2.500
2.000
1.500
1.000
0.500
-
0.327
0.247
0.49
0.49
1.24
0.93
0.70
0.70
0.70
1.47
1.18
1.64
1.34
Current (A)
2010 CCM (B)
Pool 5Yrs ExclP Thresh (C)
NP 5Yrs ExclP Thresh (D)
Pool 5Yrs Incl Thresh (E)
NP 5Yrs Incl Thresh (F)
Pool 5Yrs ExclR All (G)
NP 5Yrs ExclR All (H)
Pool 5Yrs ExclP All (I)
NP 5Yrs ExclP All (J)
Pool 5Yrs Incl All (K)
NP 5Yrs Incl All (L)
Pool Incl All (M)
NP Incl All (N)


(16) Rein Property & Financial
1.200
1.000
0.800
0.600
0.400
0.200
-
0.286
0.425
0.42
0.53
0.60
0.74
0.41
0.51
0.44
0.55
0.92
1.05
0.94
1.08
Current (A)
2010 CCM (B)
Pool 5Yrs ExclP Thresh (C)
NP 5Yrs ExclP Thresh (D)
Pool 5Yrs Incl Thresh (E)
NP 5Yrs Incl Thresh (F)
Pool 5Yrs ExclR All (G)
NP 5Yrs ExclR All (H)
Pool 5Yrs ExclP All (I)
NP 5Yrs ExclP All (J)
Pool 5Yrs Incl All (K)
NP 5Yrs Incl All (L)
Pool Incl All (M)
NP Incl All (N)

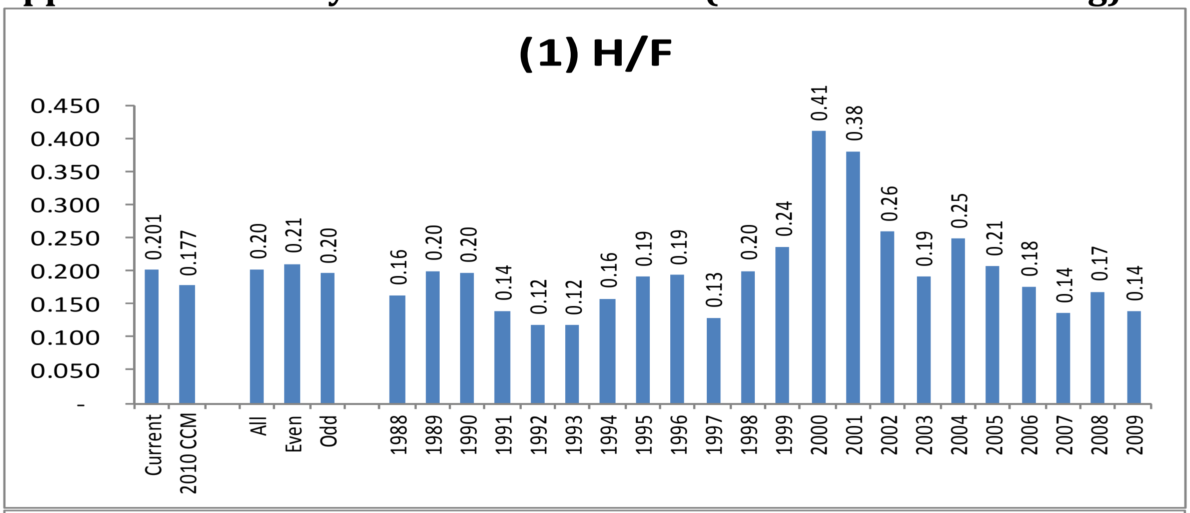

(17) Reinsurance Liab
1.600
1.400
1.200
1.000
0.800
0.600
0.400
0.200
-
0.769
0.834
0.66
0.63
1.01
0.97
0.70
0.79
0.68
0.69
1.12
1.18
1.31
1.48
Current (A)
2010 CCM (B)
Pool 5Yrs ExclP Thresh (C)
NP 5Yrs ExclP Thresh (D)
Pool 5Yrs Incl Thresh (E)
NP 5Yrs Incl Thresh (F)
Pool 5Yrs ExclR All (G)
NP 5Yrs ExclR All (H)
Pool 5Yrs ExclP All (I)
NP 5Yrs ExclP All (J)
Pool 5Yrs Incl All (K)
NP 5Yrs Incl All (L)
Pool Incl All (M)
NP Incl All (N)

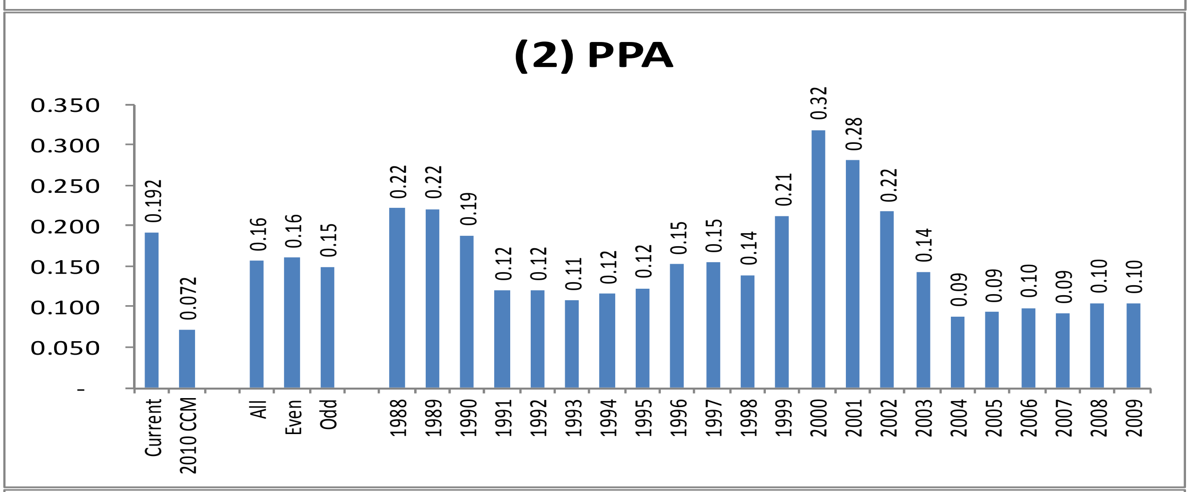

(18) Products Liability
2.000
1.800
1.600
1.400
1.200
1.000
0.800
0.600
0.400
0.200
-
0.643
0.991
0.89
0.95
1.56
1.51
1.03
1.09
0.92
1.00
1.75
1.71
1.83
1.78
Current (A)
2010 CCM (B)
Pool 5Yrs ExclP Thresh (C)
NP 5Yrs ExclP Thresh (D)
Pool 5Yrs Incl Thresh (E)
NP 5Yrs Incl Thresh (F)
Pool 5Yrs ExclR All (G)
NP 5Yrs ExclR All (H)
Pool 5Yrs ExclP All (I)
NP 5Yrs ExclP All (J)
Pool 5Yrs Incl All (K)
NP 5Yrs Incl All (L)
Pool Incl All (M)
NP Incl All (N)

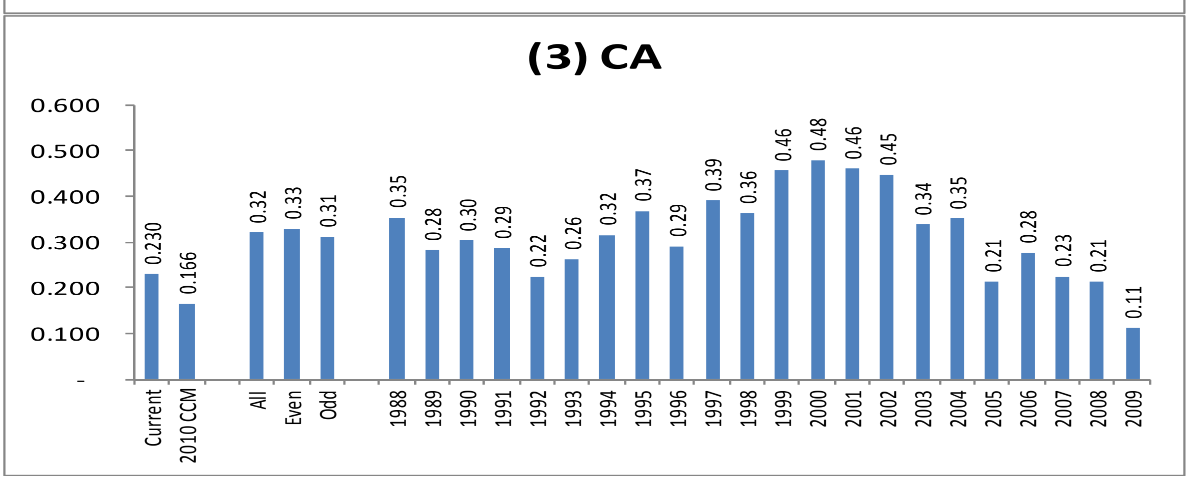
Appendix B – Table 1 Selected Baseline LOB-size Thresholds

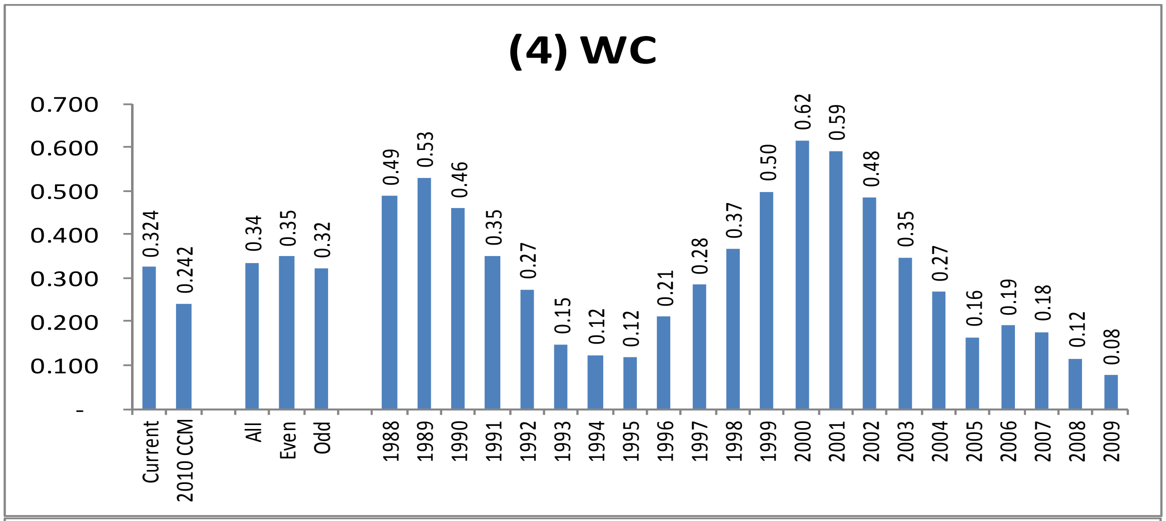
Selected Reserve-Size Threshold by LOB	
Line of Business	**Reserve (000's)**
A Homeowners/Farmowners	350
B Priv. Passenger Auto Liability	1,950
C Commercial Auto Liability.	1,250
D Workers Compensation	1,000
E Commercial Multiperil	700
F1 Medical Malpractice – Occurrence	1,650
F2 Medical Malpractice - Claims made	1,350
G Special Liability	350
H Other Liability	800
I Special Property	100
J Auto Physical Damage	150
K Fidelity & Surety	150
L Other	300
M International	100
N&P Reinsurance A &C (property and financial)	500
O Reinsurance B (liability)	1,000
R Products Liability	500
S Financial Guarantee	100
T Warranty	100

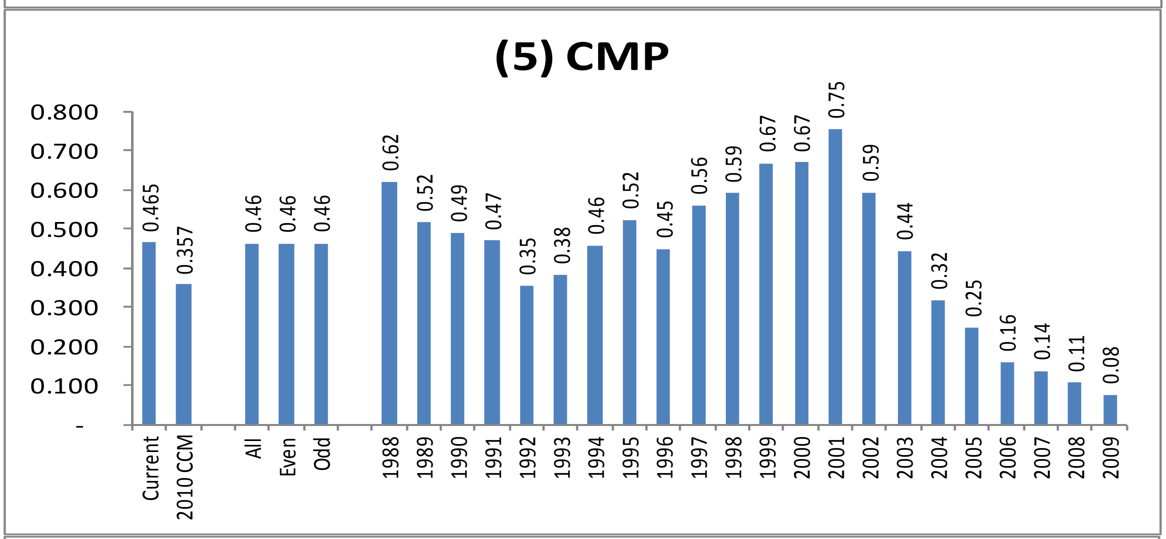
Appendix C – RRF by Initial Reserve Date (with Baseline Filtering)

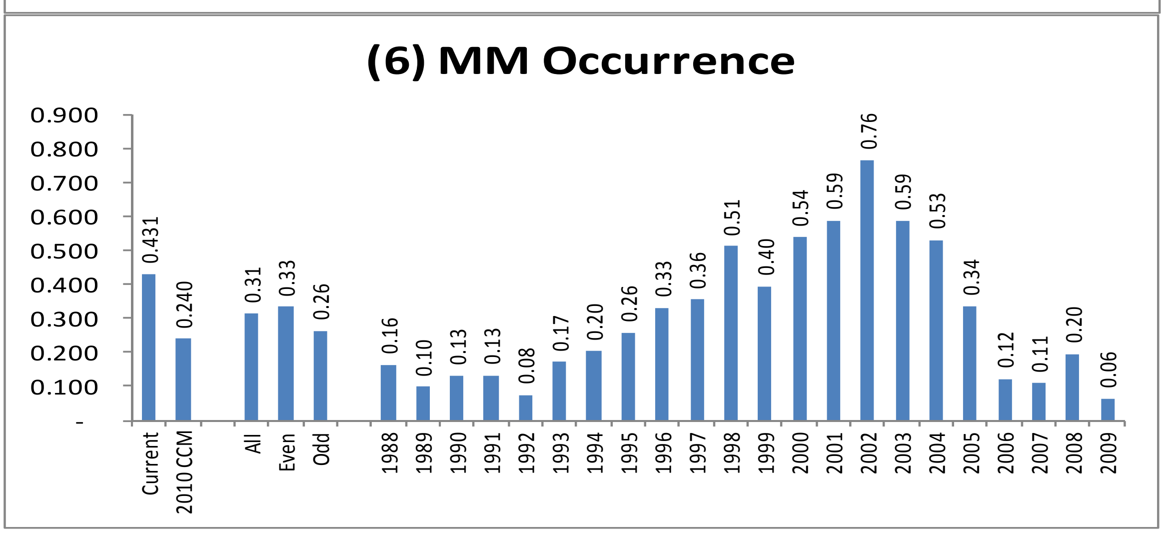


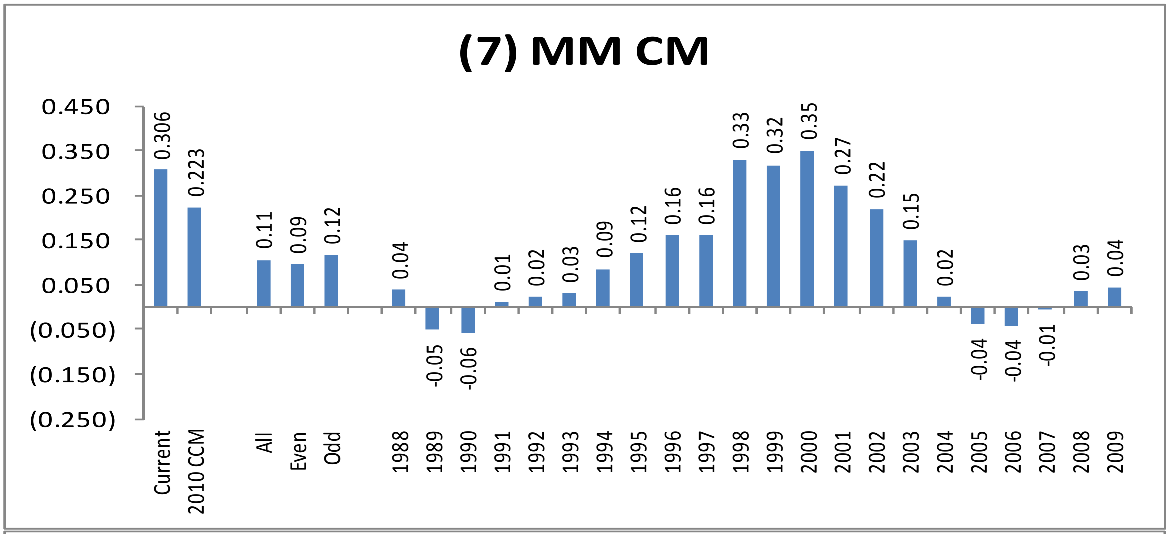


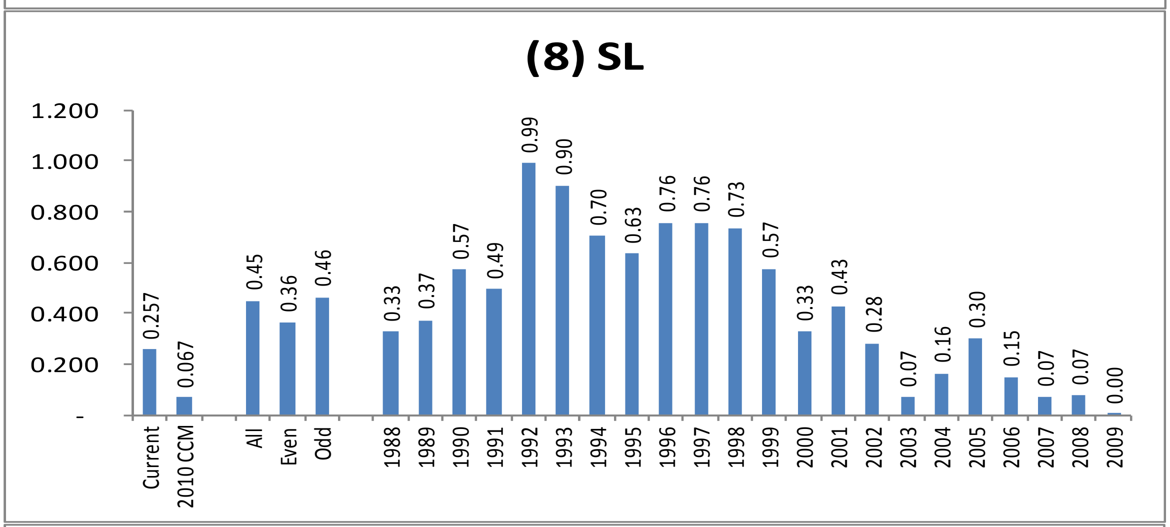


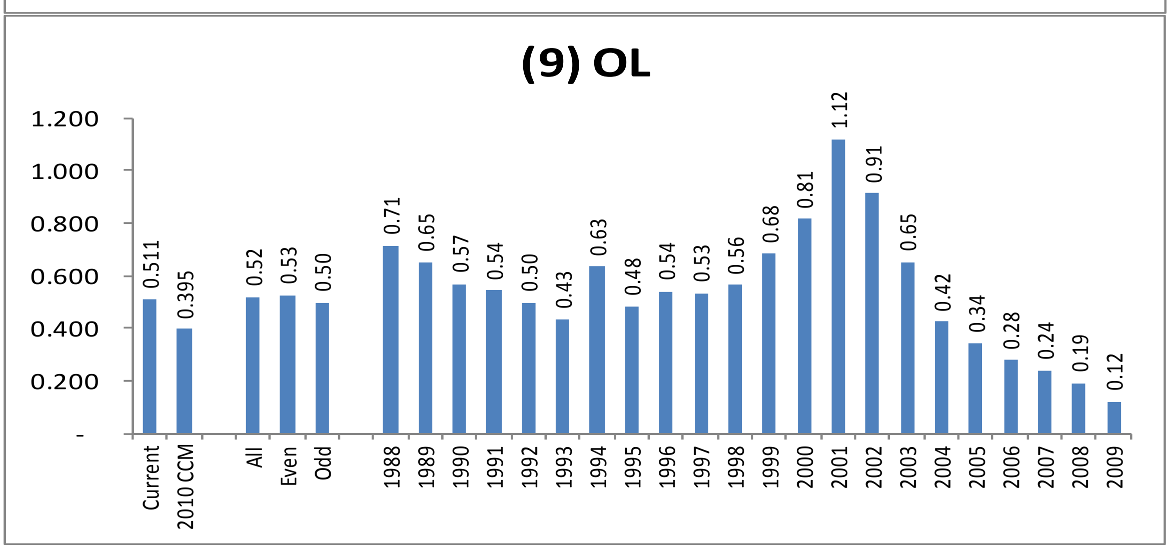

(4) WC
0.700
0.600
0.500
0.400
0.300
0.200
0.100
-
0.324
0.242
0.34
0.35
0.32
0.49
0.53
0.46
0.35
0.27
0.15
0.12
0.12
0.21
0.28
0.37
0.50
0.62
0.59
0.48
0.35
0.27
0.16
0.19
0.18
0.12
0.08
Current
2010 CCM
All
Even
Odd
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009

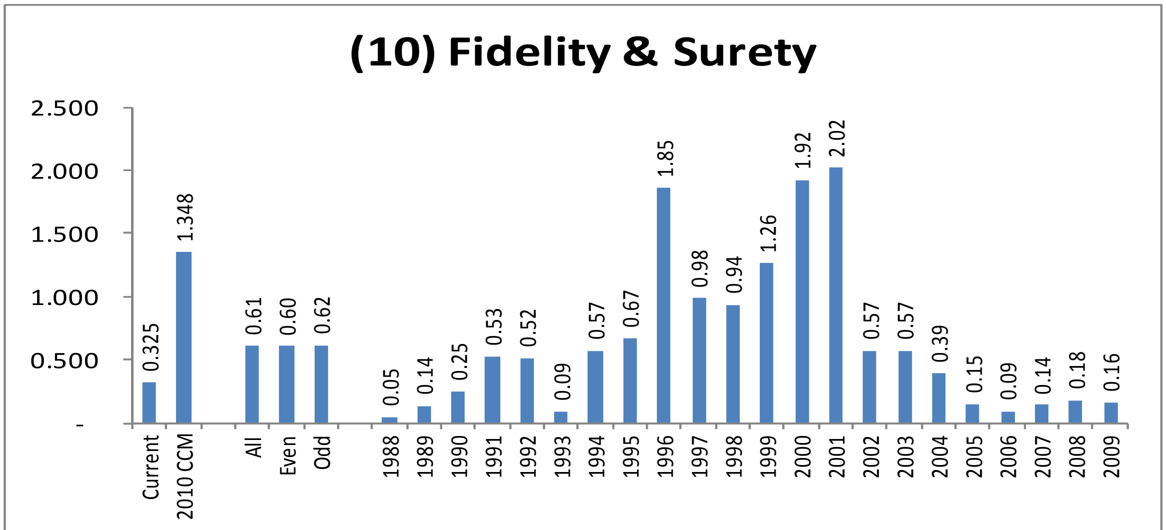

(5) CMP
0.800
0.700
0.600
0.500
0.400
0.300
0.200
0.100
-
0.465
0.357
0.46
0.46
0.46
0.62
0.52
0.49
0.47
0.35
0.38
0.46
0.52
0.45
0.56
0.59
0.67
0.67
0.75
0.59
0.44
0.32
0.25
0.16
0.14
0.11
0.08
Current
2010 CCM
All
Even
Odd
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009


(6) MM Occurrence
0.900
0.800
0.700
0.600
0.500
0.400
0.300
0.200
0.100
-
0.431
0.240
0.31
0.33
0.26
0.16
0.10
0.13
0.13
0.08
0.17
0.20
0.26
0.33
0.36
0.51
0.40
0.54
0.59
0.76
0.59
0.53
0.34
0.12
0.11
0.20
0.06
Current
2010 CCM
All
Even
Odd
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009


(7) MM CM
0.450
0.350
0.250
0.150
0.050
(0.050)
(0.150)
(0.250)
0.306
0.223
0.11
0.09
0.12
0.04
-0.05
-0.06
0.01
0.02
0.03
0.09
0.12
0.16
0.16
0.33
0.32
0.35
0.27
0.22
0.15
0.02
-0.04
-0.04
-0.01
0.03
0.04
Current
2010 CCM
All
Even
Odd
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009


(8) SL
1.200
1.000
0.800
0.600
0.400
0.200
-
0.257
0.067
0.45
0.36
0.46
0.33
0.37
0.57
0.49
0.99
0.90
0.70
0.63
0.76
0.76
0.73
0.57
0.33
0.43
0.28
0.07
0.16
0.30
0.15
0.07
0.07
0.00
Current
2010 CCM
All
Even
Odd
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009


(9) OL
1.200
1.000
0.800
0.600
0.400
0.200
-
0.511
0.395
0.52
0.53
0.50
0.71
0.65
0.57
0.54
0.50
0.43
0.63
0.48
0.54
0.53
0.56
0.68
0.81
1.12
0.91
0.65
0.42
0.34
0.28
0.24
0.19
0.12
Current
2010 CCM
All
Even
Odd
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009


(10) Fidelity & Surety
2.500
2.000
1.500
1.000
0.500
-
0.325
1.348
0.61
0.60
0.62
0.05
0.14
0.25
0.53
0.52
0.09
0.57
0.67
1.85
0.98
0.94
1.26
1.92
2.02
0.57
0.57
0.39
0.15
0.09
0.14
0.18
0.16
Current
2010 CCM
All
Even
Odd
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
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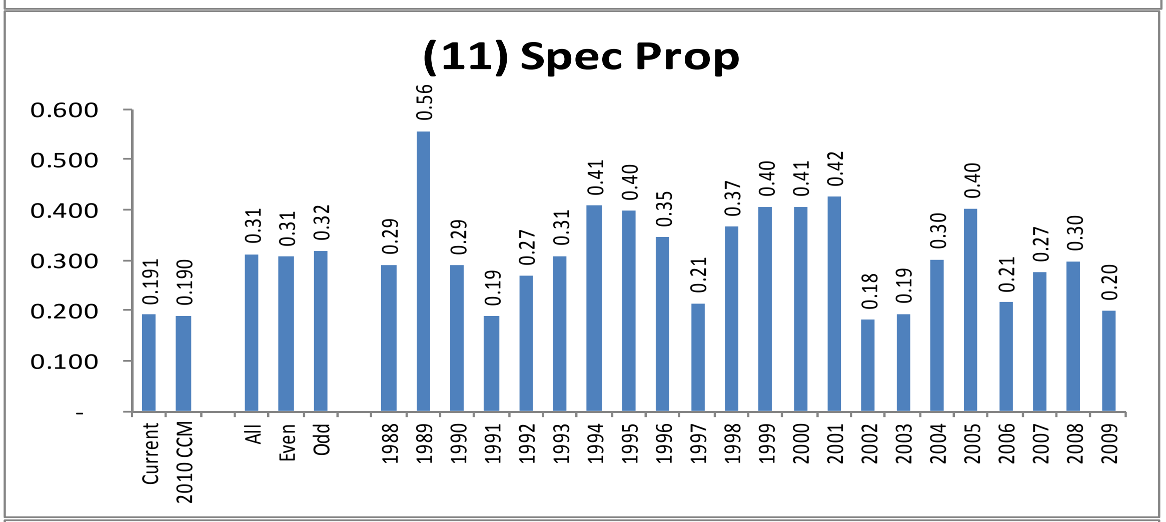
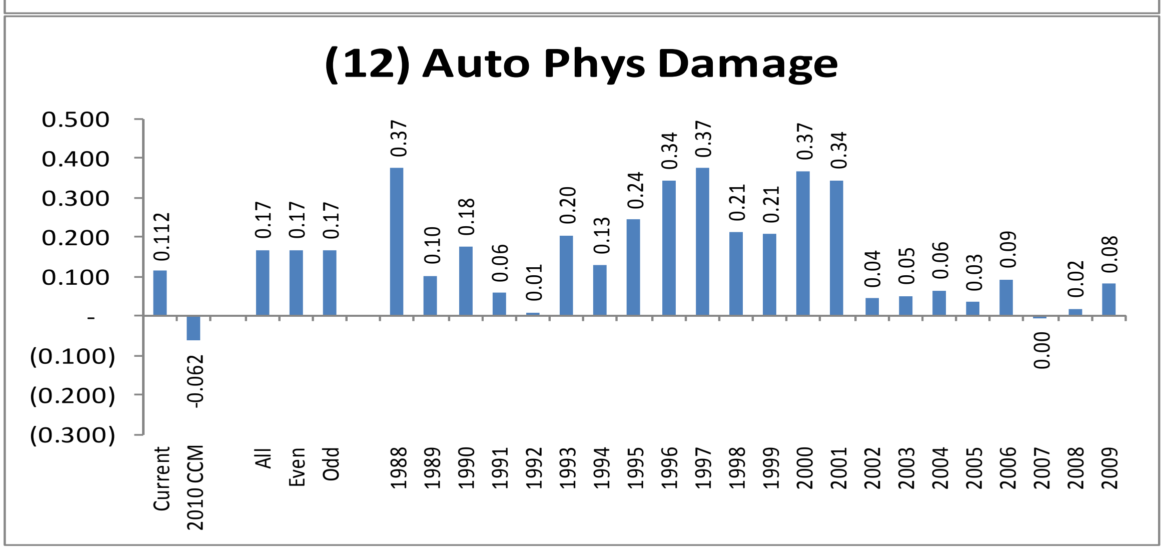
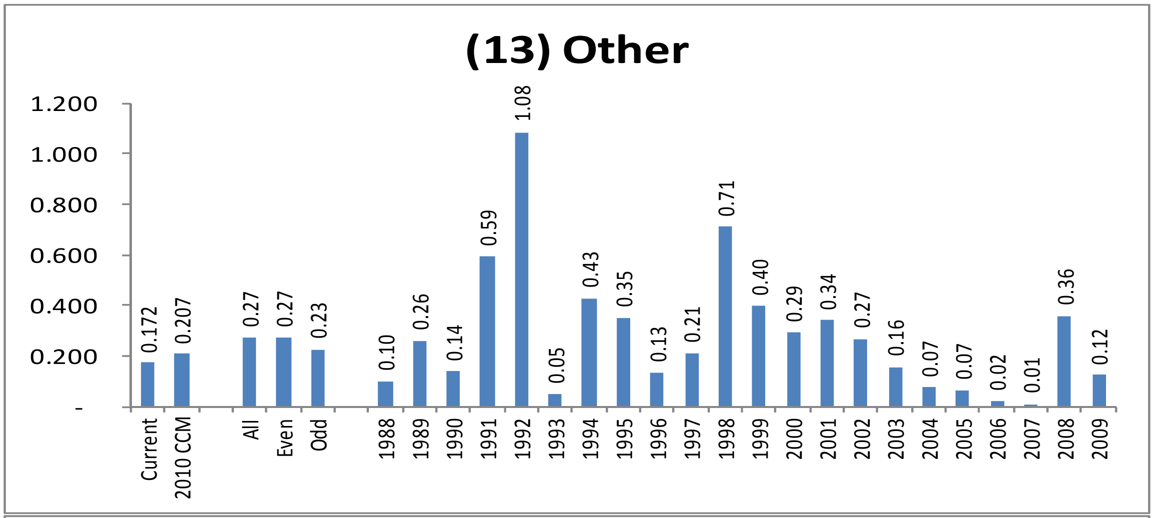
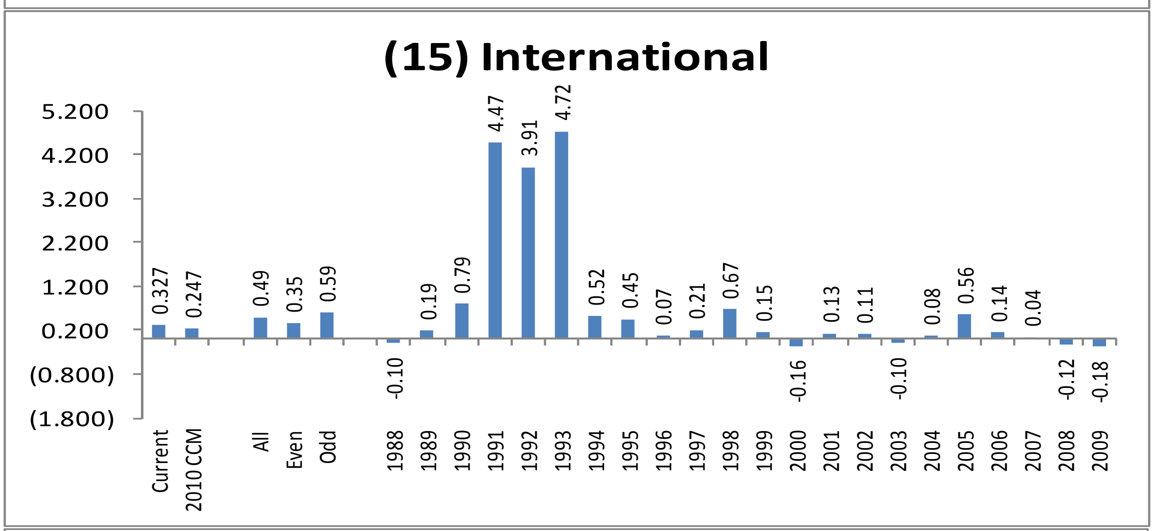
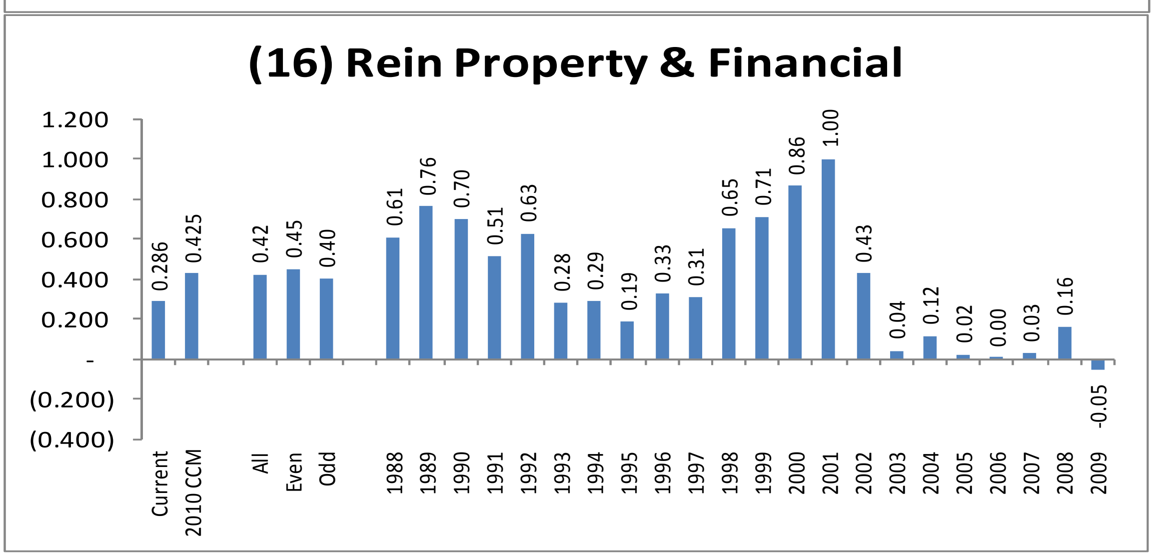
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009

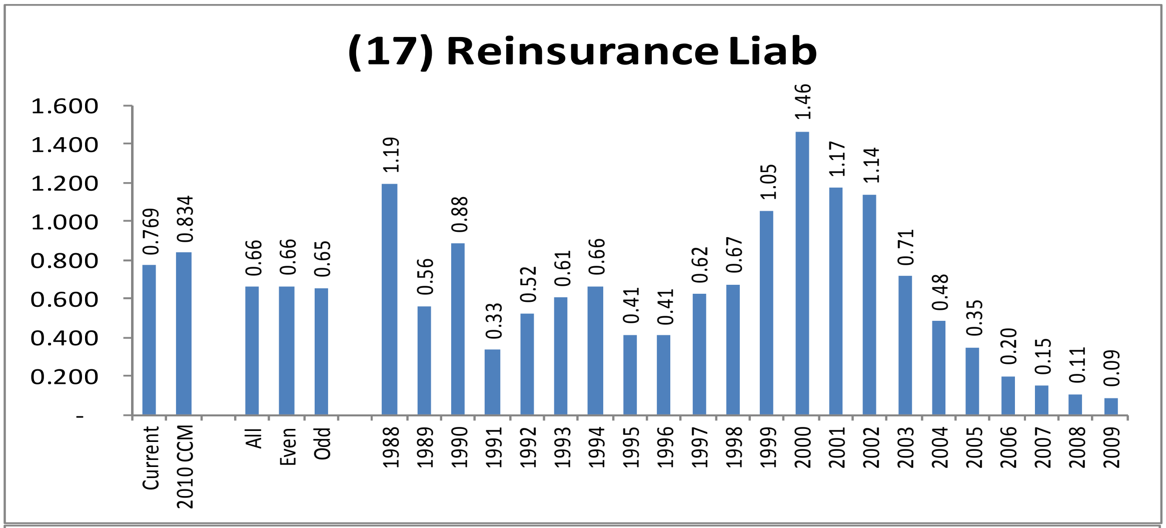

(11) Spec Prop
0.600
0.500
0.400
0.300
0.200
0.100
-
0.191
0.190
0.31
0.31
0.32
0.29
0.56
0.29
0.19
0.27
0.31
0.41
0.40
0.35
0.21
0.37
0.40
0.41
0.42
0.18
0.19
0.30
0.40
0.21
0.27
0.30
0.20
Current
2010 CCM
All
Even
Odd
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009

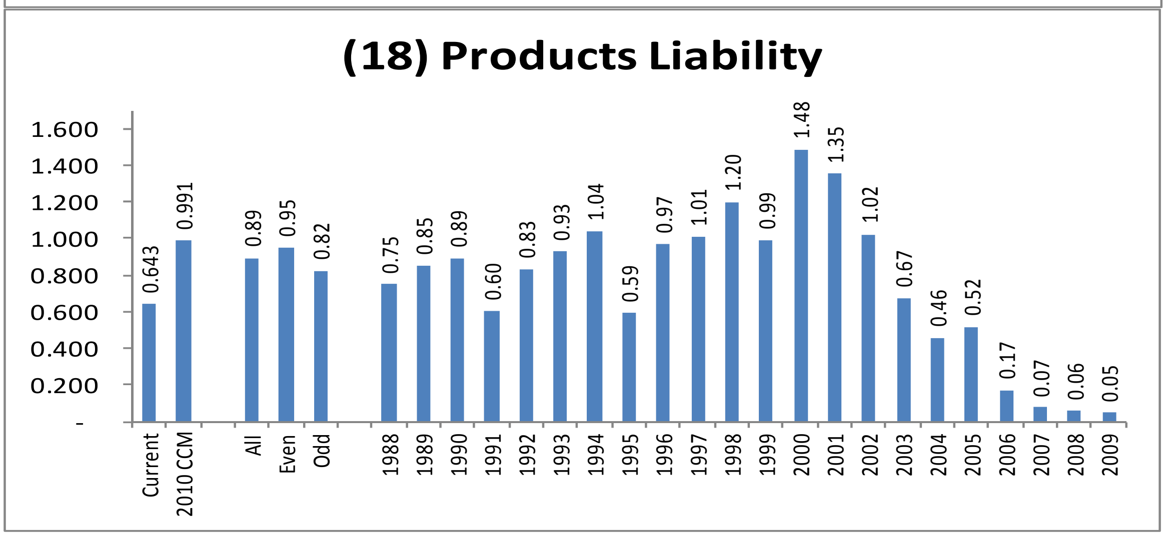

(12) Auto Phys Damage
0.500
0.400
0.300
0.200
0.100
-
(0.100)
(0.200)
(0.300)
0.112
-0.062
0.17
0.17
0.17
0.37
0.10
0.18
0.06
0.01
0.20
0.13
0.24
0.34
0.37
0.21
0.21
0.37
0.34
0.04
0.05
0.06
0.03
0.09
0.00
0.02
0.08
Current
2010 CCM
All
Even
Odd
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009


(13) Other
1.200
1.000
0.800
0.600
0.400
0.200
-
0.172
0.207
0.27
0.27
0.23
0.10
0.26
0.14
0.59
1.08
0.05
0.43
0.35
0.13
0.21
0.71
0.40
0.29
0.34
0.27
0.16
0.07
0.07
0.02
0.01
0.36
0.12
Current
2010 CCM
All
Even
Odd
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009


(15) International
5.200
4.200
3.200
2.200
1.200
0.200
(0.800)
(1.800)
0.327
0.247
0.49
0.35
0.59
-0.10
0.19
0.79
4.47
3.91
4.72
0.52
0.45
0.07
0.21
0.67
0.15
-0.16
0.13
0.11
-0.10
0.08
0.56
0.14
0.04
-0.12
-0.18
Current
2010 CCM
All
Even
Odd
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009


(16) Rein Property & Financial
1.200
1.000
0.800
0.600
0.400
0.200
-
(0.200)
(0.400)
0.286
0.425
0.42
0.45
0.40
0.61
0.76
0.70
0.51
0.63
0.28
0.29
0.19
0.33
0.31
0.65
0.71
0.86
1.00
0.43
0.04
0.12
0.02
0.00
0.03
0.16
-0.05
Current
2010 CCM
All
Even
Odd
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009


(17) Reinsurance Liab
1.600
1.400
1.200
1.000
0.800
0.600
0.400
0.200
-
0.769
0.834
0.66
0.66
0.65
1.19
0.56
0.88
0.33
0.52
0.61
0.66
0.41
0.41
0.62
0.67
1.05
1.46
1.17
1.14
0.71
0.48
0.35
0.20
0.15
0.11
0.09
Current
2010 CCM
All
Even
Odd
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009


(18) Products Liability
1.600
1.400
1.200
1.000
0.800
0.600
0.400
0.200
-
0.643
0.991
0.89
0.95
0.82
0.75
0.85
0.89
0.60
0.83
0.93
1.04
0.59
0.97
1.01
1.20
0.99
1.48
1.35
1.02
0.67
0.46
0.52
0.17
0.07
0.06
0.05
Current
2010 CCM
All
Even
Odd
1988
1989
1990
1991
1992
1993
1994
1995
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2001
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2003
2004
2005
2006
2007
2008
2009

Appendix C – RRF by Initial Reserve Date

Even/Odd Test and Every Fourth Year Test

Reserve Risk - Runoff Ratio

Baseline Filterting

Acident Year		All	Segment: Even	Segment: Odd	Segment (in fourths): 0_Mod4	1_Mod4	2_Mod4	3_Mod4	Differences: Segment minus All: Even	Odd	0_Mod4	1_Mod4	2_Mod4	3_Mod4
(1) H/F	A	0.202	0.211	0.195	0.222	0.202	0.203	0.173	0.009	-0.006	0.021	0.000	0.001	-0.028
(2) PPA	B	0.156	0.160	0.149	0.158	0.157	0.163	0.142	0.004	-0.007	0.001	0.001	0.006	-0.014
(3) CA	C	0.320	0.329	0.311	0.322	0.288	0.334	0.345	0.009	-0.008	0.002	-0.032	0.014	0.026
(4) WC	D	0.336	0.348	0.321	0.337	0.338	0.361	0.313	0.013	-0.015	0.001	0.002	0.025	-0.023
(5) CMP	E	0.462	0.462	0.463	0.423	0.463	0.495	0.460	-0.001	0.001	-0.039	0.001	0.032	-0.003
(6) MM Occurrence	F1	0.314	0.333	0.264	0.329	0.264	0.344	0.264	0.020	**-0.050**	0.016	**-0.050**	0.030	**-0.050**
(7) MM CM	F2	0.106	0.095	0.116	0.070	0.098	0.125	0.122	-0.011	0.011	-0.035	-0.008	0.019	0.017
(8) SL	G	0.449	0.363	0.464	0.330	0.467	0.480	0.405	**-0.085**	0.015	**-0.118**	0.018	0.031	**-0.044**
(9) OL	H	0.518	0.527	0.499	0.494	0.464	0.574	0.522	0.009	-0.019	-0.024	**-0.054**	**0.056**	0.004
(11) Spec Prop	I	0.311	0.306	0.318	0.332	0.336	0.286	0.299	-0.006	0.006	0.020	0.024	-0.025	-0.013
(12) Auto Phys Damage	J	0.167	0.167	0.165	0.200	0.206	0.111	0.119	0.000	-0.002	0.033	0.039	**-0.056**	**-0.048**
(10) Fidelity & Surety	K	0.611	0.605	0.616	0.716	0.473	0.493	0.779	-0.006	0.006	**0.105**	**-0.138**	**-0.118**	**0.169**
(13) Other	L	0.271	0.273	0.227	0.276	0.222	0.270	0.263	0.002	**-0.045**	0.005	**-0.050**	-0.001	-0.009
(15) International	M	0.490	0.354	0.593	0.267	0.520	0.514	0.558	**-0.136**	**0.103**	**-0.223**	0.030	0.024	**0.068**
(16) Rein Property & Financial	N&P	0.422	0.448	0.400	0.512	0.356	0.421	0.413	0.026	-0.022	**0.090**	**-0.066**	-0.001	-0.009
(17) Reinsurance Liab	O	0.657	0.662	0.653	0.618	0.605	0.711	0.679	0.005	-0.004	-0.039	**-0.052**	**0.053**	0.021
(18) Products Liability	R	0.894	0.950	0.823	0.881	0.969	1.017	0.679	**0.056**	**-0.071**	-0.013	**0.074**	**0.123**	**-0.215**
(14) Fin & Mort	S	0.000	0.200	0.000	0.778	-0.218	0.125	0.000	**0.200**	0.000	**0.778**	**-0.218**	**0.125**	0.000
(19) Warranty	T	0.032	0.043	-0.001	-0.024	-0.026	0.071	0.015	0.011	-0.033	**-0.056**	**-0.058**	0.039	-0.017

Differences over .040 shown with highlight and bold.

Appendix D –RRFs by LOB-size

(1) H/F

(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)	(K)	(L)
Size Band	Reserve ($000s)			87.5th Percentile Runoff Ratio		Average Runoff Ratio		Runoff Ratio Std. Dev		Coeff. Var.	
Endpoint Percentile	from	to	Data Points	all points in band	all points >"from"	all points in band	all points >"from"	all points in band	all points >"from"	all points in band	all points >"from"
15%	0	169	1,398	83.3%	26.3%	0.34	-0.01	6.37	2.55	18.7	-463.3
25%	169	357	926	41.1%	**22.5%**	-0.04	-0.07	1.15	0.65	-31.0	-9.8
35%	357	672	931	33.6%	20.1%	-0.04	-0.07	0.75	0.55	-19.0	-7.8
45%	672	1,274	927	28.8%	18.0%	-0.04	-0.08	0.98	0.51	-25.2	-6.8
55%	1,274	2,500	932	**27.7%**	16.5%	-0.07	-0.08	0.41	0.37	-6.1	-4.5
65%	2,500	4,819	927	27.5%	14.2%	-0.02	-0.09	0.59	0.36	-25.3	-4.2
A	4,819	9,742	930	14.2%	11.7%	-0.11	-0.10	0.32	0.26	-3.0	-2.5
85%	9,742	19,775	929	8.3%	10.4%	-0.11	-0.10	0.24	0.23	-2.1	-2.3
95%	19,775	74,324	930	12.2%	11.5%	-0.11	-0.09	0.24	0.23	-2.1	-2.4
largest 100	74,324	521,808	365	11.2%	10.4%	-0.06	-0.06	0.21	0.20	-3.5	-3.2
100%	521,808	27,109,142	100	5.6%	5.6%	-0.07	-0.07	0.16	0.16	-2.4	-2.4

Current Risk Charge Runoff Ratio (PR016, Line 4) 20.1%

(2) PPA

(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)	(K)	(L)
Size Band	Reserve ($000s)			87.5th Percentile Runoff Ratio		Average Runoff Ratio		Runoff Ratio Std. Dev		Coeff. Var.	
Endpoint Percentile	from	to	Data Points	all points in band	all points >"from"	all points in band	all points >"from"	all points in band	all points >"from"	all points in band	all points >"from"
15%	0	812	1,351	79.4%	23.0%	3.42	0.47	74.33	28.81	21.7	60.7
25%	812	1,953	903	41.0%	**17.9%**	0.00	-0.05	0.47	0.33	121.8	-7.2
35%	1,953	4,004	898	31.3%	15.6%	-0.04	-0.05	0.53	0.30	-13.7	-5.8
45%	4,004	7,446	901	26.0%	13.9%	-0.02	-0.05	0.34	0.25	-21.0	-4.7
55%	7,446	12,522	901	**19.3%**	12.0%	-0.03	-0.06	0.28	0.23	-8.2	-3.8
65%	12,522	20,740	901	13.5%	10.2%	-0.07	-0.07	0.23	0.22	-3.4	-3.3
A	20,740	42,864	902	15.7%	9.2%	-0.05	-0.07	0.31	0.22	-5.8	-3.3
85%	42,864	105,325	899	8.7%	7.4%	-0.07	-0.07	0.18	0.17	-2.7	-2.3
95%	105,325	540,618	901	5.2%	6.2%	-0.08	-0.08	0.17	0.16	-2.0	-2.1
largest 100	540,618	3,466,207	351	10.6%	8.0%	-0.07	-0.06	0.16	0.15	-2.5	-2.3
100%	3,466,207	17,069,357	100	2.2%	2.2%	-0.06	-0.06	0.09	0.09	-1.5	-1.5

Current Risk Charge Runoff Ratio (PR016, Line 4) 19.2%

(3) CA

(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)	(K)	(L)
Size Band	Reserve ($000s)			87.5th Percentile Runoff Ratio		Average Runoff Ratio		Runoff Ratio Std. Dev		Coeff. Var.	
Endpoint Percentile	from	to	Data Points	all points in band	all points >"from"	all points in band	all points >"from"	all points in band	all points >"from"	all points in band	all points >"from"
15%	0	511	996	126.5%	41.9%	3.31	0.50	63.83	24.75	19.3	49.2
25%	511	1,238	665	69.8%	**35.2%**	0.04	0.01	0.77	0.51	20.0	67.2
35%	1,238	2,531	661	45.0%	32.0%	0.00	0.00	0.52	0.47	-127.2	133.3
45%	2,531	4,551	664	39.4%	30.2%	0.01	0.00	0.78	0.46	78.1	98.6
55%	4,551	8,242	665	**35.3%**	28.0%	0.01	0.00	0.42	0.38	33.4	101.1
65%	8,242	14,666	663	32.4%	26.7%	-0.02	0.00	0.42	0.37	-20.2	206.4
A	14,666	27,042	663	26.1%	25.4%	-0.01	0.01	0.45	0.35	-79.7	42.4
85%	27,042	62,524	664	34.0%	24.8%	0.05	0.01	0.37	0.30	7.7	21.8
95%	62,524	241,029	664	23.1%	18.8%	0.00	-0.01	0.27	0.24	153.9	-26.2
largest 100	241,029	674,172	232	14.0%	13.1%	-0.03	-0.03	0.16	0.15	-5.3	-4.8
100%	674,172	2,785,549	100	11.2%	11.2%	-0.03	-0.03	0.12	0.12	-3.8	-3.8

Current Risk Charge Runoff Ratio (PR016, Line 4) 23.0%

(4) WC

(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)	(K)	(L)
Size Band	Reserve ($000s)			87.5th Percentile Runoff Ratio		Average Runoff Ratio		Runoff Ratio Std. Dev		Coeff. Var.	
Endpoint Percentile	from	to	Data Points	all points in band	all points >"from"	all points in band	all points >"from"	all points in band	all points >"from"	all points in band	all points >"from"
15%	0	1,807	1,052	69.7%	37.2%	0.07	0.03	1.23	0.65	17.6	20.5
25%	1,807	3,833	702	36.4%	**33.3%**	-0.02	0.02	0.51	0.47	-29.8	19.2
35%	3,833	7,760	702	49.0%	32.4%	0.07	0.03	0.48	0.47	7.3	15.5
45%	7,760	14,372	702	41.7%	30.2%	0.02	0.02	0.59	0.47	24.5	18.8
55%	14,372	26,469	701	**44.3%**	28.8%	0.05	0.03	0.48	0.44	9.4	17.7
65%	26,469	48,157	702	29.3%	26.0%	0.03	0.02	0.67	0.43	26.4	22.6
A	48,157	93,226	702	30.7%	25.1%	0.02	0.02	0.52	0.34	24.2	19.4
85%	93,226	258,098	702	24.0%	24.2%	-0.01	0.02	0.25	0.23	-34.2	14.3
95%	258,098	1,256,615	702	22.8%	24.2%	0.01	0.03	0.21	0.21	15.5	6.7
largest 100	1,256,615	4,867,857	251	27.0%	27.3%	0.05	0.07	0.22	0.21	4.1	3.1
100%	4,867,857	16,176,596	100	27.2%	27.2%	0.10	0.10	0.17	0.17	1.8	1.8

Current Risk Charge Runoff Ratio (PR016, Line 4) 32.4%

(5) CMP

(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)	(K)	(L)
Size Band	Reserve ($000s)			87.5th Percentile Runoff Ratio		Average Runoff Ratio		Runoff Ratio Std. Dev		Coeff. Var.	
Endpoint Percentile	from	to	Data Points	all points in band	all points >"from"	all points in band	all points >"from"	all points in band	all points >"from"	all points in band	all points >"from"
15%	0	253	1,147	135.8%	56.5%	1.02	0.21	10.34	4.05	10.1	19.0
25%	253	695	765	76.4%	**48.8%**	0.12	0.07	0.87	0.54	7.3	7.7
35%	695	1,536	765	57.0%	46.2%	0.08	0.06	0.75	0.48	9.3	7.5
45%	1,536	3,298	765	52.4%	44.3%	0.04	0.06	0.57	0.42	14.9	6.9
55%	3,298	6,279	764	**58.1%**	42.7%	0.10	0.07	0.53	0.39	5.4	5.9
65%	6,279	11,577	765	54.2%	40.8%	0.10	0.06	0.41	0.35	4.1	6.0
A	11,577	22,523	765	41.1%	37.0%	0.04	0.05	0.38	0.33	10.3	7.1
85%	22,523	48,662	765	32.9%	35.8%	0.01	0.05	0.32	0.31	46.1	6.1
95%	48,662	323,105	765	41.2%	37.5%	0.08	0.08	0.32	0.30	3.9	3.7
largest 100	323,105	1,268,089	283	35.3%	31.5%	0.09	0.07	0.25	0.24	2.9	3.2
100%	1,268,089	4,184,264	100	25.4%	25.4%	0.04	0.04	0.20	0.20	5.6	5.6

Current Risk Charge Runoff Ratio (PR016, Line 4) 46.5%

(6) MM Occurrence

(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)	(K)	(L)
Size Band	Reserve ($000s)			87.5th Percentile Runoff Ratio		Average Runoff Ratio		Runoff Ratio Std. Dev		Coeff. Var.	
Endpoint Percentile	from	to	Data Points	all points in band	all points >"from"	all points in band	all points >"from"	all points in band	all points >"from"	all points in band	all points >"from"
15%	0	1,923	183	196.0%	41.1%	0.54	0.00	2.47	1.07	4.6	-351.6
25%	1,923	5,289	122	67.8%	**30.5%**	0.03	-0.10	0.64	0.47	24.5	-4.8
35%	5,289	11,711	123	33.2%	24.8%	-0.11	-0.12	0.39	0.44	-3.6	-3.8
45%	11,711	19,746	122	31.4%	23.7%	-0.03	-0.12	0.65	0.45	-25.2	-3.9
55%	19,746	37,357	122	**17.5%**	22.5%	-0.18	-0.13	0.36	0.40	-2.0	-3.0
65%	37,357	73,248	122	58.4%	24.9%	-0.01	-0.12	0.61	0.41	-87.3	-3.4
A	73,248	113,195	123	40.1%	19.7%	-0.07	-0.16	0.43	0.33	-6.2	-2.1
85%	113,195	245,022	122	12.2%	8.7%	-0.19	-0.19	0.29	0.27	-1.5	-1.4
95%	245,022	727,276	122	7.6%	7.4%	-0.16	-0.19	0.27	0.27	-1.7	-1.4
largest 100	727,276	1,397,205	31	-4.8%	7.1%	-0.27	-0.24	0.25	0.26	-0.9	-1.1
100%	1,397,205	3,130,491	31	9.0%	9.0%	-0.20	-0.20	0.27	0.27	-1.3	-1.3

Current Risk Charge Runoff Ratio (PR016, Line 4) 43.1%

(7) MM CM

(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)	(K)	(L)
Size Band	Reserve ($000s)			87.5th Percentile Runoff Ratio		Average Runoff Ratio		Runoff Ratio Std. Dev		Coeff. Var.	
Endpoint Percentile	from	to	Data Points	all points in band	all points >"from"	all points in band	all points >"from"	all points in band	all points >"from"	all points in band	all points >"from"
15%	0	1,334	385	67.5%	14.8%	0.14	-0.15	3.16	1.29	23.3	-8.6
25%	1,334	2,976	258	20.1%	**10.6%**	-0.19	-0.20	0.77	0.41	-4.1	-2.0
35%	2,976	5,439	255	21.0%	8.9%	-0.21	-0.20	0.37	0.33	-1.8	-1.7
45%	5,439	10,535	257	14.8%	7.4%	-0.20	-0.20	0.41	0.33	-2.0	-1.6
55%	10,535	18,979	257	**12.6%**	6.6%	-0.17	-0.20	0.36	0.31	-2.2	-1.6
65%	18,979	35,056	257	12.0%	5.3%	-0.17	-0.21	0.33	0.30	-1.9	-1.4
A	35,056	62,244	256	10.7%	3.5%	-0.22	-0.22	0.31	0.29	-1.4	-1.3
85%	62,244	135,194	257	-0.6%	-0.5%	-0.21	-0.22	0.32	0.28	-1.5	-1.3
95%	135,194	396,859	257	-1.4%	-0.4%	-0.23	-0.22	0.26	0.25	-1.1	-1.1
largest 100	396,859	612,328	65	8.8%	-0.4%	-0.16	-0.20	0.26	0.22	-1.6	-1.1
100%	612,328	1,478,669	64	-4.5%	-4.5%	-0.25	-0.25	0.17	0.17	-0.7	-0.7

Current Risk Charge Runoff Ratio (PR016, Line 4) 30.6%

(8) SL

(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)	(K)	(L)
Size Band	Reserve ($000s)			87.5th Percentile Runoff Ratio		Average Runoff Ratio		Runoff Ratio Std. Dev		Coeff. Var.	
Endpoint Percentile	from	to	Data Points	all points in band	all points >"from"	all points in band	all points >"from"	all points in band	all points >"from"	all points in band	all points >"from"
15%	0	348	183	173.9%	54.6%	0.89	0.21	5.85	2.64	6.6	12.4
25%	348	1,051	123	18.4%	**44.9%**	-0.07	0.09	1.06	1.45	-15.9	15.4
35%	1,051	2,151	122	78.9%	46.7%	-0.02	0.12	0.76	1.50	-34.7	12.9
45%	2,151	3,585	123	118.8%	45.7%	0.27	0.14	0.81	1.58	3.1	11.5
55%	3,585	5,872	122	**39.6%**	32.4%	-0.11	0.11	0.51	1.68	-4.4	14.8
65%	5,872	12,749	123	35.9%	32.0%	-0.04	0.16	0.52	1.84	-14.1	11.2
A	12,749	25,045	122	35.7%	30.2%	0.36	0.22	2.87	2.07	7.9	9.3
85%	25,045	72,988	123	31.8%	28.7%	0.46	0.16	2.56	1.64	5.6	10.0
95%	72,988	152,471	122	29.5%	24.0%	-0.01	-0.03	0.30	0.26	-42.8	-8.6
largest 100	152,471	206,621	31	9.8%	6.0%	-0.11	-0.08	0.19	0.18	-1.7	-2.3
100%	206,621	507,687	31	4.9%	4.9%	-0.04	-0.04	0.15	0.15	-3.6	-3.6

Current Risk Charge Runoff Ratio (PR016, Line 4) 25.7%

(9) OL

(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)	(K)	(L)
Size Band	Reserve ($000s)			87.5th Percentile Runoff Ratio		Average Runoff Ratio		Runoff Ratio Std. Dev		Coeff. Var.	
Endpoint Percentile	from	to	Data Points	all points in band	all points >"from"	all points in band	all points >"from"	all points in band	all points >"from"	all points in band	all points >"from"
15%	0	390	1,357	155.9%	59.5%	14.05	2.41	333.09	132.06	23.7	54.7
25%	390	1,226	906	80.9%	**52.5%**	2.97	0.36	88.61	30.42	29.8	84.4
35%	1,226	2,530	904	61.5%	50.3%	-0.06	0.01	0.79	0.60	-13.4	53.7
45%	2,530	4,697	904	44.8%	49.4%	-0.06	0.02	0.57	0.57	-9.1	25.8
55%	4,697	8,730	905	**37.6%**	50.3%	-0.10	0.04	0.58	0.57	-6.0	15.2
65%	8,730	17,870	905	35.4%	52.3%	-0.06	0.07	0.52	0.56	-8.8	8.4
A	17,870	36,465	904	36.7%	57.6%	-0.01	0.10	0.44	0.57	-35.6	5.5
85%	36,465	97,337	905	55.2%	64.0%	0.07	0.15	0.67	0.61	9.2	4.1
95%	97,337	525,378	905	71.3%	69.5%	0.18	0.20	0.60	0.56	3.4	2.8
largest 100	525,378	3,368,679	353	72.3%	67.2%	0.24	0.25	0.48	0.46	2.0	1.8
100%	3,368,679	23,638,870	100	59.1%	59.1%	0.25	0.25	0.34	0.34	1.3	1.3

Current Risk Charge Runoff Ratio (PR016, Line 4) 51.1%

Appendix D – RRF by LOB-size

(10) Fidelity & Surety

(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)	(K)	(L)
Size Band	Reserve ($000s)			87.5th Percentile Runoff Ratio		Average Runoff Ratio		Runoff Ratio Std. Dev		Coeff. Var.	
Endpoint Percentile	from	to	Data Points	all points in band	all points >"from"	all points in band	all points >"from"	all points in band	all points >"from"	all points in band	all points >"from"
15%	0	81	174	188.9%	66.3%	6.62	0.96	55.00	21.44	8.3	22.4
25%	81	209	116	44.2%	**55.8%**	-0.59	-0.04	1.05	1.92	-1.8	-49.9
35%	209	483	116	101.9%	61.4%	0.19	0.03	4.04	2.00	21.4	57.3
45%	483	1,064	116	71.4%	60.3%	-0.03	0.01	1.31	1.45	-45.7	130.5
55%	1,064	1,736	117	**127.3%**	54.4%	0.28	0.02	1.99	1.47	7.2	80.6
65%	1,736	2,834	116	112.4%	43.9%	0.14	-0.04	1.59	1.33	11.7	-33.6
A	2,834	4,630	116	33.5%	38.0%	-0.19	-0.09	1.39	1.24	-7.2	-13.9
85%	4,630	8,454	116	42.4%	38.4%	-0.02	-0.05	1.48	1.17	-65.9	-24.2
95%	8,454	36,650	116	26.2%	27.9%	-0.01	-0.07	1.10	0.93	-74.3	-14.1
largest 100	36,650	67,857	30	5.8%	30.8%	-0.18	-0.17	0.41	0.38	-2.3	-2.3
100%	67,857	756,697	29	41.0%	41.0%	-0.16	-0.16	0.35	0.35	-2.3	-2.3

Current Risk Charge Runoff Ratio (PR016, Line 4) 32.5%

(11) Spec Prop

(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)	(K)	(L)
Size Band	Reserve ($000s)			87.5th Percentile Runoff Ratio		Average Runoff Ratio		Runoff Ratio Std. Dev		Coeff. Var.	
Endpoint Percentile	from	to	Data Points	all points in band	all points >"from"	all points in band	all points >"from"	all points in band	all points >"from"	all points in band	all points >"from"
15%	0	46	1,076	120.0%	40.0%	2.06	2.34	39.41	126.88	19.1	54.2
25%	46	107	713	45.3%	**33.1%**	17.30	2.39	397.62	136.67	23.0	57.2
35%	107	216	713	35.2%	31.0%	0.83	0.40	14.78	10.02	17.7	24.9
45%	216	390	711	29.0%	30.5%	-0.16	0.34	1.18	9.06	-7.3	27.0
55%	390	782	716	**27.1%**	30.9%	0.27	0.43	4.52	9.84	16.9	23.1
65%	782	1,596	713	25.9%	32.7%	0.27	0.46	7.65	10.67	27.8	23.1
A	1,596	3,290	714	26.1%	34.7%	1.54	0.51	20.64	11.38	13.4	22.1
85%	3,290	8,717	714	34.1%	37.4%	0.24	0.10	5.02	3.24	21.3	31.7
95%	8,717	44,782	714	36.4%	39.5%	0.01	0.01	0.87	0.84	114.9	65.3
largest 100	44,782	190,412	258	51.6%	43.4%	0.06	0.02	0.90	0.80	14.7	33.6
100%	190,412	2,227,919	100	16.8%	16.8%	-0.07	-0.07	0.40	0.40	-5.4	-5.4

Current Risk Charge Runoff Ratio (PR016, Line 4) 19.1%

(12) Auto Phys Damage

(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)	(K)	(L)
Size Band	Reserve ($000s)			87.5th Percentile Runoff Ratio		Average Runoff Ratio		Runoff Ratio Std. Dev		Coeff. Var.	
Endpoint Percentile	from	to	Data Points	all points in band	all points >"from"	all points in band	all points >"from"	all points in band	all points >"from"	all points in band	all points >"from"
15%	0	73	683	62.8%	23.5%	11.26	3.86	238.97	100.45	21.2	26.0
25%	73	150	455	44.6%	**19.4%**	9.35	2.55	93.03	42.29	9.9	16.6
35%	150	268	454	18.4%	16.5%	4.13	1.64	55.85	29.46	13.5	17.9
45%	268	466	455	17.1%	15.8%	2.24	1.26	21.25	22.86	9.5	18.1
55%	466	822	455	**26.7%**	15.7%	1.74	1.09	27.33	23.14	15.7	21.3
65%	822	1,527	455	15.0%	13.5%	3.48	0.94	43.47	22.10	12.5	23.5
A	1,527	2,823	455	9.4%	12.6%	0.02	0.21	5.53	9.32	365.4	43.5
85%	2,823	7,139	455	10.3%	14.4%	0.82	0.29	16.31	10.46	19.8	35.6
95%	7,139	24,827	455	24.9%	16.2%	-0.01	-0.06	2.23	2.19	-199.5	-37.4
largest 100	24,827	54,011	128	17.6%	9.2%	-0.09	-0.15	2.66	2.11	-29.9	-13.8
100%	54,011	3,404,975	100	6.5%	6.5%	-0.24	-0.24	1.06	1.06	-4.5	-4.5

Current Risk Charge Runoff Ratio (PR016, Line 4) 11.2%

(13) Other

(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)	(K)	(L)
Size Band	Reserve ($000s)			87.5th Percentile Runoff Ratio		Average Runoff Ratio		Runoff Ratio Std. Dev		Coeff. Var.	
Endpoint			Data	all points	all points	all points	all points	all points	all points	all points	all points
Percentile	from	to	Points	in band	>"from"	in band	>"from"	in band	>"from"	in band	>"from"
15%	0	140	223	118.6%	35.1%	-0.40	-0.13	17.13	6.69	-43.0	-50.0
25%	140	324	147	39.1%	**27.4%**	-0.08	-0.09	1.12	0.94	-13.4	-10.8
35%	324	771	148	37.8%	27.2%	-0.20	-0.09	0.65	0.91	-3.3	-10.4
45%	771	1,837	148	12.9%	26.3%	-0.24	-0.07	0.75	0.94	-3.1	-13.4
55%	1,837	3,161	148	**19.3%**	27.1%	-0.20	-0.04	0.57	0.97	-2.8	-24.6
65%	3,161	5,117	148	12.8%	27.4%	-0.38	0.00	0.63	1.04	-1.7	-327.6
A	5,117	9,817	148	22.0%	36.4%	-0.14	0.10	0.47	1.10	-3.4	10.6
85%	9,817	22,489	148	91.3%	40.0%	0.43	0.20	1.76	1.26	4.1	6.3
95%	22,489	60,579	148	19.0%	25.9%	0.06	0.05	0.83	0.73	14.8	13.9
largest 100	60,579	115,862	38	3.1%	27.9%	-0.11	0.04	0.36	0.46	-3.4	10.5
100%	115,862	1,215,858	37	38.9%	38.9%	0.20	0.20	0.51	0.51	2.6	2.6

Current Risk Charge Runoff Ratio (PR016, Line 4) 17.2%

(14) Fin & Mort

(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)	(K)	(L)
Size Band	Reserve ($000s)			87.5th Percentile Runoff Ratio		Average Runoff Ratio		Runoff Ratio Std. Dev		Coeff. Var.	
Endpoint			Data	all points	all points	all points	all points	all points	all points	all points	all points
Percentile	from	to	Points	in band	>"from"	in band	>"from"	in band	>"from"	in band	>"from"
15%	0	22	6	290.7%	2.9%	0.63	-0.60	1.97	1.77	3.1	-3.0
25%	22	39	4	-2.3%	**0.0%**	-0.52	-0.81	0.56	1.67	-1.1	-2.1
35%	39	69	9	0.0%	0.0%	-0.18	-0.85	0.28	1.77	-1.6	-2.1
45%	69	69	0		0.0%		-1.12		2.04		-1.8
55%	69	96	3	**-73.1%**	0.0%	-0.86	-1.12	0.16	2.04	-0.2	-1.8
65%	96	490	4	-266.3%	0.0%	-4.46	-1.16	2.32	2.20	-0.5	-1.9
A	490	665	6	0.0%	5.0%	-0.07	-0.28	0.18	1.07	-2.4	-3.8
85%	665	758	2	-134.9%	20.0%	-2.33	-0.42	1.86	1.39	-0.8	-3.3
95%	758	5,145	4	104.7%	53.9%	0.31	0.13	0.86	0.65	2.8	5.2
largest 100	5,145	15,380	2	-4.1%	-4.6%	-0.06	-0.11	0.03	0.10	-0.5	-0.9
100%	15,380	17,015	1	-23.1%	-23.1%	-0.23	-0.23				

Current Risk Charge Runoff Ratio (PR016, Line 4) 20.0%

(15) International

(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)	(K)	(L)
Size Band	Reserve ($000s)			87.5th Percentile Runoff Ratio		Average Runoff Ratio		Runoff Ratio Std. Dev		Coeff. Var.	
Endpoint			Data	all points	all points	all points	all points	all points	all points	all points	all points
Percentile	from	to	Points	in band	>"from"	in band	>"from"	in band	>"from"	in band	>"from"
15%	0	950	12	14101.3%	69.5%	55.35	7.92	93.49	39.23	1.7	5.0
25%	950	2,022	9	440.7%	**47.4%**	0.64	0.02	2.70	1.04	4.2	66.2
35%	2,022	3,410	8	12.0%	43.4%	-0.28	-0.07	0.61	0.47	-2.2	-6.4
45%	3,410	5,760	8	108.7%	43.4%	0.06	-0.04	0.72	0.45	11.2	-10.2
55%	5,760	11,423	9	**58.6%**	37.6%	0.11	-0.06	0.40	0.39	3.7	-6.3
65%	11,423	19,071	8	47.7%	32.8%	0.12	-0.10	0.32	0.39	2.6	-3.8
A	19,071	26,576	8	36.8%	23.5%	0.11	-0.16	0.20	0.39	1.8	-2.4
85%	26,576	52,353	9	2.3%	10.2%	-0.18	-0.26	0.15	0.40	-0.8	-1.5
95%	52,353	173,784	8	35.0%	25.0%	-0.08	-0.32	0.50	0.50	-6.4	-1.6
largest 100	173,784	250,205	3	-69.7%	-57.7%	-0.78	-0.70	0.10	0.13	-0.1	-0.2
100%	250,205	315,299	2	-56.4%	-56.4%	-0.58	-0.58	0.02	0.02	0.0	0.0

Current Risk Charge Runoff Ratio (PR016, Line 4) 32.7%

(16) Rein Property & Financial

(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)	(K)	(L)
Size Band	Reserve ($000s)			87.5th Percentile Runoff Ratio		Average Runoff Ratio		Runoff Ratio Std. Dev		Coeff. Var.	
Endpoint Percentile	from	to	Data Points	all points in band	all points >"from"	all points in band	all points >"from"	all points in band	all points >"from"	all points in band	all points >"from"
15%	0	536	181	74.5%	44.3%	1.48	0.17	13.57	5.30	9.2	31.9
25%	536	1,752	121	39.1%	**42.2%**	-0.13	-0.06	0.57	0.62	-4.4	-9.6
35%	1,752	4,353	120	51.3%	42.2%	-0.11	-0.06	0.88	0.63	-7.8	-11.3
45%	4,353	7,972	121	34.5%	42.1%	-0.08	-0.05	0.89	0.58	-11.6	-12.4
55%	7,972	13,285	121	**71.9%**	42.2%	0.06	-0.04	0.67	0.51	10.5	-12.2
65%	13,285	23,879	121	53.1%	40.8%	-0.05	-0.07	0.60	0.47	-12.4	-7.1
A	23,879	41,855	120	40.2%	32.5%	-0.05	-0.07	0.47	0.42	-9.0	-6.0
85%	41,855	102,342	121	42.2%	31.0%	-0.04	-0.08	0.46	0.40	-11.7	-5.2
95%	102,342	443,957	121	31.3%	25.2%	-0.06	-0.10	0.39	0.36	-6.2	-3.5
largest 100	443,957	656,684	31	5.0%	6.5%	-0.18	-0.18	0.29	0.27	-1.6	-1.5
100%	656,684	3,896,952	30	6.2%	6.2%	-0.19	-0.19	0.25	0.25	-1.3	-1.3
	Current Risk Charge Runoff Ratio (PR016, Line 4)				28.6%						

(17) Reinsurance Liab

(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)	(K)	(L)
Size Band	Reserve ($000s)			87.5th Percentile Runoff Ratio		Average Runoff Ratio		Runoff Ratio Std. Dev		Coeff. Var.	
Endpoint Percentile	from	to	Data Points	all points in band	all points >"from"	all points in band	all points >"from"	all points in band	all points >"from"	all points in band	all points >"from"
15%	0	3,688	202	114.2%	67.6%	0.58	0.24	4.19	1.80	7.3	7.6
25%	3,688	8,712	135	55.2%	**65.0%**	0.14	0.18	1.48	0.84	10.3	4.7
35%	8,712	18,749	135	78.7%	65.6%	0.21	0.18	0.76	0.72	3.6	3.9
45%	18,749	34,829	135	58.3%	63.3%	0.13	0.18	0.65	0.71	5.2	4.0
55%	34,829	69,801	136	**93.9%**	63.9%	0.31	0.19	1.01	0.72	3.2	3.9
65%	69,801	136,546	135	43.8%	61.2%	0.09	0.16	0.47	0.64	5.2	4.0
A	136,546	251,973	135	46.4%	65.3%	0.17	0.18	0.95	0.68	5.6	3.8
85%	251,973	582,726	135	68.8%	69.6%	0.12	0.18	0.64	0.53	5.4	2.9
95%	582,726	2,170,556	135	66.4%	70.8%	0.23	0.22	0.40	0.44	1.7	2.0
largest 100	2,170,556	4,502,562	34	122.8%	104.2%	0.53	0.20	0.53	0.53	1.0	2.7
100%	4,502,562	11,516,723	34	4.8%	4.8%	-0.13	-0.13	0.25	0.25	-1.9	-1.9
	Current Risk Charge Runoff Ratio (PR016, Line 4)				76.9%						

(18) Products Liability

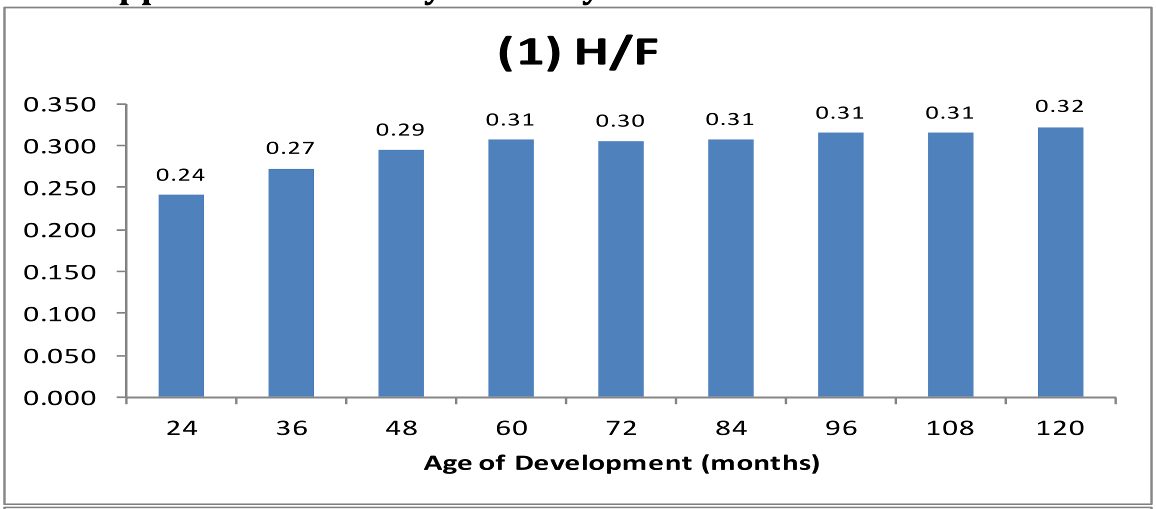
(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)	(K)	(L)
Size Band	Reserve ($000s)			87.5th Percentile Runoff Ratio		Average Runoff Ratio		Runoff Ratio Std. Dev		Coeff. Var.	
Endpoint Percentile	from	to	Data Points	all points in band	all points >"from"	all points in band	all points >"from"	all points in band	all points >"from"	all points in band	all points >"from"
15%	0	909	96	118.0%	92.4%	0.35	0.26	2.59	1.79	7.4	7.0
25%	909	1,854	64	74.7%	**89.4%**	0.77	0.24	3.76	1.61	4.9	6.7
35%	1,854	3,709	64	73.0%	90.8%	0.09	0.17	0.89	1.02	9.5	6.0
45%	3,709	7,228	64	137.1%	95.2%	0.51	0.18	1.81	1.04	3.5	5.8
55%	7,228	13,844	64	**68.1%**	74.1%	0.15	0.12	0.74	0.82	5.0	6.8
65%	13,844	23,054	64	29.7%	76.2%	0.05	0.11	1.10	0.83	23.6	7.3
A	23,054	38,020	64	180.3%	82.7%	0.37	0.13	1.12	0.74	3.1	5.6
85%	38,020	90,661	64	74.4%	50.3%	0.17	0.04	0.62	0.50	3.7	12.2
95%	90,661	188,445	64	23.5%	19.3%	0.00	-0.04	0.41	0.38	220.6	-9.0
largest 100	188,445	240,180	17	5.1%	-1.8%	-0.03	-0.13	0.34	0.28	-13.2	-2.2
100%	240,180	363,276	16	-9.9%	-9.9%	-0.23	-0.23	0.13	0.13	-0.6	-0.6
	Current Risk Charge Runoff Ratio (PR016, Line 4)				64.3%						

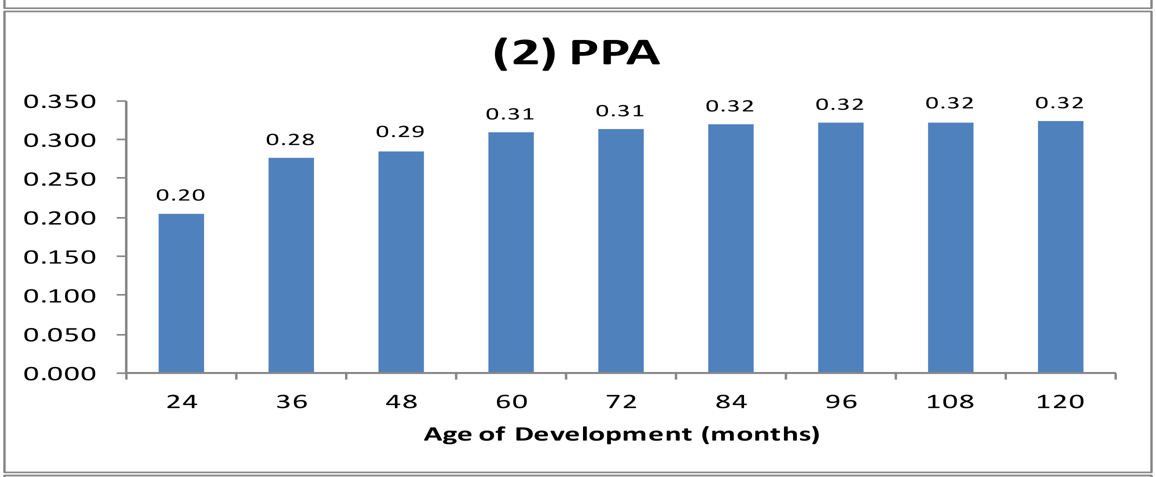
(19) Warranty

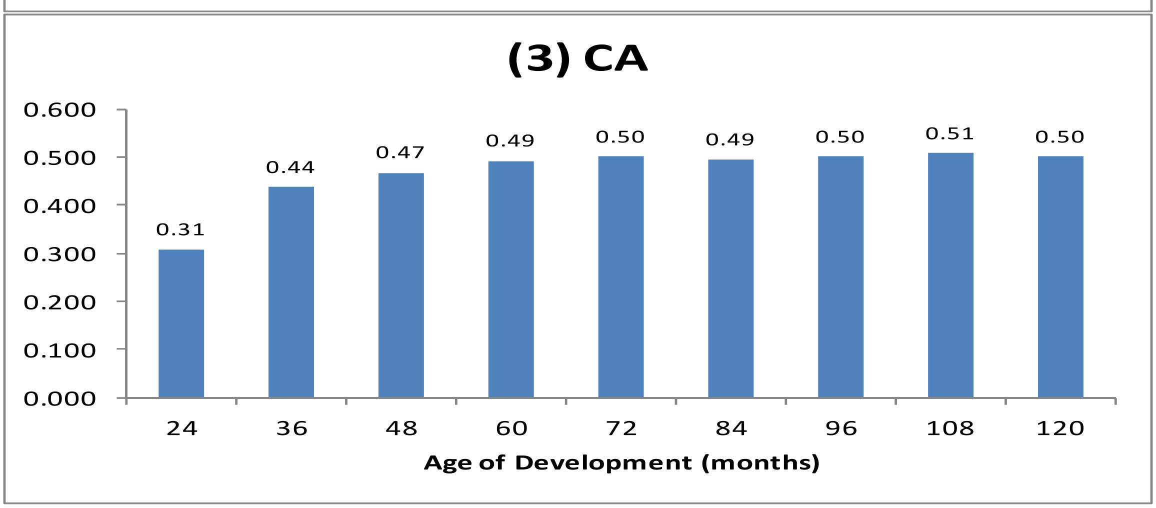
(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)	(K)	(L)
Size Band	Reserve ($000s)			87.5th Percentile Runoff Ratio		Average Runoff Ratio		Runoff Ratio Std. Dev		Coeff. Var.	
Endpoint Percentile	from	to	Data Points	all points in band	all points >"from"	all points in band	all points >"from"	all points in band	all points >"from"	all points in band	all points >"from"
15%	0	1,242	3	-19.8%	3.2%	-0.24	-0.15	0.06	0.20	-0.2	-1.4
25%	1,242	1,550	2	-30.0%	**4.4%**	-0.54	-0.14	0.45	0.22	-0.8	-1.6
35%	1,550	2,131	2	-26.8%	5.5%	-0.30	-0.09	0.06	0.13	-0.2	-1.5
45%	2,131	2,584	2	-16.7%	6.8%	-0.18	-0.06	0.02	0.10	-0.1	-1.8
55%	2,584	2,720	2	**-6.3%**	8.0%	-0.10	-0.04	0.07	0.09	-0.7	-2.6
65%	2,720	2,841	2	3.4%	9.3%	-0.01	-0.02	0.08	0.09	-8.1	-4.2
A	2,841	8,331	2	-1.2%	10.1%	-0.07	-0.03	0.11	0.10	-1.6	-4.0
85%	8,331	9,897	2	7.6%	10.3%	-0.02	-0.01	0.19	0.11	-7.8	-9.6
95%	9,897	10,944	2	7.9%	6.8%	0.02	0.00	0.12	0.08	6.8	-18.3
largest 100	10,944	14,215	1	-6.7%	0.5%	-0.07	-0.03		0.06		-2.3
100%	14,215	14,256	1	1.6%	1.6%	0.02	0.02				

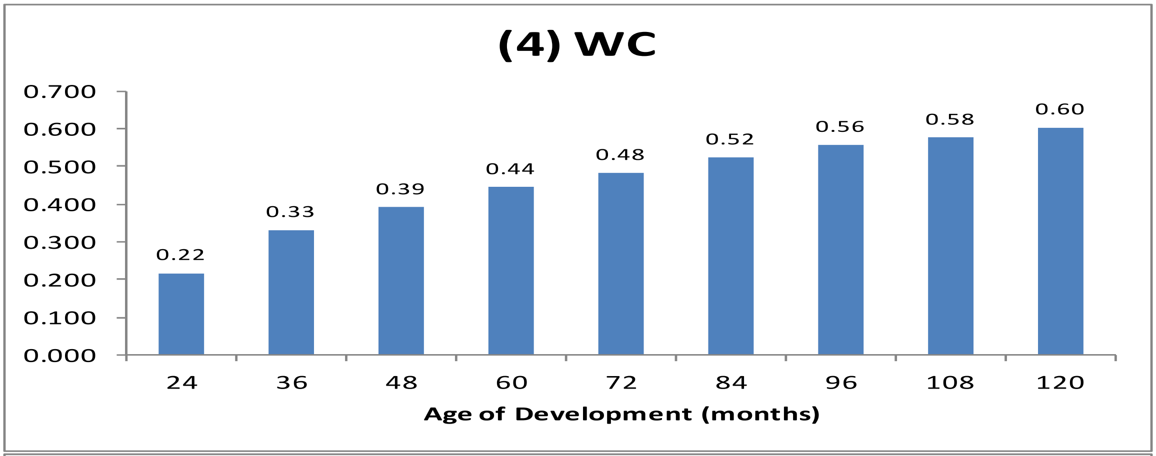
Current Risk Charge Runoff Ratio (PR016, Line 4) 32.5%

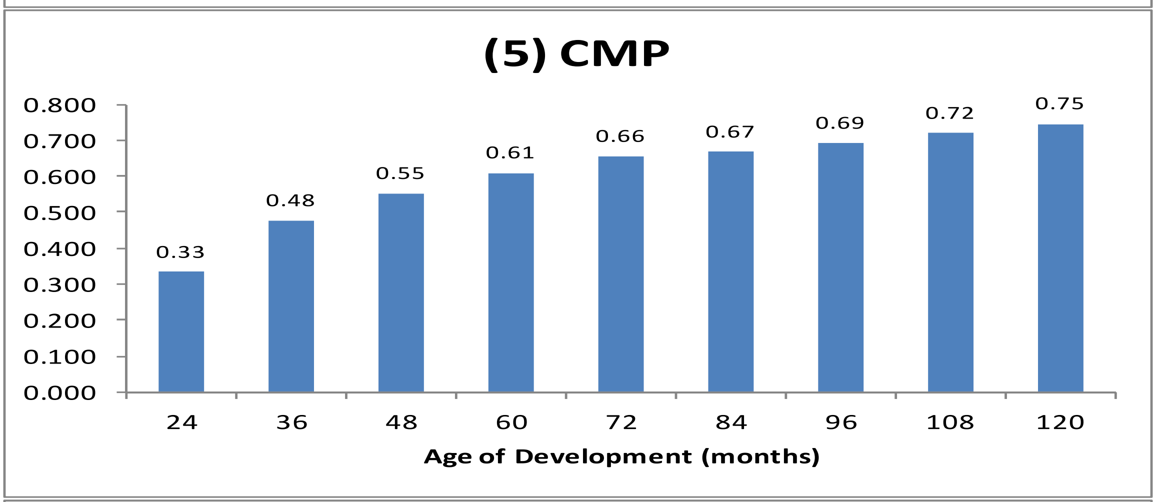
Appendix E – RRF by Maturity

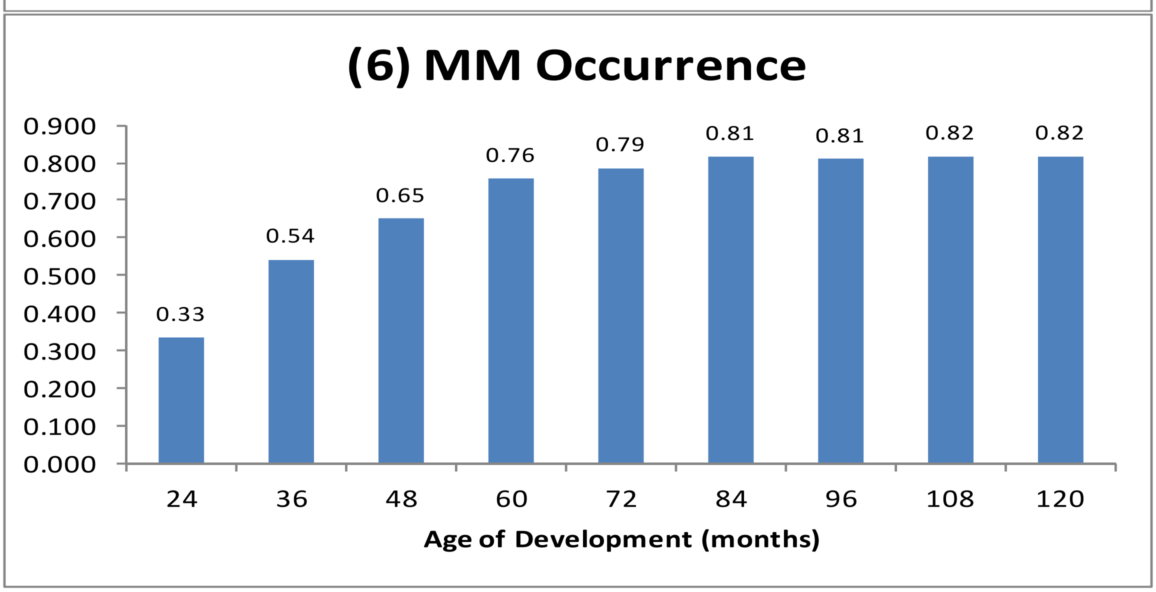


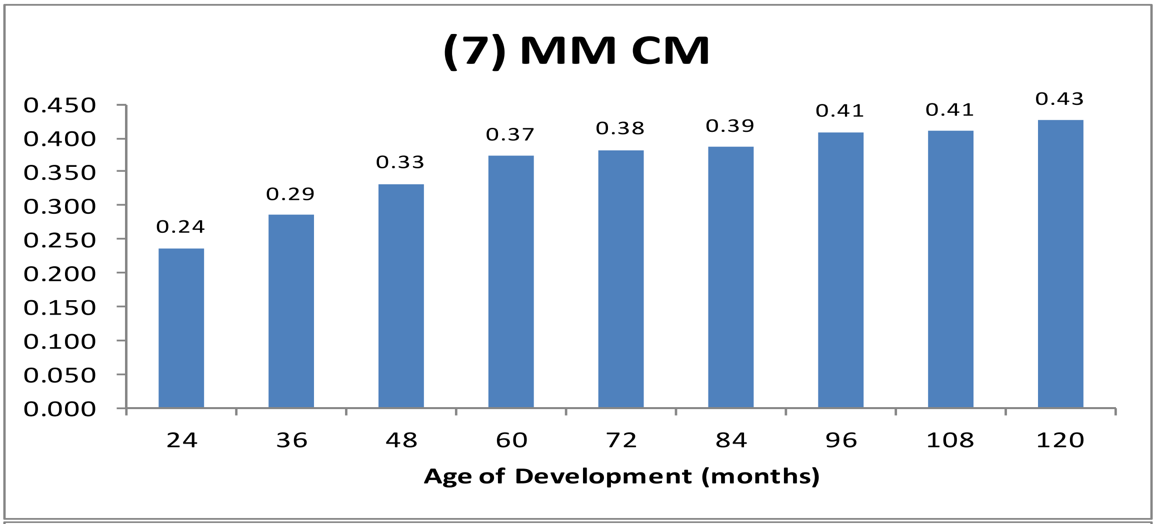


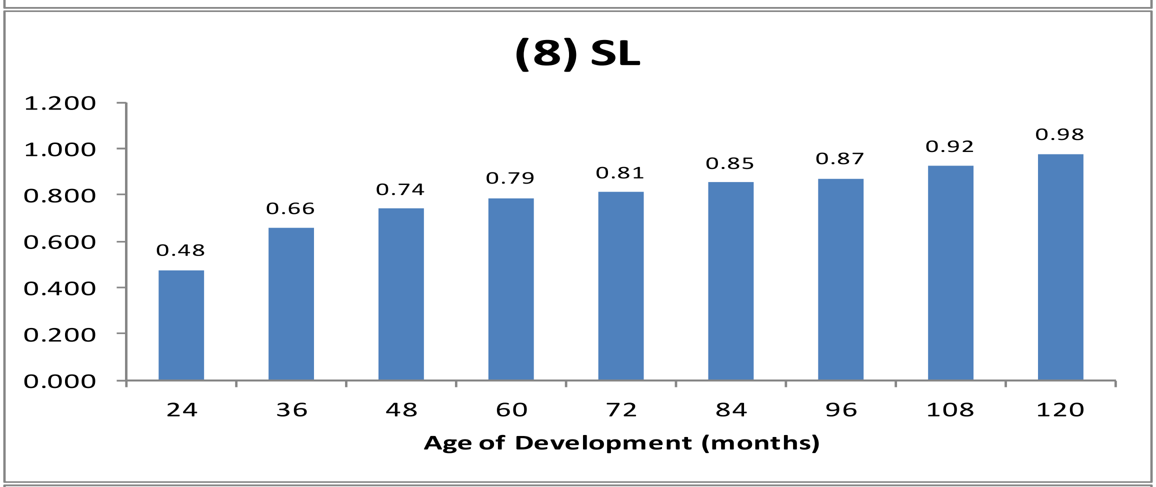


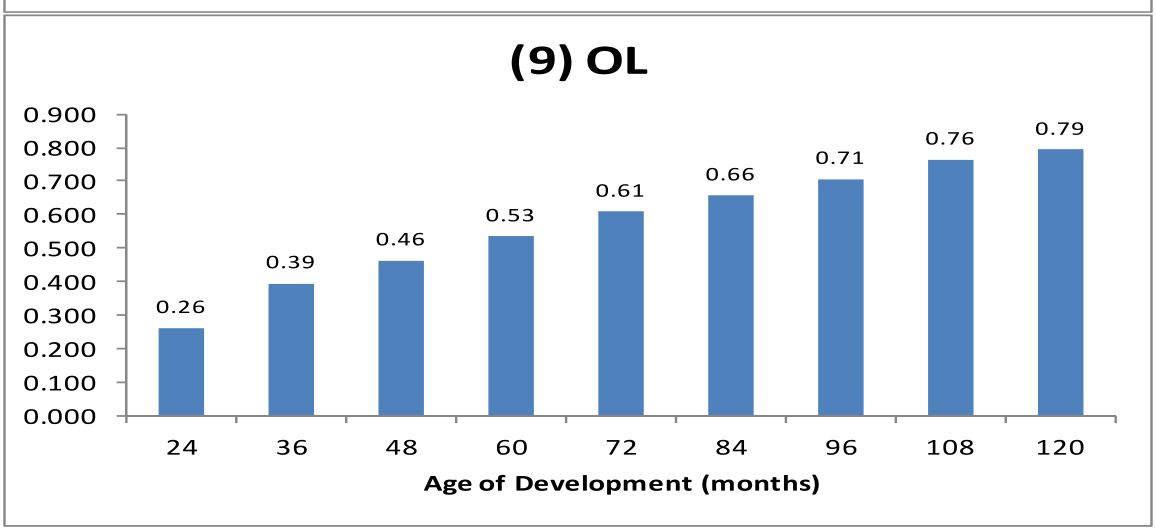

(4) WC
0.700
0.600
0.500
0.400
0.300
0.200
0.100
0.000
0.22
0.33
0.39
0.44
0.48
0.52
0.56
0.58
0.60
24
36
48
60
72
84
96
108
120
Age of Development (months)

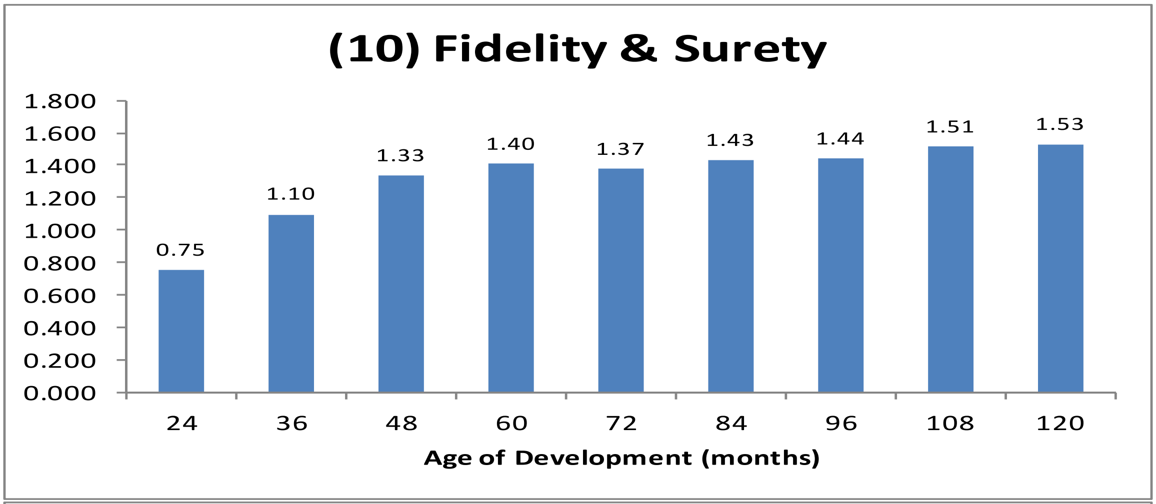

(5) CMP
0.800
0.700
0.600
0.500
0.400
0.300
0.200
0.100
0.000
0.33
0.48
0.55
0.61
0.66
0.67
0.69
0.72
0.75
24
36
48
60
72
84
96
108
120
Age of Development (months)

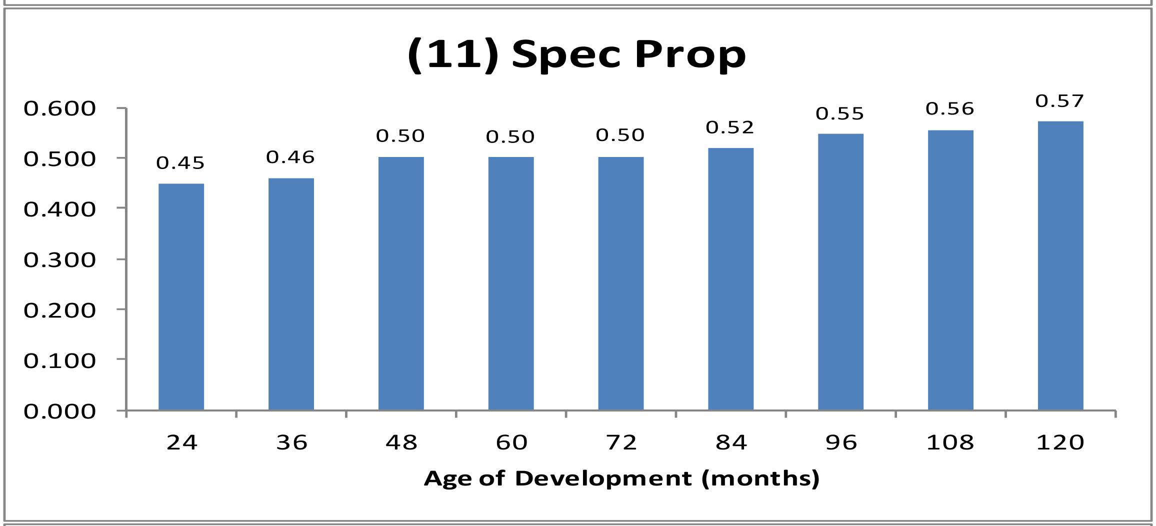

(6) MM Occurrence
0.900
0.800
0.700
0.600
0.500
0.400
0.300
0.200
0.100
0.000
0.33
0.54
0.65
0.76
0.79
0.81
0.81
0.82
0.82
24
36
48
60
72
84
96
108
120
Age of Development (months)

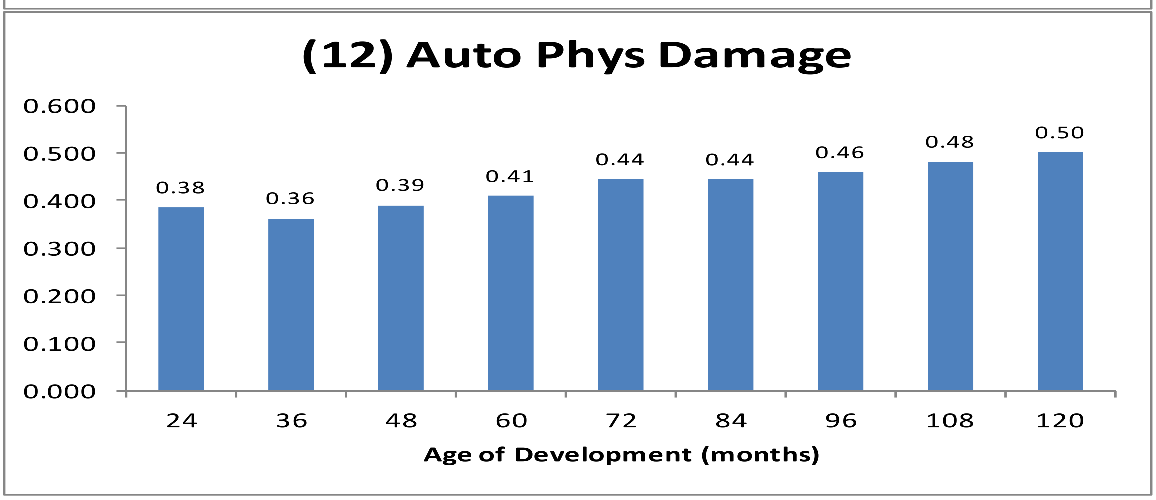

(7) MM CM
0.450
0.400
0.350
0.300
0.250
0.200
0.150
0.100
0.050
0.000
0.24
0.29
0.33
0.37
0.38
0.39
0.41
0.41
0.43
24
36
48
60
72
84
96
108
120
Age of Development (months)

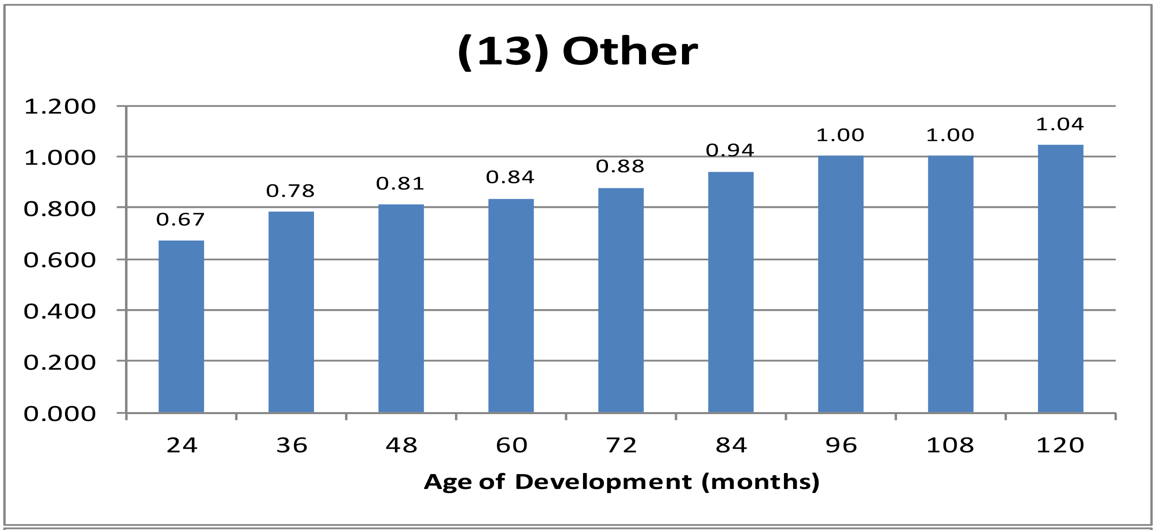

(8) SL
1.200
1.000
0.800
0.600
0.400
0.200
0.000
0.48
0.66
0.74
0.79
0.81
0.85
0.87
0.92
0.98
24
36
48
60
72
84
96
108
120
Age of Development (months)

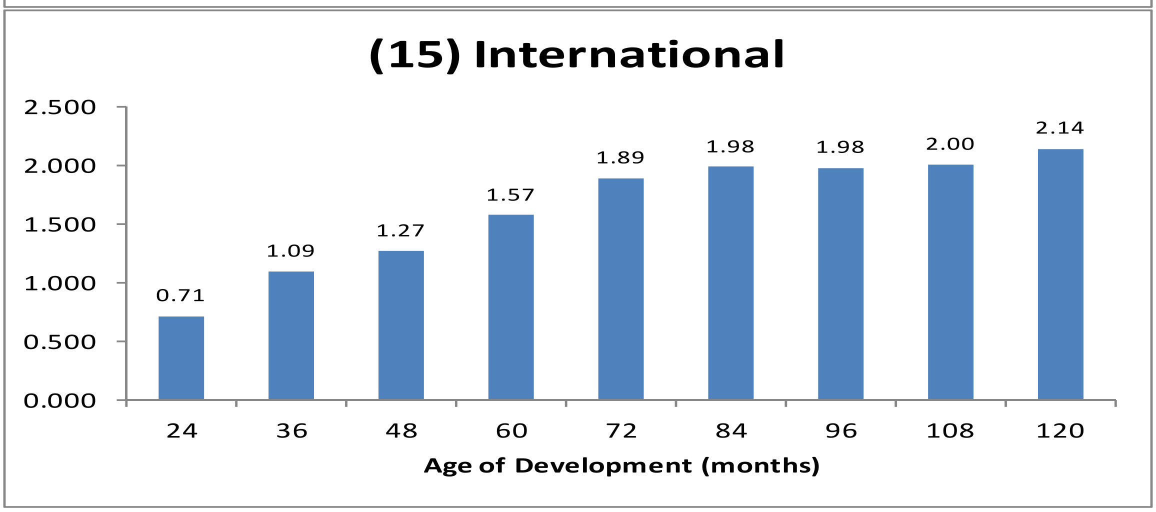

(9) OL
0.900
0.800
0.700
0.600
0.500
0.400
0.300
0.200
0.100
0.000
0.26
0.39
0.46
0.53
0.61
0.66
0.71
0.76
0.79
24
36
48
60
72
84
96
108
120
Age of Development (months)

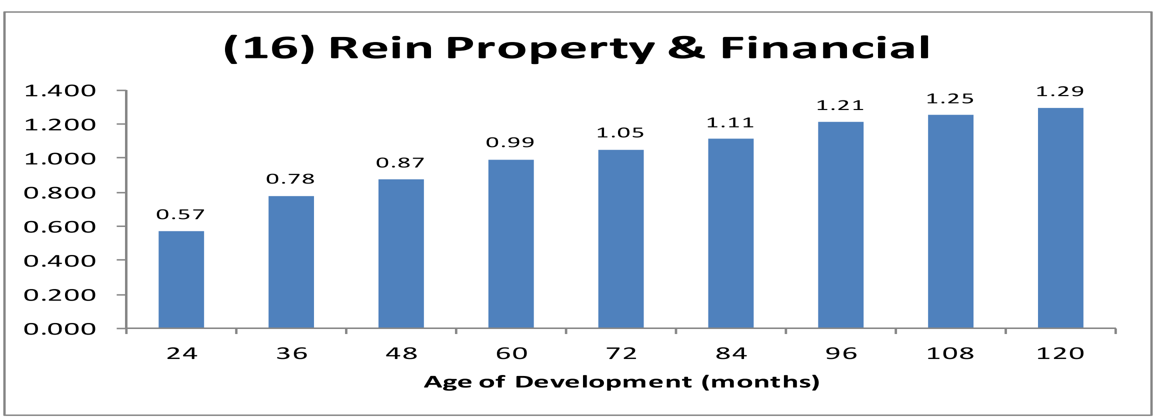

(10) Fidelity & Surety
1.800
1.600
1.400
1.200
1.000
0.800
0.600
0.400
0.200
0.000
0.75
1.10
1.33
1.40
1.37
1.43
1.44
1.51
1.53
24
36
48
60
72
84
96
108
120
Age of Development (months)

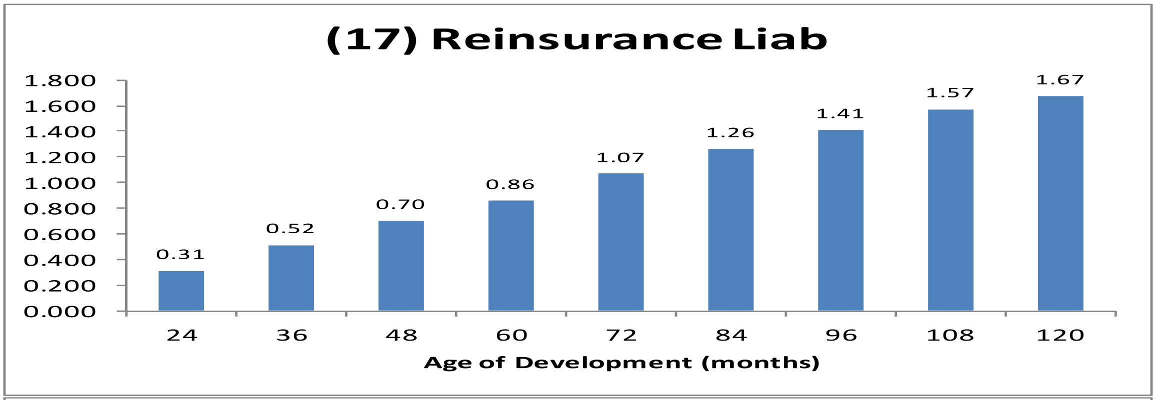

(11) Spec Prop
0.600
0.500
0.400
0.300
0.200
0.100
0.000
0.45
0.46
0.50
0.50
0.50
0.52
0.55
0.56
0.57
24
36
48
60
72
84
96
108
120
Age of Development (months)

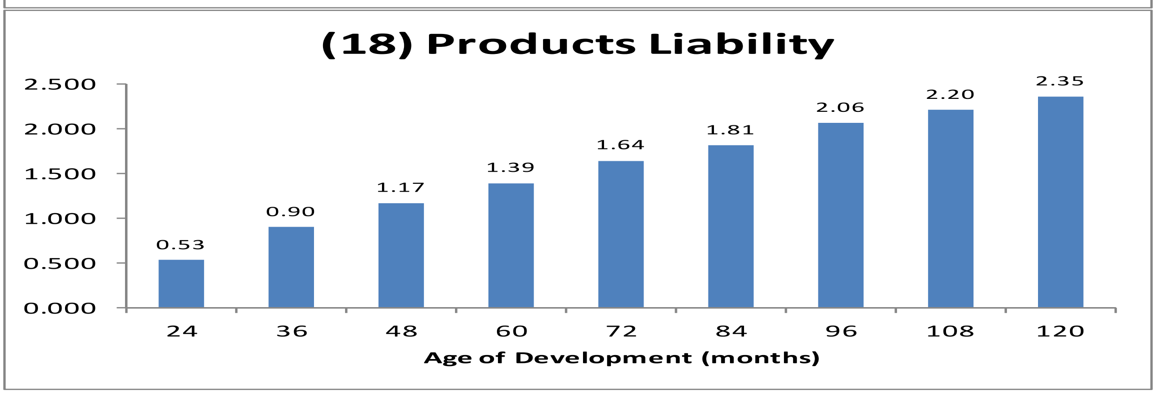

(12) Auto Phys Damage
0.600
0.500
0.400
0.300
0.200
0.100
0.000
0.38
0.36
0.39
0.41
0.44
0.44
0.46
0.48
0.50
24
36
48
60
72
84
96
108
120
Age of Development (months)


(13) Other
1.200
1.000
0.800
0.600
0.400
0.200
0.000
0.67
0.78
0.81
0.84
0.88
0.94
1.00
1.00
1.04
24
36
48
60
72
84
96
108
120
Age of Development (months)

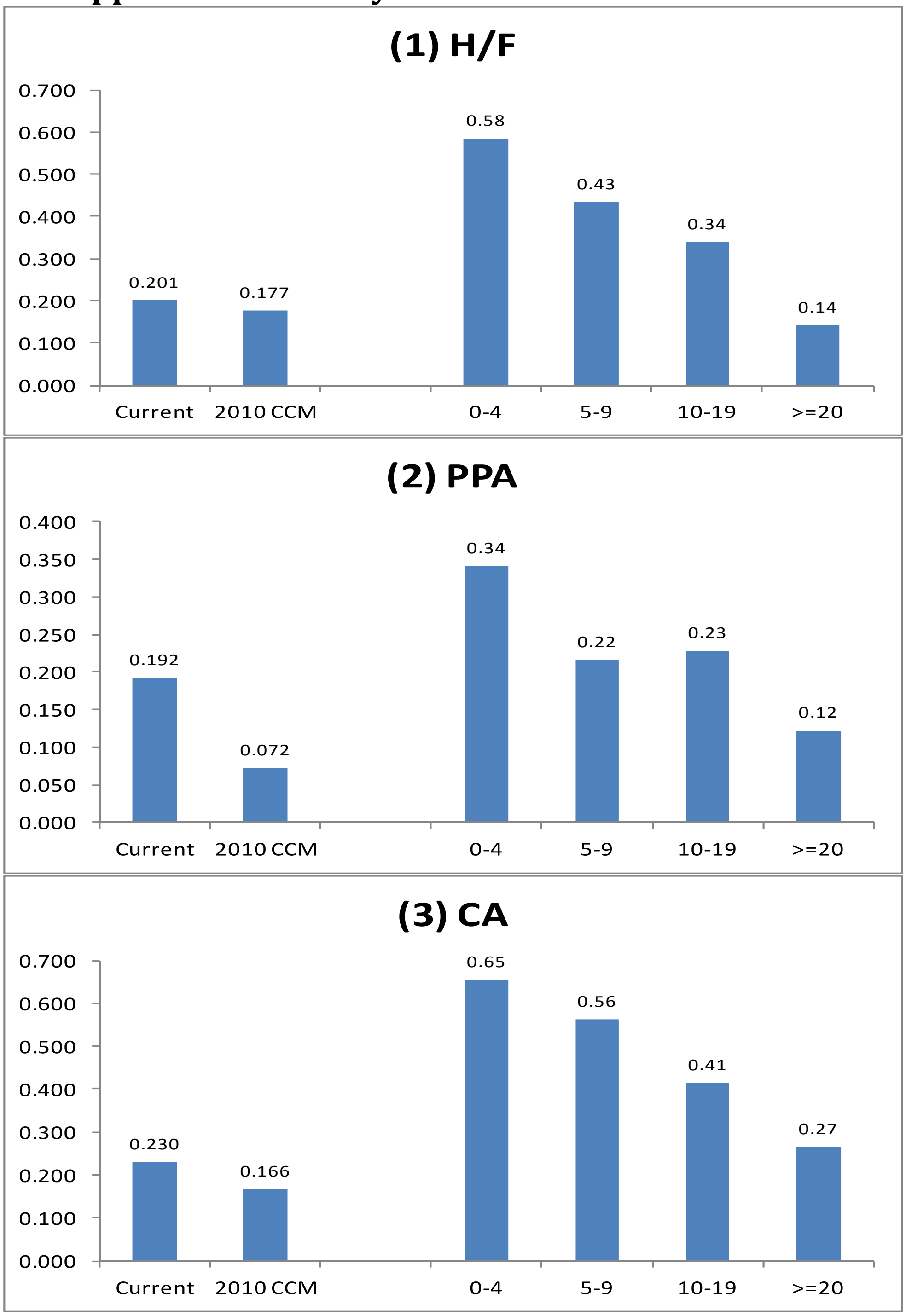

(15) International
2.500
2.000
1.500
1.000
0.500
0.000
0.71
1.09
1.27
1.57
1.89
1.98
1.98
2.00
2.14
24
36
48
60
72
84
96
108
120
Age of Development (months)


(16) Rein Property & Financial
1.400
1.200
1.000
0.800
0.600
0.400
0.200
0.000
0.57
0.78
0.87
0.99
1.05
1.11
1.21
1.25
1.29
24
36
48
60
72
84
96
108
120
Age of Development (months)

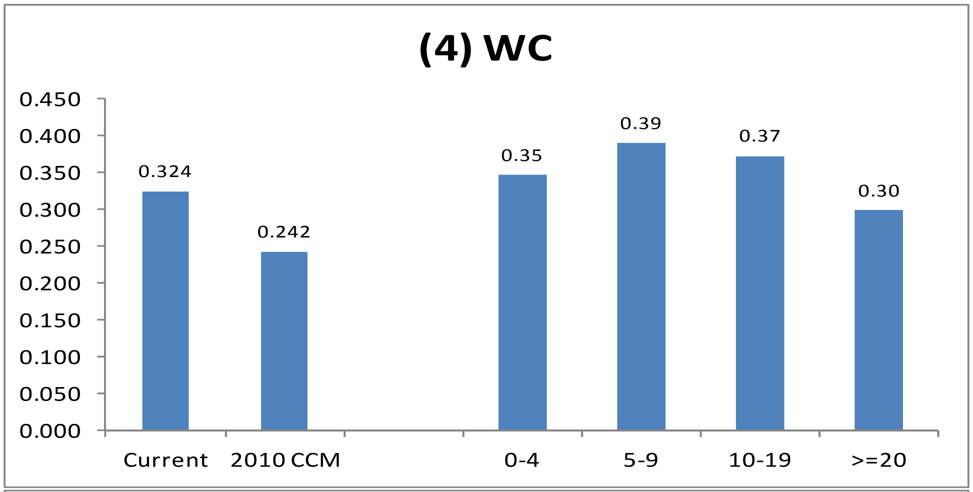

(17) Reinsurance Liab
1.800
1.600
1.400
1.200
1.000
0.800
0.600
0.400
0.200
0.000
0.31
0.52
0.70
0.86
1.07
1.26
1.41
1.57
1.67
24
36
48
60
72
84
96
108
120
Age of Development (months)

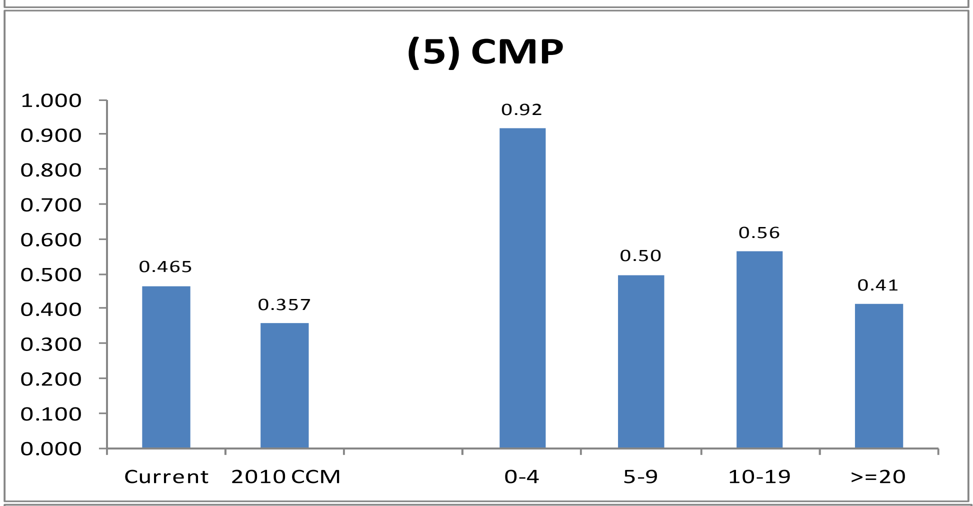

(18) Products Liability
2.500
2.000
1.500
1.000
0.500
0.000
0.53
0.90
1.17
1.39
1.64
1.81
2.06
2.20
2.35
24
36
48
60
72
84
96
108
120
Age of Development (months)

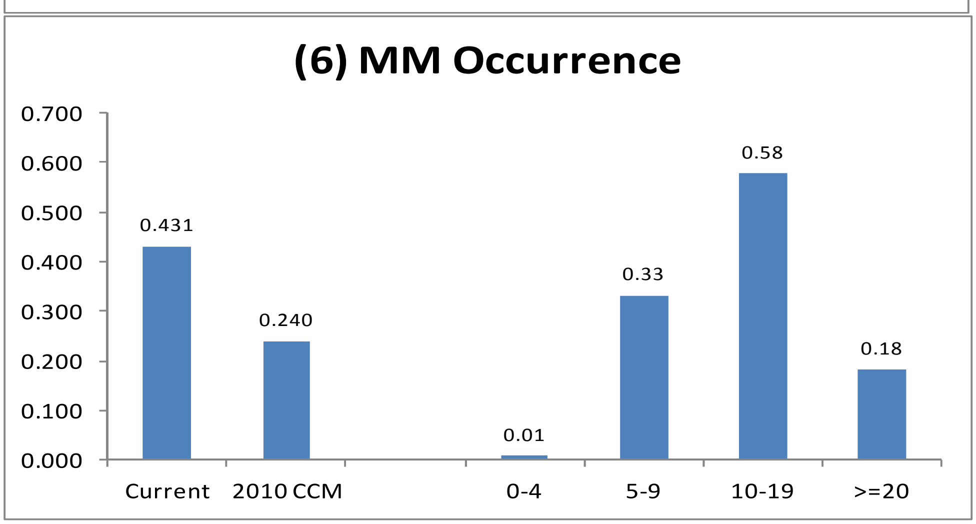
Appendix F – RRF by Number of Years of NEP>0



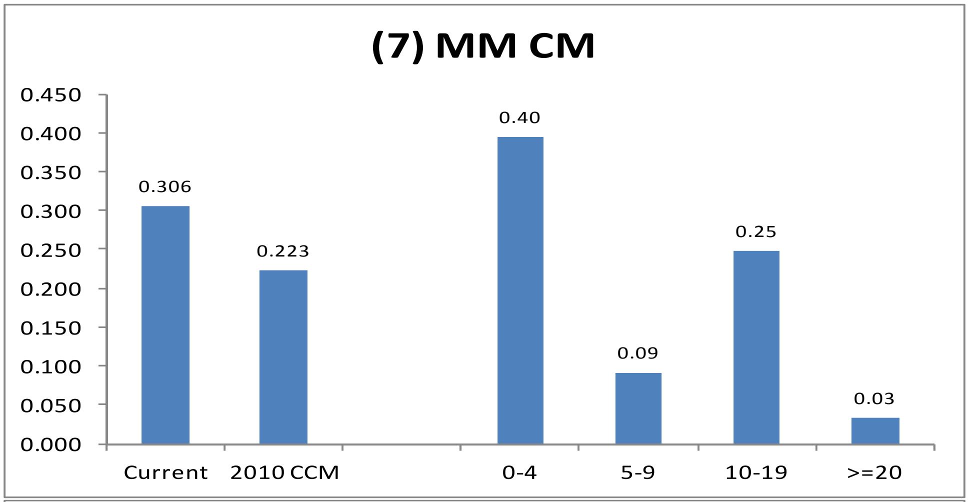
Appendix F - RRF by Number of Years of NEP>0

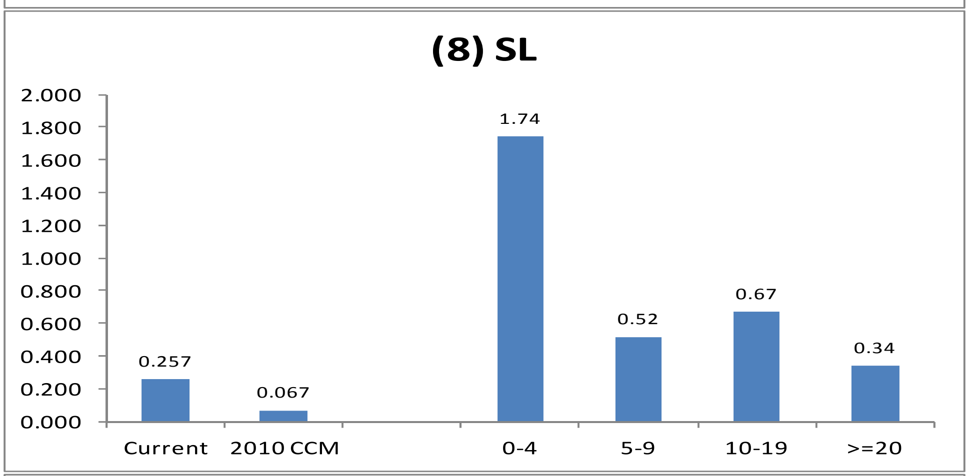


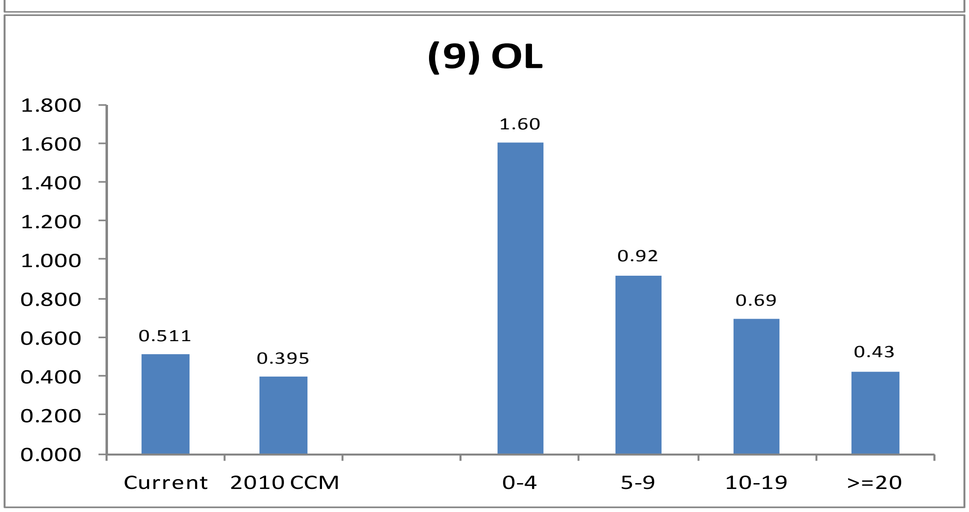




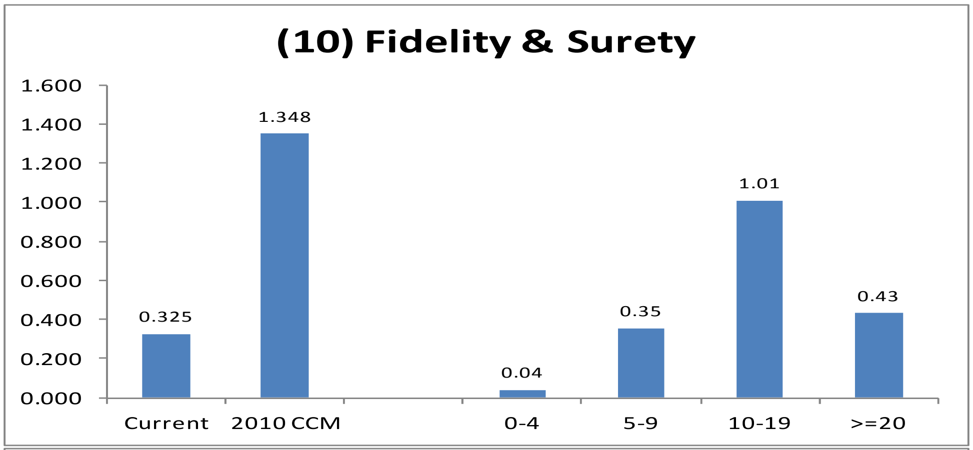
Appendix F - RRF by Number of Years of NEP>0

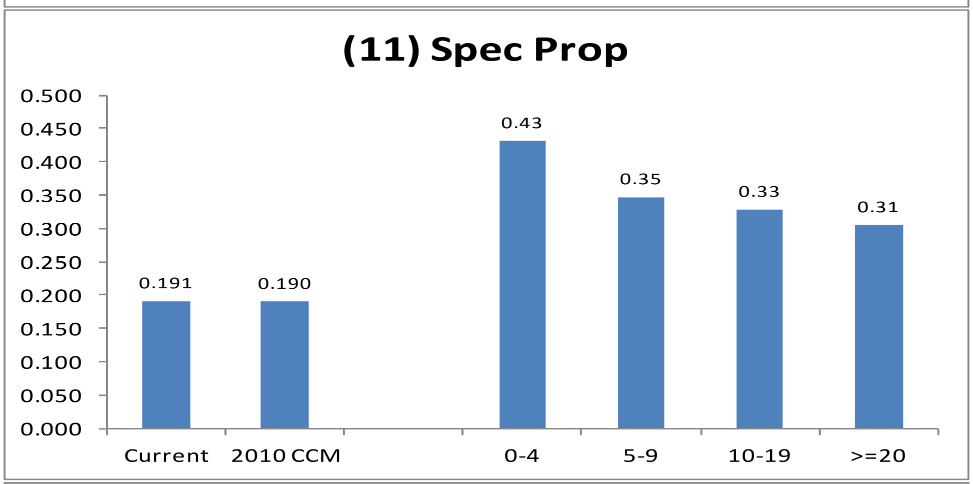


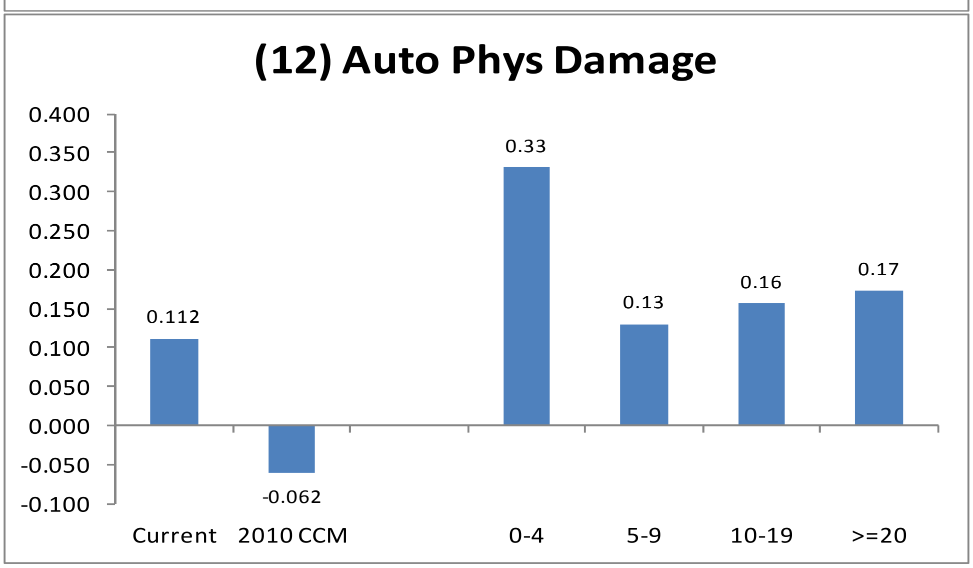




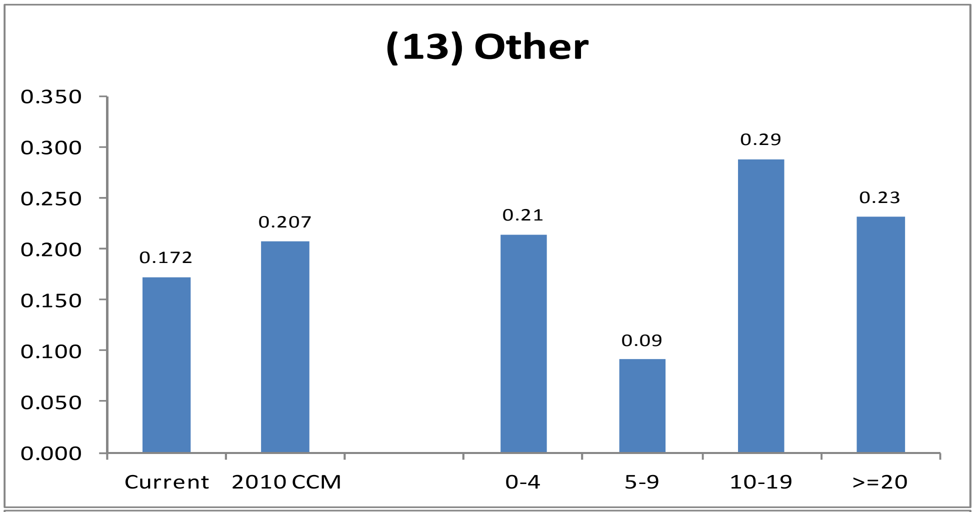
Appendix F - RRF by Number of Years of NEP>0

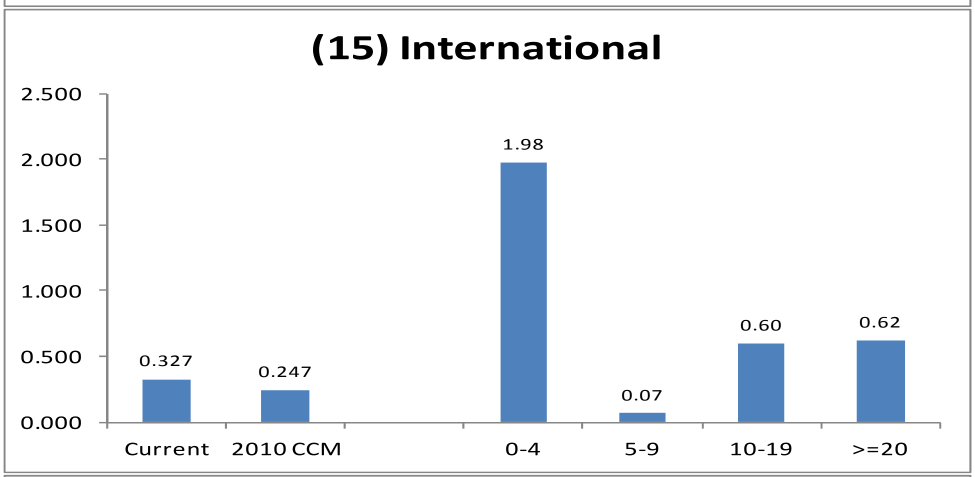


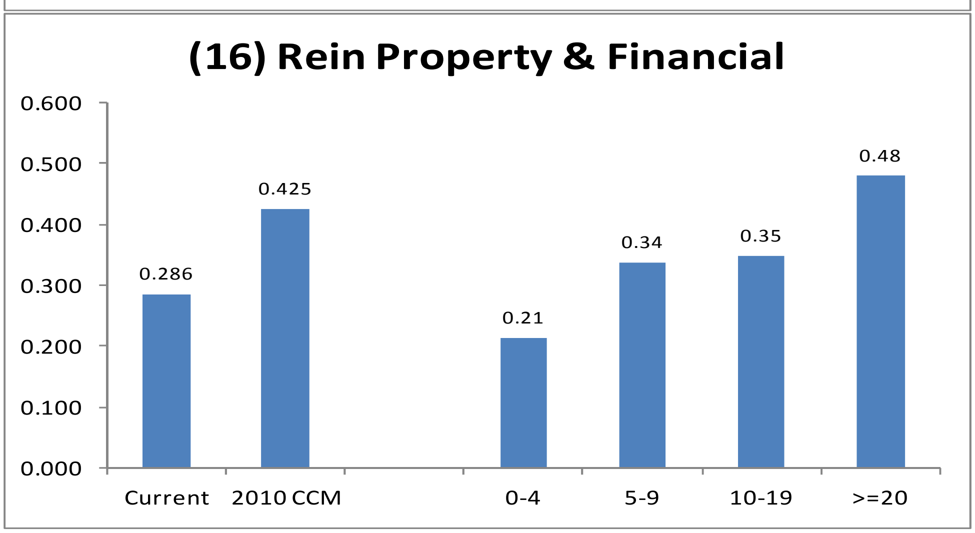




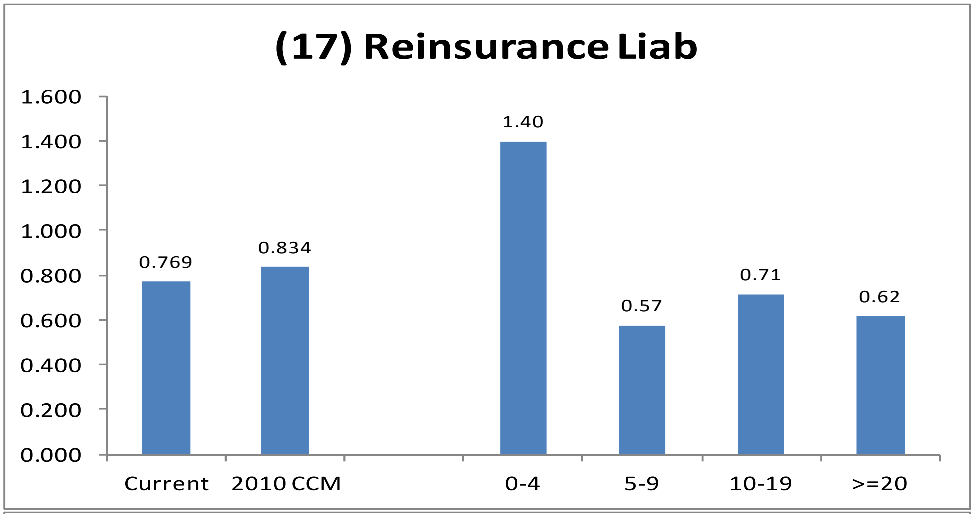
Appendix F - RRF by Number of Years of NEP>0

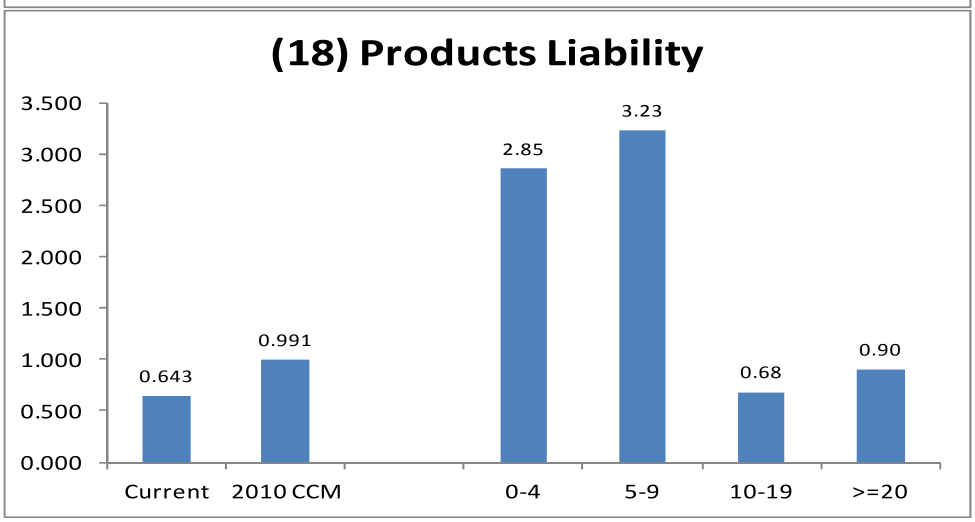






Appendix F - RRF by Number of Years of NEP>0





Appendix G

Part 1
Baseline RRFs - Effect of Excluding High Runoff Ratios

LOB	Baseline (1)	Baseline Excluding Runoff Ratio >=500% (2)	Difference (2) - (1)
(1) H/F	0.202	0.200	-0.001
(2) PPA	0.156	0.156	0.000
(3) CA	0.320	0.319	-0.001
(4) WC	0.336	0.334	-0.002
(5) CMP	0.462	0.461	-0.001
(6) MM Occurrence	0.314	0.314	0.000
(7) MM CM	0.106	0.104	-0.001
(8) SL	0.449	0.394	$\boxed{-0.055}$
(9) OL	0.518	0.513	-0.005
(11) Spec Prop	0.311	0.287	-0.025
(12) Auto Phys Damage	0.167	0.117	$\boxed{-0.050}$
(10) Fidelity & Surety	0.611	0.516	$\boxed{-0.095}$
(13) Other	0.271	0.260	-0.012
(15) International	0.490	0.438	$\boxed{-0.052}$
(16) Rein Property & Financial	0.422	0.422	0.000
(17) Reinsurance Liab	0.657	0.650	-0.007
(18) Products Liability	0.894	0.869	-0.025
(14) Fin & Mort	0.000	0.025	0.025
(19) Warranty	0.032	0.032	0.000

LOBs with effects greater than 0.05 in absolute value are marked.

Part 2
Number of data points and amount of reserve in the data set in total and after the Baseline filtering

	Reserve ($000,000s)			Data Points		
LOB	Total	Baseline	% of Total	Total	Baseline	% of Total
(1) H/F	283,744	267,042	94%	12,890	7,005	54%
(2) PPA	1,484,868	1,426,199	96%	11,825	6,759	57%
(3) CA	475,364	385,606	81%	11,725	4,969	42%
(4) WC	2,285,323	2,208,313	97%	10,767	6,336	59%
(5) CMP	606,805	565,739	93%	12,011	5,731	48%
(6) MM Occurrence	251,166	199,479	79%	3,922	1,058	27%
(7) MM CM	279,538	198,652	71%	3,695	2,179	59%
(8) SL	93,242	37,255	40%	4,559	1,042	23%
(9) OL	1,607,856	1,480,468	92%	17,557	7,200	41%
(11) Spec Prop	114,753	98,574	86%	10,970	5,435	50%
(12) Auto Phys Damage	63,697	57,898	91%	6,759	3,420	51%
(10) Fidelity & Surety	31,769	11,822	37%	3,505	915	26%
(13) Other	46,789	29,118	62%	3,758	1,124	30%
(15) International	11,818	2,986	25%	785	79	10%
(16) Rein Property & Financial	124,875	100,788	81%	3,659	1,039	28%
(17) Reinsurance Liab	713,339	582,794	82%	4,537	1,214	27%
(18) Products Liability	255,964	25,236	10%	5,235	582	11%
(14) Fin & Mort	848	59	7%	211	19	9%
(19) Warranty	319	109	34%	69	21	30%
Total	8,732,076	7,678,135	88%	128,439	56,127	44%

Appendix H- Runoff Ratios

Appendix H - Part 1 – Determining Reserve Runoff Ratios

The key statistic in the calibration of RRFs is the Reserve Runoff Ratio. The explanation below assumes that the 2010 Annual Statement has been filed.[37]

Reserve Movement – The Numerator of the Runoff Ratio

The numerator of the Reserve Runoff Ratio is the reserve movement, i.e., the change in the company's estimated ultimate incurred losses (including IBNR and DCCE) from the initial reserve date to the latest available valuation date. This Reserve Runoff Ratio is calculated from Schedule P, Part 2, an example of which is included in Part 3 of this Appendix.

For the most recent Annual Statement, e.g., 2010, the reserve movement for each of the most recent 9 initial reserve dates is the sum over all rows, (AYs) including the Prior row, of the incurred in the 2010 column (Schedule P column 10) minus the incurred in the column corresponding to the desired initial reserve date, 2009, 2008,…. 2001. The total row in the one year development and two year development columns in the Annual Statement Schedule P Part 2 (columns 11 and 12) are the reserve movements for initial reserve dates 2009 and 2008, respectively.

To obtain the movement for initial reserve date 2000, we use the 2009 Annual Statement.[38] The 2000 reserve movement is the sum of the AY 2000 row and Prior row (rows 1 and 2) of the incurred amounts in the 2009 column (column 10) minus the incurred amounts in the 2000 column (column 1) for the same rows.

Similarly to obtain the reserve movement for initial reserve date 1999, we use the 2008

[37] If the most recent Annual Statement is earlier than 2010, the same process is applied but the dates are stepped back one or more years, as necessary.

[38] We cannot use the Prior row in the 2010 Annual Statement to obtain the movement for AYs 2000 and prior. The Prior row in the 2010 statement begins with the outstanding at the end of 2001 for AYs 2000 and prior, and therefore does not include the movement of AYs 2000 and prior during calendar years 2000.

Annual Statement; the 1998 initial reserve date movement comes from the 2007 Annual Statement, and so on until the initial reserve date movement for 1988 comes from the 1997 Annual Statement, the earliest available Annual Statement.

Initial Reserve–The Denominator of the Runoff Ratio

The denominator is the total reserve, the case reserve and Incurred But Not Reported (IBNR) reserve, for loss and DCCE, at the initial reserve date, i.e., the end of each calendar year, for all AYs through that year-end.

Schedule P does not include a triangle of reserve amounts (Reserve Triangles) on that basis, but Reserve Triangles can be constructed by taking the difference between the incurred amounts in Schedule P Part 3[39] and cumulative paid amounts in Schedule P Part 2[40] in each Annual Statement. Appendix H Part 2 shows examples of Reserve Triangles constructed in this way.

For initial reserve dates 2001-2009, the initial reserve is the sum over all rows, (AYs) including the Prior row, of the reserve amount in the desired initial reserve year column. For initial reserve dates before 2001, the initial reserve is the sum of the oldest AY and the Prior rows (rows 1 and 2) from the appropriate Annual Statement, as described in the calculation of the runoff (numerator).

Reserve Runoff Ratio

We calculate reserve runoff ratios for each company/pool, for each Schedule P line of business.

For most of our analyses we use the runoff ratio at the most mature evaluation, calculated as described above.

For the maturity analysis in Section 6 we also compiled runoff ratios at all possible maturities. The initial reserve amount is the same regardless of maturity. The reserve movement is the difference between the incurred at the initial reserve date and the incurred at each calendar year end for which there is data.

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[39] Part 3 is cumulative AY **incurred** loss and defense and cost containment amounts, net of reinsurance, including IBNR

[40] Part 2 is cumulative AY **paid** loss and defense and cost containment amounts, net of reinsurance, including IBNR.

Alternative Approach and Consistency Across Annual Statements[41]

As an alternative to the approach described above, we also used Parts 2 and 3 to construct the 'trapezoids' of cumulative payments and ultimate incurred amounts for each AY for each available valuation date. At each Annual Statement date we also retain the Prior values.

For each initial reserve date, the initial reserve is the difference between (a) the sum of the incurred amounts over all AYs, in the column corresponding to the initial reserve date, including the appropriate Prior row values and (b) the sum of the cumulative paid amounts over all AYs in the corresponding column, including the appropriate Prior row values,.

The reserve movement is the difference between (a) the incurred at the desired valuation year, e.g., 9 years, or less if necessary, after the initial year, for AYs prior to and including the initial reserve date plus the appropriate Prior value, and (b) the incurred at the initial reserve date for all AYs plus the appropriate Prior value.

The two methods should be produce the same results if the Schedule P's are consistent from year to year, i.e., if Prior rows from one Annual Statement can be constructed from AY and Prior rows in earlier Annual Statements.. We found cases where the expected consistency did not exist so that the two methods do not produce the same results. This would happen, for example, if there were a change in pooling arrangements.

Appendix H Part 2 shows how we applied the consistency tests. We did not use data from companies that failed the tests.

[41] The actual calculations done by the working party used this alternative method.

Appendix H - Part 2 - Examples of Consistency Tests

Example of Test 1:

2009 Statement - Net Loss & DCCE Reserve										
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Prior	1005894	**33177**	28988	20852	14965	11295	6754	4653	4205	836
2000	13196	**9253**	8896	8094	4644	3296	3116	2860	1990	1103
2001	0	9787	11999	11862	8561	6854	6304	5804	3900	3108
2002	0	0	14546	18454	17428	13566	10923	8461	6293	5131
2003	0	0	0	25729	21918	22273	18911	12744	9329	8360
2004	0	0	0	0	22354	24441	22498	17476	12937	11122
2005	0	0	0	0	0	19444	23708	20445	15826	14441
2006	0	0	0	0	0	0	13252	12935	11613	10281
2007	0	0	0	0	0	0	0	19647	19780	18410
2008	0	0	0	0	0	0	0	0	22960	20662
2009	0	0	0	0	0	0	0	0	0	17889
Total	1019090	**52217 (Prior_2)**	64429	84991	89870	101169	105466	105025	108833	111343
2010 Statement - Net Loss & DCCE Reserve										
	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Prior	**42430**	37884	28946	19609	14591	9870	7513	6195	1939	1285
2001	9787	11999	11862	8561	6854	6304	5804	3900	3108	2332
2002	0	14546	18454	17428	13566	10923	8461	6293	5131	4868
2003	0	0	25729	21918	22273	18911	12744	9329	8360	7314
2004	0	0	0	22354	24441	22498	17476	12937	11122	9415
2005	0	0	0	0	19444	23708	20445	15826	14441	12845
2006	0	0	0	0	0	13252	12935	11613	10281	9650
2007	0	0	0	0	0	0	19647	19780	18410	17583
2008	0	0	0	0	0	0	0	22960	20662	19407
2009	0	0	0	0	0	0	0	0	17889	19973
2010	0	0	0	0	0	0	0	0	0	14500
Total	**52217 (Prior_1)**	64429	84991	89870	101169	105466	105025	108833	111343	119172

Since the difference between $42,430K in the 2010 statement and $33,177K plus $9,253K (=$42,430K) in the 2009 statement is less than 5%, the data point in the 2010 passes Test 1.

Note these reserve triangles are obtained by subtracting Schedule P Part 3 from Schedule P Part 2.

Example of Test 1 and Test 2:

2008 Statement - Net Loss & DCCE Reserve										
	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Prior	724350	198449	**184853**	149432	104512	73229	60131	33266	36871	30019
1999	23539	16625	**16212**	12979	64196	2576	1884	1440	1141	573
2000	0	16580	**14695**	14580	10610	8605	2236	1285	1187	928
2001	0	0	15808	20234	12203	10417	6690	2934	1041	981
2002	0	0	0	21899	19626	15930	15031	11027	5456	1511
2003	0	0	0	0	17371	17815	15051	14396	10021	3481
2004	0	0	0	0	0	18055	19569	17386	13664	13853
2005	0	0	0	0	0	0	12549	15050	12438	10359
2006	0	0	0	0	0	0	0	8851	15249	14718
2007	0	0	0	0	0	0	0	0	8493	15067
2008	0	0	0	0	0	0	0	0	0	14838
Total	747889	231654	231568	219124	228518	146627	133141	105635	105561	106328

2009 Statement - Net Loss & DCCE Reserve										
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Prior	775968	**201065**	162411	168708	75805	62015	34706	38012	30592	21275
2000	16580	**14695**	14580	10610	8605	2236	1285	1187	928	494
2001	0	15808	20234	12203	10417	6690	2934	1041	981	494
2002	0	0	21899	19626	15930	15031	11027	5456	1511	1276
2003	0	0	0	17371	17815	15051	14396	10021	3481	1507
2004	0	0	0	0	18055	19569	17386	13664	13853	6418
2005	0	0	0	0	0	12549	15050	12438	10359	9356
2006	0	0	0	0	0	0	8851	15249	14718	14356
2007	0	0	0	0	0	0	0	8493	15067	14321
2008	0	0	0	0	0	0	0	0	14838	17323
2009	0	0	0	0	0	0	0	0	0	16240
Total	792548	**231568 (Prior_2)**	219124	228518	146627	133141	105635	105561	106328	103060

2010 Statement - Net Loss & DCCE Reserve										
	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Prior	**887041**	176991	179318	84410	64251	35991	39199	31520	21769	11812
2001	15808	20234	12203	10417	6690	2934	1041	981	494	205
2002	0	21899	19626	15930	15031	11027	5456	1511	1276	1061
2003	0	0	17371	17815	15051	14396	10021	3481	1507	1430
2004	0	0	0	18055	19569	17386	13664	13853	6418	1346
2005	0	0	0	0	12549	15050	12438	10359	9356	4560
2006	0	0	0	0	0	8851	15249	14718	14356	12486
2007	0	0	0	0	0	0	8493	15067	14321	14215
2008	0	0	0	0	0	0	0	14838	17323	14827
2009	0	0	0	0	0	0	0	0	16240	15783
2010	0	0	0	0	0	0	0	0	0	13196
Total	**902849 (Prior_1)**	219124	228518	146627	133141	105635	105561	106328	103060	90921

In this case, data point Prior_1 in the 2010 Statement fails Test 1 but passes Test 2. Therefore, data point Prior_1 is replaced with data point Prior_2.

Appendix H – Part 3 – Annual Statement Schedule P Parts 2 and 3

ANNUAL STATEMENT FOR THE YEAR December 31, 2010 — Sample Company

SCHEDULE P - PART 2 - Private Passenger Auto Liability

		1	2	3	4	5	6	7	8	9	10	11	12
		INCURRED NET LOSSES AND DEFENSE AND COST CONTAINMENT EXPENSES REPORTED AT YEAR END ($000 OI										DEVELOPMENT	
Years in Which Losses Were Incurred		2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	One Year	Two Year
1	Prior	3,414	3,448	3,442	3,490	3,551	3,575	3,590	3,606	3,617	3,631	14	26
2	2001	5,686	5,659	5,649	5,653	5,666	5,663	5,659	5,658	5,659	5,658	(1)	1
3	2002	XXX	6,028	5,954	5,927	5,929	5,922	5,914	5,911	5,908	5,907	(1)	(4)
4	2003	XXX	XXX	6,152	5,958	5,882	5,862	5,844	5,841	5,834	5,826	(8)	(14)
5	2004	XXX	XXX	XXX	6,219	5,990	5,904	5,864	5,843	5,833	5,827	(6)	(16)
6	2005	XXX	XXX	XXX	XXX	6,317	6,104	6,034	6,007	5,984	5,970	(14)	(37)
7	2006	XXX	XXX	XXX	XXX	XXX	6,277	6,194	6,152	6,109	6,073	(37)	(80)
8	2007	XXX	XXX	XXX	XXX	XXX	XXX	6,548	6,516	6,467	6,422	(45)	(94)
9	2008	XXX	XXX	XXX	XXX	XXX	XXX	XXX	6,544	6,482	6,418	(64)	(126)
10	2009	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	6,846	6,757	(89)	XXX
11	2010	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	7,052	XXX	XXX
12	Total											(248)	(345)

SCHEDULE P - PART 3 - Private Passenger Auto Liability

		1	2	3	4	5	6	7	8	9	10	11	12
		CUMULATIVE PAID NET LOSSES AND DEFENSE AND COST CONTAINMENT EXPENSES REPORTED AT YEAR END ($000 OMITTED)										Number of Claims Closed With Loss Payment	Number of Claims Closed Without Loss Payment
Years in Which Losses Were Incurred		2001	2002	2003	2004	2005	2006	2007	2008	2009	2010		
1	Prior	0	1,533	2,330	2,759	2,972	3,091	3,165	3,221	3,259	3,290	2,071	929
2	2001	2,301	4,012	4,780	5,212	5,439	5,620	5,591	5,617	5,632	5,639	1,618	716
3	2002	XXX	2,412	4,184	4,996	5,448	5,680	5,785	5,837	5,863	5,875	1,643	724
4	2003	XXX	XXX	2,410	4,142	4,909	5,361	5,596	5,710	5,757	5,782	1,630	718
5	2004	XXX	XXX	XXX	2,438	4,150	4,925	5,379	5,613	5,710	5,754	1,590	707
6	2005	XXX	XXX	XXX	XXX	2,513	4,274	5,067	5,521	5,745	5,843	1,616	694
7	2006	XXX	XXX	XXX	XXX	XXX	2,566	4,364	5,170	5,610	5,830	1,617	708
8	2007	XXX	XXX	XXX	XXX	XXX	XXX	2,721	4,628	5,436	5,897	1,654	761
9	2008	XXX	XXX	XXX	XXX	XXX	XXX	XXX	2,696	4,566	5,373	1,510	689
10	2009	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	2,803	4,733	1,505	751
11	2010	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	2,874	1,129	654

GLOSSARY

Term	Interpretation
ALAE	Allocated loss adjustment expenses
AY	Accident year
A&O	Adjusting and Other Expense
Baseline filtering	As defined in below Table 3.4.
CCM	Current Calibration Method
Data point	Each data point is an LOB-runoff ratio, for a single company or pool, at the latest available maturity (for most analyses) or at successive annual evaluation dates (in the maturity analysis in Section 6)
DCCE	Defense and cost containment expenses
DCWP	Dependency and Calibration Working Party
Formula RBC Formula	The 2010 RBC Formula
Initial Reserve	The reserve amount at that initial reserve date for all accident years prior to the initial reserve date.
Initial Reserve Date	Each year-end in our data set, December 31, 1997 through December 31 2010
LOB	Line of Business
LOB-size	Line of business size (reserves)
Minor lines	LOB whose data points are excluded due to LOB-size versus total company size
NEP	Net Earned Premium
Reserves or Loss Reserves	Case, bulk and IBNR loss and defense and cost containment expense (DCCE) [42]reserves net of reinsurance, as shown in Schedule P – Part 2 and 3.
RRF	Reserve Risk Factor
Runoff ratio or Reserve Runoff Ratio	The ratio of the incurred movement from the initial reserve to the latest available date, for all constituent accident years combined.

[42] "Defense and Cost Containment Expenses" are called "Allocated Loss Adjustment Expenses" (ALAE) in older Annual Statements. In our analysis we treat DCCE and ALAE as equivalent.

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Actuarial Values of Housing Markets

Project Report submitted to the Casualty Actuarial Society
By Risk Lighthouse LLC
Dr. Shaun Wang, FCAS, CERA, and Han Chen, FSA

TABLE OF CONTENTS

Executive Summary

This paper discusses Risk Lighthouse's methodology of calculating actuarial housing values, with the goal of helping mortgage lenders to gauge departures of housing market values from the fundamentals, and assisting policymakers with tools for implementing counter-cyclical policies. In the aftermath of the U.S. housing bubble burst, many policymakers are in favor of having some sort of countercyclical measures: Housing prices are reined in when they depart too far (too high or too low) from the fundamentals.

The Risk Lighthouse methodology calculates actuarial values by employing a control mechanism on the metro level housing price index so that it doesn't deviate too high or too low from the fundamentals. The control mechanism is achieved through adjusted quarterly price change rates. We set both a time-varying cap and floor for the quarterly price change rate, which are set at one standard deviation above and below the moving-average quarterly change rate minus a drift term. The drift term is calibrated by incorporating macro, micro, and metro-specific data on the economic and demographic factors that affect supply and demand. Analysis of these factors is done in several steps.

We consider factors that affect supply in the housing market. We classify sellers in the market as either "willing-to-sell" or "forced-to-sell." We further divide the forced-to-sell category into sub-categories of (1) foreclosures, (2) newly built houses, (3) migration outflow, and (4) death of homeowner. We compile the percentage distributions of these sub-categories. We compare construction costs relative to housing prices in projecting housing inventory.

We explore factors that affect demand in the housing market. We compile metro-specific household income distributions, which contains richer information than the median income. We find that a higher percentile income (e.g., 65th percentile) is more relevant than the median income for analyzing the demand for housing. We track how volumes of international sales and metro-specific age distributions affect the demand of housing units. We highlight limitations of pure econometric analysis; for example, the foreclosure rate from 2008 to 2009 explained most of the variations in housing prices across zip codes, but that relationship completely disappeared in year 2010.

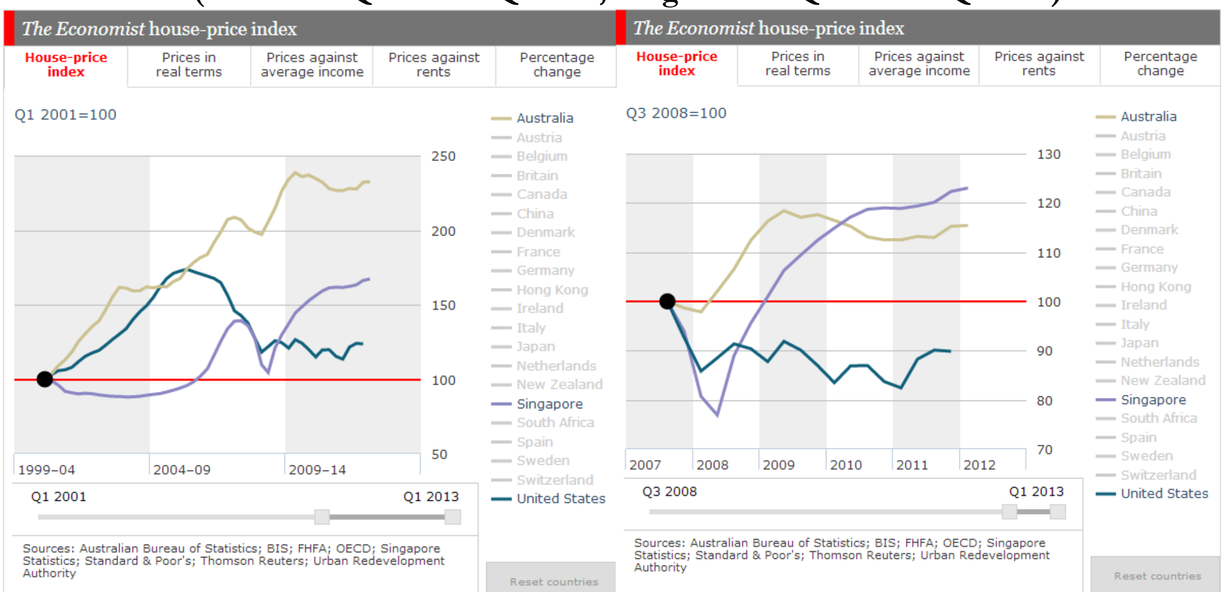
We calibrate actuarial values at metropolitan levels based on an overall analysis of the metro-specific housing market dynamics, reflecting major factors affecting the supply and demand of houses. We present the calculated actuarial housing values for several major U.S. metro areas.

The actuarial housing values can potentially help lenders and regulators in assessing collateral risk at the portfolio level. The actuarial housing values can be extended to other international markets. In the appendix of this paper we also provide some discussions of the different characteristics of China's housing markets.

SECTION 1: INTRODUCTION

The residential housing sector represents the largest asset class in many countries (e.g., Spencer, 2013). Housing boom-bust cycles are identified as a major source of widespread crisis in the financial system (e.g., Quigley, 1999). The recent 2007-2009 global financial crisis can trace its origin to the U.S. housing market and the subprime mortgage loans. Over the past decade, housing markets in various countries have diverging paths of growth (see Figure 1).

Figure 1: Housing Price Indices for Australia, Singapore and the United States (Left: from Q1 2001 to Q1 2013; Right: from Q3 2008 to Q1 2013)



Source: *The Economist*, http://www.economist.com/blogs/dailychart/2011/11/global-house-prices

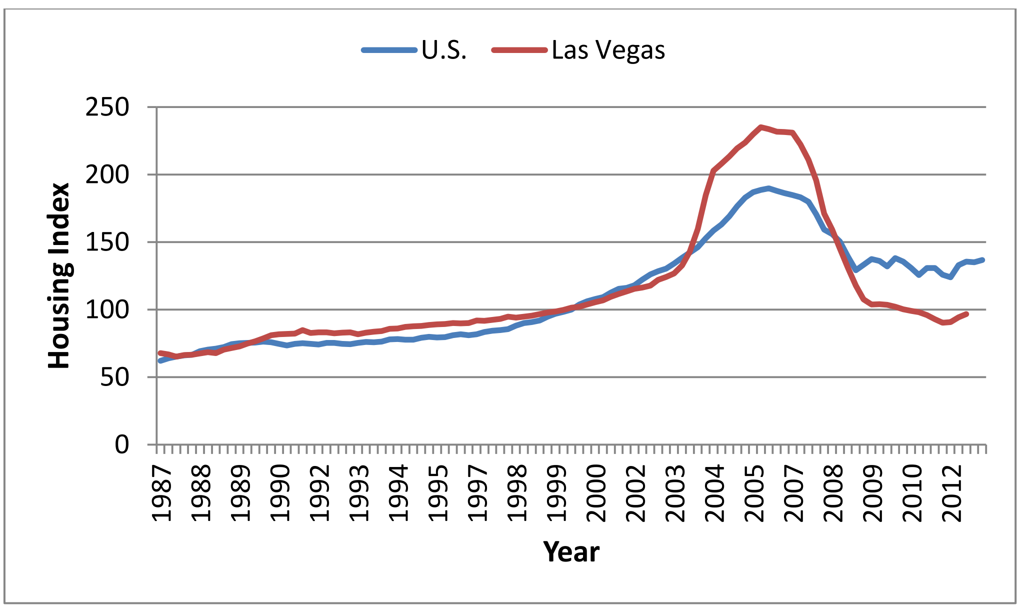
In the wake of the recent global financial crisis, there is an emerging policy debate concerning how to reduce the frequency and severity (magnitude) of these large swings of housing cycles. Policymakers need tools to track the deviation from "intrinsic" values, and to dampen the potential large swings of these housing markets cycles.

One linkage between the housing markets and the financial system is through house purchase financing (mortgage lenders make loans to homeowners against the house as collateral). Thanks to the innovation of financial products, millions of mortgage loans were packaged by Wall Street firms into mortgage-backed securities (MBS). The AIG Financial Products division and the monoline bond insurers played a key role in providing insurance against these mortgage securities.

Market values of the collaterals are subject to considerable volatility. Traditionally, mortgage lenders used the loan-to-value (LTV) ratio as a metric to provide guidelines for origination of individual mortgage loans, where the value in the "LTV" represents appraisal values, which are predominantly based on comparable sales at the time of mortgage loan origination. Zoeller (2008) discusses issues with the predominant appraisal approaches. Historically, from 1947-1996, the appraisal industry and the mortgage lending industry used multiple valuation methodologies including the cost approach. Since 1997, as the market comparable sales approach gained preeminence, the cost approach slipped out of favor and is no longer required for mortgages underwritten by Fannie Mae. With the recent housing market boom and bust, the comparable sales appraisal method proved to be pro-cyclical (i.e., cycle amplifying) and created major distortions from long-term intrinsic values. Essentially, the housing appraisals in the U.S. have been following the swings of the market values.

The U.S. housing market values are observed to be too volatile, rendering the LTV unreliable. Figure 2 shows the Case-Shiller index[1] for U.S. national housing market as well as for Las Vegas. For an average house in the U.S., 80% loan-to-value in June 2006 became 112% loan-to-value in June 2010. For an average house in Las Vegas, 80% loan-to-value in June 2006 became 184% loan-to-value in June 2010.

Figure 2: The Case-Shiller Indices for the U.S. and Las Vegas



Data Source: http://us.spindices.com/documents/additionalinfo/20131231/71337_cshomeprice-history-1231.xls

The need for some intrinsic or equilibrium values of houses, other than the market value, is evidenced in the history of the Federal Housing Administration (FHA)[2]. Edward Pinto, an

[1] The Case–Shiller Home Price Indices are repeat-sales residential house price indices for the United States. There are multiple indices, including a twenty city composite index and twenty individual metro area indices.

[2] The FHA is a United States government agency created as part of the National Housing Act of 1934. It insured mortgage loans made by banks and other lenders for home building and home buying.

Economist at the American Enterprise Institute, pointed out that the FHA had developed and implemented a definition of value for mortgage lending purposes (called "warranted value") back in 1938:

> The word "value" refers to the price which a purchaser is warranted in paying for a property for continued use or as long-term investment. The value to be estimated, therefore, is the probable price which typical buyers are warranted in paying. This valuation is sometimes hypothetical in character, especially under market conditions where abnormalities in price levels indicate the presence of serious quantitative differentials the two value concepts [warranted value and available market price]. Marked differences between "available market prices" and "values" will be evident under both boom and depression conditions of market. Attention is directed to the fact that speculative elements cannot be considered as enhancing the security of residential loans. On the contrary, such elements enhance the risk of loss to mortgagees who permit them to creep into the valuations of properties upon which they make loans. No other definition is acceptable for mortgage loan purposes inasmuch as one of the objectives of valuation in connection with mortgage lending is to take into account dangerous aberrations of market price levels. The observance of this precept tends to fix or set market prices nearer to value.

Judging by the volatility of historical housing market prices, academics and regulators realized that capital rules relying solely on market values cannot achieve counter-cyclical effects. During times of economic boom, it is politically difficult for policymakers to slam the brakes. What is needed is other metrics that are more indicative of the intrinsic value (and thus the long-term market values). At the 2013 "International Conference on Collateral Risk: Moderating Housing Cycles and Their Systemic Impact[3]," a proposal under discussion among academics and policymakers is to use counter-cyclical loan-to-value, where the value is based on intrinsic values other than market prices. This is also the context and background for this paper.

Actuarial valuation is a time-honored professional practice, which is mostly based on estimates of costs and projections of long-term trends of economic and demographic trends. There is a philosophical debate between market values and actuarial values (see Appendix A). In this paper, we derive actuarial housing values based on a controlled rate of price change that reflect the fundamentals of housing markets and are less volatile than the market prices. The actuarial values can serve as a candidate for the "value" in calculating counter-cyclical loan-to-value at the portfolio level.

In this paper we attempt to apply actuarial methods to develop metrics and tools that can be used by regulators and lenders in monitoring the departures of market values from their long-term

[3] The conference took place on July 31 and August 1, 2013, at the American Enterprise Institute. http://www.aei.org/events/2013/07/31/international-conference-on-collateral-risk-moderating-housing-cycles-and-their-systemic-impact-cosponsored-by-the-collateral-risk-network-robinson-college-of-business-at-georgia-state-university-and-aei/

sustainable values. The goal of this paper is neither to develop a complete scientific framework nor to produce ready-to-use actuarial housing values. Nevertheless, we hope to achieve a proof of context of applying actuarial methods to housing values, and to inspire more researchers to carry this research further in both the science and the practical calibration.

SECTION 2. METHODOLOGY FOR DERIVING ACTUARIAL HOUSING VALUES

Our goal is to construct actuarial housing values that reflect the fundamentals and exhibit less volatility than market values. Toward that goal, we employ a control mechanism on the metro level housing price index so that it doesn't boom too high above or crash too low below the fundamentals. The units in this control mechanism are the adjusted quarterly price change rates. We set a cap and a floor for the quarterly price change rate, and then adjust it with a drift term that incorporates the social and economic effects that affect the supply and demand for housing.

Notations:

Let $HPI(t)$ represent the housing price index at time *t*. In this paper we use $HPI(t)$ to represent the Case-Shiller indices for 20 metropolitan areas at quarterly frequencies.

The Quarterly Change ("QC") at time *t* is defined by:

$$QC(t) = \frac{HPI(t)}{HPI(t-1)} - 1$$

We use a ten-year moving window of housing prices for the past 40 quarters:

$$\overrightarrow{QC(t)} = \{QC(t-j), \quad where \quad j = 0,1,\ldots,39\}.$$

We define $Cap(t)$ and $Floor(t)$ by the following formulae:

$$Cap(t) = E\left[\overrightarrow{QC(t)}\right] + \sigma\left[\overrightarrow{QC(t)}\right] - drift,$$
$$Floor(t) = E\left[\overrightarrow{QC(t)}\right] - \sigma\left[\overrightarrow{QC(t)}\right] - drift,$$

Where E is the average, σ is the standard deviation, and the "drift" term is to be calibrated for the specific metropolitan area. The drift term in this paper is backward-looking calibrated. It is fixed from 1999 to 2012. For the future research, the drift term should be time varying, since it is recalibrated and updated over time.

We compute controlled quarterly changes, $\widehat{QC}(t)$, by imposing the updated *Cap* and *Floor* to the Quarterly Change in the Housing Price Index at time *t*.

$$\widehat{QC}(t) = max\{Floor(t), \min(QC(t), Cap(t))\}$$

We derive actuarial housing values by applying the controlled quarterly changes consecutively:

$$AHV(t) = AHV(t-1) \cdot [1 + \widehat{QC}(t)].$$

In this paper, AHV is calibrated from January 1999 for each metro area. Since the volatility of housing price was quite low in the 1990s, $(QC(t) = \widehat{QC}(t))$, the selection of the first quarter at that time will not affect the result.

The actuarial housing values are derived from the inclusion of factors specific to the metro area being measured. The key to the actuarial method is the drift term, which is calibrated to reflect the *combined effects* of economic and demographic factors impacting the supply and demand of housing units in a metropolitan area. In the following sections, we examine some of these factors.

SECTION 3. DATA USED IN THE CALIBRATION OF ACTUARIAL VALUES

Our goal is to analyze housing price data by metropolitan area and price range buckets. Below is a summary of the types and sources of data used for the calibration of the actuarial housing values. Some of the data sources are obtained from third-party data vendors.

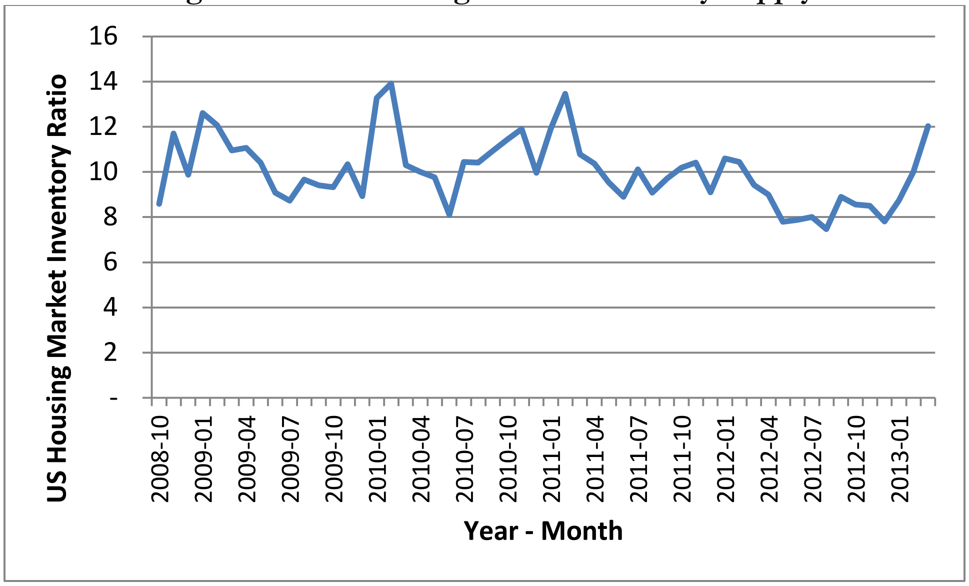
Data	**Data Source**
Case-Shiller Index	S&P
Housing Market Inventory Supply	Zillow
Foreclosure Home % in Transaction	Zillow
Newly Applied Building Permit	Census Bureau & Texas A&M University
Housing Inventory Ratio	Zillow
Construction Cost	Marshall & Swift/Boeckh
Demographic Information	U.S. Census Bureau
Households with Age Information	U.S. Department of Housing and Urban Development
Household Income at Zip Level	Internal Revenue Service
U.S. Household Formation	U.S. Census Bureau
International Sale in Housing Market	National Association of Realtors
Mortgage Loan Standard	Ellie Mae Origination Insight Report
House Price at Zip Level	Zillow

SECTION 4. FACTORS IMPACTING THE SUPPLY OF HOUSING UNITS

First, we study important factors driving the housing market from the supply side.

Figure 3 shows that only around 10% of the houses listed monthly in the market are sold and this ratio has remained steady in the past five years. Inventory Supply is the total number on listings at the end of a month divided by the number of homes sold in that month. Data source: Zillow.

Figure 3: U.S. Housing Market Inventory Supply



We make a distinction between two types of housing units available for sale: (i) willing to sell and (ii) forced to sell.

1) Some homeowners have the flexibility of withdrawing from listing if a house is not sold within a reasonable time window (such as 1-2 months). The house owner may choose to re-list again at a later date when the housing market condition changes. We shall categorize this type of houses as "willing to sell."

2) In contrast to the class of "willing to sell", we observed that some houses would have a price reduction after a period of being listed without finding a buyer at or near the asking price. We shall categorize this type of house as "forced to sell."

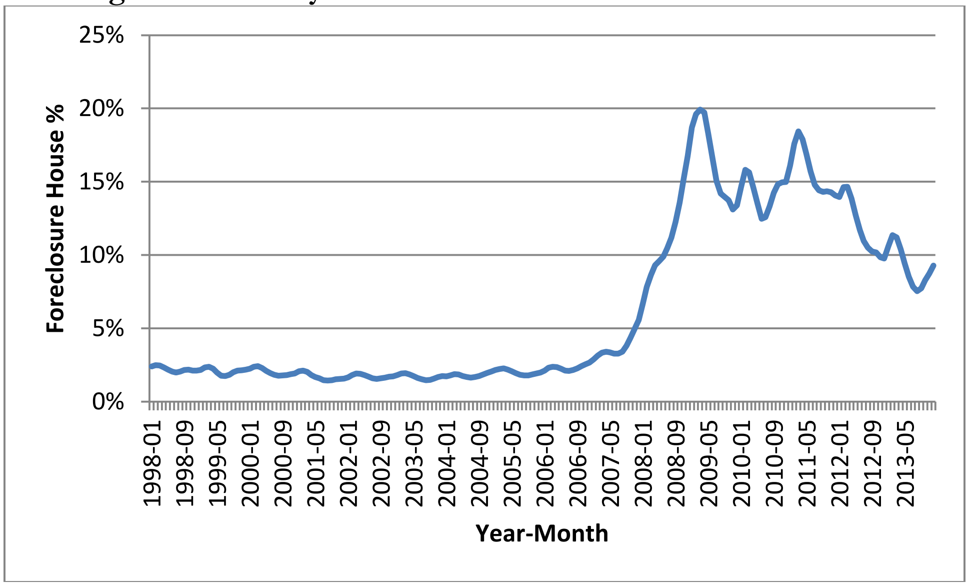
We further divide the "forced to sell" houses into four sub-classes: foreclosure, newly built, migration and death.

4.1 Foreclosure houses

A foreclosed house is one in which the owner is unable or unwilling to make his or her mortgage loan payments and the bank repossesses the house. A bank usually sells a foreclosed home through an auction process.

From Figure 4 we can see clearly that before the housing bubble, the foreclosure houses percentage of all U.S. house transactions is around 2%. This ratio jumped to 20% in 2009 and steadily decreased to about 10%, which is still much higher than before the bubble. Since late 2007, the abnormally high foreclosure rate had a material impact on the housing prices, which caused a departure from long-term "equilibrium" housing values.

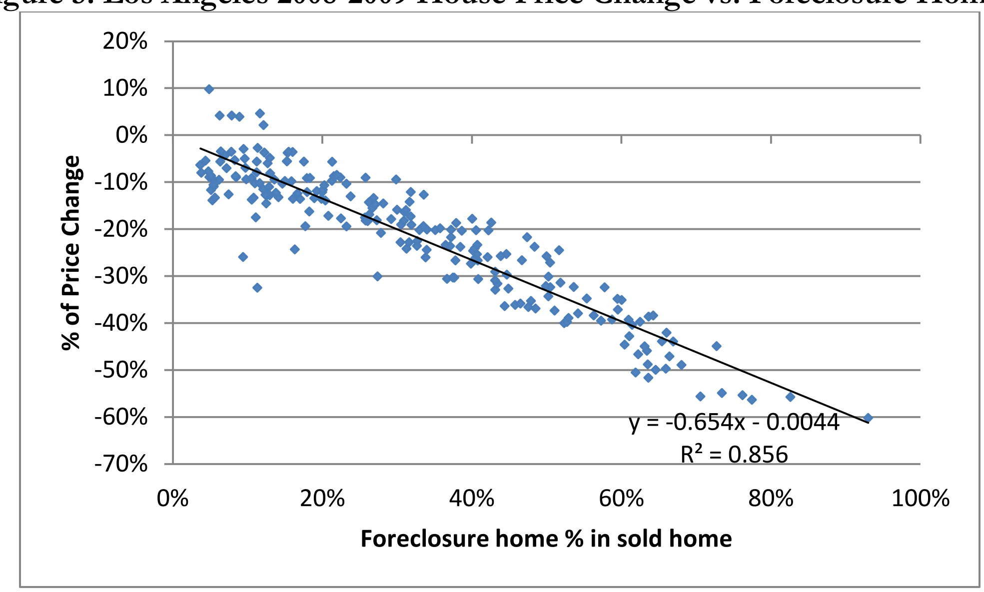
Figure 4: Monthly Foreclosure Homes as % of Transactions



Data source: Zillow.

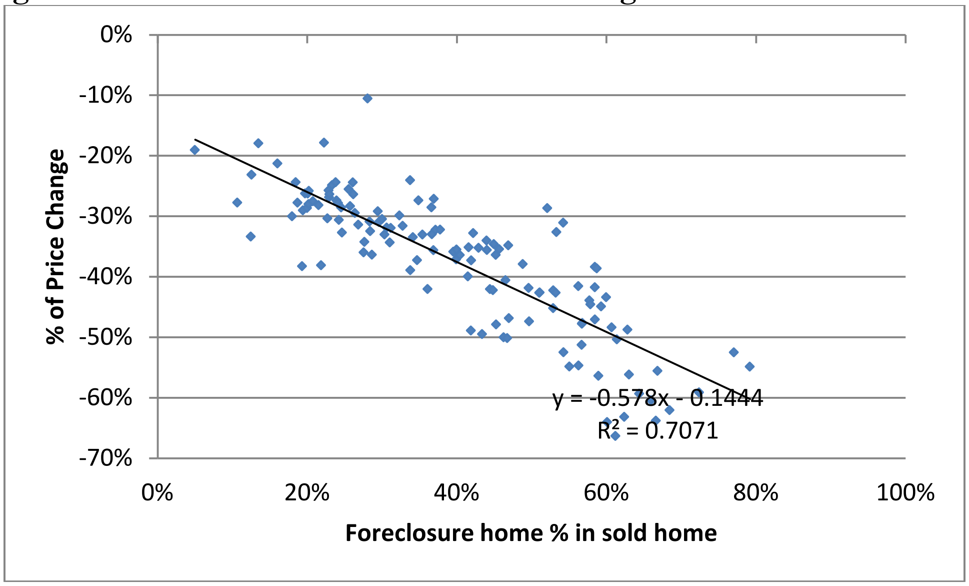
Our analysis reveals that when foreclosure home % increases to a very high level, since late 2008, this jump explains most of the price drops in various zip codes of a metro area. Figures 5 and 6 depict this relationship for Los Angeles and Phoenix, respectively.

Figure 5: Los Angeles 2008-2009 House Price Change vs. Foreclosure Home%



Foreclosure home %: The average percentage of home sales between 01/2008 and 12/2009 where the home was foreclosed upon within the previous 12 months. Each dot in the graph above represents a zip code area. Data Source: Zillow.

Figure 6: Phoenix 2008-2009 House Price Change vs. Foreclosure Home%

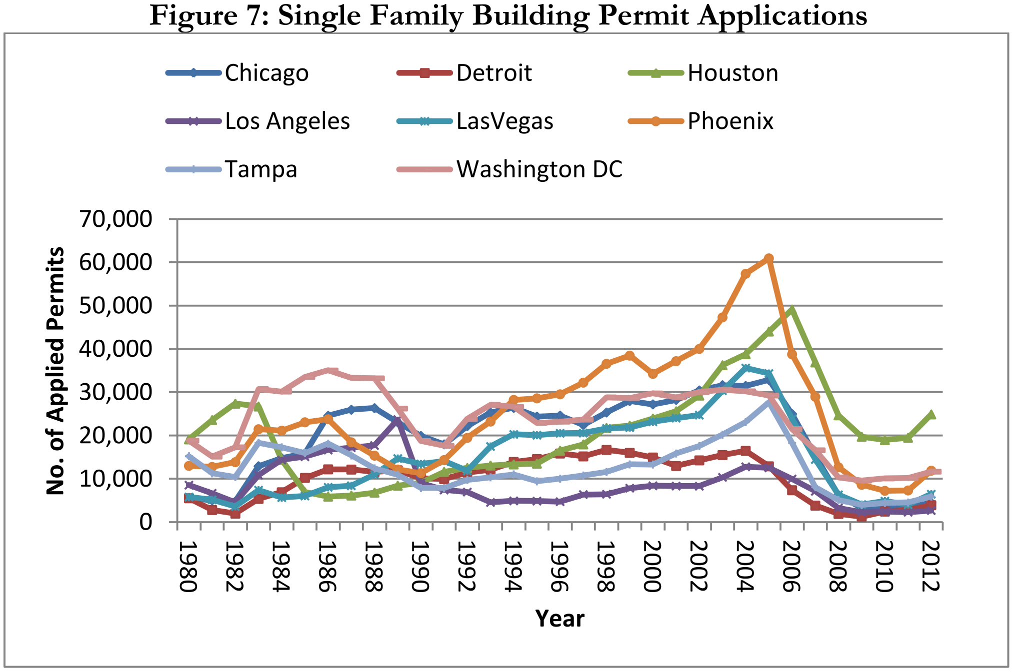


Data Source: Zillow.

4.2 Newly built houses

Generally speaking, newly built houses are under more pressure to sell in a short time than owner-occupied homes. Builders of new homes normally have liquidity constraints and incur carry-costs of serving their bank loans. However, data for newly built houses are not readily available. In this paper, we use the number of building permit applications as a proxy indicator of newly built homes.

Figure 7: Single Family Building Permit Applications



Data Source: http://www.census.gov/construction/bps/

2002-2006: A Glut of Newly Built Houses

From Figure 7 we observe that the during the time period of 2002-2006, there was a spike in building permit applications. The house permits applications in Phoenix during that time period were more than double that of the time period 1997-2001. Assuming there is a 2 to 4 year lag between building permit applications and newly built houses, and then it is reasonable to expect excess supply of new houses between 2007 and 2010.

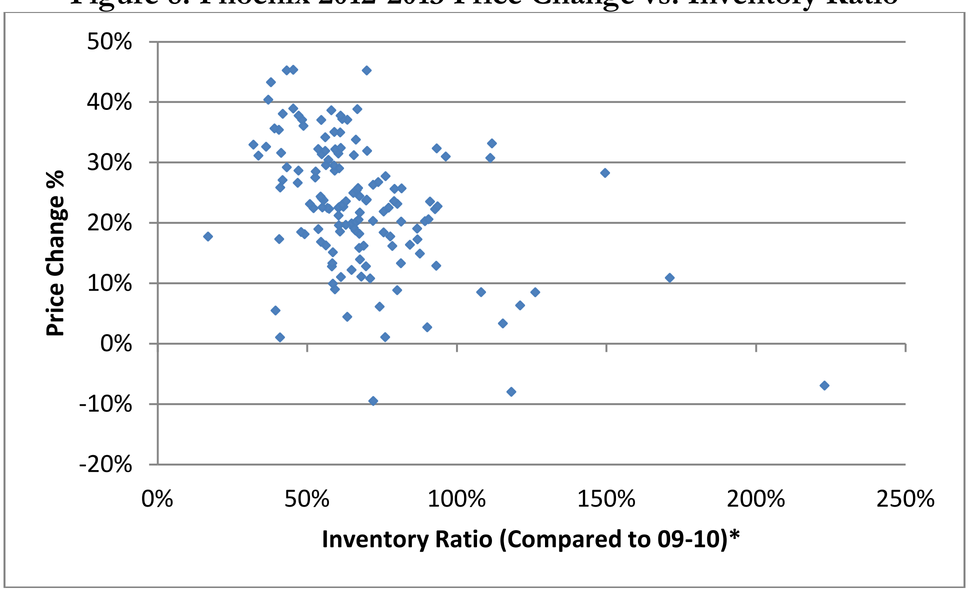
2008-2012: Scarcity of Newly Built Houses

It can be said that the strong housing market recovery in 2012 and 2013 is partially due to the reduced inventory of houses. Other factors didn't change significantly from 2011 to 2012, such as mortgage rates, foreclosure rates and the household income distribution.[4]

The cumulative effect of fewer newly built houses from 2008 to 2012 eventually led to a low inventory of housing supply, coupled with years of delayed house purchases by newly formed families, resulted in a shift of the balance in the housing supply-demand equation.

Figure 8 is a plot of Phoenix's one-year house price percentage change and the housing inventory ratio[5]. A significantly negative relationship is observed between these two ratios.

Figure 8: Phoenix 2012-2013 Price Change vs. Inventory Ratio



* Each dot in the graph above represents a zip code area. Data source: Zillow.

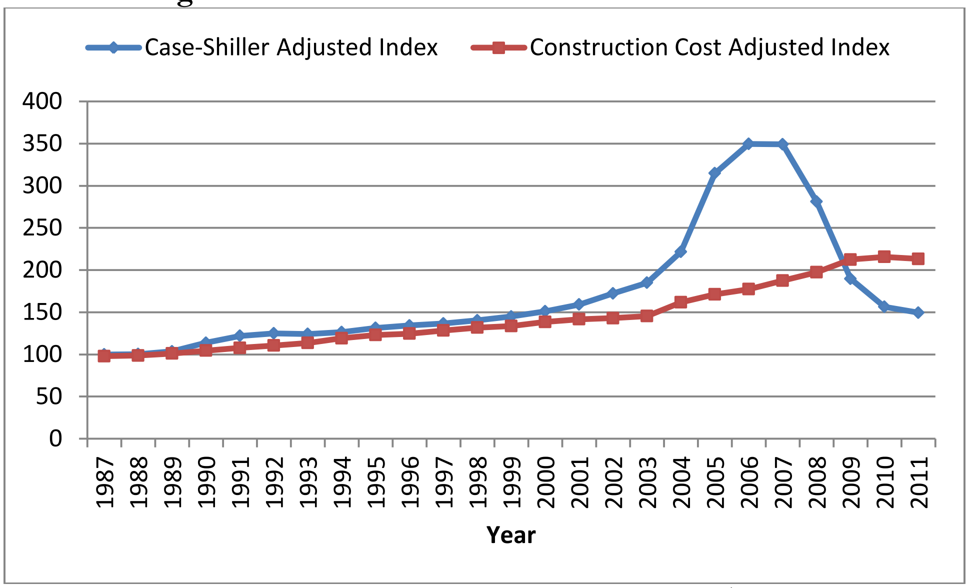
[4] Of course, a low inventory alone would not drive up prices since there needs to be more buyers relative to the inventory. There was a gradual improvement of economic outlook in 2012, which attracted potential buyers to come back to the markets.

[5] The inventory ratio is compared to 2009-2010. The ratio in the figure is the number of houses for sale in 2012-2013 divided by the number of houses for sale in 2009-2010.

Figure 9 shows the relationship between housing prices and construction costs for Las Vegas.

We find that the number of building permit applications is inversely correlated to the ratio of housing market price to construction cost. The housing price index dropped below the construction cost index after the burst of the housing bubble, which led to the recently low supply of newly built houses.

Figure 9: Las Vegas Historical House Price Index vs. Construction Cost Index



Data Source: Case-Shiller Index from S&P and construction costs are from Marshall & Swift/Boeckh (MSB).

4.3 Net Migration

The effects of demographic trends on the housing prices are well documented in academic literature (see Belsky, 2009; Myers et al, 2002).

In most cases, when people move to another city, they need to sell their original house quickly so that they can get cash for relocation and eliminate the carry cost of the empty house.

Detroit is the prime example of outflow migration. From 2000 to 2008, among our eight targeted metropolitan areas, Detroit is the only one which experienced a population decrease, and most of this decrease is due to the highly negative net migration. With its highly negative net migration, Detroit is also the only metropolitan area which had a nominal house price drop compared to 1998 among our eight targeted metro areas.

Table 1: Population and Migration Change from 2000-2008

	Detroit	Las Vegas	Los Angeles	Phoenix	Tampa	Washington DC
2000 Population	4,452,558	1,375,535	12,365,624	3,251,887	2,396,011	4,796,065
2000-2008 Net Migration	-237,573	380,112	-420,191	717,353	328,419	137,771
2000-2008 Population Change	-27,448	490,211	507,184	1,030,012	337,750	562,065
2000-2008 Population Change %	-0.60%	35.60%	4.10%	31.70%	14.10%	11.70%

Data Source: U.S. Census Bureau

While the outflow migration has a significant impact on housing supply, the inflow migration also has a material effect on housing demand. However, the effect of net inflow is trickier than outflow since different metro areas have very different population densities. For example, the population densities of Las Vegas and Phoenix are much lower than other metro areas; each is only approximately one fourth of Chicago, Washington, Detroit, Tampa, and one tenth of Los Angeles. Therefore, even though Las Vegas and Phoenix had a net population increase of over 30% during 2000 to 2008, we did not observe that strong of an increase in their local housing markets.

4.4 Death

Age distribution also has an effect on housing supply. Tampa has a significantly higher percentage of older people which leads to a higher rate of death. Table 2 shows the population and death statistics for eight metropolitan areas.

Table 2: Demographics and Death

Y2000	Total Households	Age 62+ Households	Age 62+ %	Deaths	Deaths/Total Households
Tampa	1,009,284	337,379	33.4%	28,577	2.83%
Chicago	2,971,619	676,459	22.8%	60,119	2.02%
Detroit	1,695,304	419,494	24.7%	39,407	2.32%
Houston	1,462,676	239,397	16.4%	28,319	1.94%
Las Vegas	588,350	143,105	24.3%	10,320	1.75%
Los Angeles	3,133,781	655,301	20.9%	59,352	1.89%
Phoenix	1,194,271	288,563	24.2%	24,272	2.03%
Washington	1,848,021	340,126	18.4%	29,838	1.61%

*Households with age information is from HUD (U.S. Department of Housing and Urban Development)
**Death data is from U.S. Census Bureau

In Tampa, the houses for sale from death are roughly equal to the number of newly built houses. Below is the number of single family building permit applications in Tampa from 1996 to 2000.

Table 3: Building Permit Application in Tampa

Single Family Building Permit Applications in Tampa	
1996	10,006
1997	10,745
1998	11,573
1999	13,309
2000	13,293

If we simply assume two deaths will empty one house, the number of houses for sale due to death in Tampa for year 2000 is 14,288. The five year average number of applications for single family building permits is only 11,785.[6]

Overall, death is an important factor to compare different metro areas' dynamics. It is quite stable for one metro area through time unless that metro area has a significant trend in demographic distribution.

To sum up this section, the supply of the housing market in the U.S. is composed of two

[6] We did not have detailed data of continual migration of retirees from other parts of the country into Tampa, which would have some effect on the supply-demand balance.

different groups: willing to sell and forced to sell. Historically, the number of willing to sell houses is much higher than that of forced to sell houses. The forced to sell houses are composed of foreclosure houses, newly built houses, migration outflow houses, and houses emptied by death. The latter two factors are more fundamental and are changing relatively slowly from year to year. However, those two factors are quite different from region to region, such as Detroit (high migration outflow) and Tampa (high death rate), which determine the long term trend of the housing market. The former two factors are more affected by market conditions and could fluctuate rapidly in a relatively short period. For example, the number of foreclosure houses increased dramatically after housing bubble, an effect that dominated the housing price changes between 2008 and 2010. The recent housing market boom is in part due to the low inventory supply, which is because of the extremely low volume of newly built houses since 2008.

SECTION 5. FACTORS IMPACTING THE DEMAND FOR HOUSING UNITS

The following factors determine the housing market demand curve.

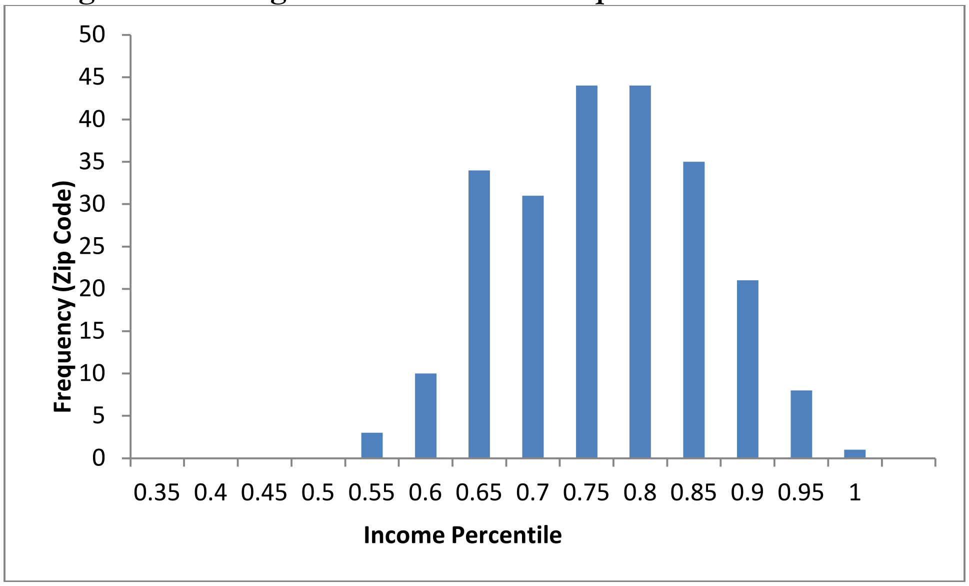
5.1 Household income distribution

Traditionally, housing economists use the ratio of median house price to median household income as the indicator for measuring housing affordability in their research. Our research indicates that such a ratio may not be the best indicator. Using a mortgage payment model, we have found that a higher percentile (e.g., 65%) of the income distribution is better metric than the median (50%) to match with transacted house prices.

In our mortgage payment model, we assume that the buyer pays a 20% down payment and takes 30-year mortgage for the remaining value of the house. We compared data for each zip code-level historical median traded house price with household income distribution within the same zip code. By using the historical mortgage rates, we match the median traded house price to a percentile of the household income distribution. By doing this calculation for all zip codes within one metro area, a house price matching income percentile distribution can be formed.

Figure 10 shows Chicago's implied income percentile distribution.

Figure 10: Chicago 2008 House Price Implied Income Percentile



*Data source: house price is from Zillow. Household income is from Internal Revenue Service (IRS).

We calculated this income percentile distribution for all eight metro areas and only Detroit has an implied income percentile distribution with a median lower than 0.5. Some metro areas' distribution medians are even higher than 0.7 or 0.8.

A possible explanation for this result is that people usually buy their houses between age 30 and 50, which is at the peak of their lifetime income curve. Therefore, if we compare their income to the total income distribution, the implied income percentile is usually higher than 0.5.

5.2 The Effect of Mortgage Rates on Affordable Prices

Changes in the mortgage rates have a parallel shift effect on demand curve of household income.

Based on the monthly cash flow formula, the affordable house price would be

$$Price = \frac{12M}{i} \cdot \left[1 - \frac{1}{\left(1 + \frac{i}{12}\right)^{12N}} \right]$$

Where:

1) i is the annual mortgage rate,

2) M is the monthly payment,

3) N is the number of years of the mortgage.

Below is a table showing how the amount of affordable price is impacted by changes in the (30-year fixed) mortgage rate assuming M=1000.

i	Price	*i*	Price
3.0%	237,000	5.5%	176,000
3.5%	223,000	6.0%	167,000
4.0%	209,000	6.5%	158,000
4.5%	197,000	7.0%	150,000
5.0%	186,000	7.5%	143,000

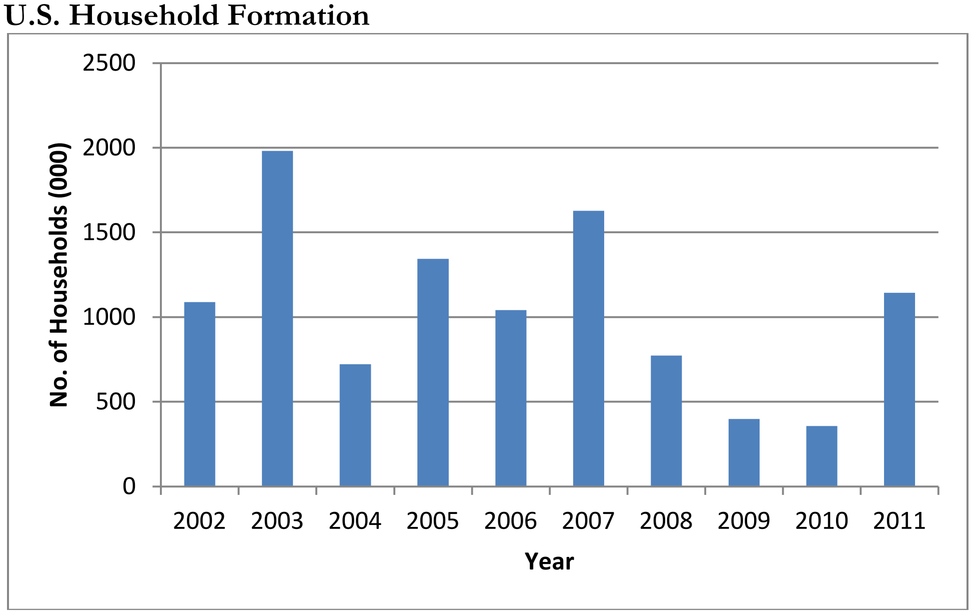
From the table above, we can observe that mortgage rate has a significant effect on the affordable price. An increase in the mortgage rate from 3.0% to 4.0% results in an almost 12% decrease (from 237,000 to 209,000) in the affordable price.

A caveat of this analysis is that homeowners incur other associated costs of homeownership, including property taxes, utilities, maintenance and homeowner's insurance.

5.3 Age distribution

After the financial crisis, a shortfall in household formation is observed during 2008 to 2010. Figure 11 shows the recent ten years of available U.S. household formation data.

Figure 11: U.S. Household Formation



Data source: Census Bureau

The temporary delay in household formation is partially due to a so called "doubling up", where recent college graduates stay in their parents' houses waiting for a more stable job before buying their own first homes. When the housing markets recover, we expect that those who were waiting may come into the housing markets, which may increase the demand of housing market. Since young adults are more likely to be the source of the household formation, it is necessary to account for the age distributions in different metropolitan areas, especially for age group 18 to 35.

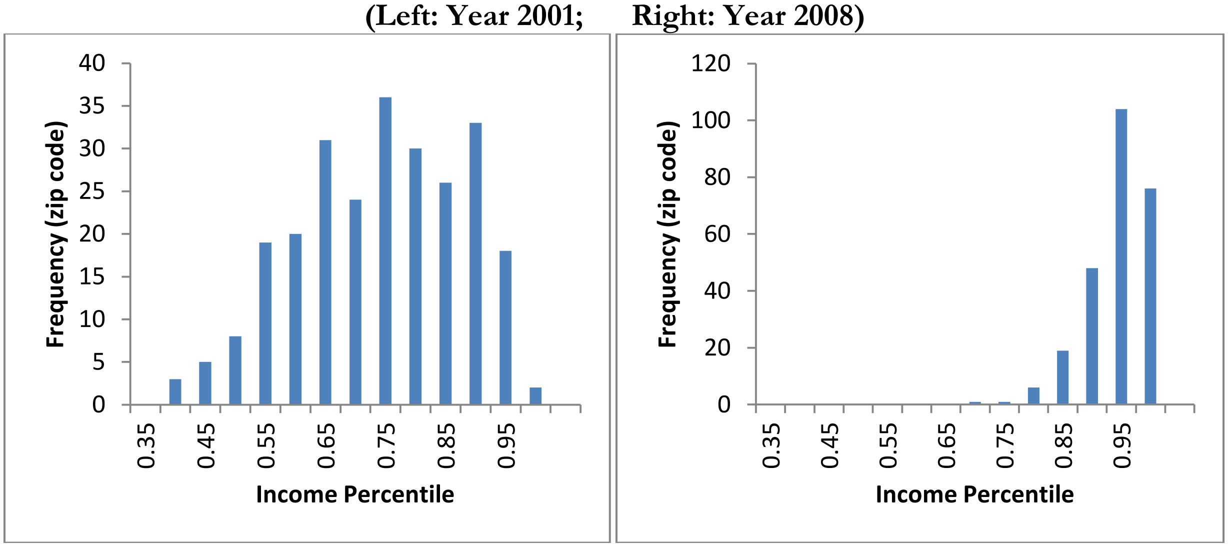
Some research papers have already proven that different age groups have varying effects on housing market. Lindh and Malmberg (2008) find that large populations of young adults are associated with higher rates of residential construction in Sweden. The effect of age group 15-29 on housing demand is more than twice of that effect of age group 30-49 and around five times that of age group 50-64.

5.4 International Sales

It is observed that more and more international buyers are entering the U.S. housing market, especially concentrated in three states: Florida, California, and Texas. Cities like Miami, Los Angeles, San Francisco, Dallas, and Houston experienced a significant international migration in the past decade. This continuing trend in net international migration resulted in a long-term boom in the local housing markets.

For example, Los Angeles experienced a continuous and significant international migration inflow since 2000. This extra international capital drove the local housing prices to an unreasonably high level. Figure 12 shows the housing price implied income percentiles before and after the housing bubble.

Figure 12: Los Angeles House Price Implied Income Percentile
(Left: Year 2001; Right: Year 2008)



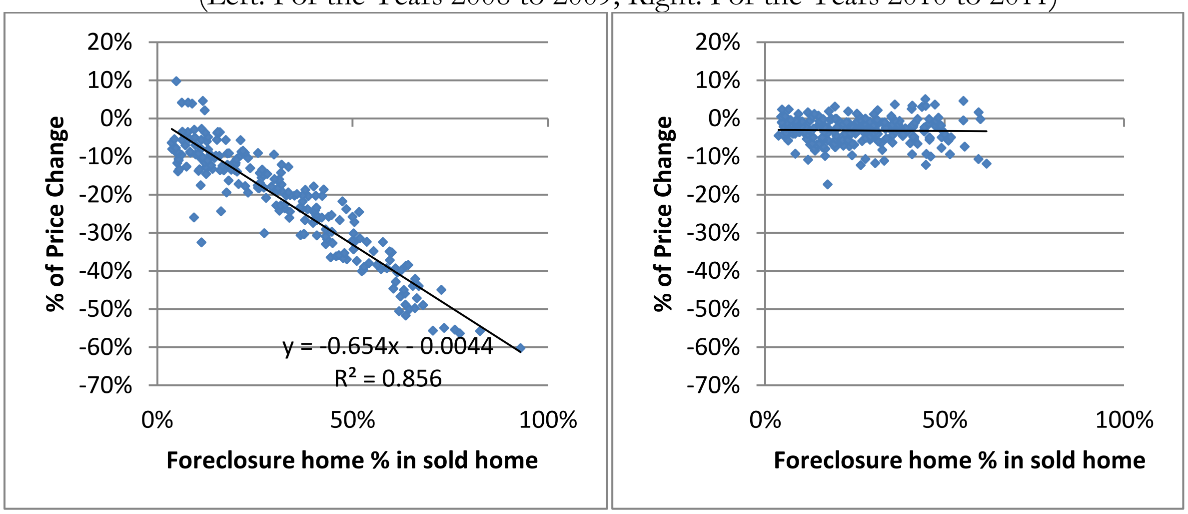
Data Source: National Association of Realtors

SECTION 6. HOUSING MARKET DYNAMICS

Traditional housing market analysis usually relies on regression techniques, which we consider to be inappropriate for housing markets. As we summarized at the end of the housing supply section of this paper, the housing market is a dynamic market, for which static analysis cannot capture the variation in price, especially in a volatile market.

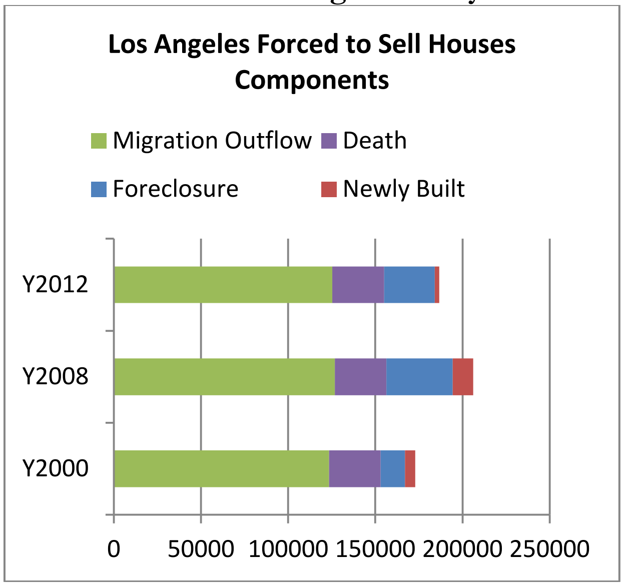
Figure 13 is the graph of relationship between housing price change and foreclosure rate in the Los Angeles metro area. We can see that the foreclosure rate is a highly significant factor in explaining the housing price change between 2008 and 2010. However, this strong relationship soon disappeared in 2011.

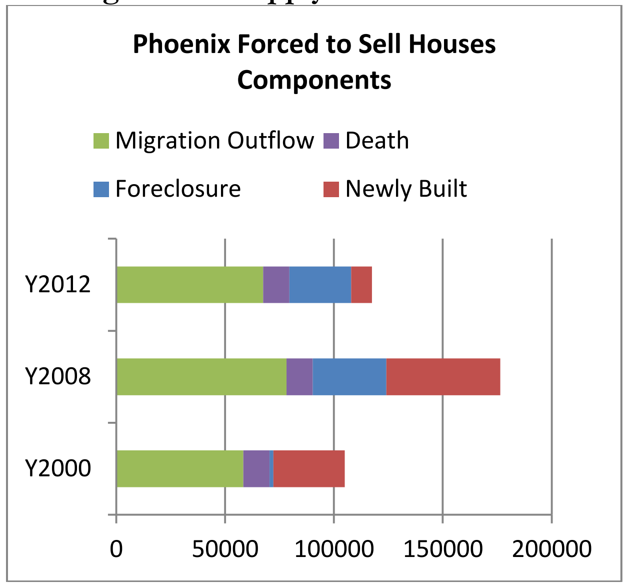
Figure 13: Los Angeles House Price Change vs. Foreclosure Home%
(Left: For the Years 2008 to 2009; Right: For the Years 2010 to 2011)



For a given housing market, one factor could dominate the influence on housing price change during a specific time period. However, when market dynamics change, this dominating influence rapidly weakens or even disappears. Figure 14 shows the different dynamics of the housing market supply of Los Angeles and Phoenix before, right after, and further after housing bubble. As we can see, different factors in the metropolitan areas in different years have varying weights. Basically, demographic and economic conditions determine the fundamentals of a local housing market. Temporary high foreclosure rates and low inventory of newly built houses can be called market responses to unfair housing price levels and revert the price level back to its mean. Calibration of the drift term in the actuarial formulae requires an analysis of the dynamics of a given housing market.

Figure 14: Dynamics of Housing Market Supply





Other Relative Price Indicators

Researchers of real estate markets often resort to inferential analysis of housing markets (see Black et al, 2006; Edelstein and Tsang, 2007; Wheaton and Nechayev, 2008). They use analysis of house price to household income, house price to rents, vacancies, absorption/time on the market, prices, and construction starts to estimate normal vacancy rates and time on the market inventory. We considered these relative factors in understanding the dynamics of the housing markets.

Instead of the regression method, we propose the actuarial valuation presented at the beginning of this paper. Actuarial value is a housing price benchmark based on a controlled rate of price change, which is calibrated based on the dynamics of the metro specific housing markets.

In the next section we present the results of the actuarial housing value.

SECTION 7. RESULTS OF ACTUARIAL HOUSING VALUES

Our calibrations of the actuarial housing values for each metropolitan area are done through a metro-specific drift term. At the heart of the methodology for actuarial housing value is a two-step calibration process of the metro-specific drift term.

Step 1. Estimation of an initial drift-term by minimizing Mean Squared Errors (MSE)

The drift term in this paper is backward-looking calibrated. It is fixed from 1999 to 2012. We estimate an initial drift term by minimizing the Mean-Squared Error. This step is purely backward-looking since it is just the mechanical exercise of minimizing Mean Squared Error.

We assign the starting point of the data series to be January 1999. It is noted that the volatility of housing price was quite low in 1990s, so the controlled quarterly changes, $\widehat{QC}(t)$, are the same as the uncontrolled quarterly changes, $QC(t)$, for the early 1990s.

For instance, for Washington DC, the average $QC(t)$ in 1998 is only 0.9% while the average cap is about 1.6% and the average floor is -0.9%.

Step 2. Validation & adjustment of the drift term.

The second step shall involve validating the estimated drift term based on the housing markets dynamics and making adjustments based on a forward-looking assessment of the fundamentals. The validation and adjustments shall involve many economic variables, including comparisons of construction costs with market values. In making forward-looking adjustments to the drift term, there is no unique scientific formula and actuarial judgment will be required, due to the complex and ever-evolving housing market dynamics.

For instance, for Detroit, the calibrated drift term is 0.012, which is significantly higher than other metro areas' drift terms (remember, a higher drift term means a lower cap and lower floor). As discussed in the previous sections, Detroit is the only metro area in our study that experienced a negative population change from 2000 to 2008, and it also has had the second highest unemployment rate since 1999.

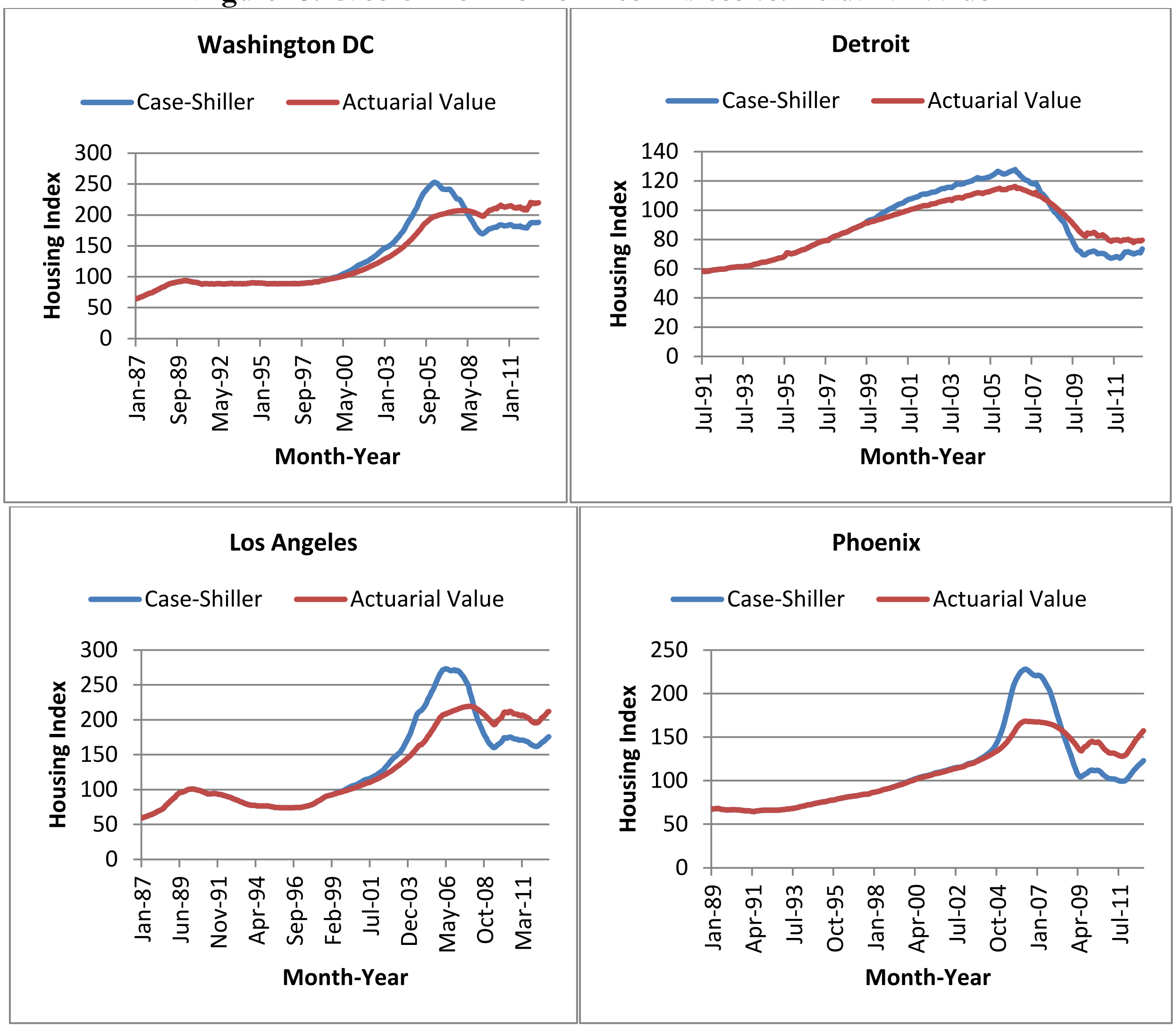
Meanwhile, Las Vegas has the lowest calibrated drift term, which is −0.005. Las Vegas experienced the highest population increase from 2000 to 2008 among the metro areas we studied and it also has had the second lowest unemployment rate since 1999. Below are some of the calibrated drift terms.

	Calibrated Drift Term
Chicago	0.003
Washington	(0.003)
Detroit	0.012
Las Vegas	(0.005)

In summary, while the actuarial housing values are functions of many variables, including migration, demographic distribution, population density, construction cost, income distribution, etc., the metro-specific drift is calibrated by minimizing the sum of squared errors between the Case-Shiller index and the actuarial housing value over the most recent ten year moving window. The calibrated drift term is further verified to be correlated with the fundamental factors of a metro area, such as unemployment rate, migration, etc.

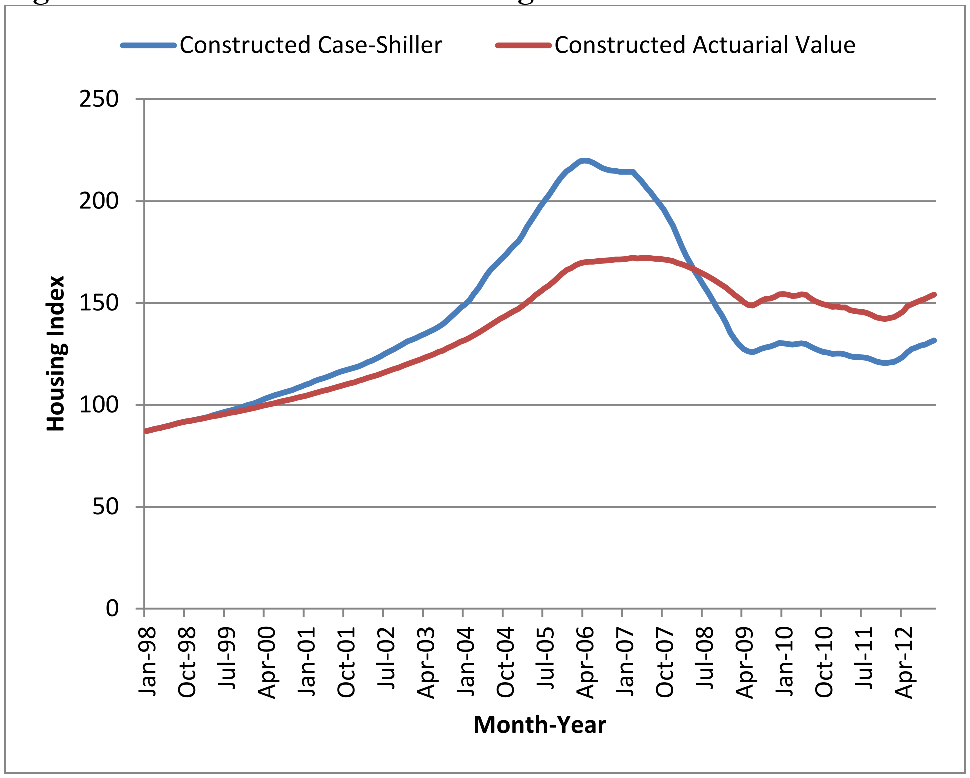
We apply the actuarial approach to housing price data at the metropolitan level. Figure 15 presents the results for Washington DC, Detroit, Los Angeles, and Phoenix.

Figure 15: Case-Shiller Home Price Indices vs. Actuarial Value



We calculated the actuarial value for the following metro areas: Chicago, Detroit, Houston, Las Vegas, Los Angeles, Phoenix, Tampa, and Washington DC. By using the annual trade volume as the weights, we derived the U.S. nationwide housing index. In Figure 16 we compare the re-constructed (or weighted) Case-Shiller index with the actuarial value for the U.S. national housing market.

Figure 16: U.S. Reconstructed Housing Case-Shiller vs. Actuarial Value



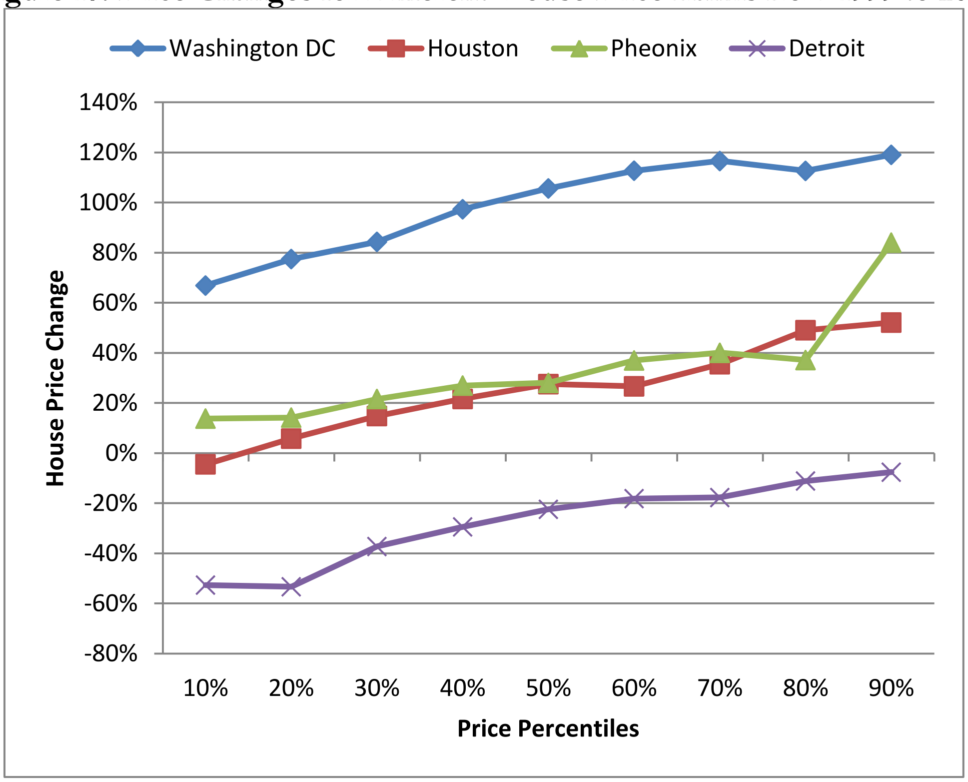
SECTION 8. POTENTIAL APPLICATIONS OF THE ACTUARIAL HOUSING VALUE

Actuarial housing values can help actuaries to offer valuable professional services to the appraisal industry and the lenders. Knowing the relative relationship of actuarial housing values and market values can help regulators to effectively measure and manage systemic risks for the housing market, and the impacts of these risks on other sectors of the economy. Indeed, if the differences between the actuarial housing values and market values had been used as an input to the Gaussian copula model (see Li, 2000; Salmon, 2009) for credit default swaps, the correlation among mortgage-backed securities would have been much higher. Actuarial housing values can enable lenders to monitor the aggregate departures of actuarial values and market values, similar to the way that insurers track their aggregate catastrophe risk exposures. Actuarial housing values can also help actuaries to perform pricing and reserving functions for mortgage insurance. The actuarial housing value can even serve as a basis for designing reverse-mortgage products. The proposed actuarial values are most applicable to those who have to mark-to-market their HPI related assets. Using this muted HPI protects them from wild swings.

SECTION 9. AREAS OF FUTURE RESEARCH

As one promising area of future research, we can derive a distribution of actuarial housing values by housing price buckets. Figure 17 shows the house price changes from 12/1999 to 12/2012 for different price percentiles of several metro areas. From Figure 18 we observe higher price changes from 1999 to 2012 for houses at higher price ranks of each metro area. The different performances across different housing price buckets can further demonstrate the power of an actuarial approach.

Figure 17: Price Changes for Different House Price Ranks from 1999 to 2012



Data Source: Zillow.

As another area of future research, we plan to adapt the actuarial valuation method presented in this paper to China's housing markets, incorporating the special characteristics of China's housing markets (as discussed in Appendix B).

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APPENDIX A. MARKET VALUE VERSUS ACTUARIAL VALUE

Mark-to-market accounting played a major role in the recent financial crisis – the volatilities of housing market values are amplified through the mark-to-market accounting of mortgage-backed securities and their CDOs.

In the boom years before the global financial crisis, market values received elevated importance, and were championed by financial economists. In contrast, actuarial values seemed to have lost favor and importance.

Adeyele and Adelakun (2010) give detailed discussions of the tensions between actuarial value and market value.

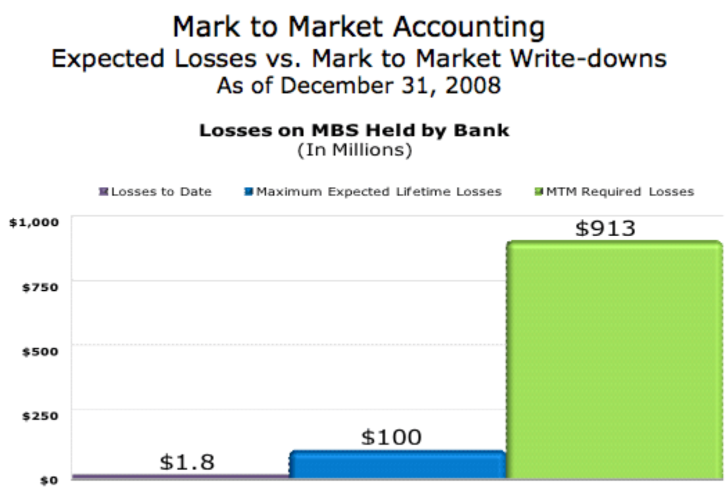
> The debate between financial economics and traditional actuarial science has continued to attract the attentions of the academics and practitioners from various disciplines around the world. A survey of the literature does not produce much consensus between the two sides of the debate (Day, 2004). A basic difference identified between traditional actuarial thinking and the philosophical framework of financial economics is encapsulated in the difference between value and price. Actuaries largely seek to place value on cash flow stream, whereas financial economists believe market should do that for them. In the view of financial economists, value is a subjective concept, whereas price is objective. However, a problem with this is that price, if it exist in a market where there is buying and selling, is, in fact, determined by the players on the margin who are willing to buy and sell at marginal price. There remains the fundamental problem that different players should hold different ideas of the intrinsic value of an investment, because they are holding the asset for different reasons.
>
> One of the consequences of the difference in philosophy between value and price is the fact that actuaries are often concerned with control systems and with managing risk in the long run. Actuaries have often been concerned with those types of control issues. Pension funding presents a similar type of problem. However, the market approach of the financial economists crystallizes a view of the future into a snapshot view, through the use of market or fair value of asset and liabilities.

William Isaac argued that mark-to-market accounting made the recent financial crisis unnecessarily more severe than it could have been if a more cost-based valuation were used. To make his points clear, William Isaac used two charts to illustrate the impact of mark-to-market accounting on just one portfolio of mortgage backed securities held by a large U.S. bank. The materials below are taken from William Isaac (2010):

"The chart (Exhibit I) showed that as of December 31, 2008, the bank held a pool of MBS totaling $3.65 billion. The bank expected a maximum of $100 million of losses on the portfolio but had enough extra collateral to cover those losses so no net losses were expected. Yet, mark-to-market accounting required the bank to write off over $900 million of the portfolio."

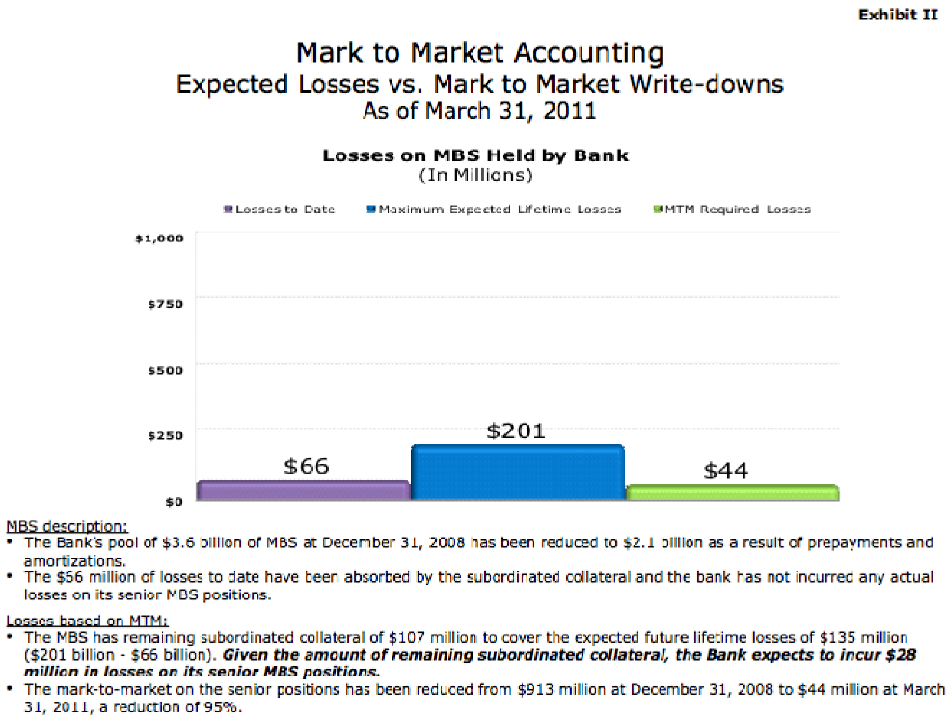
"As of March 31, 2011 the bank updated the chart showing the performance of this same portfolio (Exhibit II). The portfolio declined to \$2.1 billion due to prepayments and normal amortizations. The bank now expects total net losses of \$28 million. The mark-to-market charge on the portfolio has been reduced from over \$900 million at the end of 2008 to just \$44 million, even though nothing has really changed except market perceptions of value! It was very bad accounting during the Great Depression when President Roosevelt ordered it eliminated in favor of historical cost accounting, and it was very bad accounting during the crisis of 2008-2009 when it helped bring our nation's financial system and economy to the brink of collapse."

Exhibit I



<u>MBS description:</u>
- The Bank holds a pool of MBS totaling \$3.65 billion as of December 31, 2008
- The underlying loans are not sub-prime and are generally quality loans (average of approximately 17 months of seasoning, original FICO scores of 749, and original loan-to-value ratio of 73%)

<u>Losses based on MTM:</u>
- The MBS has subordinated collateral of \$172 million. ***The amount of subordinated collateral exceeds the worst-case loss projections, which means the Bank does not expect to incur any losses on its senior MBS positions (positions that MTM rules have required to be written down by \$913 million).***
- The MTM write-down required on this pool is more than nine times the maximum estimated lifetime losses.



We do not intend to enter the debate between the actuarial versus the financial economics approaches. Instead, we take a position that both approaches are needed to complement each other; it is by comparing the differences between the market values and the actuarial values that we derive useful metrics for navigating through the sea of uncertainty.

APPENDIX B: CHINA'S HOUSING MARKETS

B1. Carry cost and maintenance fees

Compared to the U.S. housing market, China's housing market has a much lower long term carry cost. This is mainly due to two reasons:

a) Most residences in China are apartments, which require minimal effort to maintain. The annual maintenance fee can be as low as zero for an empty apartment.

b) Currently, there is no property tax in China. The only long-term carry cost is the property management fee, which is usually lower than 0.1% of the apartment value.

Considering the high inflation rate in China, its housing market is one of the best-performing asset classes because of its low carry cost and expectations of future price appreciation.

B2. Density of Population & Migration

China has four tiers (levels) of cities, which have quite different population densities and migration conditions.

The levels one and two cities in China have very high population densities and are experiencing a continuous migration. For example, the New York metro area had the highest density of population in the U.S. in 2008, which were 2,826 people per square mile. For Shanghai, this number was more than 12,000.

Meanwhile, the levels three and four cities in China have a comparatively lower population density. And for levels three and four cities in middle and western China, the effect of migration from rural areas is offset by the trend of residents continuously moving out to levels one and two cities. The limited demand and over-supply in some levels three and four cities results in the phenomenon of "ghost cities."

Below is the population table of the levels one and three cities in China eastern and non-eastern area. Beijing, Shanghai, and Guangzhou are level-one cities and others are all level-three cities.

Table 4: China Level 1 & 3 Cities Population Change

Cities in the East	2000 Population	2010 Population	Change %	Cities not in the East	2000 Population	2010 Population	Change %
北京 (Beijing)	13,569,000	19,612,000	45%	洛阳 (Luoyang)	6,227,655	6,549,486	5%
上海 (Shanghai)	16,737,734	23,019,148	38%	开封 (Kaifeng)	4,575,500	4,671,659	2%
广州 (Guangzhou)	9,943,000	12,700,800	28%	吉林市 (Jilin)	4,485,494	4,414,681	-2%
嘉兴 (Jiaxing)	3,583,000	4,501,700	26%	宜昌 (Yichang)	4,149,308	4,059,686	-2%
珠海 (Zhuhai)	1,235,582	1,560,229	26%	柳州 (Liuzhou)	3,430,800	3,554,400	4%
金华 (Jinhua)	4,571,900	5,361,600	17%	株洲 (Zhuzhou)	3,581,820	3,803,387	6%
汕头 (Shantou)	4,671,100	5,391,000	15%	九江 (Jiujiang)	4,511,564	4,728,763	5%
温州 (Wenzhou)	7,558,000	9,232,100	22%	宝鸡 (Baoji)	3,632,351	3,716,731	2%

Data Source: China National Statistics Bureau

Age Distribution: China currently has a significantly lower ratio in the age 65+ demographic. This ratio was 8.87% in 2010. For U.S. metro areas, most of these ratios are near 20%.

Table 5: China Demographic Condition

Year 2010 (000)	Population	<15 Population	<15 %	15-64 Population	15-64 %	>= 65 Population	>=65 %
Mainland China	1,339,725	222,460	17%	998,433	75%	118,832	9%
Zhejiang	54,427	7,189	13%	39,679	73%	7,559	14%
Chongqing	28,846	4,898	17%	20,614	71%	3,334	12%
Sichuan	80,418	13,644	17%	57,966	72%	8,808	11%
Jiangshu	78,660	10,230	13%	59,862	76%	8,568	11%
Liaoning	43,746	4,997	11%	34,240	78%	4,509	10%
Anhui	59,501	10,699	18%	42,745	72%	6,057	10%
Shanghai	23,019	1,986	9%	18,704	81%	2,330	10%
Shandong	95,793	15,074	16%	71,289	74%	9,430	10%
Hunan	65,684	11,574	18%	47,686	73%	6,424	10%
Guangxi	46,027	9,991	22%	31,782	69%	4,253	9%
Hubei	57,238	7,964	14%	44,070	77%	5,204	9%
Beijing	19,612	1,687	9%	16,216	83%	1,709	9%

Data Source: China National Statistics Bureau

Table 6: U.S. Demographic Condition

Y2000	Total Households	Age 62+ Households	Age 62+ %
Tampa	1,009,284	337,379	33.4%
Chicago	2,971,619	676,459	22.8%
Detroit	1,695,304	419,494	24.7%
Houston	1,462,676	239,397	16.4%
Las Vegas	588,350	143,105	24.3%
Los Angeles	3,133,781	655,301	20.9%
Phoenix	1,194,271	288,563	24.2%
Washington	1,848,021	340,126	18.4%

However, due to the One Child Policy[7] applied in 1979, the old people % in China is projected to double before 2030. This ratio will even increase more in urban area since the One Child Policy was mainly executed in cities rather than the whole country.

B3. Capital Inflows

When additional capital comes into housing market, the market price will be driven to a higher level than the reasonable price.

In China, due to the low carry cost and housing price increase expectations in levels one and two cities, many wealthy people invest their fortune in real estate markets. The number of houses (apartments) is considered to be a sign of fortune in China nowadays. This phenomenon directly results in a high home vacancy rate. In U.S., the long term vacancy rate is below 2%. In China, some surveys like usage of electricity imply that the vacancy rate is even more than 20% in some major cities.

[7] In December 2013, the Chinese government relaxed the One Child Policy.

Introduction

Climate Change: Impact on the Insurance Industry

Vijay Manghnani, FCAS, FSA
Chairperson, CAS Climate Change Committee

Climate change is expected to have wide-ranging impacts on the insurance industry including risk management, ratemaking and reserving. There may be increases in some types of claims (e.g., fire, flood, wind, drought), but also opportunities in green insurance products and insurance investments. The actuarial profession is considering what role it could play in addressing climate change.

On behalf of Casualty Actuarial Society, the Climate Change Committee is pleased to provide a series of essays on Climate Change: Impact on the Insurance Industry. This is the result of a call for essays on the subject.

There are seven topical essays that express the opinions and thoughts of a number of authors on the subject. An essay is, essentially, a short non-fiction form of writing expressing the often subjective opinion of the author. The thoughts and insights shared herein are not necessarily those of the Casualty Actuarial Society or the authors' employers.

The first four papers are general overviews, starting with a call to action (Rudolph), discussion of economic theory (Gorvett), index-related (Anderson) and catastrophic risk mitigation (Chen and Eckles). The last three papers are more specific, with Gardner and White discussing drought, Launie discussing fire, and finally Zona, Roll, and Law summarizing the current state of green insurance.

After review and deliberation by a dedicated group of volunteer experts, the Climate Change Committee awarded prizes to:

• 1st prize: Managing Investment, Underwriting, and Production Risks from Drought-Related Agricultural Exposures by Lisa A. Gardner and Toby A. White

• 2nd prize: Peshtigo Revised by Joseph J. Launie

• 3rd prize: Sustainable/Green Insurance Products by Rita Zona, Kevin Roll and Zora Law

Overall, the essays are hopeful that climate change can be mitigated and that the world can adapt. The authors also see a role for actuaries in the impact on financial systems. Some of the themes in the essays are the impact of global activities, and the uncertainty inherent in the increasing climate volatility.

The seven essays give us much to ponder on the topic of the impact of climate change on the insurance industry. We hope these essays will provide thought-provoking discussion and commentary in the months and years to come.

Dealing with Climate Change: Mainly Adaptation, with Little Mitigation, But That Is Not Enough

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The development of the Actuaries Climate Change (ACC) Index is an excellent method to measure the impact of climate change. The ACC Index will help the insurance industry to formulate necessary adaptation techniques. Unfortunately, neither the ACC Index, nor the present insurance markets will allow the industry to fully employ its considerable mitigation expertise.

The ACC Index, hopefully providing data back to the 1970s-1980s, will provide baseline measurements, and illustrate trends of its climate change indicators. Much of the data should be readily available through sources like the Intergovernmental Panel on Climate Change (IPCC) periodic assessments. Having an index, whose authenticity is provided by a group of prestigious actuarial organizations, is extremely useful in communicating climate change trends to both industry and the public.

As noted in the "Call for Essays," "The index will highlight important indicators of climate change such as hurricane intensity, Arctic ice cover, melting of land-based glaciers, wild fires, floods, droughts, and temperature extremes." These indicators point to property insurance as bearing the most immediate impacts of climate change. While climate change liability litigation has been introduced, it mostly has been unsuccessful to date. Yet, given the similarities of potential climate change liabilities to existing asbestos and Superfund liabilities, it should be closely monitored. Life and health insurance claims will increase because of heat stress and diseases, like malaria, spreading north and south of the Equator. The industry should be able to manage these claims. Any concern about the uncertainty of life and health claims is reminiscent of the concerns for AIDS claims when they developed. AIDS claims have made up only a few percent of total life and health claims.

In looking at property insurance claims, it is expected that the industry will continue to adapt through increased underwriting, pricing, and deductibles, decreased exposure (e.g., non-renewals), appropriate reinsurance levels, and close attention to its aggregates. The typical property policy period will allow for annual adjustments. Hopefully regulators will allow insurers the market freedom to make these adjustments. The adaptation technique of last resort will be to quit writing coverage in certain high risk areas. While insurers can shift policies from high risk to lower risk areas, policyholders face much more difficulty and expense in relocating their properties and businesses.

Of the seven indicators of climate change listed in the "Call for Essays," only two, hurricane intensity and wild fires, significantly impact property insurance. The remaining five impact mainly flood and crop insurance, both of which are provided by the federal government and excluded by private insurers. The remaining five indicators could, however, also impact Difference in Conditions (DIC) insurance for commercial risks. DIC exposures should be closely monitored and managed by the industry.

Industry mitigation expertise can be successfully employed for hurricane wind risks and wild fire risks through structural strengthening and relocation. But the exclusion of private flood and crop risks limits the scope of the private insurance mitigation mechanisms. In the flood and crop insurance areas, private insurers/agents collect commissions and administrative/claims service fees, but no insurance risk coverage is provided. This lack of financial incentives reduces their mitigation efforts.

The ultimate mitigation strategy for reducing destructive climate change impacts, caused mainly by warming temperatures, is to reduce Greenhouse Gas (GHG) emissions, which are produced mainly by the burning of fossil fuels. Indeed, while dealing with climate change impacts is critical, these impacts are symptoms, not the cause of climate change. Mitigation strategies for reducing GHG emissions that are causing climate change face two major impediments.

The first involves the timing of mitigation costs and benefits. The insurance industry has excelled in mitigating dangerous life threatening risks. Its efforts have produced safe boilers, safer working conditions, and fire resistant buildings to name a few improvements. A characteristic of these efforts is that the benefits are measurable within a short time period of when the mitigation costs were incurred. Fewer buildings were damaged by explosions and fires, and worker injuries decreased. The benefits clearly exceeded the costs, so these actions were justified by cost-benefit analysis.

Mitigating climate change is much more complicated. As with all mitigation methods, reducing GHG emissions has upfront costs. Some benefits, like a reduction in energy consumption, are short term and compare favorably with the costs of say increasing insulation or using more energy efficient appliances and equipment. But with the more important benefits, such as reducing hurricane intensity, sea level rises, flooding and temperature extremes, and their damaging impacts, it will be decades, possibly centuries, before these benefits can be measured and their mitigation costs justified.

Scientific research has shown that regardless of what efforts are taken today to reduce GHG emissions, rising temperatures with their damaging impacts, will continue into the foreseeable future. Because of long lag effects, warming today is being caused by GHG emissions from decades ago.

Indeed, our best feasible strategy is to slow the rate of increase, to reduce the slope of the warming curve.

From a cost-benefit standpoint, short term mitigation costs exceed short term benefits. Only decades-long benefits are expected to exceed upfront costs of serious GHG emissions reduction, like the 80-90% reduction being called for by the scientific community. The "Stern Review on the Economics of Climate Change," a report by economist Nicholas Stern for the British government issued in 2006, estimates mitigation costs to be 1% of world GDP annually, and long-term benefits of mitigation by reducing losses) to be 5-20% of world GDP annually. These estimates clearly justify the costs of mitigation. But, the magnitude of the costs and the uncertainty of the projected benefits raise concerns and impede our ability to take action.

The actuarial profession could provide input, expertise and clarity into this cost-benefit conundrum. How do you deal with cost-benefit analysis where long term benefits of GHG emissions reductions exceed long-term mitigation costs, but short term costs exceed short term benefits? The construction and use of the ACC Index will provide critical input. Hopefully, the Index can be both retrospective and prospective. Actuaries estimate future benefits and costs all the time. Applying these skills to bring more certainty to the decades-long benefits of reducing GHG emissions would be a considerable contribution to the world.

The second major impediment to mitigating GHG emissions is the lack of government involvement. Climate change is a global risk, and any effective action requires central governments' involvement and consensus. Meaningful mitigation needs governments, businesses, individuals and Non-Governmental Organizations (NGOs) to participate. At present, many businesses have taken action to reduce GHG emissions. This includes insurers, particularly those in Europe lead by Swiss Re. Much of the actions are of the "low hanging fruit" variety, such as greater energy efficiency. Many individuals have also voluntarily taken action to reduce their carbon footprints. But the harder actions needed to be taken by businesses and individuals will require governmental regulations. NGOs have been very effective and persuasive, but only in getting businesses and individuals to change voluntarily.

Without increased government involvement, the ACC Index indicators will explode over the coming decades. Based on the scientific community, the impacts in all likelihood will be catastrophic. The scientific community also foresees tipping points, which if we go over them, will be irreversible. We need to start taking meaningful action now. The European Union (EU) has tried the hardest at reducing GHG emissions. The EU does have an operational cap and trade system in place, although the generous granting of allowances has made it less effective than expected. Setting a price on carbon through gas taxes in Europe has led to smaller automobiles, great public transportation systems and lower gasoline consumption. The lack of meaningful GHG regulations in the world's top two carbon emitters, the United States and China, has largely offset the EU's and other countries' efforts. GHG are emitted into a global atmosphere. Without a critical mass of the world's leading emitters, mitigation efforts will fall short of what is needed and the planet will keep warming, with all the resulting adverse impacts.

Absent necessary mitigation, all there is left is adaptation. Adaptation will serve the insurance industry well. Property insurance is the main exposure, at least for now. Predominantly one year policies, with proper underwriting, pricing, adequate reinsurance, monitoring of aggregate exposures, and the ability to move policies from high risk to lower risk locations are all adaptation methods that will protect the industry's financial solidity.

Conceding flood and crop risks to the federal government insulates the industry from critical climate change risks. Unfortunately, businesses and individuals lose the insurance industry expertise in risk financing and mitigation in these areas. I have argued in my writings and teaching for 40 years that the flood risk would be better handled by the private insurance industry than governments. The fact that the National Flood Insurance Program is technically insolvent by over $20 billion is evidence that the private industry would have done better.

After I received my PhD in 1970, my second published article was titled, "What Role Will the Insurance Industry Play in the Fight Against Pollution?"[i] When the industry began to confront pollution risks, one of its first actions was to include, in liability policies, a partial pollution exclusion in the early 1970s. One of my concerns expressed in the article was that the exclusion would remove the insurance industry financial incentives and expertise in mitigation in dealing with the pollution risk. I have the same feelings now, that the lack of involvement of the industry in important climate change risk areas will reduce their mitigation expertise in dealing with these risks.

The insurance industry should be able to absorb the deleterious impacts of climate change. The industry is well situated to use adaptation effectively. The ACC Index will be a major contributor to increasing the industry's adaptation strategies. From the big picture standpoint though, the insurance industry is part of the global society and the world's economy. I am concerned that its ability to adapt and insurers' removal from critical climate change insurance risks, along with their mitigation expertise, will limit their incentives to be a better partner in dealing with this critical global problem. The world needs the mitigation and risk financing skills of the insurance industry. The industry's ability to analyze the long term impacts of climate change, and the long term benefits of taking action today, could be an enormous help in moving the world's governments forward.

[i] *CPCU Annals*, Volume 25, No. 1, March 1972.

Catastrophic Risk Management, Insurance, and the Hyogo Framework For Action 2005-2015

Pei-Han Chen and David L. Eckles

Over the past few decades, nations have suffered great losses in lives and economic assets from an increasing number of natural disasters, which may be possibly due to climate change, combined with rapid economic and population growth particularly in hazard-prone areas. Although the number of people killed by natural disasters decreased steadily over the past few decades, the number of natural disasters, the number of people affected by natural disasters, and the economic losses caused by natural disasters increased substantially. According to the Emergency Events database (EM-DAT Database) from the Centre for Research on the Epidemiology of Disasters (CRED), the number of natural disasters increased from around 50 in 1960 to more than 400 in 2011, representing a 700 percent increase over the past five decades.[1] The number of people affected by natural disasters increased substantially over the past few decades as well, even as the number of people killed by natural disasters decreased steadily since the 1960s. The estimated economic damage caused by reported natural disasters increased from less than 1 billion (USD) in 1950 to more than 100 billion (USD) in 2011.[2] Due to the increasing incidence and severity of these natural disasters, identifying determinants of natural disaster losses and understanding the difference across nations has become an important issue. More and more nations are aware of the significant negative impacts of natural disasters and realize the importance of catastrophic risk mitigation cooperation among nations.

The purpose of this paper is to examine the relationship between catastrophic risk mitigation, insurance, and the Hyogo Framework for Action 2005-2015 (HFA) in 193 participating nations from 1993 to 2011 by investigating a nation's level of the HFA participation and performance, macroeconomic factors, and insurance market conditions related to the number of deaths and economic losses resulting from natural disasters based on panel data analysis. The global risk reduction policy, the Hyogo Framework for Action 2005-2015: Building the Resilience of Nations and Communities to Disasters, was established at the World Conference on Disaster Reduction in 2005 with the participation of all 193 member states of the United Nations to enhance cooperation

[1] Natural disaster as defined by the CRED refers to a natural event which has killed ten or more people, an event which has affected (injured or made homeless) one hundred or more people, an event with a declaration of a state of emergency, or an event with international assistance provided. (For more information, please visit http://www.emdat.be/).

[2] The estimated damage data obtained from the OFDA/CRED International Disaster Database are entered in US dollars in the value of the year of occurrence. The natural disaster economic losses data used in this paper are converted to constant 2005 US dollars.

among regions and nations to develop disaster risk reduction measures (UN/ISDR, 2007). Participating countries have submitted Hyogo progress reports every two years since 2007 to evaluate its natural risk mitigation progress based on the self-reporting assessments of the twenty-two indicator suggested by the HFA. These biennial assessment reports help nations conveniently monitor disaster risk reduction progress at both the country level and region level across years. Our research employs the overall score of these twenty-two indicators obtained from the HFA progress reports as proxies for a nation's HFA performance in natural disaster risk mitigation. We also consider participation levels of countries. The primary contribution of this study is to investigate the importance and effectiveness of the systematic international risk mitigation policy, the HFA, in insurance markets at the international level. The HFA promotes the awareness of disaster risk reduction and provides a sustainable development of risk mitigation management at the international and regional levels in an effort to reduce vulnerabilities and risks to hazards.

Our study extends Kahn's (2005) research and considers the effectiveness of governments' intervention in catastrophe risk management. Kahn (2005) identified several macroeconomic factors which may contribute to the number of deaths resulting from natural disasters within a country. He investigated the importance of a nation's income, geography, and democracy level in determining the number of deaths from natural disasters based on the data of 73 countries from 1980 to 2002. He found that nations with better economic development, less income inequality, and more democratic governments may suffer fewer deaths from natural disasters. We extend his research and evaluate macroeconomic factors, insurance market conditions, and level of the HFA participation in relation to human and monetary losses from natural disasters using panel data analysis. We further investigate how national determinants may influence the implementation of the HFA, and how the HFA efficiently improves catastrophe risk mitigation and decreases economic losses resulting from natural disasters. We employ a pooled ordinary least square (POLS) regression model and a zero-inflated negative binomial model used by Kahn (2005) to investigate the determinants of the number of deaths from natural disasters. For the natural disaster economic loss model, the HFA performance model, and the catastrophic risk mitigation model, we use three estimation models: the POLS model, a fixed effects model, and a random effects model with year effects. We do not employ a two-way fixed effect panel data model which includes both year and country dummy variables since certain macroeconomic variables (i.e., real GDP per capita, population, and land area) vary little (or not at all) and will capture the country effect.

Our initial sample is based on approximately 2,000 observations of 193 member states of the United Nations from 1993 to 2011. We are limited to data from 1993 to 2011 because the macroeconomic data from the World Bank are only available for those years. The sample is further reduced to 788 observations as we include the insurance market condition variables to our models.

This data is also available only from 1998 to 2011. The data for the number of deaths, the estimated economic losses (US dollars in the year of occurrence) from natural disasters over the period of 1993 to 2011 were collected directly from the EM-DAT Database created by the Centre for Research on the Epidemiology of Disasters (CRED). We converted the natural disaster economic losses to 2005 US dollars. Real GDP per capita (2005 US dollars), national income level, urban population, population density, and land area were collected from the World Bank database. Democracy level data were taken from the Polity IV: Regime Authority Characteristics and Transitions Datasets (Annual Time-Series 1800-2011) published by the Integrated Network for Societal Conflict Research (INSCR).[3] Data for insurance premiums and the market shares of world insurance markets were collected directly from the Swiss Re Sigma annual world insurance reports 1999 -2011.[4] The scores of the twenty-two HFA indicators were obtained from the Hyogo Progress Reports (2007-2009, 2009-2011, and 2011-2013), which are available on the Prevention Web.

Our results are as follows: (1) Table 1 shows that nations that did not submit any HFA progress reports with high urban population ratio, low population density, small land area, and sound insurance market conditions (high insurance density, penetration, and world market share) tend to suffer fewer deaths from natural disasters. Our results also show that rich nations with high urbanization may experience fewer losses of lives possibly due to the economies of scale in providing risk mitigation measures against natural disasters. (2) Table 2 shows that nations that submitted at least one of three available HFA progress reports with a well-developed economy, high urban population ratio, high population density, large land area, a democratic government, and sound insurance market conditions suffered more economic losses from natural disasters. These results might be caused by high property values of households in risk-prone areas and potential morale and moral hazard problems within insurance markets. In other words, developed countries (high income countries) tend to have higher economic losses from natural disasters in absolute values, (consistent with Cummins and Mahul (2009)). (3) Table 3 shows that rich nations with more democratic governments and better urban development may achieve better performance of the HFA. (4) Table 4 shows that nations with better performance of short-term mitigation measures do not necessarily reduce their economic losses from natural disasters immediately. We do not find evidence that the HFA performance in previous years efficiently improves a nation's economic losses from natural disasters. This may provide evidence that the short-term risk mitigation policies may not improve a nation's disaster losses immediately. Nations, therefore, should employ long-term risk mitigation measures to manage catastrophic risks due to the unpredictable nature of natural disasters.

[3] For more information, please visit http://www.systemicpeace.org/inscr/inscr.htm.
[4] The Swiss Re Sigma world insurance report in 1999 also includes the insurance data for 1998.

These national and insurance market factors may play a critical role in reducing the negative impacts of mega catastrophes or climate change and help both governments and international organizations in implementing adequate catastrophic risk mitigation strategies in the near future. Moreover, this study provides some insights about the Arrow-Lind Public Investment Theorem by showing that insurance market conditions are significantly related to a nation's natural disaster losses, and macroeconomic factors may be important to the evaluation of government involvement in catastrophic risk management, in addition to the policy of risk neutrality suggested by Arrow and Lind (1970). Our study may provide governments, regulatory agencies, and insurance companies with useful information related to climate change and natural disaster risk management and enhance the effectiveness of catastrophic risk policy enactment.

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AUTHORS' NOTE

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The essay we are submitting is an executive summary of an academic working paper. We agree to the publication of this essay by the CAS as long as publication does not preclude future submission of the full paper to an academic journal. In the event that the CAS wishes to retain ownership of the essay and is not willing to allow publication of the full paper elsewhere, we respectfully withdraw the essay for consideration.

APPENDIX

TABLE 1

The Natural Disaster Death Model

United Nations 193 Countries 1993-2011

Zero-Inflated Negative Binomial Estimation

Dependent Variable: Number of Death from Natural Disasters

	Macroeconomic Factors				Total Insurance Market			Life Insurance Market			Non-life Insurance Market		
Independent Variables	**Model (1)**	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**	**Model (6)**	**Model (7)**	**Model (8)**	**Model (9)**	**Model (10)**	**Model (11)**	**Model (12)**	**Model (13)**
ln(GDP per capita) (2005 US dollars)	-3.71e-07**	5.30e-06*											
	(1.55e-07)	(2.87e-06)											
Developed Country (Binary Variable)			-0.2460	-0.3600	0.2570	0.1330	0.4880	0.5720	0.9230**	0.5130	0.0120	-0.3210	0.0922
			(0.2310)	(0.9230)	(0.3420)	(0.3780)	(0.4120)	(0.3620)	(0.3810)	(0.4330)	(0.3340)	(0.3630)	(0.4180)
HFA Country (Binary Variable)	0.3270**	0.3560***	-0.0717	-0.0692	0.4010*	0.5540**	0.6660***	0.4140*	0.5050**	0.3860*	0.4030*	0.6170***	0.6830***
	(0.1350)	(0.1360)	(0.1270)	(0.1290)	(0.2170)	(0.2280)	(0.2250)	(0.2120)	(0.2150)	(0.2330)	(0.2220)	(0.2380)	(0.2360)
Urban Population Ratio (%)	-0.0245***	-0.0226***	-0.0181***	-0.0182***	-0.0208***	-0.0098*	-0.0034	-0.0230***	-0.0180***	-0.0189***	-0.0230***	-0.0129**	-0.0061
	(0.0029)	(0.0031)	(0.0031)	(0.0033)	(0.0059)	(0.0055)	(0.0059)	(0.0056)	(0.0055)	(0.0061)	(0.0061)	(0.0058)	(0.0067)
ln(Population Density)	0.7780***	0.7840***	0.8320***	0.8300***	0.7060***	0.6350***	0.8570***	0.7260***	0.7240***	0.7780***	0.7170***	0.6440***	0.7430***
	(0.0649)	(0.0649)	(0.0730)	(0.0743)	(0.1110)	(0.1160)	(0.1370)	(0.1080)	(0.1110)	(0.1390)	(0.1140)	(0.1190)	(0.1400)
ln(Land Area)	0.7550***	0.7530***	0.7840***	0.7840***	0.8200***	0.8580***	1.1360***	0.8180***	0.8420***	0.9930***	0.8280***	0.8780***	1.0250***
	(0.0387)	(0.0386)	(0.0406)	(0.0407)	(0.0627)	(0.0692)	(0.1070)	(0.0622)	(0.0651)	(0.0933)	(0.0645)	(0.0735)	(0.1240)
Democracy Level	-0.0464***	-0.0464***	-0.0297***	-0.0297***	0.0209*	0.0307**	0.0329***	0.0234**	0.0344***	0.0261**	0.0175	0.0220	0.0272**
	(0.0042)	(0.0042)	(0.0038)	(0.0038)	(0.0123)	(0.0120)	(0.0115)	(0.0110)	(0.0091)	(0.0109)	(0.0135)	(0.0147)	(0.0132)
Africa (Binary Variable)	0.4030	0.3350	0.2780	0.2850	0.8800	1.6550***	1.5620**	0.9300	1.6580***	0.9230	0.8450	1.6990***	1.6240**
	(0.2670)	(0.2700)	(0.2860)	(0.2910)	(0.5770)	(0.6330)	(0.6280)	(0.5890)	(0.6310)	(0.6310)	(0.5780)	(0.6360)	(0.6320)
Asia (Binary Variable)	0.8980***	0.8350***	0.8650**	0.8760**	1.8810***	2.8090***	2.9370***	1.9270***	2.6040***	2.4610***	1.8870***	3.1320***	3.0100***
	(0.3110)	(0.3130)	(0.3400)	(0.3490)	(0.6330)	(0.7050)	(0.6960)	(0.6470)	(0.7050)	(0.6860)	(0.6320)	(0.7010)	(0.6940)
America (Binary Variable)	0.8570***	0.7700***	1.1970***	1.209***	0.8140	2.2090***	2.2660***	0.8570	1.7660***	0.8610	0.8310	2.3980***	2.4040***
	(0.2910)	(0.2940)	(0.3310)	(0.3440)	(0.6120)	(0.6750)	(0.6640)	(0.6220)	(0.6680)	(0.6190)	(0.6130)	(0.6770)	(0.6710)
Europe (Binary Variable)	1.4170***	1.3990***	0.9250***	0.9410**	2.3820***	3.0640***	3.3790***	2.2270***	2.490***	2.8610***	2.3470***	3.0520***	3.3540***
	(0.3370)	(0.3360)	(0.3570)	(0.3790)	(0.5690)	(0.5970)	(0.6010)	(0.5730)	(0.5970)	(0.5820)	(0.5750)	(0.6060)	(0.6270)
ln(GDP per capita)* Urban Population Ratio		-1.32e-07**											
		(6.50e-08)											
Developed Country* Urban Population Ratio				0.0015									
				(0.0119)									
ln(Insurance Density) (2005 US dollars)					-0.1750**			-0.1690***			-0.0947		
					(0.0745)			(0.0512)			(0.0881)		
ln(Insurance Penetration)						-0.4370***			-0.4410***			0.1470	
						(0.1560)			(0.0685)			(0.2100)	
ln(Market Share of World Insurance Market)							-0.3320***			-0.2250***			-0.1990
							(0.0977)			(0.0802)			(0.1300)
Constant	0.1820	0.1280	0.0314	0.0353	2.1390	-2.1070**	-5.9500***	1.7610	-2.3870***	-3.2520**	0.7320	-2.4980***	-4.4500***
	(0.3980)	(0.3990)	(0.4020)	(0.4030)	(1.5210)	(0.8410)	(1.3620)	(1.1420)	(0.8290)	(1.3330)	(1.7200)	(0.8730)	(1.5860)
Observations	1,763	1,763	1,924	1,924	787	796	796	787	796	661	787	796	797

1. Robust standard errors in parentheses
2. Significance Level: * significant at 10%; ** significant at 5%; *** significant at 1%
3. Developed Country variable is a binary variable which equals to one for developed countries. The classification of country development follows World bank's methodology. Countries with high income are classified as the developed countries; countries with low income, lower middle income, and upper middle income are classified as developing countries.
4.HFA Country is a binary variable which equals to one for countries submitting at least one of three available Hyogo Framework for Action (HFA) progress reports (HFA 2007-2009, HFA 2009-2011, and HFA 2011-2013).

TABLE 2

The Natural Disaster Loss Model
United Nations 193 Countries 1993-2011
Fixed Effects Regression Estimation (Year Effects)
Dependent Variable: ln(Natural Disaster Economic Losses + 1) (2005 US dollars)

	Macroeconomic Factors				Total Insurance Market			Life Insurance Market			Non-life Insurance Market		
Independent Variables	**Model (1)**	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**	**Model (6)**	**Model (7)**	**Model (8)**	**Model (9)**	**Model (10)**	**Model (11)**	**Model (12)**	**Model (13)**
ln(GDP per capita) (2005 US dollars)	1.4380***	1.9110***											
	(0.2400)	(0.5200)											
Developed Country (Binary Variable)			2.9740***	8.1430**	0.0496	1.6080	-0.0977	0.4190	1.6550	0.4470	0.2020	1.9460	-0.0825
			(0.6960)	(3.3100)	(1.2010)	(1.2300)	(1.4700)	(1.0850)	(1.0950)	(1.5280)	(1.1630)	(1.1710)	(1.4640)
HFA Country (Binary Variable)	1.0000**	1.0190**	0.9940**	1.1020***	0.4120	0.2740	0.2190	0.2780	0.1820	-0.5380	0.2790	0.0967	0.0518
	(0.4520)	(0.4540)	(0.3910)	(0.3730)	(0.8070)	(0.8280)	(0.8100)	(0.8130)	(0.8310)	(0.7950)	(0.8020)	(0.8210)	(0.8240)
Urban Population Ratio (%)	0.0223	0.0919*	0.0769***	0.0816***	-0.0233	0.0039	-0.0278	-0.0057	0.0136	-0.0111	-0.0305	-0.0020	-0.0383
	(0.0175)	(0.0477)	(0.0116)	(0.0114)	(0.0281)	(0.0246)	(0.0272)	(0.0252)	(0.0245)	(0.0250)	(0.0313)	(0.0269)	(0.0307)
ln(Population Density)	2.6730***	2.7160***	2.6730***	2.6800***	2.5240***	2.3480***	1.3440***	2.3180***	2.2080***	1.6120***	2.7350***	2.5840***	1.4220***
	(0.1810)	(0.1690)	(0.1840)	(0.1800)	(0.2840)	(0.2830)	(0.4000)	(0.2820)	(0.2810)	(0.3340)	(0.2940)	(0.3010)	(0.4120)
ln(Land Area)	2.0210***	2.0550***	1.9610***	1.9780***	2.3920***	2.2630***	1.2430***	2.2770***	2.1940***	1.6370***	2.5220***	2.4070***	1.2320***
	(0.0980)	(0.0973)	(0.1020)	(0.1020)	(0.2100)	(0.2080)	(0.3480)	(0.2080)	(0.2130)	(0.2820)	(0.2220)	(0.2080)	(0.3670)
Democracy Level	0.0372*	0.0371*	0.0437**	0.0420**	0.0900	0.09810	0.0848	0.0880	0.0971	0.0391	0.0964	0.1060	0.0910
	(0.0198)	(0.0200)	(0.0177)	(0.0174)	(0.0650)	(0.0703)	(0.0609)	(0.0660)	(0.0700)	(0.0765)	(0.0661)	(0.0725)	(0.0614)
ln(GDP per capita)* Urban Population Ratio		-0.0090											
		(0.0069)											
Developed Country* Urban Population Ratio				-0.0703									
				(0.0427)									
ln(Insurance Density) (2005 US dollars)					1.1090***			0.7500***			1.2150***		
					(0.2650)			(0.1440)			(0.3320)		
ln(Insurance Penetration)						1.3040**			0.7210***			1.4870*	
						(0.4700)			(0.1780)			(0.6870)	
ln(Market Share of World Insurance Market)							1.1410***			0.9140***			1.3180***
							(0.3360)			(0.2720)			(0.3910)
Constant	-22.0200***	-25.7500***	-13.8100***	-14.1900***	-28.1900***	-9.4370***	4.8590	-20.3500***	-7.7210**	1.6570	-30.3500***	-9.8970***	5.2970
	(0.9690)	(3.0470)	(1.1480)	(1.0730)	(5.0370)	(2.7060)	(4.9890)	(3.4810)	(2.7290)	(3.7790)	(5.8300)	(2.6930)	(5.5210)
Observations	1,765	1,765	1,794	1,794	788	787	787	788	787	657	788	787	788
R-squared	0.264	0.265	0.246	0.248	0.164	0.157	0.161	0.163	0.157	0.165	0.163	0.155	0.162
Number of Years	18	18	18	18	13	13	13	13	13	13	13	13	13

1. Robust standard errors in parentheses
2. Significance Level: * significant at 10%; ** significant at 5%; *** significant at 1%
3. Developed Country variable is a binary variable which equals to one for developed countries. The classification of country development follows World bank's methodology. Countries with high income are classified as the developed countries; countries with low income, lower middle income, and upper middle income are classified as developing countries.
4. HFA Country is a binary variable which equals to one for countries submitting at least one of three available Hyogo Framework for Action (HFA) progress reports (HFA 2007-2009, HFA 2009-2011, and HFA 2011-2013).

TABLE 3

The HFA Performance Model
United Nations 193 Countries 2007-2011
Fixed Effects Regression Estimation (Year Effects)
Dependent Variable: Hyogo Progress Report Performance (HFA) (score is out of 110)

	Macroeconomic Factors				Total Insurance Market			Life Insurance Market			Non-life Insurance Market		
Independent Variables	**Model (1)**	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**	**Model (6)**	**Model (7)**	**Model (8)**	**Model (9)**	**Model (10)**	**Model (11)**	**Model (12)**	**Model (13)**
ln(Natural Disaster Economic Losses+ 1) (2005 US dollars)													
(one year lagged value)	0.1770*	0.1890**	0.2030	0.2490**	-0.0710	-0.0290	-0.0602	-0.0491	-0.0232	0.1910**	-0.0817	-0.0334	-0.0702
	(0.0760)	(0.0591)	(0.1010)	(0.0855)	(0.1130)	(0.1100)	(0.1170)	(0.1040)	(0.1150)	(0.0438)	(0.1140)	(0.1100)	(0.1160)
ln(GDP per capita) (2005 US dollars)	-1.5830	-5.8660*											
	(0.8190)	(2.6920)											
Developed Country (Binary Variable)			-3.3430	-52.8200***	-2.5550	-7.0690	-0.9540	-7.0700	-8.3650	-12.3400	-1.3090	-7.1390	-0.9630
			(4.3360)	(11.4300)	(12.0200)	(6.0170)	(10.6400)	(12.2400)	(7.4830)	(13.1500)	(10.3400)	(4.4150)	(8.6610)
Urban Population Ratio (%)	0.1310**	-0.4600	0.0981*	0.0078	0.1390	0.0937	0.1450	0.1130	0.1240	0.2510	0.1820	0.1100	0.1750
	(0.0438)	(0.3690)	(0.0425)	(0.0533)	(0.1240)	(0.0741)	(0.1140)	(0.0923)	(0.0749)	(0.1470)	(0.1380)	(0.0813)	(0.1170)
ln(Population Density)	6.6730**	6.3490**	6.5170**	5.7430**	4.8620**	5.0680**	7.5400	4.9500**	4.7270*	4.1060	4.4940**	4.8950**	7.6970
	(1.8090)	(1.6620)	(1.6280)	(1.3630)	(1.4060)	(1.7950)	(4.1820)	(1.6090)	(1.9140)	(3.2710)	(1.2920)	(1.7020)	(3.7260)
ln(Land Area)	4.0510**	3.9650**	3.8150**	3.6450**	2.5850	2.7930	5.4040*	2.4650	2.4760	1.8630	2.3520	2.6670	5.6900**
	(1.2220)	(1.2380)	(1.0960)	(1.0480)	(1.6680)	(1.4860)	(2.0460)	(1.6340)	(1.4710)	(1.0770)	(1.7860)	(1.5590)	(1.7100)
Democracy Level	0.5850***	0.5610**	0.4970***	0.5140***	1.9960**	1.6530*	1.9580*	1.5330	1.2250	1.5560	2.0000*	1.6520	1.9170*
	(0.1220)	(0.1320)	(0.0978)	(0.0947)	(0.7010)	(0.7110)	(0.7390)	(0.7390)	(0.7160)	(0.9420)	(0.7300)	(0.7750)	(0.7790)
ln(GDP per capita)* Urban Population Ratio		0.0752											
		(0.0474)											
Developed Country* Urban Population Ratio				0.6890**									
				(0.2070)									
ln(Insurance Density) (2005 US dollars)					-2.3610			-0.2710			-3.3290		
					(3.4710)			(2.7080)			(3.3540)		
ln(Insurance Penetration)						-1.4390			0.5400			-2.5130	
						(3.4400)			(2.7830)			(2.2880)	
ln(Market Share of World Insurance Market)							-2.8800			-0.4900			-3.4580
							(3.0330)			(2.8850)			(2.7480)
Constant	-11.8000	21.4000	-21.6200	-13.9800	25.6900	-13.1300	-47.4500	-8.1680	-10.5300	-16.8700	41.4000	-13.3800	-50.9000
	(11.1100)	(17.3600)	(10.3900)	(9.0650)	(59.3600)	(12.4400)	(39.5900)	(44.7100)	(12.0900)	(32.4500)	(56.2900)	(12.5100)	(34.4000)
Observations	436	436	475	475	230	231	232	227	228	197	230	231	232
R-squared	0.097	0.103	0.099	0.118	0.051	0.044	0.050	0.036	0.033	0.044	0.053	0.045	0.051
Number of Years	5	5	5	5	5	5	5	5	5	5	5	5	5

1. Robust standard errors in parentheses
2. Significance Level: * significant at 10%; ** significant at 5%; *** significant at 1%
3. Developed Country variable is a binary variable which equals to one for developed countries. The classification of country development follows World bank's methodology. Countries with high income are classified as the developed countries; countries with low income, lower middle income, and upper middle income are classified as developing countries.

TABLE 4

Catastrophic Risk Mitigation Model

United Nations 193 Countries 2007-2011

Fixed Effects Regression Estimation (Year Effects)

Dependent Variable: ln(Natural Disaster Economic Losses + 1) (2005 US dollars)

	Macroeconomic Factors				Total Insurance Market			Life Insurance Market			Non-life Insurance Market		
Independent Variables	**Model (1)**	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**	**Model (6)**	**Model (7)**	**Model (8)**	**Model (9)**	**Model (10)**	**Model (11)**	**Model (12)**	**Model (13)**
Hyogo Progress Report Performance (HFA) (score is out of 110) (one year lagged value)	0.0223***	0.0223***	0.0231**	0.0233**	0.0479*	0.0512*	0.0479*	0.0460*	0.0489*	0.0464*	0.0480*	0.0510**	0.0481*
	(0.0034)	(0.0034)	(0.0050)	(0.0047)	(0.0176)	(0.0164)	(0.0177)	(0.0183)	(0.0173)	(0.0183)	(0.0176)	(0.0159)	(0.0176)
ln(GDP per capita) (2005 US dollars)	1.9120**	1.8560											
	(0.3950)	(0.8650)											
Developed Country (Binary Variable)			4.2740**	2.8240	2.5100	3.4390	2.7790	2.0140	2.9630	1.5600	3.0670	3.9660*	3.6500
			(1.2140)	(2.4860)	(1.9070)	(1.4870)	(1.8910)	(1.8240)	(1.5410)	(2.6980)	(1.7990)	(1.3670)	(1.7130)
Urban Population Ratio (%)	0.0038	-0.0036	0.0752**	0.0730*	0.0190	0.0404	0.0232	0.0273	0.0493	0.0213	0.0207	0.0406	0.0308
	(0.0299)	(0.0723)	(0.0223)	(0.0243)	(0.0529)	(0.0407)	(0.0504)	(0.0428)	(0.0366)	(0.0324)	(0.0628)	(0.0493)	(0.0588)
ln(Population Density)	2.7050***	2.6990***	2.6690***	2.6500***	2.9860***	2.9100***	2.3810*	2.8390***	2.7550**	2.1540*	3.0610***	2.9910***	2.6950**
	(0.2200)	(0.1990)	(0.2460)	(0.2570)	(0.3940)	(0.4480)	(0.7900)	(0.4550)	(0.4760)	(0.6910)	(0.3160)	(0.3410)	(0.8060)
ln(Land Area)	2.1350***	2.1310***	2.1190***	2.1020***	2.3820***	2.3500***	1.7670**	2.3140***	2.2780***	1.5780**	2.4340***	2.4020***	2.0810**
	(0.2060)	(0.1890)	(0.2100)	(0.2140)	(0.3190)	(0.2890)	(0.4330)	(0.3020)	(0.2710)	(0.4550)	(0.3340)	(0.2830)	(0.5420)
Democracy Level	0.0116	0.0112	0.0123	0.0122	-0.0860	-0.0932	-0.0830	-0.0990	-0.1050	-0.1120*	-0.0771	-0.0799	-0.0720
	(0.0676)	(0.0646)	(0.0675)	(0.0673)	(0.0549)	(0.0601)	(0.0549)	(0.0478)	(0.0521)	(0.0415)	(0.0626)	(0.0720)	(0.0651)
ln(GDP per capita)* Urban Population Ratio		0.0010											
		(0.0107)											
Developed Country* Urban Population Ratio				0.0204									
				(0.0416)									
ln(Insurance Density) (2005 US dollars)					0.6830			0.6720			0.5500		
					(0.4930)			(0.2890)			(0.6390)		
ln(Insurance Penetration)						0.8090			0.7230*			0.4110	
						(0.5740)			(0.2640)			(1.0470)	
ln(Market Share of World Insurance Market)							0.6060			0.9790			0.3180
							(0.4940)			(0.4730)			(0.5880)
Constant	-26.2400***	-25.8000**	-15.7000***	-15.4700***	-26.2400**	-15.2900**	-7.6230	-24.5800***	-13.7000*	-4.3180	-24.2300**	-15.4200**	-11.6000
	(1.6070)	(4.7480)	(2.4760)	(2.6220)	(6.1030)	(4.3660)	(9.2410)	(4.0950)	(4.6060)	(7.5280)	(7.4140)	(4.0220)	(10.3700)
Observations	438	438	445	445	238	237	238	238	237	210	238	237	238
R-squared	0.290	0.290	0.271	0.272	0.221	0.224	0.220	0.226	0.229	0.243	0.218	0.222	0.217
Number of Years	4	4	4	4	4	4	4	4	4	4	4	4	4

1. Robust standard errors in parentheses
2. Significance Level: * significant at 10%; ** significant at 5%; *** significant at 1%
3. Developed Country variable is a binary variable which equals to one for developed countries. The classification of country development follows World bank's methodology. Countries with high income are classified as the developed countries; countries with low income, lower middle income, and upper middle income are classified as developing countries.

TABLE 5

The HFA 22 Indicators

Priority	Description	Number of Indicators	Score
1	Ensure that disaster risk reduction is a national and a local priority with a strong institutional basis for implementation	4	20
2	Identify, assess and monitor disaster risks and enhance early warning	4	20
3	Use knowledge, innovation and education to build a culture of safety and resilience at all levels	4	20
4	Reduce the underlying risk factors	6	30
5	Strengthen disaster preparedness for effective response at all levels	4	20
Total		22	110

THE HFA THREE STRATEGY GOALS, FIVE PRIORITIES AND TWENTY-TWO INDICATORS

Strategy 1: The integration of disaster risk reduction into sustainable development policies and practices.

Strategy 2: Development and strengthening of institutions, mechanisms and capacities to build resilience to hazards.

Strategy 3: The systematic incorporation of risk reduction approaches into the implementation of emergency preparedness, response and recovery programs.

Priority 1: Ensure that disaster risk reduction is a national and a local priority with a strong institutional basis for implementation.

Indicator1.1: National policy and legal framework for disaster risk reduction exists with decentralized responsibilities and capacities at all levels.

Indicator1.2: Dedicated and adequate resources are available to implement disaster risk reduction plans and activities at all administrative levels.

Indicator1.3: Community Participation and decentralization is ensured through the delegation of authority and resources to local levels.

Indicator 1.4: A national multi sectorial platform for disaster risk reduction is functioning.

Priority 2: Identify, assess and monitor disaster risks and enhance early warning.

Indicator 2.1: National and local risk assessments based on hazard data and vulnerability information are available and include risk assessments for key sectors.

Indicator 2.2: Systems are in place to monitor, archive and disseminate data on key hazards and vulnerabilities.

Indicator 2.3: Early warning systems are in place for all major hazards, with outreach to communities.

Indicator 2.4: National and local risk assessments take account of regional / trans boundary risks, with a view to regional cooperation on risk reduction.

Priority 3: Use knowledge, innovation and education to build a culture of safety and resilience at all levels.

Indicator 3.1: Relevant information on disasters is available and accessible at all levels, to all stakeholders (through networks, development of information sharing systems etc.)

Indicator 3.2: School curricula, education material and relevant trainings include disaster risk reduction and recovery concepts and practices.

Indicator 3.3: Research methods and tools for multi-risk assessments and cost benefit analysis are developed and strengthened.

Indicator 3.4: Countrywide public awareness strategy exists to stimulate a culture of disaster resilience, with outreach to urban and rural communities.

Priority 4: Reduce the underlying risk factors.

Indicator 4.1: Disaster risk reduction is an integral objective of environment related policies and plans, including for land use natural resource management and adaptation to climate change.

Indicator 4.2: Social development policies and plans are being implemented to reduce the vulnerability of populations most at risk.

Indicator 4.3: Economic and productive sectorial policies and plans have been implemented to reduce the vulnerability of economic activities.

Indicator 4.4: Planning and management of human settlements incorporate disaster risk reduction elements, including enforcement of building codes.

Indicator 4.5: Disaster risk reduction measures are integrated into post disaster recovery and rehabilitation processes.

Indicator 4.6: Procedures are in place to assess the disaster risk impacts of major development projects, especially infrastructure.

Priority 5: Strengthen disaster preparedness for effective response at all levels.

Indicator 5.1: Strong policy, technical and institutional capacities and mechanisms for disaster risk management, with a disaster risk reduction perspective are in place.

Indicator 5.2: Disaster preparedness plans and contingency plans are in place at all administrative levels, and regular training drills and rehearsals are held to test and develop disaster response programs.

Indicator 5.3: Financial reserves and contingency mechanisms are in place to support effective response and recovery when required.

Indicator 5.4: Procedures are in place to exchange relevant information during hazard events and disasters, and to undertake post-event reviews

Managing Investment, Underwriting, and Production Risks from Drought-Related Agricultural Exposures

Lisa A. Gardner, Ph.D. and Toby A. White, Ph.D.

INTRODUCTION

Consequences of global climate change include changes in the frequency, intensity, duration and timing of droughts (Intergovernmental Panel on Climate Change 2012). While low levels of rain or snowfall contribute to drought conditions, so, too, do rising surface temperatures, which accelerate moisture evaporation into the atmosphere, drying land surfaces and lowering water levels in streams, lakes and oceans. The evaporated moisture eventually returns to earth through precipitation, but not necessarily in the locations from which it was evaporated (U.S. Environmental Protection Agency 2013). The result can be unexpected precipitation shortfalls in some locations, and unusually large amounts of precipitation in others.

While predicting future weather patterns involves uncertainty, modeling techniques have advanced enough so that some experts feel able to make reasonable predictions about drought. In what might be the best analysis of climate change evidence to date, the Intergovernmental Panel on Climate Change reports "medium confidence that droughts will intensify in the 21st century in some seasons and areas", including in Central North America (Intergovernmental Panel on Climate Change 2012). Average temperatures will continue to increase, and in the Midwest, summers will be hotter and with longer dry periods, while winters will be warmer and wetter (U.S. Environmental Protection Agency 2013). Still, winter moisture is not expected to compensate for summer precipitation shortfalls and more evaporation in most of the Midwest (U.S. Environmental Protection Agency 2013). Thus, many water levels will likely fall, including in the Great Lakes (U.S. Environmental Protection Agency 2013), (Select Committee on Energy Independence and Global Warming n.d.). Consequently, water will become less available for agricultural uses.

The consequences of Midwestern droughts seem far-reaching, especially given the region's role in corn and soybean production. This paper provides an overview of the consequences of drought for farmers, crop insurers, the FCIC, reinsurers and more broadly, insurance company investment strategies.

DROUGHT CONSEQUENCES

The Midwest, consisting of Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, Ohio, North Dakota, South Dakota and Wisconsin, accounts for much of the nation's annual crop and livestock production. The region is especially well known for corn and soybean production, and generates most of the world's supply of these two products (Carlson 2012). According to the U.S. Department of Agriculture, the region "produced 85 percent of the more than 10.4 billion bushels of corn binned, and 81 percent of the more than 3 billion bushels of soybeans produced" in 2011 (Carlson 2012). Much of that product gets shipped abroad, making the U.S. the world's leading corn exporter and frequently, the largest soybean exporter as well (Carlson 2012).

Even short-lived droughts can reduce corn and soybean yields if they occur at the wrong time. Those who buy corn and soybeans will try to adjust by substituting other products, but in some cases, good substitutes will not exist. Thus, the impact from drought conditions, even if only temporary, can include a decrease in food supply, a correspondent increase in food prices, and indirectly, more hunger and starvation in countries that are especially price elastic (Determining the Impact of Climate Change on Insurance Risk anbd the Global Community 2012).

Beyond the immediate increases in food prices caused by shortages, droughts during production season also raise the costs of farming, providing a second upward jolt to food prices. Failure to mitigate against these conditions creates greater volatility in farm income, making foreclosure more likely. Foreclosures make banks less stable, adding contagion risk to the entire financial system. As a result, the cost of agricultural lending to farmers in drought-susceptible areas rises.

RISK MANAGEMENT STRATEGIES FOR CORN AND SOYBEAN PRODUCERS

There are some viable risk management strategies for farmers to protect against drought. In the short-term, they can plant more drought-resistant varieties of corn and soybeans, but over time, temperatures may rise to the point that these varieties are no longer sustainable. They may then try planting other types of crops, but this can be risky because of the crop-specific nature of some farming equipment. (i.e., a corn picker cannot be used to harvest wheat). Many farmers will need to install irrigation systems, raising demand for water during a time of increased water scarcity, driving up water prices. Clean water may also become more expensive as less water is available to dilute existing emissions into bodies of water, necessitating more expenses to clean the water.

Farmers can diversify their sources of income with off-farm income sources, since all livestock and crop production depend partly on a steady water supply. They can also simply save more money and spend less, so that they have a greater financial cushion for absorbing drought-related income losses.

Turning to the financial markets, they can use weather derivatives to hedge precipitation shortfall risk (Considine 2000), realizing that hedges are typically less than perfect and the amount of capital available to back them somewhat limited. Weather derivatives have payoffs triggered by weather-related metrics, usually tied to temperature or precipitation. Since corn and soybean yields depend on both factors, derivative payoffs tied to temperatures being unusually hot or precipitation unusually low might help replace income lost to low yields. Most weather derivatives are traded over the counter (OTC) or at the Chicago Mercantile Exchange, but OTC transactions have become increasingly popular recently (Weather Derivatives, Come Rain or Shine 2012). In OTC markets, farmers need to beware of counter-party risk presented by derivatives sellers who may be unable to fulfill these contracts if overexposed. Insurance companies with large concentrations of underwriting risk tied to drought, or investment assets adversely affected by drought would make poor counter-parties for corn and soybean farmers seeking to hedge drought crop losses.

Farmers can purchase Federal Crop Insurance, also an imperfect hedge for yield and revenue risks, but should expect to pay more for it if weather related disasters become more frequent. They may also seek assistance through the Noninsured Crop Disaster Assistance Program.

In sum, in times of drought, corn and soybean producers will pay more for agricultural capital, experience more volatility in production yields and revenues, incur higher production costs, and hold more capital in liquid sources to help them smooth the peaks and valleys of income fluctuations. Corn and soybean prices will rise, contributing inflationary pressures throughout the world. We now consider the effects of drought on crop insurance and reinsurance companies.

CAPITAL, INVESTMENTS, AND CROP INSURERS/REINSURERS

Among the 17 private property insurance companies writing crop insurance, most bear only a portion of yield risk and administrative expenses, passing much of this on to the Federal Crop Insurance Corporation (FCIC) through reinsurance agreements (Risk Management Agency/U.S. Department of Agriculture 2013). These companies typically specialize in agriculture insurance, and thus, cannot rely on other aspects of their operations to offset their drought losses.

Claims, which account for most liabilities, will likely be more frequent, more severe and thus, more volatile. When significant drought loss potential exists, these insurers should adjust their asset portfolio to better cover liabilities. They can, for example, increase liquidity by investing proportionately more assets in cash or marketable securities, and replacing some long-term bonds with short-term bonds. However, the investment actuary must balance the need for liquidity with the need for yields adequate to support underwriting losses and greater claims processing costs. The insurer may need to consider alternative investment classes that generate a higher expected rate of return, while still satisfying any risk tolerance and regulatory constraints. Another strategy is to consider investing some funds in assets that increase in value during drought periods (e.g. stock from irrigation systems manufacturers) so that drought-related losses might be at least partially offset by an uptick in other revenues.

In any event, capital resources must be sufficient to cover reasonably pessimistic scenarios. This may necessitate a higher "provision for deviation from expected" component in rates if market and regulatory conditions allow it, and price elasticities are conducive to revenue increases. The insurer could also purchase more reinsurance or employ weather derivatives as a hedge.

Crop insurance companies transfer much of their insurance risk to the FCIC. While farmers pay premiums for crop insurance, which then get funneled in part to the FCIC, most FCIC funding is through federal taxes. More drought claims mean more demand from taxpayers to fund them. If these funds cannot be secured, then the FCIC may bear less risk, either by requiring crop insurance companies to retain more risk, or by relying more on reinsurance. If laws and regulations permit, they may generate capital using weather derivatives.

When the FCIC purchases reinsurance (which is technically retrocession, since they are a reinsurer of crop insurance companies), the costs will vary based on both claims experience and demand for reinsurance/retrocession globally. More drought-related losses should raise demand for reinsurance/retrocession coverage worldwide. If rates rise, more capital may be attracted to reinsurance/retrocession, enhancing the worldwide supply of coverage. Rates of return must be sufficient to keep the capital engaged, meaning that costs of reinsurance/retrocession will likely need to remain higher for a sustained period of time to ensure coverage availability.

Crop insurance and reinsurance companies may use weather derivatives to help offset drought losses in a couple of different ways. They may write weather derivatives that will likely be "out of the money" (i.e., not require them to pay out any money) if drought conditions do not materialize in regions other than where they have exposure (Gandel 2012). They may also buy weather derivatives that will likely be "in the money, with a closer hedge formed if they can purchase them for the region where they are likely to suffer drought related losses. Of course, the ability to use these strategies depends on availability of counter-parties. In the next section, we consider how drought affects insurance company investment portfolios.

INVESTMENT STRATEGIES FOR MANAGING THE EFFECTS OF DROUGHT

Through investments, drought-related corn and soybean losses may directly affect even those insurance companies who do not write crop insurance. Adverse effects may arise from a specific asset class (e.g. equities heavily concentrated in drought-prone locations), industry sector (e.g. agriculture), or individual security (e.g. a food processor who relies heavily on corn or soybeans). While some partial offsets to drought losses may exist (e.g. investing in equities of air conditioning manufacturers whose revenues will likely rise during hot spells), they will likely not be large enough to completely offset the negative consequences of drought.

If the drought is widespread across a broad geographic region, or is especially severe in length and scope, market or contagion risk may also adversely impact equity returns. Default risk and credit risk may increase on corporate bonds issued by firms in affected regions and industries. Thus, the investment actuary may have to reweight the asset portfolio by either asset class or industry sector. A related concern is that the portfolio be not too heavily concentrated by region. For example, an insurer with an asset portfolio overly weighted in local companies may be undiversified, and thus, have significant exposure if a drought permeates the local area.

Insurers should also avoid investing in firms that are clearly making negative contributions to climate change (e.g., utilities with factories that use obsolete coal-burning technologies, and thus introduce extra pollutants into the environment). If the insurer discovers that any of its current holdings are not practicing or promoting "green" technology, these holdings could be sold and replaced by otherwise similar holdings that are more eco-friendly.

CONCLUSION

Evidence of climate change continues to mount, with results including adverse weather conditions like lower precipitation and higher surface warming, which raises the prevalence and potential severity for drought in regions like the Midwestern United States. Crop insurance consumers, writers, and reinsurers must prepare for more volatility in claims, and be proactive in managing the consequences. So, too, must insurance companies with agriculture exposures in their investment portfolios.

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Actuaries and Climate Change: Insights from Economic Theory

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As with any large complex system involving multifaceted parameters and processes, our planet's climatological system is a network of interconnections and interrelationships. Actuarial science, perhaps the ultimate interdisciplinary field, is well-positioned to add value to the study of climate change and its potential socioeconomic impact. The actuary's quantitative and analytical skills, along with an understanding of economic and financial processes, provide a basis for better measuring and evaluating the risks posed by global warming. In addition, with the emergence of enterprise risk management over the last twenty years, actuaries have become accustomed to analyzing the risk inherent in complicated organizations and systems on a holistic basis, something that is critical to an appreciation of the implications from climate change.

In this essay, three possible avenues for future actuarial innovation and research are suggested, each based on economic and financial theory. First, the implications for evaluating organizational decisions within an option pricing framework are described. Second, behavioral incentives and tax policy are considered. Finally, the value of climate change indices within market-based systems is discussed.

THE OPTION FRAMEWORK

Consider a stock insurance company. The stockholders that own the company have a right to the "residual value" of the company – i.e., due to limited liability, the stockholders essentially own a call option on the assets of the company, with an exercise price equal to the liabilities of the company. To the extent that the company's assets exceed its liabilities, that excess amount – or the payoff of the call option – represents the value to the stockholders. That call option, as can be shown via put-call parity, can also be characterized as a put option, which the owners hold, giving them the right to "put," or sell, the company to the debtholders (bondholders, etc.) of the company in the event its liabilities exceed its assets. This "default option" becomes more valuable when, among other factors, the volatility of the company's operational results increases. In particular, and with respect to climate change, assume that the company is permitted to take advantage of the opportunity, presented by the societal recognition of the potential adverse impact of climate change on insurers, to increase its policy premiums. The impact on the owners of the company would be non-symmetric: the low-loss scenarios are welcome, and result in profitability; however, in scenarios involving large climate-generated losses, the owners have a stop-loss provision, since they can "put," or default-away, the company. Thus, in this situation, the insurer's owners might not mind, and would perhaps even welcome, the additional volatility associated with climate change.

Of course, in the real world, the company's ability to increase premiums might very well be limited by regulators. In this event, the company will be motivated to provide policyholders with incentives to act in a manner that addresses, and hopefully minimizes or even diminishes, their contributions to overall climate risk, and thus loss. This could take on many forms, including provisions in policies with premium-reduction opportunities, direct risk mitigation services from the insurer, etc.[i]

The actuary's contribution in this area is essential: to identify and model losses (as well as company value and the value of the default option) under various future scenarios – scenarios which vary according to assumed type and level of climate activity, and according to the proposed risk mitigation strategies that might be undertaken by companies and / or the insurance industry.

INCENTIVES AND TAXES

Closely related to the incentive issues described above are Pigovian taxes and negative externalities. The economist Richard S.J. Tol (2009) has commented, "Climate change is the mother of all externalities: larger, more complex, and more uncertain than any other environmental problem."

An economic negative externality occurs when an activity or transaction is undertaken that is favorable to the primary party or parties, but that produces costs to one or more third parties – e.g., to society. Thus, part of the total cost of a decision or transaction is borne not by the primary party or parties, but rather by an outside party. Frequently, such externalities are found in proximate geographic relationships, but depending upon the size and complexity of the externality, the impact can be felt by third parties which are significantly physically distant from the original activity or transaction (think: climate change / global warming). The end result is that, where there is a negative externality, costs will be imposed upon consumers and society typically in the form of higher prices and / or higher taxes.

Possible solutions to this situation can be either interventionist, or market-based. An interventionist solution is to provide an incentive to not undertake the externality-producing activity, for example via an appropriately-defined tax that would be assessed against the firm undertaking the activity. The size of such a "Pigovian tax" (named after economist Arthur Pigou, 1920) might be determined by estimating the marginal cost of the loss to society from the activity. In this way, the tax can be set to provide a disincentive, and encourage behavior that is in the public interest.

Another possible interventionist approach toward a negative externality like climate change is through direct regulation and control. Similar to the Pigovian tax, this involves estimating the societal cost associated with various activities.

Insofar as actuaries are skilled in the economic and financial modeling of risks, they are well-positioned to contribute significantly to the discussion of whether, and to what magnitude, to implement such interventionist mitigation strategies.

INDICES AND MARKET-BASED STRATEGIES

Yet another approach to dealing with an externality is via a market-based strategy. With respect to climate change, probably the technique in this category that has been most frequently discussed is a carbon permit-and-trade (or cap-and-trade) system[ii], which might allow the market to self-determine a price for a tradable permit at which the market would clear. However, a straight carbon tax is a very credible alternative to cap-and-trade. In fact, most economists, if confronted with a choice between these two methods, would probably prefer the carbon tax approach. This is because it is more direct and straightforward, and (at least conceptually) can be calculated more easily; also, it is unclear how to properly set the cap amount, or the overall "permissible level," of carbon in a permit-and-trade system.

With a carbon tax approach, the creation of an appropriate index which measures the incidence and impact of climate change is essential. Once such an index (or, more likely, indices, as each application of an index-based system will likely have different specific needs and goals) is determined, however, its uses will be many. Two are mentioned as examples here: a carbon tax measure that would vary with a global warming index and a system of futures and / or options based upon such an index.

Economist Ross McKitrick (2007) identified an interesting possible use for an index within the context of a carbon tax. Because

> "… climate models predict that, if greenhouse gases are driving climate change, there will be a unique fingerprint in the form of a strong warming trend in the tropical troposphere… this will be an early and strong signal of anthropogenic warming… only sustained greenhouse warming will (yield this pattern)."

He suggests implementing a carbon tax in each country that is a function of the mean tropical tropospheric anomaly (the "index"), updated annually. (In McKitrick's version, the carbon tax would be revenue-neutral, as income taxes would be reduced and offset by the amount raised by the carbon tax.) If the tropical troposphere temperature increases abnormally, the anomaly figure will rise and the tax amount will increase – as it should, as this would indicate anthropogenic carbon-based warming. If the temperature, and thus the anomaly, do not increase (or possibly decrease), the tax would remain low, or perhaps even disappear (or possibly even become negative, producing a subsidy for carbon emission, although certainly a floor limit might be enacted so that the tax would not fall below zero) – as it should, as this would indicate that human-based carbon emissions are not a cause (or at least a questionable cause) of climate change.

One could envision this general idea going further, and leading to a market for climate change futures and / or options which are based upon appropriate indices. These derivative products could either be stand-alone securities, or their prices might also be the basis for a version of a carbon tax. In any case, over the last decade or so, a large and successful market in weather derivatives has evolved; with the innovation of appropriate climate change indices, this range of products could be extended to allow for capital markets trading and hedging of global warming risks. An active derivatives market would also facilitate the writing of insurance policies in which indemnity is defined as a function of such indices; with derivatives trading on the same basis, climate change-related insurance policies and derivatives would have a common measurement foundation, and hedging opportunities and price determination would be enhanced.

Regardless of the public policy implemented, it is an extremely complex and difficult task to measure the impact of a policy provision on carbon emissions, on damages, and on other socioeconomic factors. This will be a challenging and important area for actuarial innovation and research. In addition, future strategic and operational planning for both public and private organizations would be hugely affected, in terms of their estimated economic and financial impacts, by projected future values of such indices. This would make their accurate and efficient determination critical, and would undoubtedly result in extensive analytical efforts to understand and improve the calculation of these indices. Actuaries would logically have great input, if not into the calculation of the indices themselves, certainly into the modeling and projections associated with the socioeconomic and financial implications of index values.

* * * * *

The issues discussed in this essay are largely optimization problems: determining organizational strategy, or countrywide or global public policy, that might be expected to maximize benefits within certain risk-level constraints. Actuaries, with their quantitative skill set and interdisciplinary perspective, are uniquely positioned to be a key player in these deliberations, and in risk mitigation and financial risk management efforts associated with climate change.

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[i] Climate change has the potential to affect a company's risk profile, for example through potential increases in frequency and/or severity, relative to numerous risk exposures – e.g., raw materials procurement and other production chain factors, impacts on markets due to changes in public attitudes, etc. Both traditional and innovative risk management techniques will help to address these risks. See, for example, Baglee, et al (2012).

[ii] Of course, for the sake of this discussion, it has been assumed that climate change is anthropogenic and works through a largely carbon-based greenhouse effect.

Peshtigo Revisited

Joseph J. Launie, PhD, CPCU, FACFE

One of the effects of climate change is a decrease in rainfall in the American Southwest including California. In the last year, there were the usual number of rainstorms but instead of dropping two to four inches of rain each, they dropped less than 1/4 inch. The brush lands are dry and frequent fires are forecast.

Underwriting and casualty actuarial managers must adopt a new algorithm to provide adequate forecasting of the effect of climate change on brush fire losses. Usually we use incurred loss data to determine our estimates of loss frequency and severity. This has been compared to driving a car by looking out the back window. If there are no fundamental changes that would affect loss frequency and severity, historical data will work quite well. If the climate is warming, then the assumption that the past is prologue may not hold.

We have some early warning signs. Brush fire loss severity is up. Today's fires are five times as large as those in the 1980s.[1] Projection of that growth rate out another ten years produces huge numbers. An Arizona brush fire just killed 19 out of 20 men of a Hotshot fire fighting crew. That is the worst loss of firefighters' lives in a brush fire in many decades. Such a loss of life among firefighting personnel is unacceptable. Perhaps we should take it as a wake-up call to review our assumptions about woodland fire.

Brush fires impact fire insurance underwriting and actuarial calculations on two levels. First, the probability of loss of individual dwellings must be considered. This impacts line underwriting and pricing. Second, the estimation of the probable maximum loss from a brush fire related catastrophe is critical. Reinsurance treaties must be reviewed to ascertain that they can respond to the greatest foreseeable catastrophe. A number of the elements comprising maximum probable loss are increasing. On the one hand, population shifts are increasing the number of homes particularly in the Southwest that are located in that urban/forest zone that is especially exposed to brush fire.

In addition, with climate change, loss probabilities for both individual risks and aggregate books of business will increase. The amount of the increase is difficult to ascertain. Climate change can increase temperatures, drying out brush and making fires more likely. Another effect of climate change is disruption of long term rainfall patterns. Such disruptions may bring additional rainfall to one area and drought to another. From the standpoint of brush fire underwriting, increasing temperature and drought adds up to a bad day at the office. The problem facing the fire actuary is that these increases are almost

1 "Scientists losing fight to predict wildfire behavior," *Los Angeles Times,* July 4, 2013, pp. A1 - A15.

certain to represent a sharp change from existing estimates. The growth in loss estimates may be exponential. The jump in loss severity will be particularly difficult to measure. The new distributions may not fit conventional mean/variance models but more closely resemble chaos.

How bad can it get? There are some who feel that if something has happened in the past, it can happen again. Yogi Berra would refer to this as deja vu again. The Great Fire in Peshtigo happened. Can it happen again? A review of that fire is in order when considering probable maximum loss.

On October 8, 1871, the entire Middle West was blanketed by an enormous windstorm. For those who spend their lives fighting brush fires, wind is the dreaded enemy. There were two momentous events at that time and due to a clever reporter one of them got all the publicity.

The first event was a fire in Chicago. It burned a great many buildings. This fire became famous, because of a fable made up by a reporter. He reported that Mrs. O'Leary's cow kicked a lantern over on to some straw, starting the fire that ate Chicago. Current thinking among historians is that the Chicago fire was a brush fire that burned into the city. When you look at the weather maps for that date, the brush fire is a very likely possibility.

There was another fire on October 8, 1871 but it occurred in a more remote area. Destruction was so complete and total, it took awhile for the news to get out to the rest of the world. Most of the world had not heard of the village of Peshtigo, Wisconsin. This fire is a catastrophe where dry statistics can never tell the story, but the insurance industry runs on numbers. The population of Peshtigo was about 1,500. It is estimated that the brush fire killed 800 of those residents. The total loss of life including the surrounding Sugarbush area was between 1,200 and 2,400.2

Can this happen again? The newspaper accounts of the day refer to a "tornado" devastating Peshtigo and accompanying the fire. It is likely they were referring to the fire storm that great fires can create. Over a certain size, a fire creates its own wind sweeping everything before it. Then, what is the likelihood that a fire storm will sweep into a rural community trapping the residents? Many feel this is unlikely considering the modern communication systems such as reverse 911 calling. Communication is not the entire answer.

During the Tea Fire in Santa Barbara, California, in April of 2009, my wife and I were responding to a reverse 911 evacuation order. We took both our cars, and our two cats with no time to grab anything else. As we drove down Tunnel Road, moving down the mountain above the city, I watched 100 foot high flames in the next canyon two miles away. The flames were being driven by a north wind so the flames were moving south, as we were. The problem is that the evacuation route was overloaded with traffic and we were bumper to bumper moving at about 3 miles an hour. A brush fire can travel at 15

[2] Deanne C. Hipke, "The Great Peshtigo Fire of 1871" (website), www.peshtigofire.info.

miles an hour.3 (If you want to outrun one, plan on doing a sub four minute mile). If the wind had shifted to the east, it would have taken about 8 minutes for those flames to reach the string of cars caught in traffic on Tunnel Road. A wind shift would have turned Tunnel Road into a car wrapped shish kabob. The reverse 911 calls had triggered a massive simultaneous evacuation in Mission Canyon overwhelming the roads. Most of the fatalities in the Oakland Hills Fire died in their cars.

Just as climate change is making the urban/forest interface more dangerous, suburban expansion is making it more popular for new building. Urban planners tend to focus on the large rectangles of space when making zoning and population density rules. They should be focusing on the lines joining those spaces, the road infrastructure. Population density should be confined to the maximum number who can be safely evacuated in the face of a brush fire. During the seemingly endless time it took for the bumper to bumper traffic to move out of the forest, it became clear to me that Mission Canyon, in the hills above Santa Barbara was over-populated. Fortunately, the wind stayed in the north and we escaped. How likely was an east wind in that situation? It was forecast but it did not occur until later that evening.

Later that evening, as we sat in the yacht club trying not to look out the window at the fire roaring through the forest, I felt the wind shift to the east. It closed the distance to Tunnel Road to about a mile. Suddenly I started grinning. The wind had shifted to the south. Mission Canyon was spared from this fire that burned out a monastery with its northern movement.

It is this element of capriciousness that makes brush fire prediction so difficult. While reverse 911 phone systems can alert the residents to the outbreak of a fire, evacuation is dependent on an adequate road system. After a particular fire is out, it is difficult to keep urban planners aware of the critical link that evacuation routes provide.

The maze of jurisdictions that control evacuation route construction is formidable. State, city and county boundaries weave their way around the territories adjacent of the federally governed national forests. It would take a brilliant conductor to get that array of competing interests to dance to the fire evacuation tune. In Santa Barbara, for example, the county is aware of the problem and working to mitigate it. They are powerless when the City of Santa Barbara, with different priorities, constructs "traffic calming" schemes such as bulbous sidewalks that have the effect of narrowing streets, which are important evacuation routes.

Another Peshtigo tragedy could occur as a result of converging forces. First, new building moves more and more homes and people into the urban/forest zone. Second, climate change makes major forest fires more likely by higher temperatures and droughts that dry out the forest vegetation. Third, urban planners fail to recognize the need to keep the population in the urban/forest interface, particularly box canyons such as Mission Canyon, down to the number that can be evacuated. If our

[3] Stephen J. Payne, *Fire in America*, p. 422, University of Washington Press, 1997.

luck runs out and these all converge then insurance executives will need adequate catastrophe reinsurance in more lines than just property fire. A large death toll will affect third party liability, workers compensation and life insurance.

The Earth Is Warming: It Doesn't Matter Why

By Max J. Rudolph, FSA CERA CFA MAAA

Few issues solicit extreme views from everyone you ask. Yes, no, black, white. Abortion rights are one such issue. Most argue adamantly for the side they have chosen, ignoring any conflicting statements. Sustainability defines a state that can continue over time without degradation. Over the last year I have become more aware of the risks to the earth's sustainability due to human interaction. I have found the same unwillingness on this topic to have a reasonable discussion among friends. Even some actuaries who, on other issues, attempt to substitute facts for appearances will argue very strongly on this topic. Bringing up global warming seems in particular to be a non-starter. While many believe that human activities are driving the earth's warming, others point to natural and recurring cycles driven by the sun. If the earth's climate passes a tipping point and spirals out of control, and the human population is no longer supported, it really does not matter why. We should be taking steps now to adjust to the world where we will live in the future rather than waiting to see what caused the devastation. Small adjustments and investments made now can avoid larger changes and societal breakdowns later.

Pascal's Wager

What I hope to accomplish in this essay is to make an argument similar to one made by Blaise Pascal. In the well-known Pascal's Wager, the eminent mathematician said that each person lives their life based on a bet about the existence of God. If you believe he indeed exists, then you live your life in an exemplary manner and give up some worldly rewards. If you do not believe in a deity, then you perhaps have more fun and collect more possessions but risk being wrong. Forever is a long time. In his argument, logic dictates that all should bet on the existence of God since the downside is small if wrong and there is the great upside of eternal life if correct.

Carrying this idea over to the future of planet earth and, by extrapolation, the human population that lives on it, humans should treat the future much as insurers treat capital. You don't need to manage as if a large asteroid is sure to hit the earth, but we should consider outlier scenarios if we want to survive for the next 10,000 years. This would cover both man-made global warming and potential mini ice age or warming periods. Low lying areas like Miami are at severe risk of even slight rises in ocean levels. Areas dependent on agriculture require steady weather patterns rather than volatile cycles of hot and cold, drought and flood. Resource depletion, whether it is freshwater, oil or minerals, will likely lead to increasing violence and wars between neighbors.

Malthusian fears

The data show that the earth is warming in most places; ice caps are melting, ocean levels rising and weather patterns becoming more volatile. Some say this is due to human activities such as burning fossil fuels and polluting the environment. Thomas Malthus, an 18th century demographer, argued that population could not continuously increase without eventually overwhelming a planet with finite resources. Due to scientific improvements, carrying capacity of the earth has increased and delayed an overshoot and collapse for many years, but the concept remains valid.

There are numerous "tipping points" that generate concern. Many species are threatened with extinction or are already gone, leading to reduced biodiversity. Some of these have been sources of food for humans. This impacts the delicate balance of nature. Once gone, an animal population is difficult to rebuild. The human population is at 7 billion and counting. According to Jorgen Randers' book *2052: A Global Forecast for the Next Forty Years*, the earth's population will level off and then start to drop after the next generation. This slowing is driven by the reducing demographic factor of children born per female. Science and economic growth have spread this reduction from developed countries to those that are developing. This will slow resource depletion and may extend the time before crisis. Just as Malthus' predictions were not initially realized, scientific improvements in crop management using fertilizers, watering systems or other discoveries could extend the human era.

Increased climate volatility

It is hard to argue with the statement that overall the earth is getting warmer. The melting Arctic ice cap has led to higher ocean levels and increased acidity of the oceans, lowering their ability to naturally absorb carbon dioxide gas. Skeptics do not challenge these facts. One unintended consequence of this phenomenon is changing weather patterns. As the ice caps melt and expose water, lower temperature differentials drive smaller atmospheric pressure changes. The result is that the jet stream does not push weather patterns through an area. A storm front will maintain its position for days while nearby areas do not get the needed moisture. This volatile feature of a warming planet has large societal implications based on food production and planning for catastrophes. Some have traced the Arab Spring events to the American use of corn for ethanol production that reduced exports and increased food prices around the world. From an insurance perspective, modeling future weather driven catastrophes has gotten much harder. The past no longer predicts the future, and there are nuances in the data that will take years to recognize. Human ingenuity may have met its match.

There are positive implications to a melting polar ice cap. The long sought after Northwest Passage to Asia is nearly upon us. Crops such as corn and soybeans grow further north than ever before, increasing the value of land in northern latitudes like Canada and Russia. But weather patterns spawning tornados have followed those temperature rises north. As ice melts, areas that used to reflect heat back out into space now absorb that heat. This could form a runaway spiral as less challenging conditions will encourage search and discovery of oil and gas, leading to further warming and melting. Greenland is an area, as the ice sheet covering it melts, that will have untold risks and opportunities as methane gas is released from the frozen tundra and resources are found.

A warmer planet that continues to expand its human population increases susceptibility to disease. Many viruses have evolved with animal populations for millions of years, living benign lives inside these reservoirs. When they jump from these species to humans, who have not previously encountered them, they can have great impact. These reservoirs are hard to isolate at times, but we know that chickens hold influenza and bats seem to be where many severe African viruses live (e.g., Ebola). As humans expand their territory and become regularly exposed to these animals, previously unseen viruses will spill over to humans.

Insurers and a changing world

All types of insurers should track these developments. Weather patterns are changing. Tornados and hurricanes are acting differently than they have historically as the earth warms at higher latitudes and ocean levels rise. Southern Florida at its highest rises only a few feet above sea level, making much of this large state at risk of reverting to ocean or marsh. The city of Miami is at great risk over the next 50 years. Hurricane Sandy showed what can happen when a tidal surge aligns its timing with a large storm, but its devastation could have been much worse had the storm not weakened before moving inland. Convection storms seem to spawn more and stronger tornados and sustained winds, and seem to sit over an area and flood it rather than dissipate and get pushed out by the jet stream. We continue to build in areas that are not sustainable in the long run, and governments threaten insurers when they charge actuarially sound rates reflecting the higher claims. Business and public policy need to work together.

Viruses require extreme diligence. Influenza has proven an ability to impact the human population worldwide. Concentrated urban living will increase the contact rate, a major factor in the ability for an airborne illness to spread. The 1918 era influenza pandemic killed as much as 1% of the world's population, 0.6% in the developed world and as much as 10%

in some regions of the undeveloped world. The ability to limit contact probably had more to do with the differential than medical options. Hospitals today would immediately be overrun by patients, and supplies would quickly run short as "just in time" supply chains quickly broke down for basic materials such as protective gloves and oxygen. Mortality and morbidity may change steadily or jump to a new distribution. Fat tails at both extremes may become the norm as some prove susceptible and others immune.

Two scenarios with ties to sustainability could cause interest rates to stay at low rates or even become negative for material periods of time. One is that more volatile climate drives additional catastrophes and high rebuilding costs, slowing GDP growth. The other considers historical growth rates before the manufacturing era, which were near zero, and considers the possibility that growth over the past 250 years is really due to mispricing where "goods" are included but "bads" are ignored. The costs to clean up the pollution and other disturbances were not included so those need to be "caught up" by reducing growth in the future.

What can we do?

The bottom line is that it doesn't matter what the driver is if the result is negative to planet earth and its future ability to support the human population. If we can alter a negative path, nations need to work together and make adjustments. Whether global warming is due to human activities or merely a 200 year cycle that will correct itself over time doesn't matter. We need to work together to ensure that our grandchildren have a reasonable place to live. I don't want to be part of the generation whose actions led to the end of the world as we know it today. Reaching a tipping point around climate change is a risk we should not take.

Insurers, and especially actuaries, should take a leading role to study and quantify this issue. Our British peers at the Institute and Faculty of Actuaries have gotten the ball rolling by funding a survey of existing literature (Dr. Aled Jones at Anglia Ruskin University led the project, found at http://www.actuaries.org.uk/research-and-resources/documents/research-report-resource-constraints-sharing-finite-world-implicati), and other actuarial organizations are seeking out ways to get involved. But it can't be something we do in our spare time. This issue is too big. Companies and professional organizations should help fund research that looks at sustainability through objective glasses. Actuaries with backgrounds in casualty, life, health and pensions should work together to bring varying perspectives to the table. This is where the Joint Risk Management Section can play a role, as it already is a place where actuaries from many backgrounds have worked together to meet common goals. Together we can make the world a better place!

Sustainable/Green Insurance Products

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To achieve marketplace success, many insurers focus constantly on their growth, increasing their market share and retaining better risks. Insurers should always look for new ways to differentiate themselves from their competitors. Developing and offering new products related to potential climate change and the corresponding sustainability/green movement can be the answer.

> "Just as the industry has historically asserted its leadership to minimize risks from building fires and earthquakes, insurers have a huge opportunity today to develop creative loss-prevention solutions and products that will reduce climate change-related losses for consumers, government, and themselves."
>
> – E. Mills, Ph.D., CERES "From Risk to Opportunity Insurer Responses to Climate Change"[1]

Changes in climate put an emphasis on limited resources and volatility in weather patterns, among other effects, which drive the need for sustainable products and behaviors. Our discussion of the impact of climate change on underwriting is comprised of sustainable and green products currently offered by insurers and reinsurers. Some products discussed were developed by insurers to respond to the potential impacts of climate change and other products promote sustainability or green behaviors which are, in turn, expected to help combat climate change. Our discussion is organized into the following sections:

- Defining Sustainable/Green Products
- A Survey of Sustainable/Green Products Currently Offered
- Direct Benefits of Offering Sustainable/Green Products
- Future Trends for Sustainable/Green Products

DEFINING SUSTAINABLE/GREEN PRODUCTS

Sustainable products are those products that provide environmental, social and economic benefits while protecting public health and the environment over their whole life cycle, from the extraction of raw materials used to produce the product until their final disposal.[2]

Similarly, sustainable and green insurance products are those that cover the design, production and use of these sustainable products, or the liability associated with their production and use. They also indemnify against the environmental consequence of potential climate change decisions (or indecisions) made by executives in Directors & Officers coverage. Also broadly covered in this definition of sustainable/green products would be policies where certain features promote sustainable or green behavior.

Therefore, sustainable and green insurance products include a large spectrum of insurance products which we will describe in more details in the next section.

A SURVEY OF SUSTAINABLE/GREEN PRODUCTS CURRENTLY OFFERED

Based on insurance company websites and papers research[3], we are aware of the following sustainable and green insurance products currently available in the market.

Personal Lines

1. Green Property Rebuilding

In general, after a covered loss, this type of coverage pays for the use of:

- Environmentally friendly or more energy-efficient materials when making repairs
- More energy efficient equipment or appliances.

For those policyholders who are already green, discounts are sometimes offered on their insurance premiums.

2. Property Renewable Energy Reimbursement

This type of coverage protects a homeowner who uses an alternative-energy system in the case of a power outage. It may provide indemnification for:

- Loss of income generated from selling surplus energy to the local energy company
- Extra costs to purchase replacement electricity
- Utility or governmental fees for inspections, re-connections or permits when the homeowner's alternative energy system is brought back online.

3. Property Loss Mitigation Device Discount

Premium credits are offered to homeowners who install mitigation devices or choose storm-resistant construction techniques in catastrophe-prone areas. An example is window shutters to protect homes during severe storms.

4. Pay As You Drive/Low Mileage Discount

Pay-as-you-drive automobile insurance products inherently give incentives to drive less which leads to less pollution that may be contributing to global warming. These programs provide a customer with personalized automobile insurance rates (and hence savings) based on how well and how much they drive.

5. Fuel Efficient/Low Emission Vehicle Discount

Many insurers provide discounts for hybrid or electric passenger vehicles.

Commercial Lines

6. Upgrade to Green Commercial Fleets

This type of product offers an option to upgrade the company's fleet to hybrid vehicles for new vehicle replacement as part of an endorsement to the policy.

7. Insurance for Renewable Energy Projects

These products provide coverage for companies in the renewable industry (ex. solar, wind, hydraulic…) to help them in managing risk, defending against lawsuits and protecting assets. These insurance products and services are designed to cover all stages of a project from design to distribution.

8. Insurance for Renewable Energy Property, Equipment and Loss of Use

In order to keep up with the rapid technological change of the renewable energy field, this type of policy provides replacement cost coverage for equipment with more efficient equivalents. Equipment currently in operation, under construction or newly purchased can be added to the policy. Green roofs are examples of what would be covered.

9. Insurance for Green Building

As part of this coverage, insurers offer help to customers to build sustainably by evaluating designs and specifications for new structures and suggesting ways to ensure high-quality construction and exceptional loss prevention. Similar to the Personal Lines green property policy, these products also cover green materials and construction following a covered loss.

10. Energy Savings Insurance

Energy savings insurance policies can provide a backstop for energy savings guarantees given by energy service companies. An insurer pays any shortfall in energy savings below a pre-agreed baseline over the term of the policy, typically in the 5-10 year range.

11. Insurance for Carbon Capture & Storage/ Emission Reduction Projects

Insurance products and services are offered to organizations involved in the capture and storage of large volumes of carbon dioxide and other greenhouse gases. These emission reduction projects typically occur at large point-sources of these gases, such as power plants, before they can have a harmful effect on the environment.

12. Green Building Coverage Against Adverse Publicity

This reputation coverage provides protection when a green building experiences adverse publicity. Funds are made available to employ crisis management specialists to manage adverse publicity; guide and counsel key company personnel; and provide other services to assist in restoring a company's reputation.

13. Perishable Food Reduction Products

These products encourage the use of devices that can be used to reduce the amount of produce lost and improve the overall quality of produce during the distribution process from the grower to the retailer. Technology devices continuously monitor the temperature and condition of produce as it travels, estimating the remaining shelf life. This information is used to route products to maximize quality, salability and reduce unnecessary perishable waste.

14. Global Weather Insurance

This product is used to bridge the gaps left by traditional insurance coverage within general property damage policies. Insureds are covered against unpredictable weather conditions and climate change. This may be beneficial for event promoters who want to hedge against a defined weather variable such as rain/wind exceeding a defined threshold during the hours of coverage.

15. Political Risk Insurance for Carbon-Trading

Interested parties such as project sponsors, investors, and lenders are given financial protection from risks arising from governmental interference, embargo, license cancellation, war and political violence which could interrupt the production, certification and delivery of carbon credits.

Specialty Lines

Given the media attention to global warming and the potential for new lawsuits or governmental actions against entities that may be potentially contributing to climate change, additional specialty insurance products such as the following may be needed in the normal course of business:

16. Insurance for Pollution/Environmental Liability

This coverage has implications for a broad range of risks and industries. Examples include commercial general liability, pollution legal liability, and environmental responsibilities stemming from legislation and court rulings. Losses can arise from different hazards or activities and can have impacts on large corporations to small subcontractors in construction.

17. Directors & Officers Insurance

It has been noted that there is increasing litigation occurring against companies that are believed to be contributing to climate change. Even a company's inaction to disclose, assess or implement adaptation strategies could leave the door open to future litigation. Some insurers now offer directors and officers policies with optional global warming litigation protection.

Other specialty lines encouraging more green behavior include:

18. Architects & Engineering Professional Liability Insurance Discount for Building Commissioning

Some insurers believe that there is a correlation between sustainable practices such as energy-efficiency and a low-risk profile. Building commissioning is the process of verifying that all of the subsystems (electrical, plumbing, HVAC,…) are working effectively, efficiently and as designed. Not only is this good for the environment, it also reduces the likelihood of professional liability claims. As such, architects and engineering firms implementing building commissioning as part of the construction process are given insurance premium credits.

19. Professional Liability insurance for Raters and Home Energy Survey Professionals

Suitable insurance coverage is often lacking for many specialist professionals who provide energy-efficiency services. Certain qualified raters and home energy survey professionals are offered professional liability, general liability, and property coverage in order to protect themselves from accidents and potential lawsuits that may occur as a result of business operation.

DIRECT BENEFITS OF OFFERING SUSTAINABLE/GREEN PRODUCTS

There are indirect benefits from insurance companies offering sustainable/green products such as encouraging environmentally friendly behaviors or by providing risk protection for a new green technology or project. The direct benefit to an insurer offering sustainable and green insurance products is that they can create competitive advantages over their peers. Examples include:

- Increased market share: For example, by providing discounts on hybrid/electric vehicles, insurers can increase their penetration on this expanding sector of the automobile insurance market.
- Expansion into new/niche businesses: Given the government incentives, the renewable energy sector is booming. Due to its innovative and technologically intensive nature, insurance can likely play a big part in each of these projects. Insurers who get into this sector earlier may be able to harvest the rewards of these new/niche businesses.

- "Positive" adverse selection: It may be argued that customers who are environmental/sustainability-conscious are more mindful of the way they drive their vehicles or the security and safety features they place in their homes, hence they represent the better risks for insurability.
- Building green brand name: An insurer who is proactive in offering innovative sustainable/green products is seen as environmental-friendly, corporate responsible and thinking ahead of others. This can certainly help in its brand building and marketing strategies.

FUTURE TRENDS FOR SUSTAINABLE/GREEN PRODUCTS

The sustainable/green products and its associated need for green insurance products are growing at a remarkable rate. Given the available government incentives and the cultural shift of a growing environmentally-conscious population, the future market for green insurance markets are optimistic. There are still a lot of coverage gaps insurers can make efforts on, as well as the advancing of green technologies which provide enormous opportunities for those who are bold enough to take them.

Some potential sustainable/green products as suggested by CERES' report "From Risk to Opportunity Insurer Responses to Climate Change"[4] include:

- Warranty and Service contracts for green technology
- Insurance in relation to carbon offsetting projects
- Insurance in relation to carbon trading projects
- Green crop insurance
- Green insurance discount applying to workers compensation
- Professional Liability for energy auditing professionals

Developing new sustainable/green products and mastering climate change and green technologies do not happen in a day. Hence those insurers who are willing to invest earlier on will likely reap a promising harvest. It takes time and experience to build up the expertise in this innovative and ever-changing new field, and now should be the time to act before it becomes too late.

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End Notes

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Introduction to the National Council on Compensation Insurance Experience Rating Plan and Its Actuarial Methodology

Jon Evans

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1. INTRODUCTION

Workers compensation individual risk experience rating, and particularly the National Council on Compensation Insurance's (NCCI's) Experience Rating Plan (ERP), date back to the first years of workers compensation laws in the United States and the Casualty Actuary Society, in the 1910's and 1920's (see early volumes of *Proceedings of the Casualty Actuarial Society*, available at www.casact.org). What makes workers compensation experience rating special is the central role of credibility methods and the emphasis on a predictive perspective from these earliest years. It is also unique in its universal adoption in the United States. Today (2013), all states and the District of Columbia, require some type of workers compensation experience rating. All but 9 states allow for the use of NCCI's ERP for interstate rating.

NCCI provides extensive services related to the ERP, including assigning risk IDs, tracking the experience over time and across different insurance carriers for over 600,000 different employers, and then calculating ERP modification factors. NCCI files state loss costs (generically referred to as "rates"), and in some cases full rates that include underwriting expenses and profit provisions, per $100 of payroll by individual classification codes that categorize types of employment. *Manual rates* are determined using these classification code rates. The NCCI ERP produces an experience modification factor, or *mod*, by comparing actual loss experience for an individual risk to expected losses underlying manual rates. Predictive performance testing consistently confirms that, including situations where performance is less than ideal, *modified rates* (where the mod has been used to adjust manual rates) almost always produce a very big improvement over unmodified manual rates in the equity of rates for individual risks. This results in a secondary, but more often publicly cited, social benefit of incentivizing employers toward improving workplace safety.

In this study note, we will discuss not only the structure of the calculation in the latest version of the NCCI ERP, but also the actuarial methodology behind the plan. The reader who understands this study note should not only acquire a good understanding of the NCCI ERP specifically, but also a facility with some valuable and more general actuarial methods. However, we will not go deeply into very specific details of some of the elaborate underlying calculations, such as the calculations underlying partial factors for ELRs and D-ratios, or all the special rules in the ERP. These cumbersome details are not necessary to understand the principles, function, and basic operation of the ERP.

Many simplified examples are provided and are necessary to understand the material. Be warned that many of these examples will be to varying degrees unrealistically simple and/or unrealistically extreme in the interest of illustrating the concepts. Exercises are also provided. For a more in depth treatment of quantile testing, there is a related paper "The Optimal Number of Quantiles For Predictive Performance Testing of the NCCI Experience Rating Plan," by Evans and Dean. Exercises covering material in that paper are also included in this study note.

Another caution is that the actual ERP changes over time and across the many dozens of jurisdictions in which it applies. In a real world situation, where some part of this study note does not seem to agree with the actual NCCI ERP, the ultimate authoritative written sources are NCCI's Experience Rating Plan Manual and NCCI's Experience Rating Plan User's Guide.

The information is presented in the following sections:

- Section 2 explicitly lays out the predictive perspective, as distinguished from the static perspective, for actuarial models. Aside from being a more desirable objective, the predictive perspective makes better use of what data is available for individual risk rating.
- Section 3 explains how the individual risk loss process for workers compensation is complicated enough that standard textbook credibility and statistical models are not quite adequate for the task of experience rating.
- Section 4 discusses the generalizations to basic credibility models that are required by both the predictive perspective and the complicated loss processes described in the earlier sections.
- Section 5 explains how industry data collected through the NCCI Workers Compensation Statistical Plan is used to determine the experience period actual and manual basis expected losses that appear in the ERP formula.
- Section 6 covers some of the other miscellaneous adjustments, such as the maximum cap on ERP modification factors, which are part of the ERP.
- Appendix A provides a brief history of the evolution of the structure of the ERP.

Prerequisites for fully understanding this study note are a basic general knowledge of property and casualty actuarial methods and knowledge of actuarial models and the empirical determination of such models, particularly credibility theory, as presented in recent years in the syllabi for Online Courses CA1 and CA2 and Exams 3L and 4 of the Casualty Actuarial Society. Some familiarity with workers compensation ratemaking is also helpful.

2. PREDICTIVE ESTIMATION

In this section we will describe and contrast the predictive perspective, which has always been important for experience rating, and is growing in popularity for other actuarial models, with the more traditionally common static perspective. We will use overly simplistic models of loss processes in this section, and then introduce the complications that arise in more realistic loss processes in Section 3. The predictive perspective and complications in the loss process require a more generalized credibility method, which will be described in Section 4.

2.1 Contrast With Static Estimation

Although actuarial rate calculations are intended as estimates of future losses, most follow a more *static* perspective. A static perspective involves making the best estimate of the loss process underlying past experience and assuming the same loss process will underlie future losses, possibly including some anticipated systematic changes such as inflationary trends and different statutory benefit levels.

Example 2.1 Suppose a risk's true manual pure loss ratio prior to observation is randomly distributed with mean 100% and standard deviation 50%. Also, the observed loss ratio is randomly distributed around this mean with standard deviation 100%. Then the greatest accuracy credibility of the observed loss ratio will be 20%. If the observed manual loss ratio is 300% for a specific risk, this results in a credibility-weighted estimate of 140% for the true manual loss ratio for that risk, which suggests that a modification factor of 1.40 should be applied to its manual rate in the future.

A more *predictive* perspective focuses directly on the optimal estimate of future losses using past loss experience as explanatory information.

Example 2.2 Suppose that an analysis of past experience has shown that observed manual loss ratios for individual risks have a mean of 100%, an overall variance that is fairly constant over time, and a serial correlation of 15% from one year to the next. If the observed manual loss ratio for a risk in the prior policy period is 300%, this suggests for the next policy period an estimate of 130% for the true manual loss ratio for that risk and a modification factor of 1.30 should be applied to its manual rate.

Because loss processes tend to change over time, even if slowly in some cases, the predictive perspective can produce different estimates using the same data, usually involving lower credibility of experience than credibility from the static perspective.

NCCI's aggregate and classification ratemaking procedures for manual rates follow a mostly static perspective. It is worth noting that the large sample size in some manual rating classes, at least at a countrywide level, and the even larger data volume available for statewide aggregate calculations, lends itself to such a static perspective.

A static perspective can be difficult to apply to individual risks. There is only one observation for the total losses of a single risk in each individual policy period, albeit including varying numbers and amounts of individual claims. This makes it difficult from a static perspective, to determine the split out of the systematic and random components of variance that is necessary to determine the credibility which is vital to individual risk experience rating. However, by following a very predictive perspective, the NCCI Experience Rating Plan can combine data across risks, where each observation includes the combination of prior and subsequent experience relative to manual rate levels for a single risk.

Example 2.3 If we have the manual loss ratios for 1,000 equally sized individual risks in a single policy year and the sample mean is 100% with sample variance 1.25, we cannot determine the greatest accuracy credibility, or for that matter a predictive estimate, without extraneous information and/or assumptions.

Example 2.4 If we have the manual loss ratios for 500 equally sized risks over two sequential policy years, we can use the serial correlation, together with the sample means and sample variances in each policy year, to estimate a predictive credibility formula based on simple linear regression between the policy years.

Example 2.5 Alternatively in Example 2.4 from a static perspective we could try to split out the random component of the total variance, but this involves the hazards of (in a certain sense) using samples of size 2.

The NCCI ERP compares actual losses to manual basis expected losses, with many special adjustments to be described in subsequent sections, to produce a credibility-adjusted modification factor or *mod*. Three recent policy periods are used as the experience period. A manual basis rate for the risk, determined prospectively for an upcoming policy period, is multiplied by the modification factor. There is a one year gap between the three experience period "years" and the prospective policy effective year to allow for reports of actual losses to be made.

Time →

1st Experience Policy Period	2nd Experience Policy Period	3rd Experience Policy Period	Gap Policy Period	Prospective Policy Period

Example 2.6 The manual basis expected loss of $10,000 for a policy effective on 7/1/2015 might be multiplied by an experience modification factor of 0.90, resulting in a modified expected loss of $9,000, because actual losses on policies effective 7/1/2011, 7/1/2012, and 7/1/2013 were only about 60% of manual basis expected losses. Credibility procedures might determine that a 10% credit is the predictively meaningful information that can be derived, and the rest of the 40% lower than manual expected experience is random and non-predictive.

2.2 Lift and Equity Performance Objectives

The objective of the NCCI ERP is to improve the equity of rates for individual risks, where equity is defined in terms of how closely the relative rate for a risk matches its relative expected losses. Although the mod has an overall off-balance effect (see Section 6.1), the mod does not directly address the overall or absolute adequacy of rates, which is handled directly by manual rate levels. Operationally, equity of the mod itself is defined in a more limited way; specifically, equity is viewed in terms of equalizing modified expected loss ratios across the range of different mod values. However, this says nothing about how much improvement to overall rate equity the mod adds.

Example 2.7 A trivial and meaningless mod of 1.00 for every risk would be completely equitable in the sense that expected modified loss ratios would not vary by mod, but it would do nothing to improve the equity of rates.

To capture the magnitude of potential improvement in rate equity, another objective for the mod is high lift. Lift is the variation in manual loss ratios captured by the mod.

Example 2.8 If the prospective manual loss ratio is 150% for risks in the highest decile of mod values and 50% for those in the lowest decile, then lift is high.

Example 2.9 For Example 2.8, if the average mod is 1.05 for the highest decile and 0.95 for the lowest decile, then despite high lift, as shown by the decile manual loss ratio spread of 50% to 150%, the mod is not very equitable.

Example 2.10 For Example 2.8, if the average mod is 1.50 for the highest decile and 0.50 for the lowest decile, then the mod is likely very equitable and together with high lift, does much to improve rate equity.

Example 2.11 If the prospective manual loss ratio is 101% for risks in the highest decile of mod values and 99% for those in the lowest decile, then lift is so low that even if the mod is perfectly equitable it can only do a little to improve rate equity.

2.2.1 Safety Incentives as a Secondary Benefit

A secondary benefit of experience rating is that individual risks are incentivized to promote safety. Fewer claims and less severe claims generally lead to lower mods and hence lower future premiums. However, even if there were no safety incentive or no possibility for individual risks to improve safety, experience rating would still be justified if it made a significant improvement in rating equity.

Example 2.12 The mods in Example 2.10 would very much improve rate equity even if every risk had already implemented the highest possible standards of workplace safety.

2.3 Quantile Testing Predictive Performance

As mentioned earlier, there is only one observation of the actual manual loss ratio for a single risk in a single policy period. However, many observations are available for risks with the same mod value or mod values within a certain interval.

Example 2.13 In a recent policy year in a small state, there were about 3,600 risks with mods in the interval [0.84, 0.90).

By splitting mod values into intervals and combining experience for risks into an overall manual loss ratio for each interval, most of the random effects for individual risks can be averaged away.

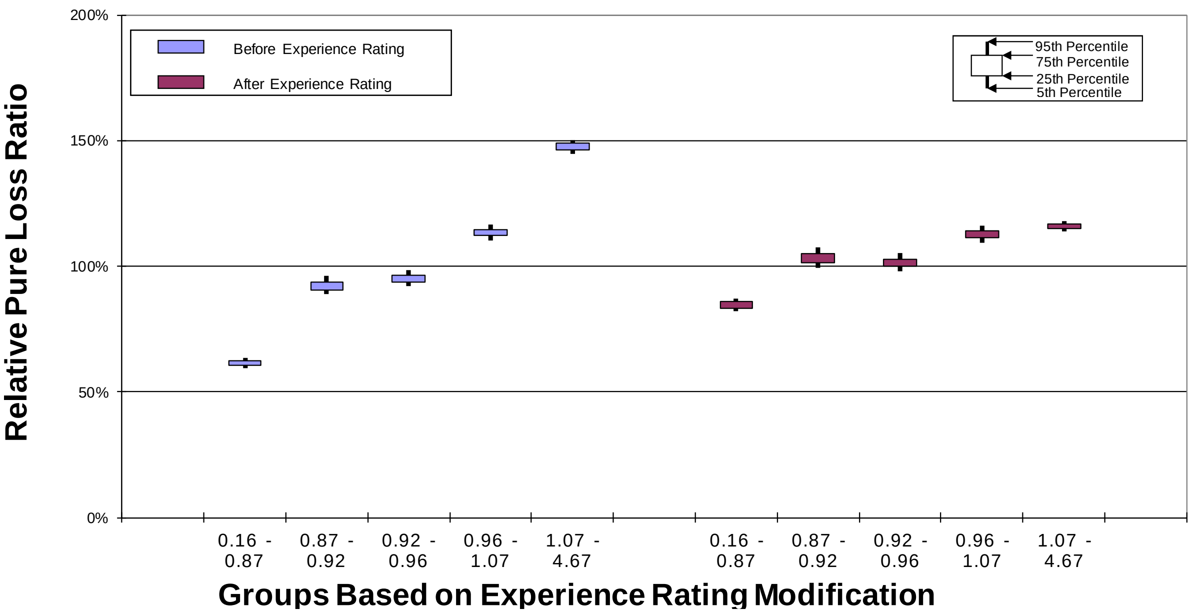
Example 2.14 In the 1934 paper by Paul Dorweiler (see Bibliography), tables are shown that combine data for risks based on premium size and mod ranges of width 0.10. The tables showed that modified loss ratios had higher equity than manual loss ratios. This result further improved when regression lines were fit to the loss ratios to filter out much of the remaining random effects.

To perform a similar analysis, NCCI focuses on a *quintile* test, which is specifically the five category version of the more general concept of a *quantile test*. A quantile test divides risks into intervals, each containing an equal number of risks and called *quantiles*, based on the value of the ERP modification factor. This test reveals both lift, shown by the quintile loss ratios before the mod is applied, and equity, shown by the quintile loss ratios after the mod is applied.

Example 2.15 The following candle chart displays the results of an actual quintile test of the NCCI ERP Countrywide for Policy Year 2010. The percentiles of the candles demonstrate bootstrap confidence intervals of the relative pure loss ratios. This test shows that the lift is very high, as can be seen by the steeply ascending candles on the left side of the chart (Before Experience Rating). It also shows that the application of the mod improves the equity, but the slight slope of the candles on the right side (After Experience Rating) suggests the ERP should be more sensitive. In fact, effective in 2013, NCCI implemented a significant increase in the split point (see Appendix A) which is expected to improve equity and result in the candles on the right side of a quintile test being much flatter.

Example 2.15

Policy Year 2010: Countrywide Quintile Analysis



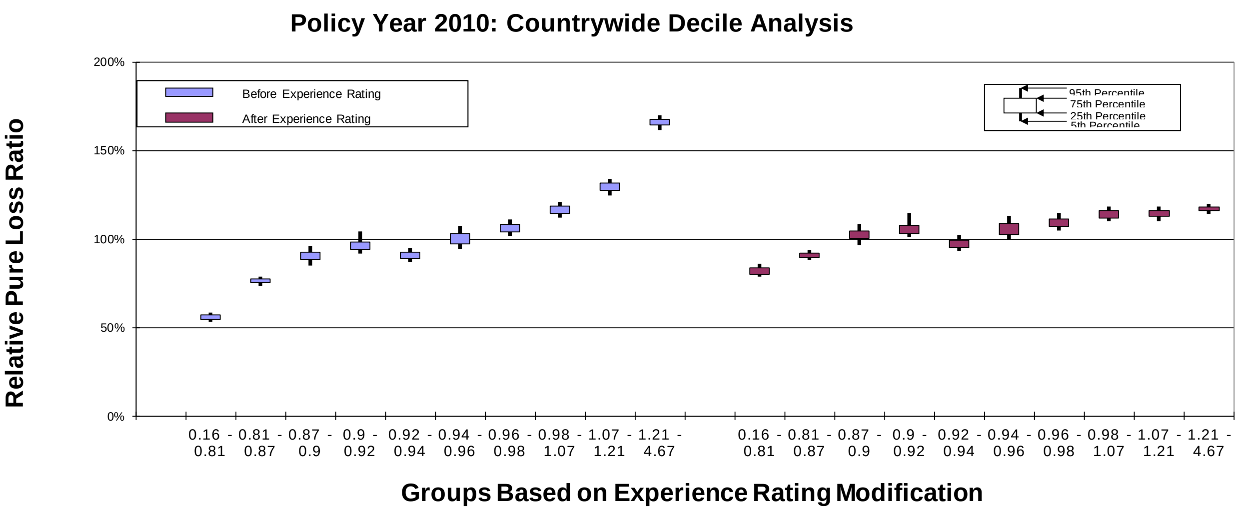
To put numerical scalar values on the concepts of lift and equity NCCI considers two statistics. The *old quintile test statistic* is B*/A*, where A* is the variance of the un-modified quintile loss ratios and B* is the variance of the modified quintile loss ratios. This traditional statistic measures equity and ideally should be as close to 0 as possible. The *new quintile test statistic* is sign(A-B)|A-B|0.5, where A and B are equivalent to A* and B*, but may be calculated to include some extra variance due to bootstrapping the test. This newer statistic measures the amount of the lift which is actually resulting in improved rate equity and ideally should be as large as possible.

Example 2.16 For the quintile test in Example 2.15, A = 0.0806, A* = 0.0803 and B = 0.0124, B* = 0.0120. The old quintile test statistic is 0.149 and the new quintile test statistic is 0.261.

NCCI uses the quintile test, with its relatively small number of five quantiles, specifically because large volumes of risk data are required to average away random effects and isolate both the lift and equity aspects of predictive performance. It turns out there is a very large penalty for increasing the number of quantiles in terms of the statistical clarity of a quantile test (see Evans and Dean in Bibliography). A decile test, with only twice as many quantiles, requires eight times as much data to provide the same level of statistical clarity as a quintile test.

Example 2.17 Here is a decile test on the same underlying data used in Example 2.15 The comparable old "decile" test statistic is 0.140 and the comparable new "decile" test statistic is 0.265 for this decile test. Although the patterns are still relatively clear, the vertical size of the candles, that is their bootstrap confidence intervals, has increased at the same time as the distances between the vertical positions of the candles has decreased. In many smaller categories than this countrywide example, such as individual states, a quintile test will produce acceptably clear results but a decile test will not.

Example 2.17



2.4 No Guarantee of Individual Risk Outcomes

Although a mod with good lift and equity improves the relative estimate of expected losses for an individual risk, there is no guarantee that the actual losses that occur will be anywhere close to this estimate. To the contrary, actual losses for an individual risk will generally be much larger or much smaller than modified expected losses.

Example 2.18 For the situation in Example 2.2, if the variance of the manual loss ratios is 1.00 then the standard deviation of the modified loss ratios will be $\sqrt{(1\text{-}0.152)} = 0.99$ Thus, actual losses in the subsequent policy year will likely differ by at least +50% from modified expected losses for 250 or more of the 500 risks.

Furthermore, if the modified expected loss were highly accurate at predicting actual losses on an individual risk basis, then credibility would tend to be close to 100%. In such a situation, the risk would almost certainly be self-insured for all losses, except possibly extreme tail events.

Example 2.19 Suppose for the situation in Examples 2.2 and 2.18 that the serial correlation, and hence credibility for this example, was 99% instead of 15%. The standard deviation of the modified loss ratios would be √(1-0.992) = 0.14 and the actual losses would still likely differ by at least +14% from modified expected losses for 150 or more of the 500 risks. To achieve a standard deviation of 5% would require the serial correlation/credibility to be 99.9%.

The value of experience rating can be seen through tests, such as quantile tests, that combine data across individual risks, but not for specific individual risks except in the case of extremely large, and effectively self-insurable, risks.

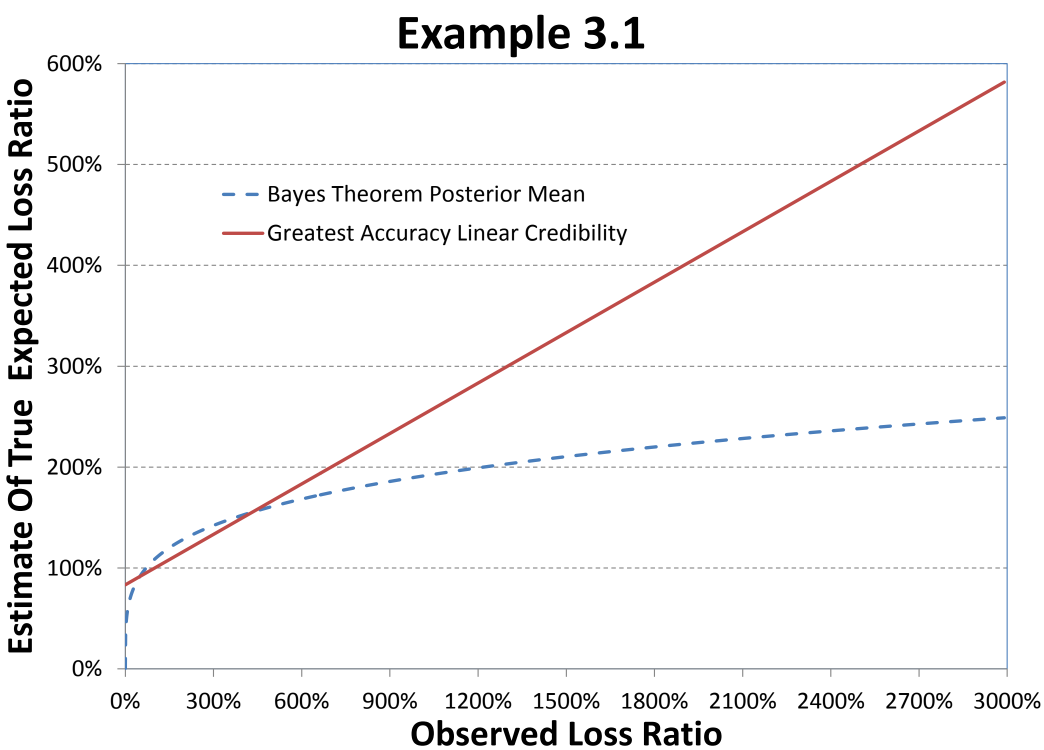
3. COMPLICATING PROPERTIES OF THE INDIVIDUAL RISK LOSS PROCESS

In this section we describe some complications in the individual risk loss process that, together with moving from a static perspective to a predictive perspective, as described in Section 2, require generalizing the basic credibility/statistical models, as will be described in Section 4, for the context of individual risk experience rating.

3.1 Contrast With Simplifying Assumptions of Basic Credibility and Statistical Models

Greatest accuracy credibility methods use simple linear (more precisely, affine) functions of observed losses to estimate true expected losses with minimal expected squared error (see Klugman et. al. in Bibliography). Similarly, simple linear regression models use least squares to fit parameters. Both of these models work very well for data processes that follow symmetric distributions with relatively thin tails, especially the Normal Distribution. However, the individual risk loss processes for workers compensation and most property/casualty insurance are very different.

Example 3.1 Suppose that prior to observing an actual loss ratio, the true mean loss ratio for a specific risk is lognormally distributed with mean 100% and standard deviation 50%. Also, suppose the observed loss ratio is lognormally distributed around the true mean with coefficient of variation 100%. The standard greatest accuracy linear credibility of the observed loss ratio as an estimate of the true loss ratio of the risk is Z = 16.7%. For very low or very high observed loss ratios, this produces very different estimates of the true mean compared to the Bayes Theorem posterior mean, which greatest accuracy linear credibility is intended to estimate.



3.2 Frequency and Severity Components of Total Loss

The total loss for a risk is the sum of a number of individual claim amounts.

Example 3.2 Suppose Risk A experienced one claim of $300,000 and Risk B experienced 10 claims each of $30,000. Both risks experienced $300,000 in total losses.

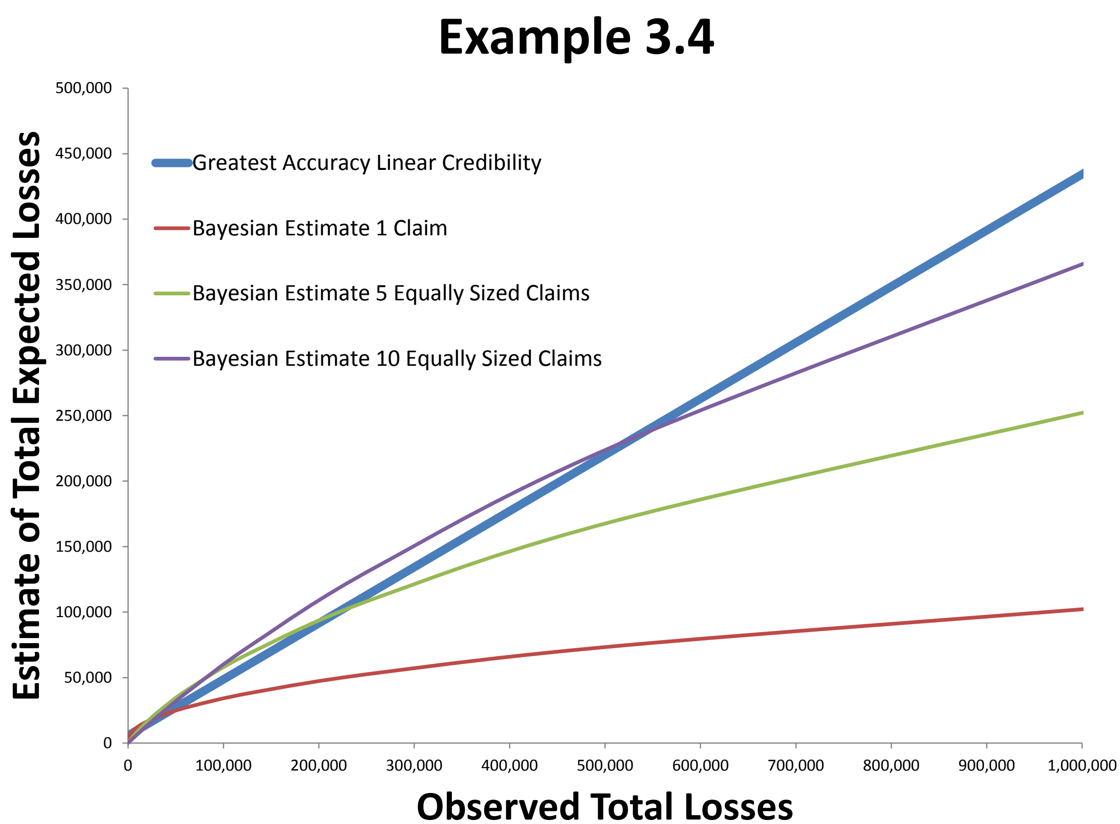
The underlying expected loss is the product of an expected number, or *frequency*, of claims, and the expected amount, or *severity*, of an individual claim. A certain fixed amount of total loss for a risk might have different implications for frequency and severity parameter estimates depending on the number and amounts of individual claims occurring.

Example 3.3 Suppose both risks in Example 3.2 had a prior manual basis expected loss of $10,000 based on a frequency of 1.0 and severity of $10,000. Risk A's experience suggests a higher severity, but Risk B's experience also suggests a higher frequency. As observed frequency tends to be more credible than an observed severity, Risk B likely has a higher true expected total loss than Risk A.

Example 3.4 Suppose that:

- Prior to observation, a risk's true claim frequency is exponentially distributed with mean 1.0.

- The true severity of its claims is independent of the true frequency and exponentially distributed with mean $10,000.
- The number of claims is conditionally Poisson distributed.
- The amount of each of the claims is conditionally independent of the number of claims and the amount of the other claims, and conditionally follows an exponential distribution.



Then the credibility of the total observed loss is Z = 42.9%. Not only does the basic credibility estimate fail to capture the curvature in the Bayesian estimate as a function of total loss dollars that are observed, but it makes no distinction regarding the frequency and severity composition of the loss dollars.

Example 3.5 Suppose the risks in Example 3.2 both had the underlying loss process in Example 3.4. The Bayesian estimates for the two different outcomes are very different from each other and from the greatest accuracy linear credibility estimate.

Risk	Observed Number of Claims	Observed Amount of Each Claim	Greatest Accuracy Linear Credibility Estimate of True Expected Losses	Bayesian Estimate of True Frequency	Bayesian Estimate of True Severity	Bayesian Estimate of True Expected Losses
A	1	$300,000	$134,286	1.0	$57,220	$57,220
B	10	$30,000	$134,286	5.5	$27,404	$150,722

Furthermore, there may be statistical dependencies between the numbers of claims and the amounts of claims that occur. There may also be dependencies between the individual amounts.

Example 3.6 If a risk experiences only one claim, the expected severity might be $9,000 but this might increase to $15,000 for each claim if two claims occur.

Example 3.7 If two claims occur, there might be a 25% correlation between the severities. If this were the situation in Example 3.6, then if one claim was $55,000 the expected value for the second claim would likely be closer to $25,000 than $15,000.

3.3 Skewness of Frequency and Severity Processes

Typically, the frequency process and the severity process are each asymmetric. Frequency processes are very positively skewed where frequency is low, but much less so when frequency is high.

Example 3.8 Suppose the frequency process is conditionally Poisson distributed with uncertainty in the frequency being Gamma distributed with coefficient of variation 10%. If the overall frequency is 1.0, then the probability of 0 claims is 37.0% versus a probability of 26.4% for 2 or more claims. If the overall frequency is 100.0, then the probability of 99 or fewer claims is 50.0% versus a probability of 47.2% for 101 or more claims.

Severity processes tend to be extremely skewed with extremely heavy tails.

Example 3.9 An overly simplistic, but not totally unrealistic, model for the overall severity process for workers compensation individual claim amounts, combining all levels of injury ranging from medical only to permanent total, would be a lognormal distribution with mean $20,000 and coefficient of variation of 700%. This model implies $2,282 is the median, $20,000 is the 83.9th percentile, 3.6% of claims exceed $100,000, and 1 in 665 claims exceed $1,000,000.

3.4 Severity Differences Between States and Over Time

The various rules for benefit levels, average wages, medical costs, and other conditions can vary considerably between states, leading to significant differences in average severity.

Example 3.10 In one recent case, the average indemnity amount on lost time claims was about three times higher in one state than in a similar neighboring state sharing a very long border and a significant concentration of population straddling the border. (See any yearly edition of NCCI's Annual Statistical Bulletin for specific examples along these lines.)

Severity also experiences very significant trends over time.

Example 3.11 The overall severity of claims more than tripled from the mid 1990's to circa 2010. (Compare average claim severity statistics from different editions of NCCI's Annual Statistical Bulletin.)

4. GENERALIZING CREDIBILITY METHODS FOR THE CONTEXT OF EXPERIENCE RATING

Having discussed the predictive perspective in Section 2 and complications in the individual risk loss process in Section 3, in this Section we show how basic static credibility is generalized to address both of these challenges. This generalized credibility is the essence of the framework that has been in place for the NCCI ERP over the last century. See Appendix A for some history.

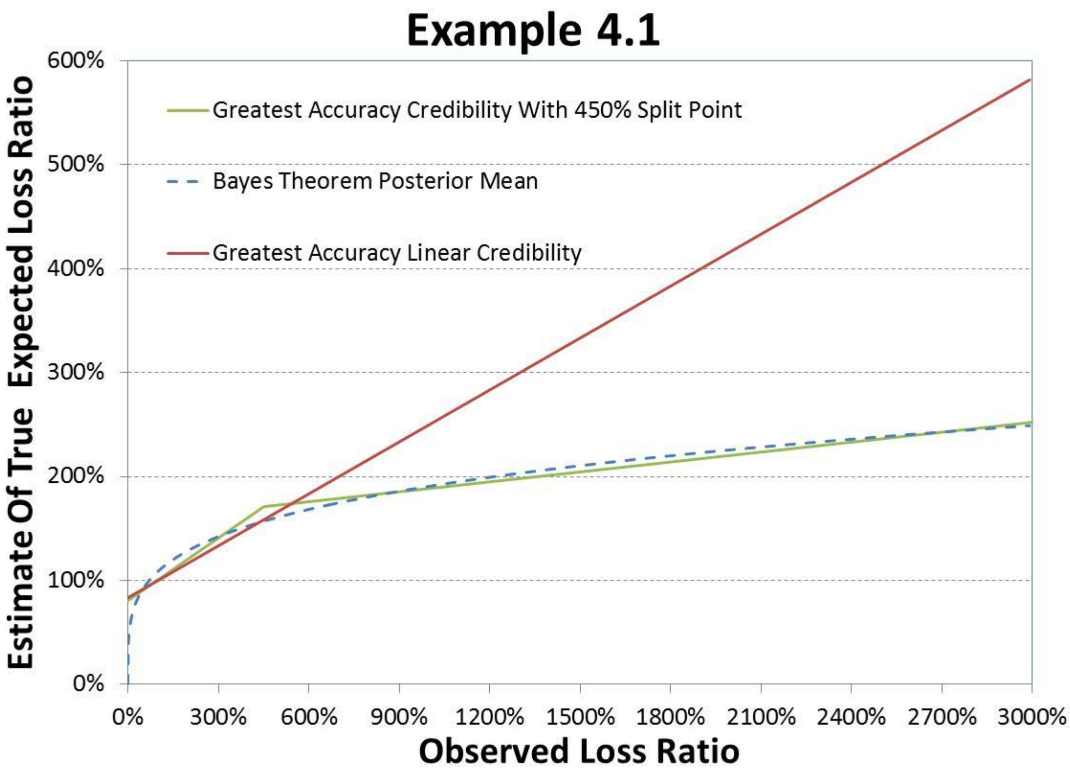
4.1 Splitting Losses Per Claim: Primary, Excess, and Over a Loss Limit

To address the highly skewed nature of losses, losses are split into separate components with linear credibility applied to each component. The combined credibility-weighted estimate for the overall true expected loss ratio can then be expressed as:

$$Z_p\, A_p + \left(1 - Z_p\right)E_p + Z_e\, A_e + (1 - Z_e)E_e$$

where the subscripts "p" and "e" are used to denote the primary and excess components of the actual observed loss ratios (Ap and Ae) and the expected loss ratios (Ep and Ee)..

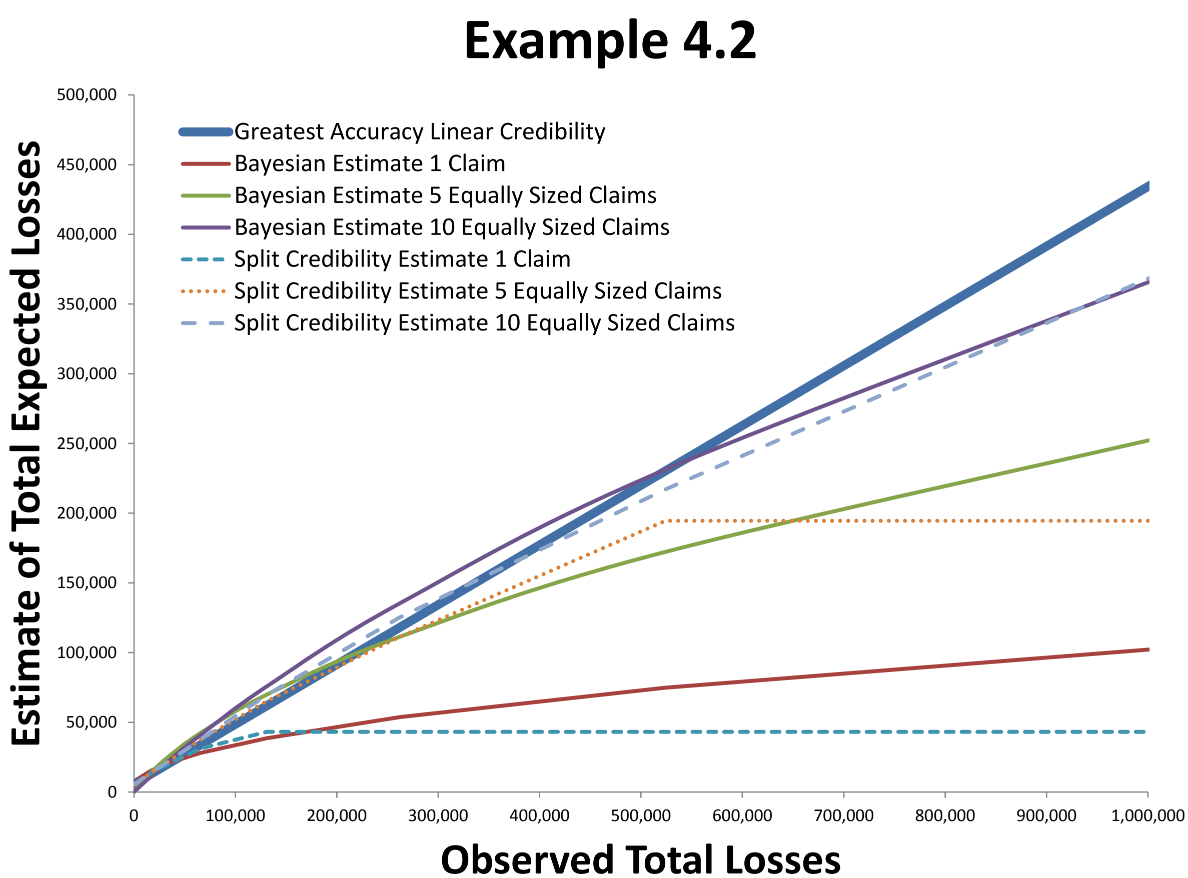
Example 4.1 In Example 3.1 we can split the observed loss ratio into a primary part under 450% and an excess part above 450%. The greatest accuracy credibilities, for each component, calculated separately with no adjustments for statistical dependencies, are Zp = 20% and Ze = 3.2%. The means prior to observing the loss ratio of the expected partial loss ratios of the layers are Ep =0.954 and Ee = 0.046.



Example 4.1 shows the power of using linear credibility in a piecewise fashion to accommodate a highly skewed loss process and much more closely approximate the Bayesian posterior mean.

To also accommodate differences arising from frequency and severity, losses can be split on a per claim basis rather than on an aggregate basis.

Example 4.2 We can apply a per claim split to Example 3.4. Suppose losses are split per claim into a primary layer of losses below $20,000 and excess losses above $20,000. Also, individual losses are capped at $100,000, which reduces losses in the excess layer to a maximum of $80,000 per claim. Greatest accuracy credibility gives Zp = 47.9% and Ze = 34.2%. Correspondingly Ep = $6,908 and Ee = $2,857. Since the loss limit reduces losses overall by -2.35%, the raw split credibility estimate should be increased by +2.41%, as the estimate is still intended to cover unlimited losses. Compared to credibility without a split, the split credibility estimates are dramatically better for 1 single claim and 5 claims, and slightly better for 10 claims.



Example 4.3 Applying the $100k split credibility from Example 4.2 to Example 3.5 produces estimates much closer to the Bayesian estimates for Risk A and slightly closer for Risk B.

Risk	Observed Number of Claims	Observed Amount of Each Claim	Greatest Accuracy Linear Credibility Estimate of True Expected Losses	$20k Split $100k Limit Credibility Estimate of True Expected Losses	Bayesian Estimate of True Frequency	Bayesian Estimate of True Severity	Bayesian Estimate of True Expected Losses
A	1	$300,000	$134,286	$43,207	1.0	$57,220	$57,220
B	10	$30,000	$134,286	$138,430	5.5	$27,404	$150,722

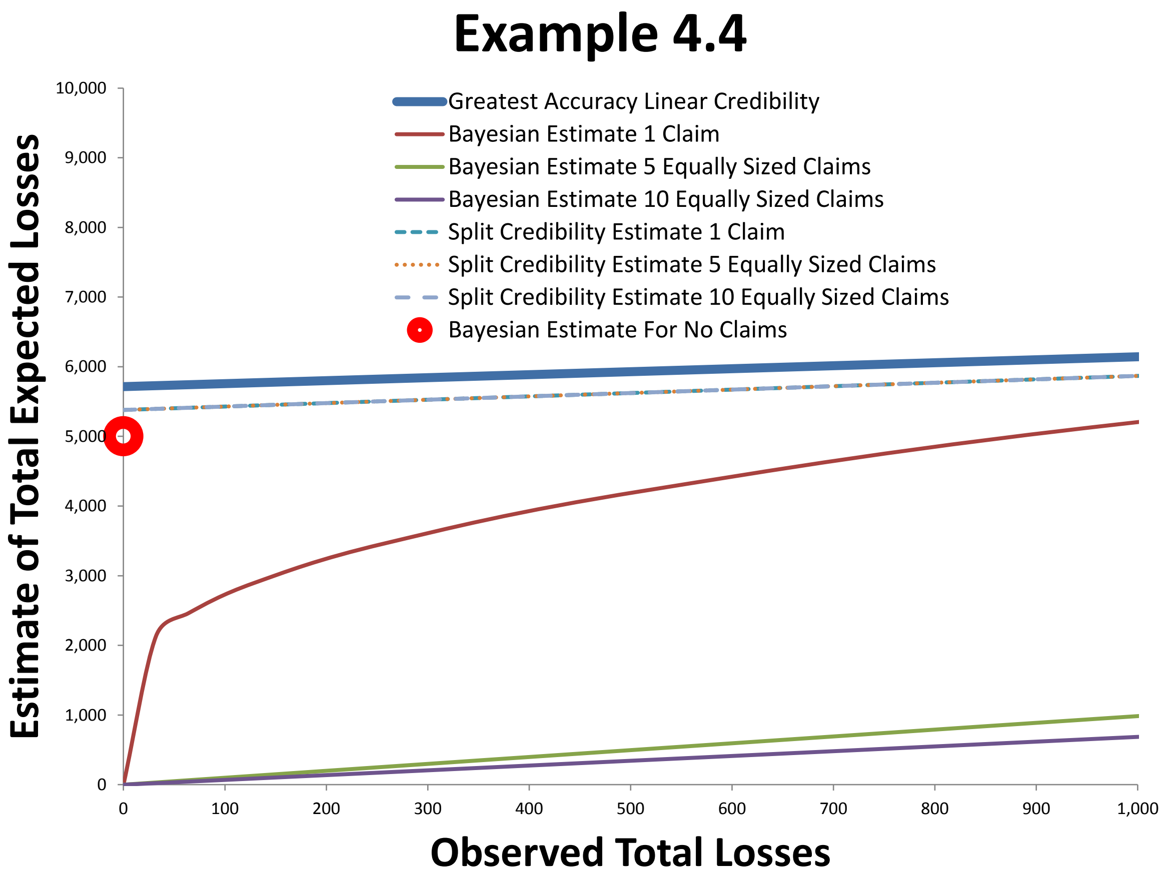
A natural question is why to not simply use a Bayesian estimate instead of a credibility approximation, split or otherwise. There are several practical reasons, including:

- Bayesian estimation requires specifying prior and likelihood distributions, but credibility only requires a much simpler specification of a few variance parameters that are not distribution specific.
- Bayesian estimation involves integral calculations and/or simulations that are usually computationally complex, but credibility only requires simple arithmetic calculations.

Another question is why to not apply credibility directly to frequency and severity rather than layers of losses split per claim. This would be a more viable alternative. However, here again the severity piece on its own is still highly skewed and would likely require some sort of non-linear adjustment. Additionally, a separate frequency estimate would be very sensitive to the claim count, which is driven by small claims and particularly medical only claims. More specifically, a particularly odd feature is that the Bayesian estimate would tend to reward a few very small losses over no losses at all.

Example 4.4 In Example 4.2, the Bayesian estimates have a discontinuity near zero observed total losses, between zero observed claims and one or more observed claims. The credibility estimates do not suffer from this problem, but gradually drop to reasonable estimates, as observed losses approach zero, independent of the number of observed claims.

Observed Number of Claims	Observed Amount of Each Claim	Greatest Accuracy Linear Credibility Estimate of True Expected Losses	20k Split 100k Limit Credibility Estimate of True Expected Losses	Bayesian Estimate of True Frequency	Bayesian Estimate of True Severity	Bayesian Estimate of True Expected Losses
0	NA	$5,714	$5,379	0.5	$10,000	$5,000
1	$100	$5,757	$5,428	1.0	$2,725	$2,725
10	$100	$6,143	$5.869	5.5	$125	$686



Also, as will be shown subsequently, the split credibility approach leads to certain parameters that can be empirically fit to optimize predictive performance. This empirical fitting implicitly leaves some slack to, at least partially, account for potential frequency and severity process correlations and other complications of the loss process.

4.2 The Current Parameterization of Credibility

The basic form of the ERP modification formula is:

$$1 + Z_p \frac{A_p - E_p}{E} + Z_e \frac{A_e - E_e}{E}$$

Ap = actual primary ratable loss from the experience period

Ae = actual excess ratable loss from the experience period

Ep = expected primary ratable loss from the experience period

Ee = expected excess ratable loss from experience period

E = Ep + Ee = expected total ratable loss from experience period

Zp = primary credibility

Ze = excess credibility

The split between primary and excess is done on a per claim basis and there is a limit on individual losses, similar to Example 4.2. See Sections 5 and 6 for details on the individual loss limit and various other adjustments. The resulting experience mod is applied to manual basis premium.

Example 4.5 Suppose the split point is $15,000 and the individual loss limit is $300,000. One claim of $50,000 and another claim of $500,000 in the experience period would lead to Ap = $30,000 and Ae = $320,000.

Example 4.6 If manual basis pure premium is $20,000 and the mod is 1.15, then the modified pure premium is 23,000.

Example 4.7 Here is a hypothetical example of how the basic mod formula would react to some different actual loss outcomes for the same risk.

			Actual Loss Outcomes		
Zp	50%				
Ze	4%	Ap	$0	$30,000	$15,000
		Ae	$0	$0	$90,000
Ep	$10,000				
Ee	$15,000	Mod	0.78	1.38	1.22

The current methodology for parameterizing Zp and Ze was implemented in 1991 (see Gillam, William R.., "Parametrizing..." in the Bibliography). We will demonstrate the motivation, or more properly inspiration, for this parameterization in terms of static credibility theory. The specific values of the parameterization are then empirically fit and validated from the predictive perspective performance goals for the ERP.

Basic credibility models like those extensively used in Sections 3 and 4 determine Z as:

$$Z = \frac{VHM}{VHM + EPV}$$

where,

VHM = variance of the hypothetical means

EPV = expected process variance

When the quantity being estimated is a ratio to the quantity of exposure (or measure of data volume), such as a manual loss ratio of losses to manual expected losses for an individual risk, standard assumptions are that VHM is constant and EPV is inversely proportional to the exposure.

$$VHM = b \qquad EPV = \frac{a}{E}$$

E = quantity of exposure (such as manual basis expected losses)

a, b = positive constants

This leads to the familiar formula for Z in terms of data volume:

$$Z = \frac{E}{E+K} \qquad K = \frac{EPV(for\ E=1)}{VHM} = \frac{a}{b}$$

More general assumptions prevent the variability around the true expected value from asymptotically going to 0 for large data volume (large risks in our context) and also recognizes that the heterogeneity of true expected values is likely greater for small data volume (small risks in our context).

$$VHM = e + \frac{f}{E} \qquad EPV = c + \frac{d}{E}$$

c, d, e, f = positive constants

This leads to a more general form for K:

$$K = E\left(\frac{cE + d}{eE + f}\right)$$

K can be rewritten as:

$$K = E\left(\frac{CE + D}{E + F}\right)$$

where C = c/e, D =d/e, and F =f/e are an alternative set of positive constants. This shows that there are only three degrees of freedom in determining K from c, d, e, and f.

Since credibility is more tied to the expected number of claims than expected losses, another generalization is to substitute a measure of expected claims for expected losses in the credibility formulae:

$$K = \frac{E}{G}\left(\frac{C(E/G)+D}{(E/G)+F}\right) = \frac{E}{G}\left(\frac{CE+GD}{E+GF}\right) \qquad Z = \frac{(E/G)}{(E/G)+K} = \frac{E}{E+K_*} \quad K_* = GK = E\left(\frac{CE+GD}{E+GF}\right)$$

G = an index of severity that may vary over time and between states

Example 4.8 Z is the same when E=$25,000 and G =5 as when E=$50,000 and G=10. In each case the implied expected number of claims is E/G = 5,000.

Example 4.9 The introduction of the severity index G could have been done earlier, with the same result, by specifying the VHM and EPV relationships as:

$$VHM = e + \frac{f}{E/G} \qquad EPV = c + \frac{d}{E/G}$$

Now if we use the credibility formulae just developed separately for primary and excess losses, but retain the same E/G measure of data volume in each case, we have the following parameterization of primary and excess credibility values:

$$Z_p = \frac{E}{E+K_{p*}} \qquad K_{p*} = E\left(\frac{C_p E+GD_p}{E+GF_p}\right)$$

$$Z_e = \frac{E}{E+K_{e*}} \qquad K_{e*} = E\left(\frac{C_e E+GD_e}{E+GF_e}\right)$$

Cp, Dp, Fp, Ce, De, Fe = positive constants

Example 4.10 The most recent NCCI update from the late 1990s of the constant credibility parameter values is shown below. There are also minimum values of 2500G and 60,000G imposed on Kp* and Ke*, respectively.

Cp	0.10	Ce	0.375
Dp	$2,570	De	$150,000
Fp	$700	Fe	$5,100

The G value can be determined easily from claim statistics and E is determined from classification payroll data for an individual risk. The six constants were determined to maximize the predictive performance of the mod formula, as will be discussed in Section 4.3

4.2.1 W and B Representation Versus Zp and Ze Representation

A simple no split modification formula using a basic credibility formula takes the form:

$$1 + Z\left(\frac{A-E}{E}\right) = 1 + \frac{E}{E+K}\left(\frac{A-E}{E}\right) = \frac{A+K}{E+K}$$

It has been long recognized that K acts as a kind of "ballast", stabilizing the mod calculation across different values of E, or effectively different risk sizes. For split credibility, Ze is generally less than Zp and it makes sense to think of Ze = W Zp, where W, on the interval [0%, 100%], is a kind of weight given to excess losses. Using this framework, and renaming Kp* as B so that Zp = E / (E + B), we can restate the split credibility mod formula as:

$$1 + Z_p\left(\frac{A_p - E_p}{E}\right) + Z_e\left(\frac{A_e - E_e}{E}\right) = \frac{A_p + WA_e + (1-W)E_e + B}{E + B}$$

Example 4.11 Consider an individual risk where E = $25,000, Zp = 50% and Ze = 4%. This is equivalent to B = $25,000 and W =0.08.

As a result, credibility values can be expressed entirely in terms of this alternative W and B representation, rather than the Zp and Ze representation, without any substantial difference. The W and B representation has been more common for the actual publication of tables and calculation of mod factors. When the ERP began about 100 years ago, in an era before inexpensive computing power, this form had the advantage of slightly reducing the complexity of the arithmetic calculations.

4.2.2 Primary/Excess Correlation

The ERP does not make any explicit adjustment for correlation between the primary and excess loss layers, which is generally high.

Example 4.12 The correlation between the primary and excess layers in Example 4.1 is 32.7%

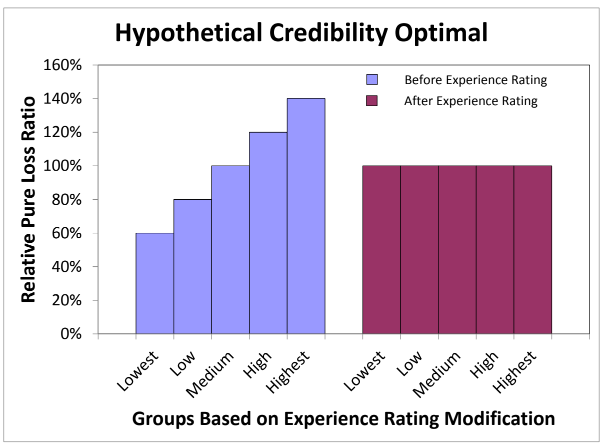
Example 4.13 The correlation between the primary and excess layers in Example 4.2 is 64.2%

Correlation between explanatory variables is generally undesirable in statistical models, particularly linear models. However, as we saw with Examples 4.1 and 4.2 for hypothetical static estimation scenarios, the sum of separate layer credibility estimates, without any correlation adjustment, can still do a good job of estimating total expected losses. Furthermore, as will be discussed in Section 4.3, the credibility parameters are empirically fit to optimize the predictive value for total expected losses, as measured by quintile tests. This predictive value has also been proven through many subsequent quintile tests over the years.

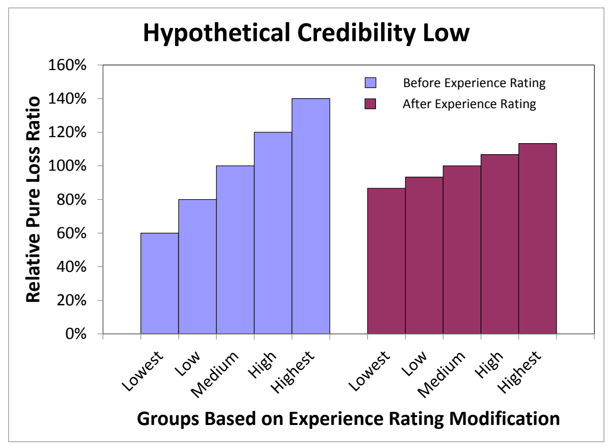
4.3 Predictive Fitting and Validation of Credibility Parameters With the Quintile Test

The parameterization set up in Section 4.2 was based on applying a static model for greatest accuracy credibility to split primary and excess layers of loss. The pure premium underlying actual modified rates is used to estimate all expected losses (save for some exceptions discussed in Section 6.5). However, the six constants from this model have not yet been estimated. So, the estimation step is where the predictive perspective objectives for estimating future total expected losses come in.

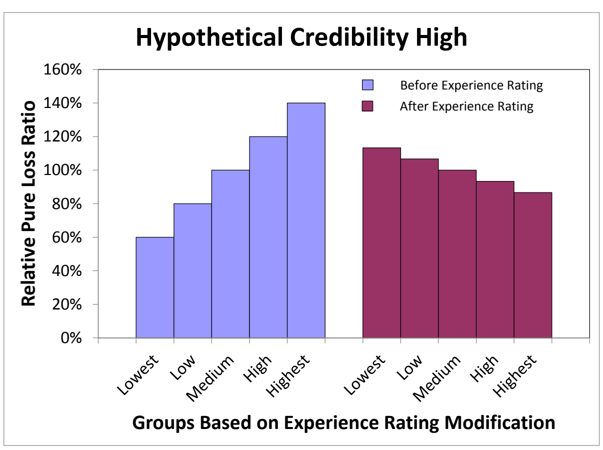
Example 4.14 Hypothetical example of desirable credibility.



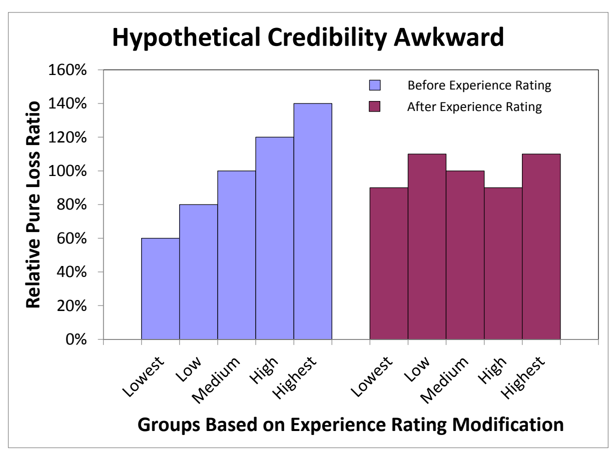
Example 4.15 Credibility should be increased likely by some combination of lower Cp, Dp, Ce, De, and/or higher Fp, Fe.



Example 4.16 Credibility should be decreased likely by some combination of higher Cp, Dp, Ce, De, and/or lower Fp, Fe.



Example 4.17 Credibility should be optimized by some combination of changes in Cp, Dp, Ce, De, Fp, and/or Fe.



Although the constants Cp, Dp, Fp, Ce, De, and Fe were derived from assumptions about parameter and process variances, no direct estimates of such variances are used to determine values for these constants. Instead, the actual values are selected to flatten the quintile test described in Section 2.2, specifically by bringing the old quintile test statistic close to 0. Effective credibility decreases as Cp, Dp, Ce, and De increase. Effective credibility increases as Fp and Fe increase. These constants were determined in the 1990s to simultaneously flatten quintile tests for different risk size ranges. The determination was made through a general hands-on trial and error iteration process, not any special mathematical search algorithm. Although the old quintile test statistic only measures mod equity, lift has always been high for ERP plans tested. By optimizing predictive performance, these six constant values are, to some extent, implicitly accommodating various complications in the loss process, such as possible correlations between frequency and severity.

After the constant values were determined, the high predictive performance of the ERP has continued to be validated by subsequent quintile tests, with credibility automatically adjusted across time and different states by the severity index G.

4.4 Indexations By Severity

Part of the parameterization of the credibility values was the inclusion of the severity index G. The individual loss limit is also indexed with each new manual rate filing. The split point will now also be subject to routine indexation. Quintile testing has demonstrated that the values for Cp, Dp, Fp, Ce, De, and Fe determined in the 1990s continue to work well due to the indexation updates built into the ERP.

Example 4.18 Suppose the split point is $5,000 and the individual loss limit is $100,000. If severity triples, then a split point of $15,000 and an individual loss limit of $300,000, along with Zp and Ze corresponding to a G-value three times higher should give close to the same performance as before severity tripled. As a first approximation, tripling severity is equivalent to exchanging all dollar amounts for a synthetic currency that trades at three units for every one dollar.

Several different types of severity indexes are utilized in the ERP. Aside from special rounding rules, these are all multiples of the State Average Cost per Claim (SACC). These indexes include:

G-value (G) -> 0.001 SACC

State Accident Limit (SAL) -> 25 SACC

State Reference Point (SRP) -> 250 SACC

The SAL is used to set the individual loss limit by state and over time. The SRP is used only as an intermediate step in calculating the SAL.

Example 4.19 G-value = 10.0 is equivalent to SAL = \$250,000 is equivalent to SRP = \$2,500,000 is equivalent to SACC = \$10,000.

4.5 The Minimum Size Eligibility Threshold

For a specific risk to be eligible for the ERP, its average premium for the three most recent years must exceed a standard amount that varies by state. The standards were established in the 1980s with few changes since, based on an estimate of the average premium for an employer with 10 employees. Current values range from a low of \$2,250 to a high of \$5,500.

Applying the ERP to a risk involves some effort and expense, both in terms of service performed at NCCI and by insurers. For very small risks with very low credibility, the potential improvement in rate equity, or at a more basic level the maximum potential dollar change in premium, is so small that applying the ERP is not practical.

Example 4.20 Consider the following hypothetical illustration. Suppose a risk has manual premium of \$1,000 for the prospective policy period. Ep = \$600, Ee = \$900, Zp = 3.85% and Ze = 0.33% and the SACC = \$10,000. For this risk, the minimum mod would be 0.98 and the mod cap (see Section 6.2) would be 1.16. Typically, this small risk will be claim free, and would receive a \$20 credit due to the minimum mod; more rarely, actual claims could produce up to a \$160 debit due to the maximum mod. Even a modest expense associated with the calculation and application of the mod would offset the small premium impact of applying experience rating for this risk.

5. EXPERIENCE PERIOD ACTUAL LOSS DATA AND EXPECTED LOSS CALCULATION

Having now set up the basic ERP mod formula with its split credibility formula in Section 4, this section will describe how experience period actual and expected losses are determined. The NCCI Workers Compensation Unit Statistical Plan, which is used to collect data for manual ratemaking, is also used in the ERP to determine actual reported losses and corresponding manual basis expected losses for the experience period.

5.1 The NCCI Unit Statistical Plan

NCCI collects audited exposure, premium, and loss information by policy in states for use in ratemaking, experience rating, actuarial analysis, and other NCCI products and services. In addition to its use in manual ratemaking, this data is also used by NCCI to calculate mods. Individual risk ID numbers are assigned to all employers, including interstate employers having payroll in more than one state. Employers may change insurance carrier, name, location, or in other respects, but in general as long as the fundamental nature of the business and its ultimate owner does not change, the risk ID is intended to be maintained. Unit statistical plan data is first reported as of 18 months past the policy effective date (called 1st report), and subsequently at 12 month intervals (called 2nd, 3rd, etc. reports) up to 126 months (10th report). Among other information, key data elements include payroll by class code and individual claim incurred loss amounts.

Example 5.1 A premium unit at 1st report from policy year 2007 might contain payroll of $500,000 for class XXXX and $1,500,000 payroll for class YYYY.

A corresponding loss unit at 3rd report might also show a permanent partial claim with $300,000 and several medical only claims totaling $50,000.

5.2 ELRs

Payroll by class from the unit reports for the three experience policy periods is multiplied by Expected Loss Rates (ELRs), which are filed together with regular manual rates by class, both specified as rates to $100s of payroll, to determine the expected experience ratable loss.

$$E = ELR \times (Payroll/100)$$

Ratable losses for the experience period differ from total prospective ultimate losses, which are included in manual rates, in several ways, such as:

- Ratable losses include losses incurred over the three experience period years, rather than the single prospective year policy.
- Losses are valued as of 1st, 2nd, and 3rd reports, respectively, for the experience years used, and are not developed to ultimate.
- Losses are adjusted by benefit levels and trends to correspond to the experience period rather than prospective policy period.
- Individual claims are limited by the State Accident Limit (SAL).
- 70% of the loss amount on medical only claims is excluded.
- Catastrophes and certain other special non-ratable losses are excluded.

Example 5.3 This table demonstrates the difference in practice between ELRs and manual pure loss costs for a hypothetical Risk A in State X. (Note: in some states, actual manual loss costs also include loss adjustment expenses)

Class	3 Year	ELR (per	Experience	Prospective	Prospectiv	Prospective

	Experience Period Payroll	$100 payroll)	Period Expected Ratable Loss	Policy Period Expected Payroll	e Pure Loss Cost (per $100 payroll)	Policy Period Expected Pure Loss
XXXX	$1,000,000	1.10	$11,000	$500,000	1.50	$7,500
YYYY	$1,500,000	1.80	$27,000	$600,000	3.00	$18,000
Total	$2,500,000		$38,000	$1,100,000		$25,500

Note, even though the prospective expected manual basis losses often tends to be of the same broad order of numerical value as the experience period expected ratable losses, the nature of these two expected loss numbers is very different.

The underlying ELR factors for a state are determined by Hazard Group, separately for indemnity and medical losses. Hazard Groups (HGs) are a partition of class codes into 7 groups (A through G) based on ascending claim severity. By calculating ELR factors separately by HG, differences in the impact of the state accident limit, which is much greater for the higher severity HGs, can be better accounted for. Calculating ELR factors separately for indemnity and medical losses allows a better accounting of differences with regard to loss development. The ELR for a class is determined by multiplying the ELR factors for the Hazard Group of the class by the indemnity and medical components of the pure loss cost.

Example 5.4 This table demonstrates the calculation of the hypothetical ELRs in Example 5.3 in terms of ELR factors.

Class	Hazard Group	Hazard Group Indemnity ELR Factor	Prospective Indemnity Pure Loss Cost (per $100 payroll)	Indemnity ELR (per $100 payroll)	Hazard Group Medical ELR Factor	Prospective Medical Pure Loss Cost (per $100 payroll)	Medical ELR (per $100 payroll)
XXXX	M	0.763	0.80	0.61	0.700	0.70	0.49
YYYY	N	0.650	1.20	0.78	0.567	1.80	1.02

We will not delve further into the underlying nuts and bolts of the ELR calculation except to highlight one particularly special part of this calculation, the ELAFs.

5.1.1 ELAFs

Excess Loss Adjustment Factors (ELAFs) are used in the calculation of ELRs to remove expected losses in the layer between the state accident limit and the $500k claim limit used in class ratemaking. Although SALs are currently still smaller than this $500k limit, the calculation is designed to add more expected loss, even if the SALs at some point exceed $500k.

The ELAFs are based on a totally separate excess ratio curve model rather than the excess ratio curves underlying NCCI's more familiar Excess Loss Factors (ELFs). ELAFs are designed for undeveloped losses about as mature as the actual losses in the experience period, whereas ELFs are designed for losses developed and stochastically dispersed to ultimate. The current generation of ELAF excess ratio curves consists of the arithmetic inverses of a set of simple cubic polynomials, one for each injury type.

Example 5.5 The ELAF excess ratio curve for Permanent Total claims is

$$E(r) = (0.003148\, r^3 + 0.054149\, r^2 + 1.299625\, r + 1)^{-1}$$

where E(r) is fraction of expected loss excess of r, which is the *entry ratio*, or a specific loss amount as a ratio to average severity. So, if PT claims in State X average $1,000,000 for Hazard Group Y and the SAL is $250,000 then a factor of (1-E(0.25))/(1-E(0.50)) = 0.619786 would be applied to expected undeveloped PT losses limited to $500k as derived from class ratemaking data to account for the $250k limit in the ERP.

The actual ELAFs are determined by state and by HG for all injury types combined through scaling and weighting individual injury type excess ratio curves, in a process similar to that used for ELFs.

5.3 D-Ratios

Expected ratable losses, as determined by ELRs times payroll, must be split into primary and excess layers. *D-ratios* are estimates of the fraction of total ratable losses that are primary, and are also filed alongside manual rates and ELRs by class.

$$Ep = \text{D-ratio} \times E \quad Ee = E - Ep$$

Example 5.6 If the D-ratios for class codes XXXX and YYYY are 0.40 and 0.30, respectively, then for Risk A from Example 5.3, primary and excess experience period expected ratable losses are:

Class	Experience Period Expected Ratable Loss	D-ratio	Experience Period Expected Ratable Primary Loss	Experience Period Expected Ratable Excess Loss
XXXX	$11,000	0.40	$4,400	$6,600
YYYY	$27,000	0.30	$8,100	$18,900
Total	$38,000		$12,500	$25,500

Similar to the partial ELR factors, the underlying partial D-ratios for a state are determined by Hazard Group separately for indemnity and medical losses, and then weighted together in proportion to the indemnity and medical components of the pure loss cost for each class.

Example 5.7 This table demonstrates the calculation of the hypothetical D-ratios in Example 5.6 in terms of D-ratio factors.

Class	Hazard Group	Hazard Group Indemnity D-ratio Factor	Hazard Group Medical D-ratio Factor	Indemnity Fraction of Prospective Pure Loss Cost (per $100 payroll)	Medical Fraction of Prospective Pure Loss Cost (per $100 payroll)	D-ratio
XXXX	M	0.450	0.350	50.0%	50.0%	0.40
YYYY	N	0.360	0.260	40.0%	60.0%	0.30

6. ADJUSTMENTS FOR OTHER CONSIDERATIONS

In Section 4 we arrived at the basic ERP mod formula and its credibility. Section 5 described the data collection and basic calculations behind determining experience period actual and expected losses for the mod formula. This section covers various other special adjustments.

6.1 Off-balance

The ratio of total modified pure premium in a state to total manual pure premium is called the *off-balance*. This is equivalent to the pure premium weighted average mod including non-rated risks, which have an implicit mod of 1.00. The off-balance tends to be less than 1.00, primarily because large risks with high credibility tend to have lower actual to manual basis expected experience than small low credibility risks which tend to have higher actual to manual basis experience. NCCI adjusts its manual rates overall to target statewide adequacy of pure premium on a modified basis, which rather than manual basis is indicative of the effective rate in practice.

Example 6.1 Suppose overall statewide NCCI level off-balance is 0.95. Then modified pure premium is 5% lower than manual basis NCCI level pure premium. NCCI targets rate adequacy on a modified pure premium basis. Therefore, aggregate manual pure premium is a little more than 5% higher than if the off-balance were 1.00, but the actual aggregate modified pure premium is the same as if the off-balance were 1.00.

6.2 The Cap on the Maximum Mod

Mods are limited to a maximum value of 1.10 + (0.0004 x E/G), where E is the experience period expected loss and G is the G-value or approximately the State Average Cost per Claim (SACC) / $1,000.

Example 6.2 Suppose a small risk with E = $5,000 and Ep = $2,000 in a state with SACC = $10,000 experiences two claims of $5,000 each in different occurrences over the experience period. The mod formula produces a mod of 1.50, but the actual mod is reduced to the cap of 1.30

This cap offers a further buffer, in addition to split credibility and the loss limit, against the impact of extreme actual loss outcomes for small risks.

6.3 Exclusion of 70% of Medical Only Losses

In some cases, the total increase in future modified premium and other employer administrative expenses due to a small claim can exceed the cost of the claim itself. If these claims involve only medical expenses, policyholders might be inadvertently incentivized to pay the losses directly and not report them to insurers.

Example 6.3 In Example 6.2, had the risk experienced no losses in the experience period the mod would have been 0.87. Alternatively, if this risk experienced one $5,000 medical only claim, the mod without the 70% exclusion of medical only losses, would have been 1.19. If annual manual policy premium for this risk is $7,000, the difference between the mod due to the one claim and a loss free mod would amount to $2,240 per year in additional premium, or a total of $6,720 over the three years in which this claim remains in the experience period. The employer might be incentivized to pay the claim directly and fail to report it to the insurer, in order to save $1,720 and possibly some other administrative expenses.

These small claims, if not reported, still contain predictively valuable information that is not available for the mod calculation. Therefore, losses on medical only claims, which make up the vast majority of the small claims are reduced by 70% to minimize this non-reporting incentive.

Example 6.4 Applying the 70% exclusion of medical only losses in Example 6.4, only $1,500 of actual loss would be used in the mod formula, leading to a mod of 0.96. The 3 year increase in premium due to reporting the claim would only total $1,890 and the insurer would not likely see any net incentive to directly pay the $5,000 claim rather than reporting the claim to the insurer.

6.4 Caps on Multiple Claim Occurrences

Total primary actual losses from a single occurrence are limited to twice the split point.

Example 6.5 Suppose a risk has a multiple claim occurrence resulting in 3 lost time claims of $15,000 each. Assuming a split point of $15,000, only $30,000 of the total incurred loss would be counted as actual primary loss, with the remaining $15,000 counted as excess loss.

Total ratable actual losses from a single occurrence are limited to twice the SAL.

Example 6.6 Suppose in Example 6.5 the SAL was $250,000 and the three lost time claims from this single occurrence were $200,000 each. The primary actual loss would still be $30,000 but the actual excess loss would be limited to $470,000, even though none of the individual claims exceeded the SAL.

These per occurrence limits offer yet another buffer against the impact of extreme actual loss outcomes, particularly for small risks.

6.5 Exclusions of Catastrophes and Certain Non-ratable Losses

Some types of non-ratable losses are not used to calculate the mod. Similarly, some types of premium charges are not multiplied by the mod factor. Examples of non-ratable losses or charges which the mod usually does not apply to include: some types of catastrophes and terrorism, expense constants, premium discounts, and some types of disease exposures.

Example 6.7 A risk with payroll $500,000 might be charged $0.10 /($100 payroll), or $500 total for this risk, as a provision for terrorism to which the mod is not applied. If the risk had a mod of 1.10 and manual premium of $10,000, not including the terrorism provision, then after modification the total including the terrorism provision would be $11,500.

6.6 Net Experience Rating (or Net Reporting)

NCCI's ERP is intended to be used with losses gross of any deductible that may be elected by the employer. Some states, however, require the use of losses net of deductibles for experience rating. (In rare cases, states require the reporting of net losses in unit data. This is referred to as net reporting.) In these states, while the actual experience period losses are net of policy deductibles, the ELRs and D-ratios do not account for deductibles. This mismatch results in double counting the impact of the deductible. In addition to producing systematically lower mod values, a deductible credit is also applied to manual basis premium.

Example 6.8 Suppose a risk with $10,000 in manual premium has a deductible that reduces expected losses by 10%. Due to net reporting, the expected mod for this risk might average 0.95 rather than 1.00. Although actuarial principles suggest the expected premium should be $9,000, the double counting effect of net experience rating results in an expected premium of $8,550.

Although NCCI aggregate ratemaking procedures prevent net experience rating from resulting in a statewide inadequacy, it does create an inequitable benefit for risks with deductible policies versus those without. In the rare case of net reporting, the claim values gross of the deductible are not even reported to NCCI. In a few rare cases, an option exists for no deductible credit and the premium benefit flows through the mod after a while, thereby eliminating any potential double counting.

Example 6.9 If there were no deductible credit in Example 6.8, the mod calculated on a net reporting basis would, on average, partially account for the deductible due to credibility limits. For example, the deductible might, through the mod, result in an expected credit of $500.

What is most consistent with actuarial principles is to treat deductibles as non-ratable proportional credit. This would involve calculating the mod with both actual and expected experience period losses gross of deductibles and applying deductible credits separately to premium.

Example 6.10 If the mod were calculated gross of deductibles in Example 6.8, the expected premium would be $9,000.

6.7 Interstate Risks

As of this writing (2013), 41 states and DC participate in NCCI's interstate ERP. Nine states have their own form of workers compensation experience rating. For interstate risks, experience mods must be calculated separately for the ERP and each of the nine non-ERP states.

Example 6.11 A interstate risk might have a mod of 0.85 calculated entirely based on its exposure and losses in ERP states and a mod of 1.10 calculated entirely based on its losses and exposure in California. These mods are not combined, but are separately applied to manual rates in the ERP states and California, respectively. If the manual pure premium in the ERP states is $500,000, then modified pure premium is $425,000; likewise, if manual pure premium in California is $200,000 then modified pure premium is $220,000.

When a risk has payroll exposure in more than one of the states participating in the interstate ERP, experience period actual and expected losses must be separately calculated according to the SALs, ELRs and D-ratios in each state. These losses are summed across states, and a single set of credibility values must be determined for the mod formula. The current procedure is to weight together individual state W and B credibility values using experience period expected losses.

Example 6.12 Suppose Risk A has $8,000 of experience period expected ratable losses in State X where the SACC is $7,000 and $12,000 of expected loss in State Y where the SACC is $15,000.

State	Experience Period Expected Ratable Loss	State Weights	State Average Claim Cost	Weight	Ballast
X	$8,000	40%	$7,000	0.060	$17,500
Y	$12,000	60%	$15,000	0.054	$37,500
Total	$20,000	100%		0.056	$29,500

At the time of this writing, NCCI is considering replacing the current weights and ballasts with a method of combining implied claim counts across states to determine Zp and Ze for interstate risks.

Example 6.13 Here is Example 6.12 repeated with an implied claim count method of determining credibility.

State	Experience Period Expected Ratable Loss	State Average Claim Cost	Implied Claim Counts	Zp	Ze
A	$8,000	$7,000	1.143		
B	$12,000	$15,000	0.800		
Total	$20,000		1.943	43.7%	3.1%

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APPENDIX A: A BRIEF OVERVIEW OF HISTORICAL GENERATIONS OF THE NCCI EXPERIENCE RATING PLAN

A.1 Early 20th Century

Individual risk experience rating adjustments were being implemented in workers compensation in the years immediately following the passage of the first state workers compensation laws in the United States in 1911. Even before the NCCI itself was formed in 1922, its two predecessor organizations (the National Workmen's Compensation Service Bureau and the National Council on Compensation Insurance) had recognized the importance of credibility in experience rating and also the need to split experience period losses into pieces with separate credibility values. By 1918, these organizations began to offer experience rating plans that split losses into two categories, "Death and Permanent Total" losses and "All Other" losses. By 1923 the categories had been changed to "normal" and "excess". The credibility formulas followed the familiar forms of:

$$Z = \frac{P}{P+K} \quad \text{or} \quad Z = \frac{P+C}{P+K+C}$$

Early plans also typically included minimum thresholds for experience rating and a self-rating point at which a large risk was given 100% credibility.

A.2 Mid-20th Century

By 1940, the ERP used a multiple split for primary losses by dividing individual claims into layers of \$500 with the loss in the nth layer allocated to primary in proportion to (2/3)n . This formula rises toward an asymptotic limit of 1,000 as the actual loss for a claim becomes large.

Example A.2.1 Under the 1940 split formula, an actual experience period claim of \$7,000 would be allocated \$500(2/3) + \$500(4/9)+…+\$500(2/3)14 = \$997 to primary and \$6,003 to excess.

In 1961, the split of primary and excess was changed to a continuous split that counted all losses for a claim of \$2,000 or less as primary and used the following formula for claims exceeding \$2,000.

$$A_p = \frac{10000A}{8000 + A} \qquad A > 2000$$

This formula rises toward an asymptotic limit of \$10,000 as the actual loss for a claim becomes large.

Example A.2.2 Under the 1961 split formula, an actual experience period claim of \$7,000 would be allocated \$4,667 to primary and \$2,333 to excess.

For both the 1940 and 1961 ERPs, the credibility values were determined by three constants: K, Q, and S. S was the self-rating point, above which both Zp and Ze were 100%. Below Q, excess credibility was 0%.

	$0 < E < Q$	$Q < E < S$	$S < E$
Zp	$\frac{E}{E+K}$	$\frac{E}{E+(1-W)K}$	1
Ze	0	$\frac{W\,E}{E+(1-W)K}$	1
W	0	$\frac{E-Q}{E-S}$	1

B	*K*	*(1-W)K*	*0*

A.3 RERP

In 1991, NCCI introduced the Revised Experience Rating Plan (RERP) with the following main changes:

1. A single split point was adopted where losses per claim under $5,000 count as primary.
2. The Ballast formula was changed to increase with risk size.

$$B = Max\left[7500, E\left(\frac{0.1E + 2570G}{E + 700G}\right)\right]$$

3. The Weight formula was changed, resulting in an increase in weight for small risks and a decrease in weight for large risks.

$$W = Max\left[0.07,\ \frac{E + B}{E + Max\left[150000,\ E\left(\frac{0.75E + 203825G}{E + 5100G}\right)\right]}\right]$$

4. The limit on individual losses, or State Accident Limit (SAL), was changed from 10% of the Self Rating Point (SRP) to a smaller value based on 25 times the State Average Claim Cost (SACC).

The new W and B formulas were based on a parameterization motivated by some assumptions about systematic and random variances of the primary and excess losses. These formulae kept primary and excess credibility always below 100% and eliminated the SRP.

A.4 GERT

In 1995, NCCI introduced the Graduated Experience Rating Table (GERT) with the following main changes:

The minimum Ballast value was changed to be 2,500 G where the G-value is the SAL / $25,000.

$$B = Max\left[2500G, E\left(\frac{0.1E + 2570G}{E + 700G}\right)\right]$$

The Weight formula was change to include an indexed component, also using the G-value.

$$W = \frac{E + B}{E + Max\left[60000G,\ E\left(\frac{0.75E + 203825G}{E + 5100G}\right)\right]}$$

The cap on the maximum mod was changed from a table of interval ranges to a continuous formula, partially indexed by the G-value.

1 + 0.00005(E + 2 E/G)

The cap for interstate risks was set at the effective cap for the state with largest experience period expected losses.

A.5 ERA

In 1998, NCCI introduced the Experience Rating Adjustment (ERA) with the following main changes:

1. 70% reduction on ratable medical only claims to reduce underreporting incentives
2. A change in the weight formula to improve performance by increasing weight values.

$$W = \frac{E + B}{E + Max\left[60000G,\ E\left(\frac{0.375E + 150000G}{E + 5100G}\right)\right]}$$

ERA also included a provision for indexing the split point, based on review of country wide averages costs per case. However, this review process had no fixed schedule and claim severities were fairly flat around the time when ERA was introduced. As a result, the split point remained at $5000.

A.6 2013 ER Changes

In 2013, NCCI introduced several changes to the ERP based on a multi-year review. The main changes included:

1. The split point was raised beginning in 2013, from $5,000 to an initial $10,000 in year one, $13,500 in year two, and $15,000 plus two years of severity indexation adjustment in year three.
2. Subsequently, the split point will be updated with annual rate filings based on the countrywide cost per case index.
3. The mod cap was changed to a fully indexed form which is higher for the smallest risks and lower for other risks.

$$1.10 + 0.0004\ (E/G)$$

Exercises

These exercises may require computer capability for calculation, simulation, and/or graphics. Some exercises require creative answers and/or may not have a definite correct answer. Although all calculations can be done with algebra, calculus, and numerical analysis, other approaches include simulation and specifically Gibbs sampling (using WinBUGS, JAGS, etc.).

Section 2

1. In Example 2.1 what is the expected squared error of the credibility estimate ?
2. In Example 2.2 what is the expected squared error of the predictive estimate ?
3. In Example 2.3 create some hypothetical extraneous information and/or assumptions and calculate the greatest accuracy linear credibility ? What sort of testing would you do to validate this model ?
4. In Example 2.4 what is the formula for the slope and intercept of the linear regression model in terms of the items mentioned ? What sort of testing would you do to validate this model ?
5. Suppose an individual risk's true expected manual loss ratio prior to observation is uniformly distributed on [50%, 150%] and the actual manual loss ratio was exponentially distributed around this mean. Construct a static perspective estimate of the true manual loss ratio, using the actual observation that has very good lift but almost no equity.
6. Repeat the previous exercise, but this time reduce the lift by "half" but maximize the equity.
7. Repeat the previous exercise trying to get very good lift and very good equity at the same time.

8. Describe as many economic and social benefits that you can think of from experience rating individual risks.
9. Can you think of any ways in which experience rating might complicate some economic or social objectives?
10. Considering Example 2.10, can you describe several different plausible situations where there would be no safety incentives resulting from experience rating individual risks ?
11. Below is the result for a hypothetical quintile test.

Quintile	Experience Period Loss Ratio	Prospective Period Unmodified Loss Ratio	Prospective Period Modified Loss ratio
1	0.30	0.60	0.90
2	0.55	0.80	1.05
3	1.10	1.05	0.95
4	1.50	1.20	1.10
5	2.00	1.40	1.30

  a. Calculate the old and new quintile test statistics.
  b. Estimate the effective scalar credibility Z in this mod.
  c. Estimate the optimal effective scalar credibility Z in this situation.
  d. Recalculate the old and new quintile test statistics using your credibility estimate from c.

12. Use Lognormal distributions, including negative values, to approximate all of the distributions in Example 2.1 Estimate the values of the unmodified and modified quintile loss ratios if you determined the credibility estimate for a large set of different risks in one year and then applied the corresponding modification factors to another year of data. Calculate the old and new quintile test statistics.
13. For Example 2.2 assume the annual variance of loss ratios is 1.25 and repeat quintile loss ratio and statistics calculations as in the last exercise for the 15% serial correlation derived modification factors.
14. For Example 2.1 using a Lognormal distribution derive an estimate for the prospective modified loss ratio of a single risk with a mod value of m > 0.
15. For Example 2.2 using a Lognormal distribution derive an estimate for the prospective modified loss ratio of a single risk with a mod value of m > 0.
16. In Example 2.1 suppose that the expected loss of each risk changed from one year to the next by a multiplicative factor, independently distributed between different risks with mean 1.0 and standard deviation 0.10. What should the credibility factor Z be?
17. Discuss the contradiction between an insurable loss process for an individual risk and a loss amount that can be accurately predicted for an individual risk.
18. Explain the sense in which a cross subsidy between risks can occur if individual risk experience rating is not applied.
19. Contrast manual ratemaking with individual risk experience ratemaking.
20. Is individual risk ratemaking more valuable for a simple manual ratemaking system or a more complicated manual ratemaking system?
21. Would it be meaningful or practical to apply a quintile test to a retrospective individual rate plan? Discuss lift and equity for this context.
22. You are given the following data:

	Year 1		Year 2		Year 3
Risk #	Manual Expected Loss	Actual Loss	Manual Expected Loss	Actual Loss	Manual Expected Loss
1	$5	$0	$5	$0	$4
2	5	1	5	2	3
3	10	2	5	22	6
4	20	5	23	2	18
5	25	0	19	3	15
6	50	11	30	34	28
7	75	353	70	26	85
8	100	109	142	179	107
9	150	105	106	4	122
10	200	179	265	1,170	296
11	300	470	447	248	471
12	500	356	488	147	381
13	750	2,029	506	720	388
14	1,000	763	582	1,015	704
15	2,000	1,667	1,243	442	1,121
16	4,000	4,100	2,616	2,796	3,232
17	6,000	5,794	7,103	6,014	9,339
18	8,000	17,481	5,408	12,471	7,475
19	9,000	9,887	8,500	8,848	7,047
20	10,000	4,787	6,972	5,575	7,335

Using manual expected loss as a measure of volume calculate the empirical non-parametric estimate for the credibility constant K and for each risk the corresponding estimate for Year 3 expected losses. Recalculate K and the Year 3 expected losses from a predictive perspective.

23. Using the actual outcome losses below perform a 2 category quantile test on each of the results from #22 and make a chart of the results.

	Year 3
Risk #	Actual Loss
1	$2
2	0
3	2
4	18
5	122
6	5
7	38
8	39
9	172
10	565
11	369
12	219
13	125
14	918
15	1,191
16	2,698
17	9,212
18	13,296
19	4,923
20	5,395

Section 3

1. For Example 3.1 prove (show through calculation) that the credibility is Z = 16.7%
2. In Example 3.1 if the standard deviation of the true mean prior to observation is $x > 0$, instead of 50%, and the conditional coefficient of variation is $y > 0$, instead of 100%, what is the general formula for the credibility Z.
3. Redraw the chart in Example 3.1 using x = 75% and y = 200% as defined just defined in 2.
4. Redraw the chart in Example 3.1 using an Inverse gamma distribution with coefficient of variation 100% instead of a lognormal distribution for the conditional distribution of the loss ratio.
5. Why does the Bayesian estimate in Example 3.1 show the curvature it does?
6. What assumptions about credibility lead to the straight line in Example 3.1?
7. For Example 3.4 prove (show through calculation) that the credibility is Z = 42.9%
8. Discuss qualitatively why the number and amount of claims for the same total dollars should lead to such different estimates.
9. For Example 3.5 recalculate all the estimates for 2 claims of $500,000 each and then for 8 claims of $125,000 each.
10. Discuss how the situation in Example 3.6 might affect the estimation of expected losses.

11. Discuss how the situation in Example 3.7 might affect the estimation of expected losses.
12. Calculate probabilities of various numbers of claims, as in Example 3.8, when the Gamma distribution has coefficient of variation 15% and the overall frequency is 0.5 or 50, respectively.
13. Calculate probabilities of various claim amounts, as in Example 3.9, using an Inverse Gamma distribution, instead of a Lognormal, with a mean of 15,000 and standard deviation of 75,000.
14. Discuss in general terms, the practical impact of skewness on loss data and actuarial estimation.
15. Why do ordinary credibility and basic statistical models handle skewness poorly?
16. Discuss the real world reasons that drive large changes in severity over time.
17. Discuss the real world reasons that lead to big differences in severity between states.
18. Why do differences in severity between states and over time complicate actuarial estimation?

Section 4

1. For Example 4.1 prove (show through calculation) that Zp = 20%, Ze = 3.2%, Ep = 0.954, and Ee = 0.046
2. For Example 4.1 recalculate Zp, Ze, Ep, and Ee for x = 75% and y = 200% as described in Exercise 3 for Section 3.
3. For Example 4.1 recalculate Zp, Ze, Ep, and Ee using 300% as the dividing line between primary and excess losses.
4. For Example 4.2 prove (show through calculation) that Zp = 47.9%, Ze = 34.2%, Ep = $6,908 and Ee = $2,857.
5. For Example 4.3 suppose the loss limit at $100,000 was another split point. Calculate Zx for the layer excess of $100,000.
6. For Example 4.3 suppose split point was $30,000 and the loss limit was $90,000. Recalculate Zp, Ze, Ep, and Ee.
7. For Example 4.3 recalculate all the estimates for 2 claims of $500,000 each and then for 8 claims of $125,000 each.
8. For Example 4.4 recalculate all the estimates for 1 claims of 10 and then for 5 claims of 150 each.
9. Discuss the relative merits of split credibility and loss limits versus a direct Bayesian calculation.
10. What is the difference between a split point and a loss limit?
11. Discuss why correlation between covariates, such as the primary and excess experience losses, is a problem for linear regression models.
12. Discuss the difference between linear regression models and credibility models.
13. How does the Weight and Ballast representation of credibility slightly reduce the complexity of calculating the mod?
14. What is the effective result for credibility of placing a minimum value on the Ballast?
15. Write Ze and Zp as functions of x = E/G for the latest credibility constants and minimum constraints in the ERP.

16. Using the latest credibility constants and minimum constraints in the ERP calculate the credibility values for the table below.

E	Ze	Zp	W	B
10 G				
100 G				
1,000 G				
10,000 G				
100,000 G				
1,000,000 G				
10,000,000 G				
100,000,000 G				
1,000,000,000 G				

17. For Example 4.1 estimate optimal values for Zp and Ze in terms of flattening a quintile test.
18. For Example 4.2 estimate optimal values for Zp and Ze in terms of flattening a quintile test.
19. Why is credibility more dependent on the expected number of claims than on the total expected loss amount?
20. Why is it important to test the ERP, or for that matter statistical models in general, on a data set other than the data set used to fit the parameters of the model?
21. What changes over time in the loss process for individual risks might severity indexation fail to capture?
22. Aside from practical limitations to what extent, in principle, can experience rating improve rate equity for very small, low-credibility risks?

Section 5

1. Why is it necessary to assign risk IDs to individual employers and track them over time?
2. Discuss the challenges and ambiguities of assigning risk IDs to individual employers and tracking them over time.
3. Discuss why expected ratable losses differ from prospective expected losses in all the ways listed in Section 5.2
4. If the 70% exclusion of medical only losses were eliminated what impact would you expect it to have on ELRs, ELAFs, and D-ratios?
5. If the SAL limit on individual losses were eliminated what impact would you expect it to have on ELRs, ELAFs, and D-ratios?
6. If ELRs increase, all other things staying the same, what impact would you expect on mod values and on the equity and lift of the mod?
7. If D-ratios increase, all other things staying the same, what impact would you expect on mod values and on the equity and lift of the mod?
8. If the fraction of losses attributable to Permanent Total claims increases what impact would you expect it to have on ELRs, ELAFs, and D-ratios?
9. If D-ratios were used that were much too high what effect would it have on the quintile test? Draw a hypothetical chart of such a quintile test.
10. If D-ratios were used that were much too low what effect would it have on the quintile test? Draw a hypothetical chart of such a quintile test.

11. If ELRs were used that were much too high what effect would it have on the quintile test? Draw a hypothetical chart of such a quintile test.
12. If a ELRs were used that were much too low what effect would it have on the quintile test? Draw a hypothetical chart of such a quintile test.
13. Discuss the relative importance of Ze, Zp, ELRs, and D-ratios for mod performance.

Section 6

1. Discuss the contrast between off-balance versus equity and lift.
2. What would be the consequence if off-balance became an extreme value, such as below 0.50 or above 1.50?
3. What determines the minimum possible mod value?
4. Using the latest credibility constants and minimum constraints in the ERP and the cap on the maximum mod calculate the values for the minimum and maximum possible mods for the table below.

E	Minimum Mod	Maximum Mod
10 G		
100 G		
1,000 G		
10,000 G		
100,000 G		
1,000,000 G		
10,000,000 G		
100,000,000 G		
1,000,000,000 G		

5. If there are three claims in the experience period, each of which exceeds the split point but is less than half of the SAL, how does the multiple claim occurrence limit affect the mod value?
6. Could a debit mod under rating gross of deductibles become a credit mod under rating net of deductibles?
7. Could a credit mod under rating gross of deductibles become a debit mod under rating net of deductibles?
8. Is predictive information lost by excluding 70% of medical only losses?
9. Why does it make more sense to use the total size across states of an interstate risk to determine credibility values rather than just calculating an intrastate mod in each state for an interstate risk?
10. For interstate risks under what circumstances does weighting W and B versus determining Zp and Ze by implied expected claim counts result in the greatest and least differences, respectively, for the mod calculation ?
11. Discuss arguments for and against applying the mod to typical non-ratable losses or charges which the mod usually does not apply to, such as: some types of catastrophes and terrorism, expense constants, premium discounts, and some types of disease exposures.

APPENDIX B: EXERCISES

1. Discuss some plausible differences in underlying assumptions between these two familiar formulas for credibility.

$$Z = \frac{P}{P+K} \quad \text{or} \quad Z = \frac{P+C}{P+K+C}$$

2. Discuss arguments for and against a self rating point in terms of risk size.
3. What would a generalized version of the 1940 split formula (as in Example A.2.1) be?
4. How could the 1940 split formula (as in Example A.2.1) be rewritten to include a severity index?
5. What would a generalized version of the 1961 split formula (as in Example A.2.2) be?
6. How could the 1961 split formula (as in Example A.2.2) be rewritten to include a severity index?
7. How could the 1940 and 1961 formulas for Zp, Ze, W, and B be rewritten to include a severity index?
8. Suppose and the 1940/1961 formulas for Zp and Ze use K = \$50,000, Q=\$25,000, and S = \$1,000,000. For what values of G and E would the ERA formulas for Zp and Ze give the same values, lower values, and higher values, respectively?
9. Compare the mod cap under GERT to the mod cap under ERA. For what values of E and G are the caps equal, the GERT cap higher, and the ERA cap higher, respectively?
10. Draw a line chart of Zp under RERP, GERT, and ERA, respectively, for E ranging from \$100 to \$1,000,000 and G = 5, 10, and 15, respectively.
11. Draw a line chart of Ze under RERP, GERT, and ERA, respectively, for E ranging from \$100 to \$1,000,000 and G = 5, 10, and 15, respectively.

Related Paper: "The Optimal Number of Quantiles For Predictive Performance Testing of the NCCI Experience Rating Plan"

1. Ignoring noise-to signal resolution limits on statistical clarity constraints per se, discuss whether more quantiles might or might not reveal more information about ERP performance.
2. Can you think of similar simple alternative metrics to the old and new quintile test statistics?
3. Discuss the difference between lift and what exactly is being measured by the new quintile test statistic.
4. The difference between A* versus A and B* versus B is a historical anomaly, as bootstrapping was done when A and B were defined for the new quintile test statistic. Nevertheless, discuss what significance there might be to this difference between including bootstrapping or not in these variances.
5. Suppose an individual risk has a 10% chance of having total losses > 0 and these aggregate losses > 0 conditionally follow a log normal distribution with mean \$10,000 and coefficient of variation 500%. How many such risks must be sampled so that there is a 99.9% probability that the sample average will lie in the interval from \$8,000 to \$10,000.
6. Redraw Figure 4, from the paper, using the individual risk loss process in the last problem.
7. In Example 3.1, in this study note, estimate σ/R for: a. the Bayes theorem estimate, and b. the greatest accuracy credibility estimate.
8. In Example 3.1, in this study note, estimate the minimum sample size for a quintile test to produce a noise-to-signal ratio <= 0.25 for: a. the Bayes theorem estimate, and b. The

greatest accuracy credibility estimate.

9. In Example 3.1, in this study note, estimate the minimum sample size for a decile test to produce a noise-to-signal ratio <= 0.25 for: a. the Bayes theorem estimate, and b. the greatest accuracy credibility estimate.
10. In Example 3.4, in this study note, estimate σ/R for: a. the Bayes theorem estimate, and b. the greatest accuracy credibility estimate.
11. In Example 3.4, in this study note, estimate the minimum sample size for a quintile test to produce a noise-to-signal ratio <= 0.25 for: a. the Bayes theorem estimate, and b. The greatest accuracy credibility estimate.
12. In Example 3.4, in this study note, estimate the minimum sample size for a decile test to produce a noise-to-signal ratio <= 0.25 for: a. the Bayes theorem estimate, and b. the greatest accuracy credibility estimate.
13. In Example 4.1, in this study note, estimate σ/R for the split credibility estimate.
14. In Example 4.1, in this study note, estimate the minimum sample size for a quintile test to produce a noise-to-signal ratio <= 0.25 for the split credibility estimate.
15. In Example 4.1, in this study note, estimate the minimum sample size for a decile test to produce a noise-to-signal ratio <= 0.25 for the split credibility estimate.
16. In Example 4.2, in this study note, estimate σ/R for the split credibility estimate.
17. In Example 4.2, in this study note, estimate the minimum sample size for a quintile test to produce a noise-to-signal ratio <= 0.25 for the split credibility estimate.
18. In Example 4.2, in this study note, estimate the minimum sample size for a decile test to produce a noise-to-signal ratio <= 0.25 for the split credibility estimate.
19. Would you pick another rule of thumb in Section 3.2, from the paper, rather than $Z \approx Zp/2$? Discuss the reasons for your pick or the reasons for sticking with $Z \approx Zp/2$.
20. Make tables like the tables shown in Table 2, from the paper, for all of the estimates in Examples 3.1, 3.4, 4.1, and 4.2. There should be 6 tables in total.
21. Using the credibility rule of thumb, and any other reasonable assumptions you might make, estimate what the N/S would be expected to be for Figures 8-12. What would you expect the maximum number of quantiles that would still keep the N/S <= 0.25 to be in each of these situations?
22. Recalculate Table A1 for: a. a quintile test b. a 20 category quantile test.
23. How does the whole concept of the R value described in the paper break down when the distribution of estimates follows an unbounded distribution, like a lognormal, and the number of quantiles used becomes very large ? Construct an example.
24. Discuss the problems with the noise-to-signal measure when the loss process is very skewed, as it usually is, and the sample size is small?
25. NCCI usually does not limit actual loss amounts from the prospective policy period in quintile tests but relies on large data volume. Discuss the possible advantages and disadvantages of using loss limits in the prospective policy period. Particularly, what types of biases might these limits might cause?

5. REFERENCES

Accompanying this study note is a more in depth paper on quantile testing the NCCI EXP:

[1] Evans, Jonathan; and Dean, Curtis Gary, "The Optimal Number of Quantiles For Predictive Performance Testing of the NCCI Experience Rating Plan," to appear in CAS eForum.

The ultimate written sources on the specifics of the NCCI ERP are:

[2] National Council on Compensation Insurance, *Experience Rating Plan Manual for Workers Compensation and Employers Liability Insurance.*

[3] National Council on Compensation Insurance, *Experience Rating Plan User's Guide for Workers Compensation and Employers Liability Insurance.*

For basic statistics on individual claim severity see:

[4] National Council on Compensation Insurance, *Annual Statistical Bulletin.*

Aside from NCCI itself the most important resource on the history and theory behind workers compensation experience rating, and related actuarial methodology is:

[5] *Proceedings of the Casualty Actuarial Society*, 1914-2005, available at www.casact.org.
Superseded by:

[6] *Variance*, 2006-present, also available at www.casact.org.

Also of note for related actuarial methodology is:

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The classic landmark paper on workers compensation experience rating is:

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The Recent Review and Changes to the National Council on Compensation Insurance's Individual Risk Experience Rating Plan

Jon Evans

Abstract

Motivation. The goal of experience rating is to improve the equity of individual risk rates. The National Council on Compensation Insurance (NCCI) periodically reviews the performance of its Experience Rating Plan, and makes changes to the Plan as warranted by the results of such reviews.

Method. NCCI recently completed an extended review of its Experience Rating (ER) Plan. NCCI Staff presented the results of its analyses at regular meetings of the NCCI Individual Risk Rating Working Group (IRRWG). The IRRWG, which is comprised of actuaries representing workers compensation insurers affiliated with NCCI, discussed and reviewed these analyses and the actuarial methodology underlying the ER Plan with NCCI staff.

Results. Although no major changes had been made for many years, testing indicated that ER Plan performance was still generally good. The primary cause of deteriorating performance was the use of a fixed split point between primary and excess losses while average claim severity increased dramatically. The review process uncovered many interesting facets of actuarial methodology related to experience rating, but the changes coming out of the review did not fundamentally change the structure of the plan. NCCI has implemented an increase in the split point from $5,000 to $15,000+ inflation (over three years), and subsequent procedures to periodically increase the split point in the future corresponding to an index of claim severity. Along with the split point increase, the maximum cap on modification factors was changed. As part of the review, NCCI also made changes to several components of the calculation of primary and excess experience period expected losses to conform to changes in NCCI's class ratemaking procedures.

Conclusions. A well-constructed experience rating plan can perform very well for a very long time with appropriate indexation applied to components. Simplicity, consistency, transparency, and an automatic indexation are particularly important for industry-wide bureau plans such as the NCCI Experience Rating Plan.

Keywords. NCCI, Individual Risk Rating, Experience Rating, Workers Compensation, Credibility, Split Credibility.

1. INTRODUCTION

Experience rating for individual workers compensation risks dates back to the beginning of the Casualty Actuarial Society (CAS) and workers compensation insurance in the United States. Early volumes of the Proceedings of the Casualty Actuarial Society (PCAS) contain numerous papers on experience rating individual workers compensation risks and the credibility of individual risk experience ([4], [5], [6], [10], [12], [13], [14], [17], [20], [21], [22], [26]). This area of ratemaking is also somewhat unique in CAS history in that from the beginning, fitting credibility values and performance testing of consequent modification factors has involved a "predictive" framework, simultaneously comparing data on previous loss experience and subsequent loss experience (particularly see [4]).

This paper describes a recent multi-year review of the NCCI's Experience Rating Plan. NCCI Staff performed many different analyses. These analyses were presented for review and discussion at periodic meetings of NCCI's Individual Risk Rating Working Group. The IRRWG consists of actuaries representing workers compensation insurers that are affiliates of NCCI.

The review process confirmed that the ER Plan was performing well into the first years of the 21st century. In more recent years, quintile testing (Figure 1) began to show slight upward slope in modified relative pure loss ratios. (See the first part of Section 2 and Section 2.1.4 for a detailed description of quintile testing.) This was ultimately diagnosed to be a consequence of the split point remaining fixed while severity had increased significantly. The severity index associated with the split point had remained relatively flat for some years after NCCI's 1998 adjustments to the ER Plan. However, by Policy Year 2006 the severity index had more than doubled (Figure 2) and anticipated trends placed it on course to triple by around 2011-2013.

Figure 1

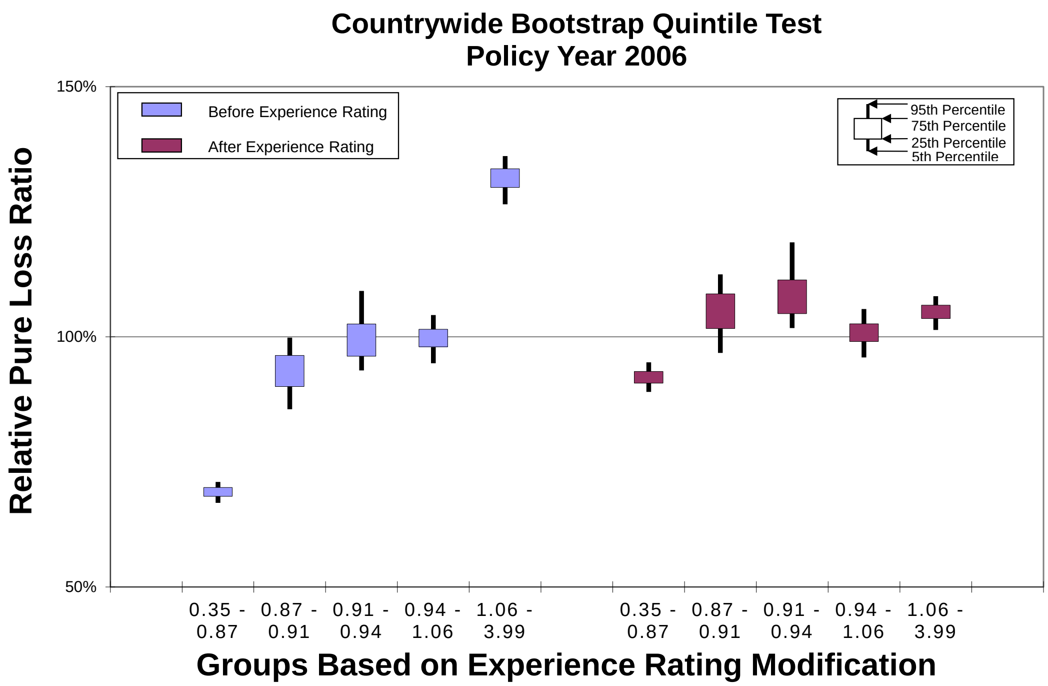
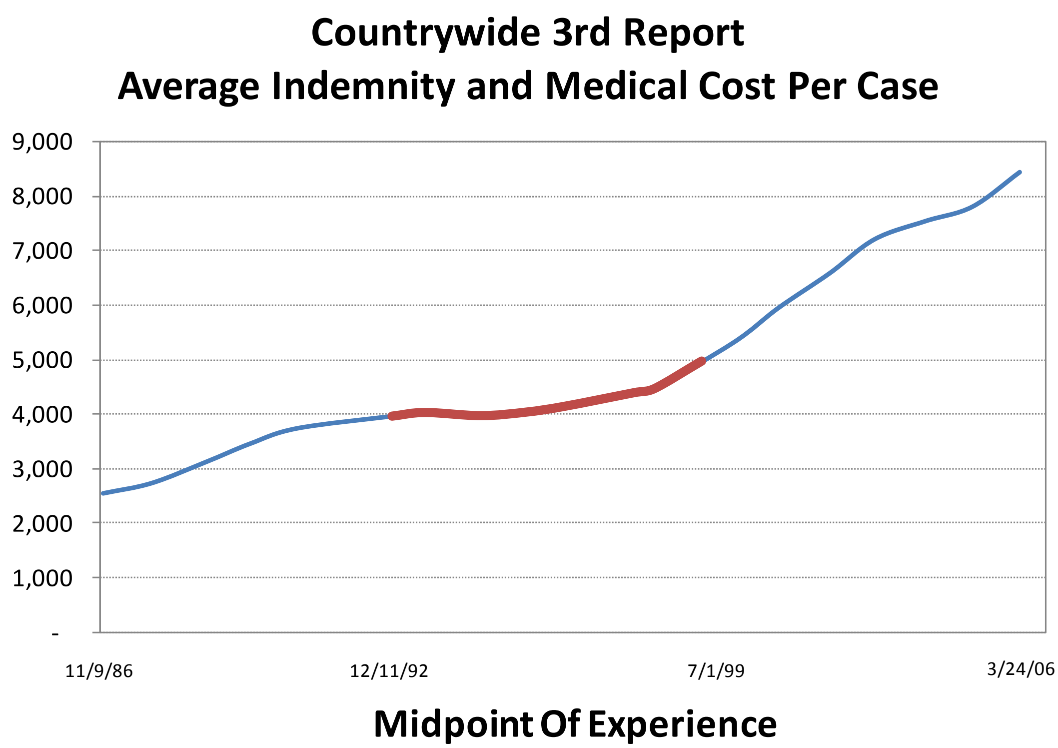


Figure 2



In response, NCCI has implemented a major increase in the split point from $5,000 to $15,000+ inflation (to be phased in over three years), and subsequent procedures to periodically increase the split point in the future corresponding to an index of claim severity. Along with the split point increase, the maximum cap on modification factors was changed.

While the ER review was being conducted, NCCI also implemented several changes to its class ratemaking methodology ([3]). To accommodate class ratemaking changes in the ER Plan, changes were made to the calculation of D-ratios, which determine the fraction of expected experience period loss which is primary, and Expected Loss Rates (ELRs), which are rates of experience period expected ratable losses.

1.1 Research Context

The content of this paper is primarily related to individual risk rating and credibility. Although the application is to workers compensation specifically, the methods shown are generally applicable to other casualty insurance. Background and specific details on the NCCI Experience Rating Plan will not be repeated here. Before undertaking this paper all readers, particularly those who do not routinely deal with the details of the plan, would be well advised to review one or more of several readily available references ([7], [8], [9], [15], [16], [18], [25]). The most complete documentation of the specifics of the plan can be found in [19]. A number of papers from the early decades of the Proceedings of the CAS deal with individual risk rating in workers compensation ([4], [5], [6], [10], [12], [13], [14], [17], [20], [21], [22], [26]). There are also a few other directly relevant PCAS papers from the middle of the 20th century ([1], [23], [24]).

1.2 Outline

Section 2 will describe some highlights of the review. The major changes to the ER Plan resulting from the review will be discussed in Section 3.

2. REVIEW OF THE EXPERIENCE RATING PLAN

The purpose of experience rating is to improve the estimate of future expected losses for an individual risk using previous actual loss experience for that risk. The basic formula for the experience rating modification factor, or *mod*, is (2.1).

$$\frac{A_p + WA_e + (1-W)E_e + B}{E + B} \tag{2.1}$$

Ap = actual primary ratable loss from the experience period

Ae = actual excess ratable loss from experience period

Ep = expected primary ratable loss from the experience period

Ee = expected excess ratable loss from experience period

E = Ep + Ee = expected ratable loss from experience period

B = ballast value

W = weight value

An alternative form that more directly illustrates the credibility values used in the mod formula is (2.2).

$$1 + Z_p \frac{A_p - E_p}{E} + Z_e \frac{A_e - E_e}{E} \tag{2.2}$$

Zp = primary credibility

Ze = excess credibility

Ratable loss in the experience period includes a subset of total loss, determined through various exclusions such as individual loss limit, 70% exclusion of medical only losses, etc. Various specifics of the basic formula components and other aspects of the mod calculation have been changed in recent decades through special NCCI item filings. These filings include the revised Experience Rating Plan (RERP) in 1991, the Graduated Experience Rating Tables (GERT) in 1995, the Experience Rating Adjustment (ERA) in 1998, and the recent split point and maximum mod changes in 2012 based on the review described in this paper (and contained in Item Filing E-1402). As of this writing (2013), among states where NCCI files loss costs or rates, almost all have adopted ERA and Item E-1402.

Experience Rating Plan performance is measured by the extent to which manual basis pure loss ratios vary by mod, increasing as mod values increase, and the uniformity of modified basis loss ratios across different mod values. It can be shown empirically through a *quintile test* of effective period relative pure loss ratios that the mod performs fairly well according to these two criteria (Figure 1). For the quintile test, risks are sorted by mod value and then grouped into five quintiles, each having an equal number of risks. Relative pure loss ratios on a manual and modified basis, respectively, for each quintile are shown in a chart. The review focused on how various aspects of the calculation affected performance of the plan, extensively using quintile testing to measure performance.

2.1 Stages of the Review

The review was intended to be fairly comprehensive, and aspects of the plan to be reviewed were organized into four categories to be reviewed in roughly sequential stages, or tiers:

1. Severity Index
2. Data and Caps
3. Expected Losses
4. Credibility

2.1.1 Severity Index

Severity indexation is used to update the maximum mod cap, the state accident limit, and the weight and ballast credibility values as part of NCCI class rate filings, which generally occur at the state level on an annual basis. The NCCI Experience Rating Plan Adjustment (ERA) of 1998 ([18]) also provided for indexation changes of the split point separating primary and excess losses on a national basis, but with no regular schedule or connection to periodic rate filings specified. Severity indexation is used to ensure that future performance will not be eroded by inflation in average claim amounts.

NCCI produces several different indices for experience rating that are substantially the same, but in practice are specified differently (Table 1):

1. State Average Cost Per Case (SACC), for all claims including medical only

2. State Reference Point (SRP) ≈ 250 x SACC

3. State Accident Limit (SAL) ≈ 25 x SACC

4. "G value" ≈ SACC / 1000

The ERA filing referenced a countrywide Average Cost Per Case (ACC), very similar to the State Average Cost Per Case, in connection with the split point (Figure 2).

Table 1

Severity Index Example Calculation*

Policy Period	Total Undeveloped Cases	Total Undeveloped Incurred Losses	Average Cost Per Case
7/2003-6/2004	22,255	$144,819,582	$6,507
7/2002-6/2003	22,939	$150,662,284	$6,568
7/2001-6/2002	23,259	$150,531,909	$6,472
Total	68,453	$446,013,775	$6,515

State Average Cost Per Case (SACC)	$6,515
State Reference Point (SRP) = [(250xSACC)] round to 5,000	$1,630,000
State Accident Limit (SAL) = SRP / 10	$163,000
“G” Value = SRP / 250,000 round to 0.05	6.50

*Taken from an NCCI rate filing made in 2006

An alternative index merits consideration if it varies between states and/or over time distinctly from the current index. Note, as will be described later, the severity index used for split point adjustments is on a countrywide basis and does not vary by state, unlike other severity indices used in the ER Plan. Alternative indexes that are very highly correlated to each other can be pared down to a single representative alternative. Secondly, the percentage of excess claims and fraction of excess losses at the state accident limit implied by an index should be relatively constant between states and over time. Several alternatives were investigated:

• State Average Claim Cost with 70% Exclusion of Med Only Losses

• State Average Cost Per Lost Time Claim

• State Average Cost Per Serious Claim

• State Average Weekly Wage (SAWW) capped at 150k on an annual basis

• Medical CPI

Only the State Average Cost per Lost Time Claim showed any promise of being both distinct from the current State Average Claim Cost basis and potentially more constant in terms of the excess percentage criteria (Figures 3, 4, and 5). However, ultimately this potential advantage was judged not great enough to warrant further investigation or the potential expense of such a fundamental change to the indexation bases.

Figure 3

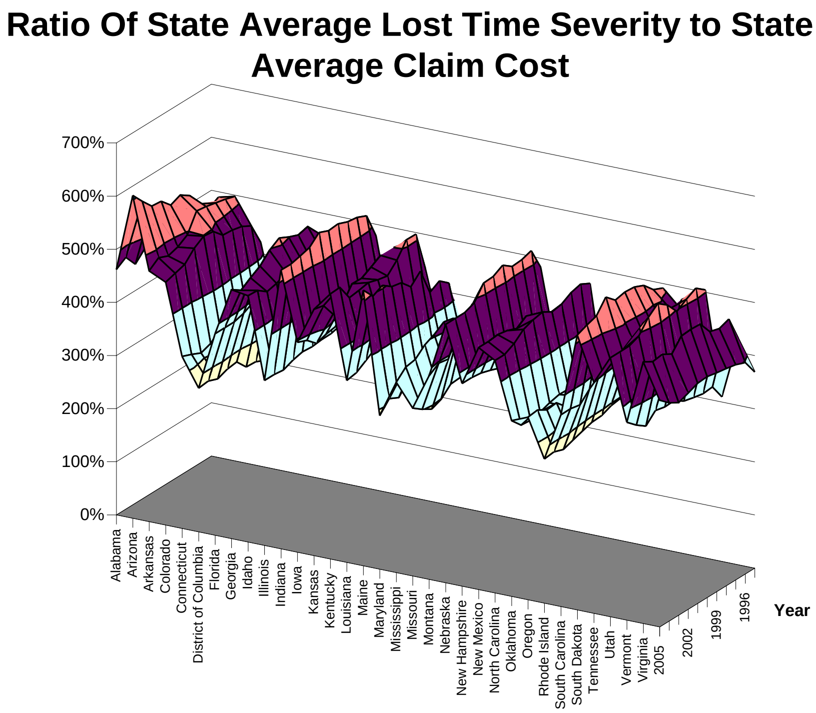


Figure 4

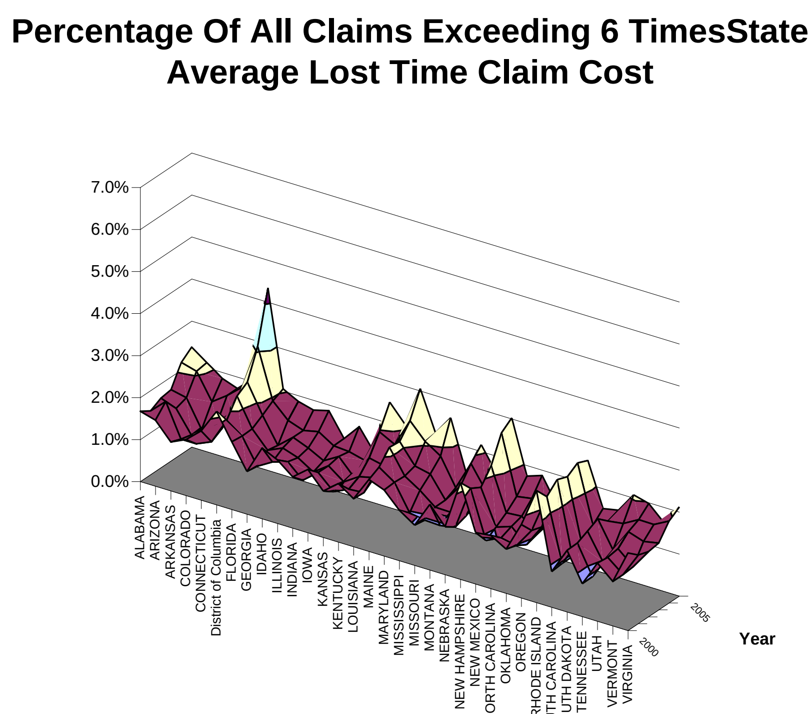
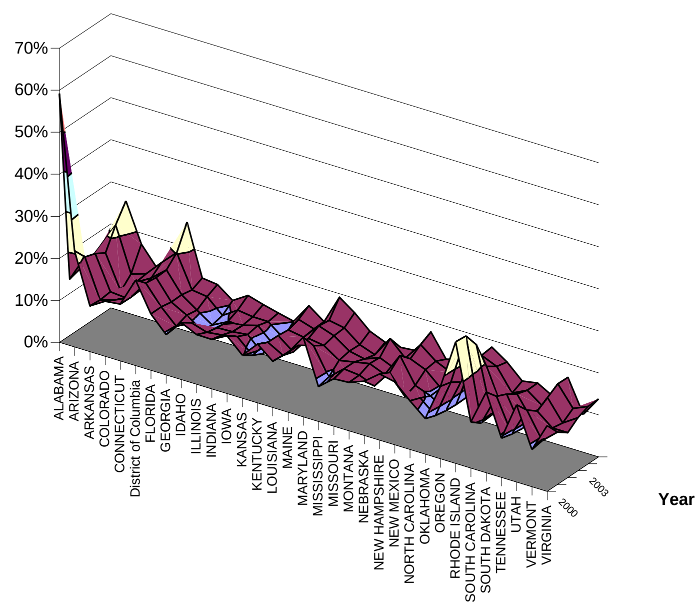


Figure 5

Percentage Of Loss Exceeding 6 Times State Average Lost Time Claim Cost



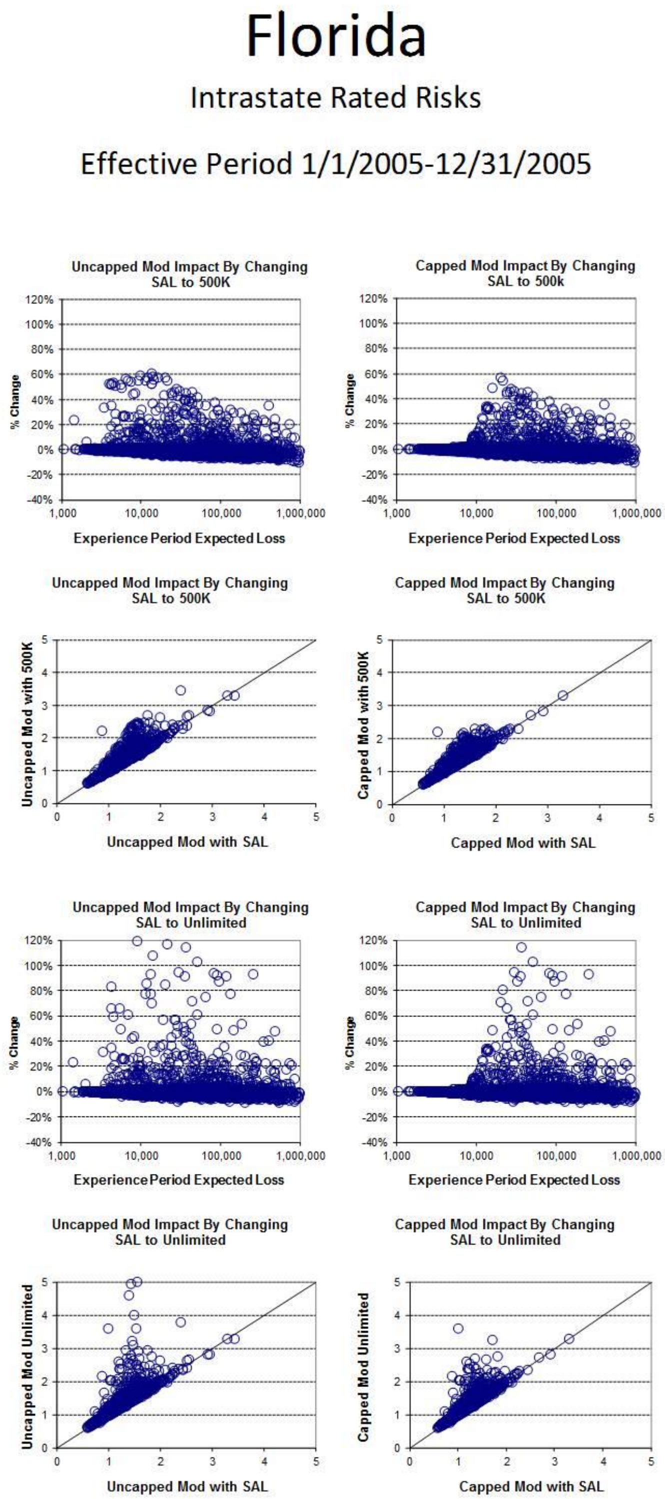
2.1.2 Data and Caps

This tier included topics such as the per claim limit (State Accident Limit), multiple claim limit, exclusions of catastrophic losses, maximum mod cap, 70% medical only exclusion, experience period, and special state and class exceptions to standard calculations. These features of the plan are less geared toward statistical or performance optimization but are selected with regard to practical considerations and buffering the impact of the mod in special cases for individual risks (as shown in Figure 6). For example, 70% of medical only losses are excluded from the mod calculation to remove the potential incentive for employers to not report small medical only claims. Figure 6 shows some examples of the impact of the maximum mod cap and the State Accident Limit on the mod at the individual risk level.

Analysis and discussion with members of the IRRWG uncovered no areas of great concern, aside from a longstanding issue with the practice of net reporting, which occurs in a small number of states where losses net of deductibles are used in experience rating. In most states requiring net reporting, actual experience period losses utilized in the mod calculation are net of policy deductibles, but experience period expected losses must be calculated gross of deductibles. This introduces a subsidy between policyholders without deductibles and those that choose deductibles. Previous NCCI attempts to adjust expected loss calculations (another tier of the review) for deductibles had been rejected by regulators in some net reporting states. In those jurisdictions, the subsidy is acknowledged by regulators and considered appropriate public policy as a means to encourage use of deductibles (the assumption being deductibles are a safety incentive). The 70% med only deduction overlaps some of the loss that would be under deductibles and partially mitigates the actuarial problem caused by the mismatch between actual and expected experience period losses in net reporting states.

Figure 6

Individual Risk Impact of State Accident Limit and Mod Cap



2.1.3 Expected Losses

Expected Loss Rates (ELRs) are multiplied by payroll in the experience period to produce total expected ratable losses for calculating the mod. The D-ratio, an estimate of the fraction of ratable losses which are primary, is used to separate this total into primary and excess components. Several statistical measurements of actual to expected losses for the experience period were explored, but none were found particularly insightful or resulted in any recommendations for changes to ELR or D-ratio calculations.

The calculation methodology and details underlying the ELRs and D-ratios were reviewed and found to be basically sound.

There was some concern that performance might be unequal between risks in different hazard groups. Hazard groups are a partition of employment classifications to reflect claim severity. For quintile testing purposes, risks were "assigned" to hazard groups according to the classification which generated the largest manual premium. Quintile testing demonstrated that performance was effectively uniform across hazard groups (Figures 7-11). Although performance was uniform, there were some differences in the average mods between hazard groups, such as a general decrease in average mod with increasing hazard group. These differences were somewhat equalized by class ratemaking changes, not directly part of the ER review, in how ELRs and D-ratios are calculated.

A more immediate concern arose due to changes in class ratemaking that affected the ELR and D-ratio calculations and were being implemented simultaneous to the ER review ([3]). These changes primarily consisted of the consolidation of non-serious and serious indemnity partial pure premiums into a single indemnity partial pure premium, calculation of loss development factors using losses limited at 500k, the use of excess loss factor (ELF) derived excess loss provisions instead of provisions based on spreading actual excess losses, and the shift from four to seven hazard groups. Significant changes were made to the ELR and D-ratio calculations to accommodate changes to class ratemaking, as described in Sections 3.3 and 3.4.

Figure 7

Lowest Quintile

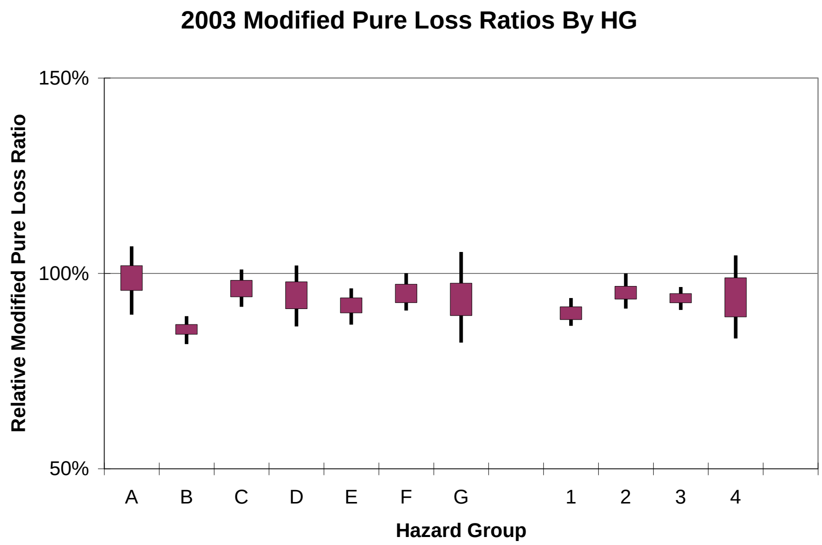


Figure 8

Low Quintile

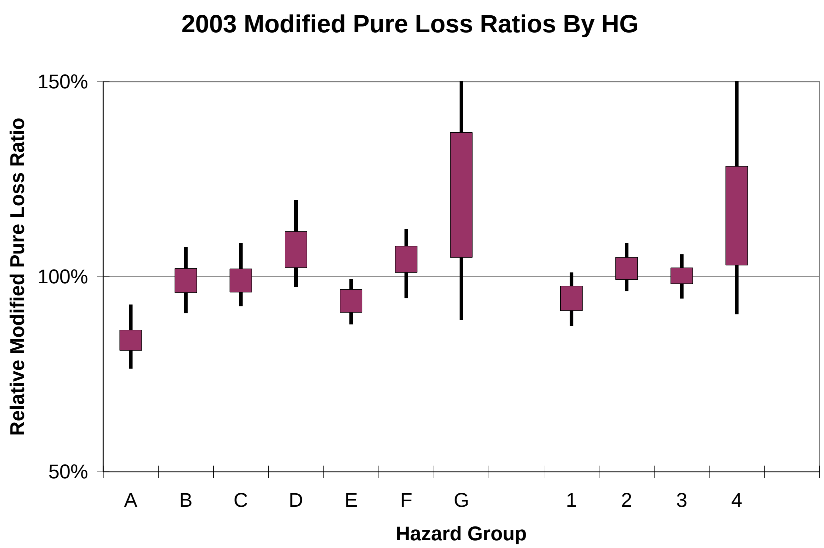


Figure 9

Middle Quintile

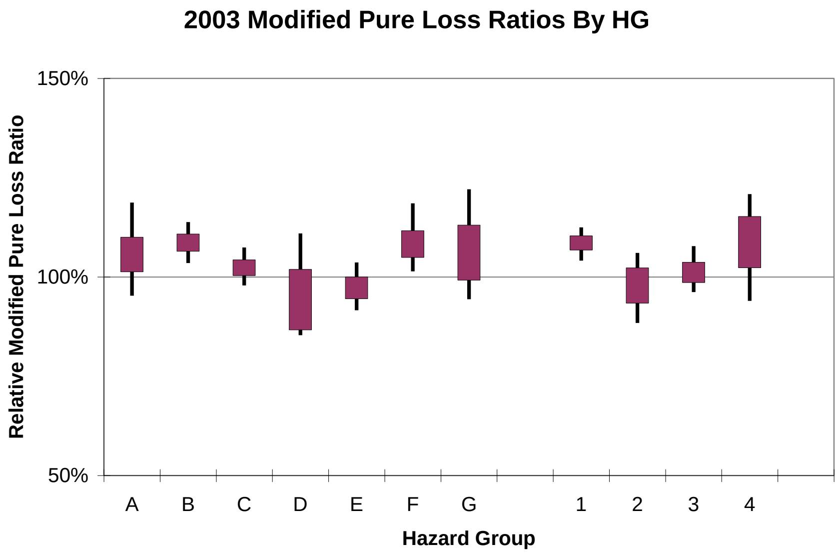


Figure 10

High Quintile

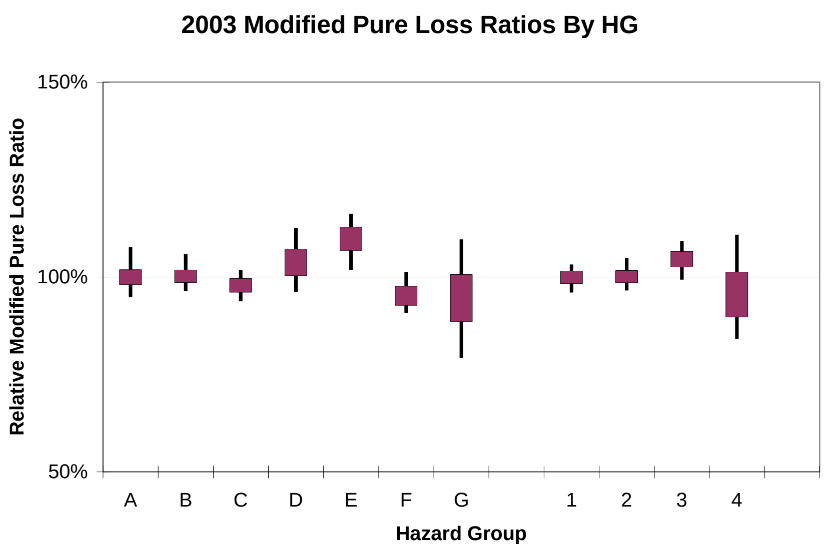
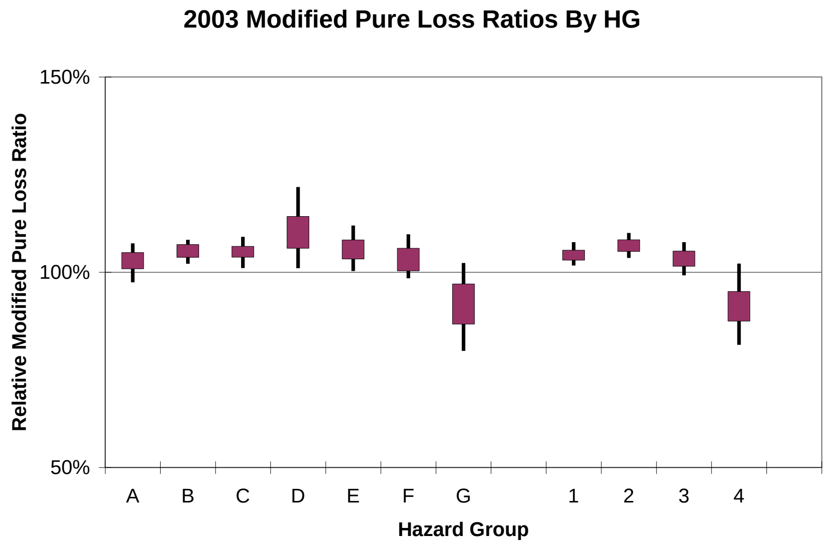


Figure 11

Highest Quintile

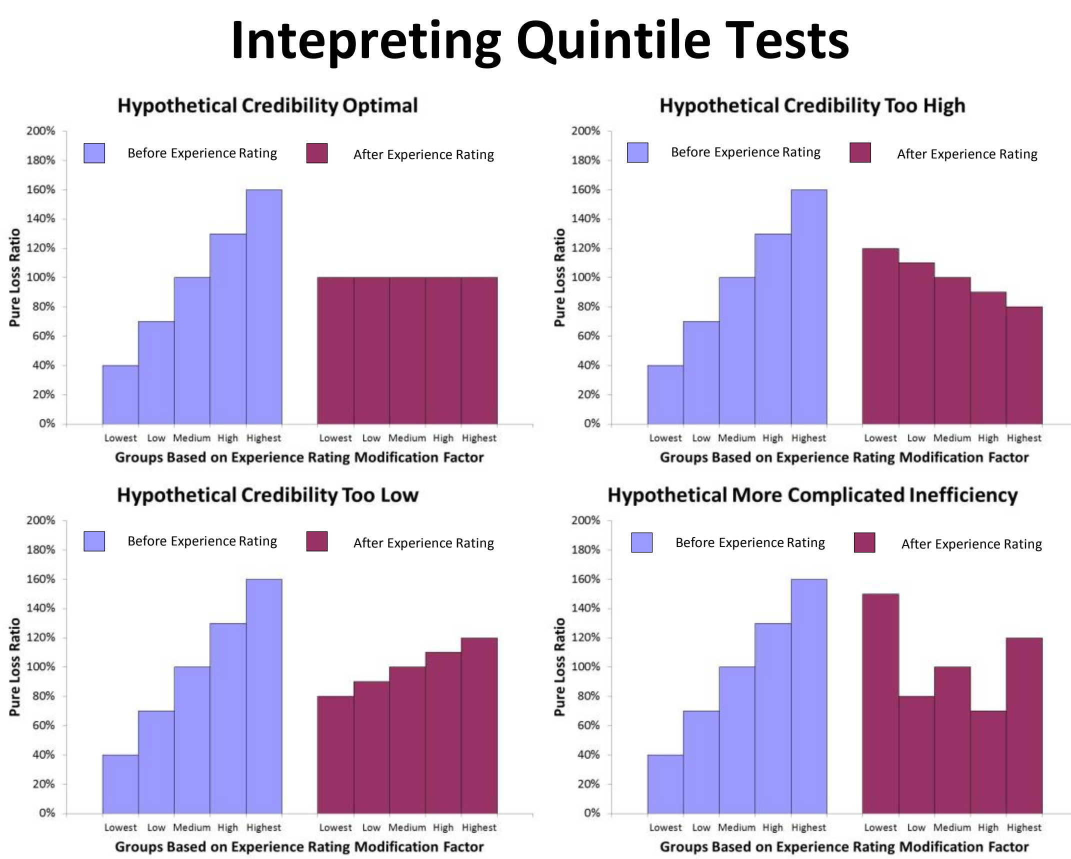


2.1.4 Credibility

The performance of credibility underlying the mod is demonstrated by the patterns in the modified basis relative pure loss ratios in the quintile test (Figure 12).

If the modified loss ratios show upward or positive "slope", credibility is too low. Downward slope indicates credibility is too high. The quintile test was the analytical workhorse of the review and similar empirical predictive tests have always been central to experience ratemaking ([4], [23]). Over the course of the review, quintile tests were performed on many specific categories, such as by state, by hazard group, by risk size, and combinations thereof, and with mods as currently calculated as well as possible alternative mod calculations. To illustrate the credibility of a quintile test, a particular concern in categories with sparse data, bootstrap-derived confidence intervals around the relative pure loss ratios (Figure 1) were usually presented instead of point estimates.

Figure 12



In recent years quintile testing began to show slight upward slope (Figure 1). As previously noted, this was ultimately diagnosed to be a consequence of the split point remaining fixed while severity had increased dramatically (Figure 2).

The review did explore several different alternative models (rank correlation criteria, Generalized Linear Models, etc.) to the underlying parameterization of the weight and ballast credibility values. These alternatives were challenging to implement, particularly with regard to handling credibility differences by size of risk, a consideration that is well handled through parameter and process assumptions underlying the current parameterization model ([7], [18]). An additional concern was that changes in ELRs and D-ratios resulting from class ratemaking changes would not be available in data for credibility fitting purposes for some years in the future. Ultimately, NCCI determined that current parameterization worked well when the indexation updates were fully implemented. Since the indexation of weights, ballasts, and the State Accident Limit were automatically tied to routine rate filings they had kept up, but the split point had fallen behind.

Quintile testing that maintained the underlying credibility parameterization for alternative split points was performed. Two numerical statistics were calculated. The "Old Quintile Statistic" measures the degree to which the modified pure loss ratios are uniform; this statistic should be as small as possible. The "New Quintile Statistic" measures the amount of manual loss ratio variation eliminated by applying the mod; this value should be as big as possible. Review of these statistics suggested that by Policy Year 2006 the optimal split point, where the old statistic tended to be lowest and the new statistic tended to be highest, was likely slightly higher than $10,000 (Figure 13, Table 2 and 3). Severity trends subsequent to the Policy Year 2006 pointed to an optimal split point that would reach upwards of $15,000 sometime in the years following Policy Year 2011.

Figure 13

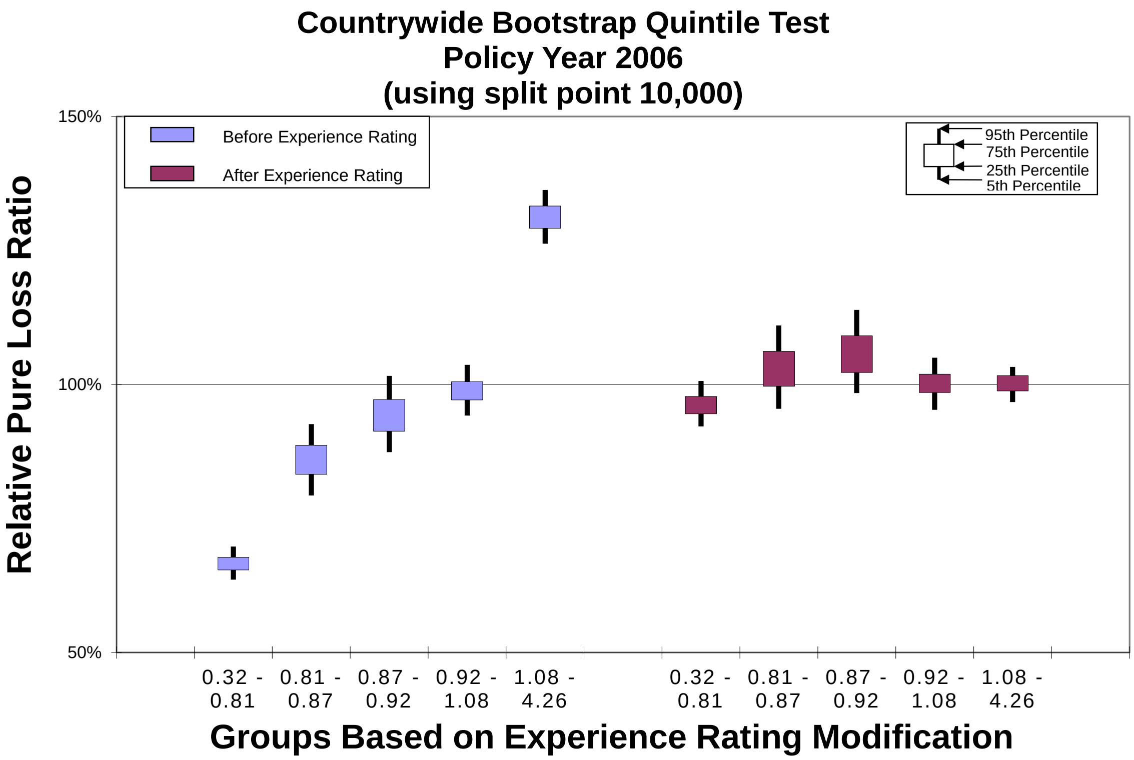

Countrywide Bootstrap Quintile Test
Policy Year 2006
(using split point 10,000)
Before Experience Rating
After Experience Rating
95th Percentile
75th Percentile
25th Percentile
5th Percentile
150%
100%
50%
Relative Pure Loss Ratio
0.32 - 0.81
0.81 - 0.87
0.87 - 0.92
0.92 - 1.08
1.08 - 4.26
0.32 - 0.81
0.81 - 0.87
0.87 - 0.92
0.92 - 1.08
1.08 - 4.26
Groups Based on Experience Rating Modification

Table 2

Old Quintile Test Statistic =B*/ A*

A* = variance of un-modified loss ratios without bootstrapping
B* = variance of modified loss ratios without bootstrapping

PY 2002

		Risk Size			
Split Point	Countrywide	1000-10,000	10,000-100,000	100,000-1M	1M-10M
2500	0.064	0.258	0.097	0.057	0.034
3750	0.037	0.163	0.071	0.054	0.026
5000	0.021	0.107	0.032	0.043	0.015
7500	$\boxed{0.007}$	0.034	$\boxed{0.006}$	0.032	0.019
10000	$\boxed{0.007}$	$\boxed{0.027}$	0.011	0.021	0.013
15000	0.043	0.109	0.095	$\boxed{0.020}$	$\boxed{0.009}$
20000	0.093	0.218	0.271	0.022	0.014
25000	0.191	0.415	0.524	0.035	0.015
50000	1.027	2.211	3.614	0.137	0.066

PY 2006

		Risk Size			
Split Point	Countrywide	1000-10,000	10,000-100,000	100,000-1M	1M-10M
2500	0.167	0.296	0.134	0.080	0.231
3750	0.098	0.211	0.105	0.078	0.224
5000	0.081	$\boxed{0.109}$	0.071	0.064	0.205
7500	0.082	0.235	0.027	0.048	0.176
10000	0.026	0.236	$\boxed{0.014}$	0.037	0.179
15000	$\boxed{0.023}$	0.352	0.075	0.020	0.179
20000	0.060	0.628	0.149	0.013	0.176
25000	0.120	0.885	0.229	$\boxed{0.008}$	$\boxed{0.150}$
50000	0.870	3.649	1.527	0.068	0.180

Table 3

New Quintile Test Statistic = sign(A-B)*|A - B|$^{0.5}$

A = variance of un-modified loss ratios with bootstrapping
B = variance of modified loss ratios with bootstrapping

PY 2002

		Risk Size			
Split Point	Countrywide	1000-10,000	10,000-100,000	100,000-1M	1M-10M
2500	0.218	0.239	0.241	0.275	0.273
3750	0.225	0.246	0.252	0.281	0.271
5000	0.234	0.252	0.255	0.279	0.264
7500	0.241	0.253	0.260	0.279	0.271
10000	0.247	0.241	0.263	0.282	0.272
15000	0.240	0.228	0.249	0.282	0.269
20000	0.235	0.205	0.223	0.282	0.264
25000	0.221	0.166	0.173	0.278	0.266
50000	-0.052	-0.212	-0.395	0.259	0.252

PY 2006

		Risk Size			
Split Point	Countrywide	1000-10,000	10,000-100,000	100,000-1M	1M-10M
2500	0.181	0.157	0.231	0.299	0.225
3750	0.187	0.170	0.237	0.304	0.229
5000	0.192	0.177	0.238	0.307	0.231
7500	0.197	0.167	0.248	0.306	0.230
10000	0.206	0.159	0.251	0.308	0.226
15000	0.203	0.126	0.253	0.308	0.230
20000	0.198	0.078	0.235	0.309	0.227
25000	0.190	-0.034	0.218	0.306	0.224
50000	0.063	-0.239	-0.173	0.290	0.227

Another aspect of credibility is the minimum threshold for experience rating by size of risk. Credibility and the cap on the maximum mod both decrease with decreasing risk size. For very small risks, the variation in modified premium versus manual premium is small enough that it makes experience rating impractical for these risks.

The minimum premium threshold table was set in the early 1980s, with only a few minor changes since, to correspond to roughly 10 employees based on state average weekly wages and the state average rate level. To be eligible for experience rating, subject premium for the experience period either exceeds Column A for the most recent 24 months or average annual subject premium for the entire experience period exceeds the Column B level in the threshold table (Table 4). The current thresholds are much lower in real dollars than when established in the 1980s.

Table 4

Current Eligibility Thresholds
State Table of Subject Premium Eligibility Amounts

State	Col A	Col B	State	Col A	Col B	State	Col A	Col B
AL	10,000	5,000	IA	7,500	3,750	NH	11,000	5,500
AK	5,000	2,500	KS	4,500	2,250	NM	9,000	4,500
AZ	6,000	3,000	KY	10,000	5,000	NC	5,000	2,500
AR	8,000	4,000	LA	10,000	5,000	OK	10,000	5,000
CO	8,000	4,000	ME	9,000	4,500	OR	5,000	2,500
CT	11,000	5,500	MD	10,000	5,000	RI	10,000	5,000
DC	7,000	3,500	MN	6,000	3,000	SC	9,000	4,500
FL	10,000	5,000	MS	9,000	4,500	SD	7,500	3,750
GA	10,000	5,000	MO	7,000	3,500	TN	9,000	4,500
HI	5,000	2,500	MT	5,000	2,500	UT	7,000	3,500
ID	6,000	3,000	NE	6,000	3,000	VT	8,000	4,000
IL	10,000	5,000	NV	6,000	3,000	VA	7,000	3,500
IN	5,000	2,500						

Severity indexation would be more desirable from a credibility standpoint since it would imply a standard of a minimum expected number of claims. Based on review of the pervasive use of severity indexation in other parts of the plan, it would be desirable for consistency and simplicity to use severity indexation for the eligibility threshold also. In the review, NCCI explored several different possible severity index based standards for eligibility. However, as of this writing (2013), NCCI has no specific plans regarding new eligibility thresholds.

2.2 Other Findings

2.2.1 Rank Versus Expected Loss

In the course of the review, the use of a criterion of 0% rank correlation to fit credibility values, as introduced by Glenn Meyers ([16]), was explored. It became apparent that the criterion Meyers used of 0% rank correlation between modification factors and subsequent actual modified pure loss ratios was generally not consistent with the key criterion of equal expected values for subsequent modified pure loss ratios, as evidenced empirically by flat modified relative pure loss ratios in a quintile test. The high degree of departure between these two criteria was surprising and the author is preparing a separate paper for the CAS on this topic.

2.2.2 Optimal Number of Quantiles

Quintile testing is central to performance testing and credibility fitting for the ER Plan ([7], [25]). A natural question arises as to why NCCI uses five quantiles (quintiles) for this purpose. The author presented an explanation of the optimal number of quantiles in terms of a "noise to signal ratio." The key result was that this noise to signal ratio is proportional to $k^{1.5}$ where k is the number of quantiles and inversely proportional to $n^{0.5}$ where n is the number of risks of approximately the same size. Thus there is a tremendous penalty, in terms of data volume required, for adding more quantiles to the test. Doubling the number of quantiles requires eight times as much data to maintain the same resolution, in terms of the noise to signal ratio. The author is preparing a separate paper for the CAS on this topic.

3. CHANGES TO THE EXPERIENCE RATING PLAN

Several changes emerged from the review, some having already been implemented and others pending in the near future as of this writing.

3.1 Split Point

Split points of about $10,000 for Policy Year 2006 and about $15,000 for Policy Year 2013 were determined to be appropriate updates for the split point. These selections were made with consideration to both historical changes in the severity index and quintile testing. The split point was initially raised to \$10,000 with further gradual changes over a three year period to reach the equivalent of \$15,000 plus index changes over the intervening time. Subsequent indexation of the split point based on the countrywide Average Claim Cost will be an automatic part of NCCI's annual rate filings.

At any given time the split may vary by state due to differences in the schedule of rate filings by state, but will generally coincide when all of the seasonal filings have been made and before the next filing season.

3.2 Mod Cap

The previous mod cap formula was (3.1)

$$1 + 0.00005\ (E + 2E/G) \tag{3.1}$$

where E is experience period expected losses and G is the G value form of the severity index. This was updated to (3.2).

$$1.10 + 0.0004\ (E/G) \tag{3.2}$$

This new formula will allow slightly more room for debit mods on the smallest risks. The new formula is also entirely a function of implied expected claims (expected losses/average severity) between states and over time, whereas the previous formula was partially dependent on the absolute value of expected losses.

3.3 D-ratio Calculation

Part of NCCI's recent revision of class ratemaking methods involved a shift from the three categories of partial pure premiums (serious indemnity, non-serious indemnity, and medical) to only the two categories of indemnity and medical ([3]). Partial D-ratios had been calculated for each premium component statewide and then weighted by the partial premiums in each class to produce the class D-ratio. To compensate for this loss of refinement, the new partial D-ratios for medical and indemnity losses were estimated separately for each hazard group. Since D-ratio factors should tend to decrease for higher hazard groups, a monotonicity smoothing algorithm was applied to indicated D-ratio factors. This smoother iterates several times, averaging a D-ratio factor with factors in the adjacent hazard group(s) in cases where a factor is lower than the factor in the adjacent higher hazard group and/or higher than the factor in the adjacent lower hazard group.

3.4 ELR Calculation

The Expected Loss Rates (ELRs) are applied to experience period payrolls to calculate expected ratable losses. One key part of the calculation of ELRs is the Excess Loss Adjustment Factor (ELAF), which removes expected losses above the State Accident Limit. The ELAF calculation had been based on some simple excess loss ratio curves for undeveloped losses by entry ratio from the 1970s ([11]), represented in terms of quadratic and cubic polynomials for Fatal, Permanent Total, and Major Permanent Partial injury type categories. Recent NCCI Excess Loss Factors (ELF) were not well suited for this purpose as they reflect losses that are developed and stochastically dispersed to ultimate values instead of the immature values for ratable experience period losses ([2]). A set of replacement excess ratio curves for the ELAFs, still represented in terms of polynomials (3.3) but fit separately to Fatal, Permanent Total, Permanent Partial, Temporary Total, and Medical Only, was fit to more recent NCCI claims data (Table 5). The new excess ratio curves, still on an undeveloped basis, were significantly higher for higher entry ratios.

The new class ratemaking procedures use loss development of claims limited to $500k, with an excess provision derived from ELFs added to estimate ultimate unlimited losses. The previous ELAF procedure had "de-developed" ultimate expected losses and then subtracted an excess provision derived from the older undeveloped excess ratio curves. The new ELAF procedure first removes the ELF based excess provision at ultimate, de-develops losses, then subtracts an excess provision, derived from the updated undeveloped excess ratios curves, for the layer from the SAL to the 500k class ratemaking limit (Figure 14). It is worth noting that if at some point an SAL exceeds 500k, the calculation will add rather than subtract an excess layer provision, which is still actuarially sound.

$$E(r) = \text{Undeveloped Excess Ratio} = \frac{1}{ar^3 + br^2 + cr + 1} \qquad r = \text{Entry Ratio} \qquad (3.3)$$

Table 5

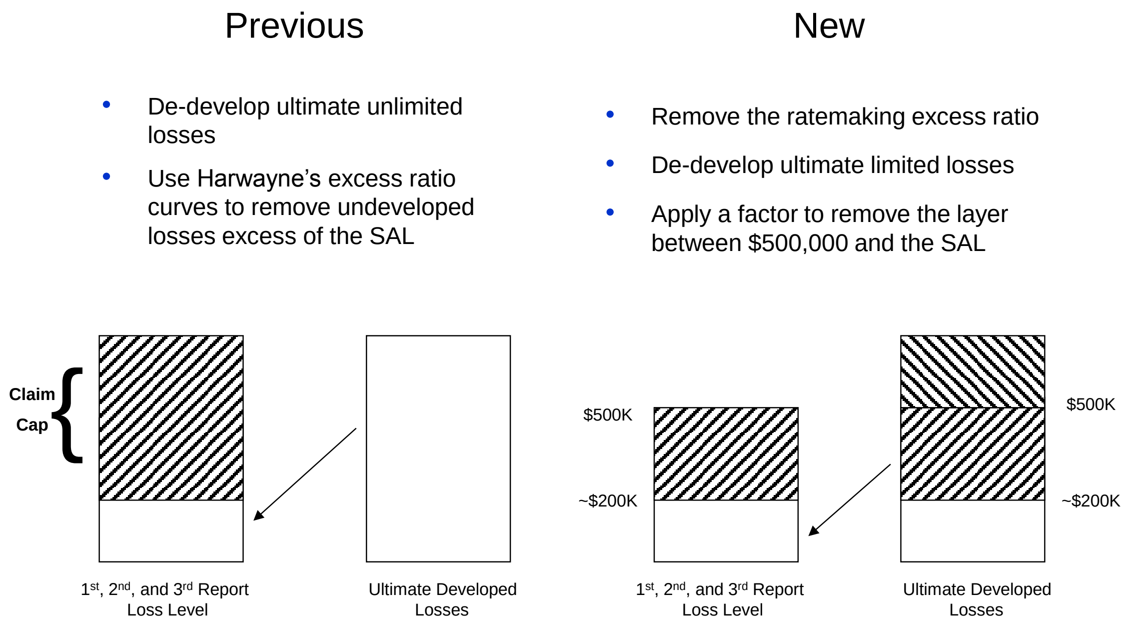
Previous Coefficients

Injury Type Category	a	b	c
Fatal	0.000000	2.310000	0.185000
Permanent Total	0.000000	2.310000	0.185000
Major Permanent Partial	0.167000	2.044000	0.805000

Revised Coefficients

Injury Type Category	a	b	c
Fatal	0.000000	1.017249	0.696561
Permanent Total	0.003148	0.054149	1.299625
Permanent Partial	0.000000	0.384102	1.086560
Temporary Total	0.001267	0.000000	0.876747
Medical Only	0.003165	0.000000	1.199899

Figure 14



4. CONCLUSIONS

The parameterization and severity indexation scheme for credibility underlying the NCCI ER plan implemented in the 1990s has well stood the test of time. Recent performance testing indicates that experience rating continues to dramatically improve estimates of individual risk future expected losses versus the expected losses underlying the class loss costs. However, the indexation of parameters has lagged with regard to the split point, leading to a gradual deterioration of performance over time due to the resulting low credibility.

There is value to simple representation and presentation of the components of the ER formula even when such simplicity does not materially affect the actual calculation. Such simplicity facilitates understanding on the part of the many people over many years in many different circumstances who must deal with the formula.

Acknowledgment

In addition to the author, many other members of NCCI Staff contributed significant work to the review. A notable, but not exhaustive, list of major contributors includes Ampegama Perera, Tom Sheppard, Chris Poteet, Tony DiDonato, Barry Lipton, Melissa Brown, Anna Elez, and Meghan Gaier. Members of the Individual Risk Rating Working Group employed by NCCI affiliates contributed time and feedback through their attendance at dozens of meetings, held approximately quarterly during the course of the review from August 2006 through February 2011.

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Abbreviations and notations

ACC, Average Cost Per Case
Ae, Actual Excess Ratable Loss From Experience Period
Ap, Actual Primary Ratable Loss From The Experience Period
B, Ballast Value
C, Multiple of SACC Used for Eligibility Threshold
CAS, Casualty Actuarial Society
CPI, Consumer Price Index

D, D-ratio
E, Experience Period Expected Ratable Loss
E(r), Undeveloped Excess Loss Ratio
Ee, expected excess ratable loss from experience Period
Ep, Expected Primary Ratable Loss From The Experience Period
ELAF, Excess Loss Adjustment Factor
ELF, Excess Loss Factor
ELR, Expected Loss Rate
ER, Experience Rating
ERA, Experience Rating Adjustment
G, G Value
GERT, Graduated Experience Rating Tables
HG, Hazard Group
IRRWG, Individual Risk Rating Working Group
k, Number of Quantiles
Mod, Experience Rating Modification Factor
n, Number of Risks in Data
NCCI, The National Council on Compensation Insurance
PCAS, Proceedings of the Casualty Actuarial Society
PY, Policy Year
r, Entry Ratio
RERP, Revised Experience Rating Plan
SACC, State Average Cost Per Case
SAL, State Accident Limit
SAWW, State Average Weekly Wage
SRP, State Reference Point
TX, Texas
W, Weight Value
WCSP, Workers Compensation Statistical Plan
y, Implied Expected Number of Claims
Ze, Excess Credibility
Zp, Primary Credibility

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The Optimal Number of Quantiles For Predictive Performance Testing of the NCCI Experience Rating Plan

Jon Evans and Curtis Gary Dean

Abstract

Motivation. Quantile testing is a key technique for fitting parameters and testing performance in workers compensation experience rating and the number of quantile intervals must be specified for such a test.

Method. A model is developed to compare the error in the quantile test empirical estimates of relative pure loss ratios to the interquantile differences between expected pure loss ratios. The ratio of these two quantities can be interpreted as a kind of noise-to-signal ratio which must be kept below a certain tolerance for the results of the quantile test to be sufficiently clear in a statistical sense. The formula for this ratio is a function of the random variation in individual risk loss ratios, a measure of the variation in experience modification (mod) values, the sample size of risks, and the number of quantiles. Theoretical model predictions are compared to empirical results from bootstrap quintile tests of the National Council on Compensation Insurance (NCCI) Experience Rating Plan (ERP). A generic type of individual risk credibility, though very different from the credibility values in the ERP, can be used to estimate the ratio of the standard deviation in individual risk loss ratios to a measure of variation in the mod values.

Results. The model predicts that the noise-to-signal ratio grows in proportion to the 1.5 power of the number of quantiles and in inverse proportion to the 0.5 power of the sample size of risks. Empirical quintile and decile tests of NCCI's Experience Rating Plan are consistent with model predictions.

Conclusions. Increasing the number of quantiles requires a much greater proportional increase in data volume to maintain a constant noise-to-signal ratio. Combined with the typical large magnitude of individual-risk loss process variance to loss parameter variance, this explains the use of few quantiles, specifically quintiles, for testing NCCI's Experience Rating Plan.

Keywords. Quantile Test, Quintile Test, Experience Rating, Workers Compensation, Predictive Modeling, Credibility, Lift, NCCI

1. INTRODUCTION

The National Council on Compensation Insurance (NCCI) Experience Rating Plan (ERP) is routinely tested by sorting risks based on experience modification factor (mod) values into *quintiles*, each containing an equal number of risks. A natural question is why specifically are quintiles, that is five *quantiles*, used to test the ERP. Naïve intuition would suggest that more quantiles would reveal more details about performance. However, like virtually all statistical tests, quantile testing attempts to uncover underlying systematic or signal information by filtering out random or noisy information. Using more quantiles affects both the signal and noise properties of each quantile. This paper will explain how a constraint on the relative size of noise to signal in the quantile test suggests criteria for selecting an optimal number of quantiles.

The content of this paper is primarily related to individual risk rating, predictive testing, and credibility. Although the application is to workers compensation specifically, the methods shown are generally applicable to predictive models of losses for individual risks in all lines of property and casualty insurance. The predictive testing of individual risk rating plans has been discussed previously in [4], [8], [12], and [17]. Specifics of the NCCI Experience Rating Plan can be found in [15].

1.1 Objective

This paper will provide a justification for selecting a given number of quantiles, or comparing different possible numbers of quantiles, for testing the ERP. No pretense is made of meeting the standards of mathematical rigor or rock solid logical derivation, but the model will follow from a sensible line of reasoning and whatever specific parameter values selected are intended for application with empirical data. Some model results will be shown to be reasonably consistent with patterns seen in some empirical quintile and decile tests, providing validation to the extent of practical use.

1.2 Outline

The remainder of the paper proceeds as follows. Section 2 will describe a noise-to-signal (N/S) model for the resolution of a quantile test. Section 3 shows how the properties of this model are consistently demonstrated in both empirical data and hypothetical examples. Appendix A will show a connection between the N/S ratio model and credibility.

2. BACKGROUND AND METHODS

The purpose of experience rating is to improve the estimate of future expected losses for an individual risk using previous actual loss experience for that risk. The basic underlying formula for the workers compensation experience rating modification factor is (2.1).

$$1 + Z_p \frac{A_p - E_p}{E} + Z_e \frac{A_e - E_e}{E} \tag{2.1}$$

A_p = actual primary ratable loss from the experience period

A_e = actual excess ratable loss from experience period

E_p = expected primary ratable loss from the experience period

E_e = expected excess ratable loss from experience period

$E = E_p + E_p$

Z_p = primary credibility

Z_e = excess credibility

Although there are many other refinements to this basic formula as used in the ERP, the mod essentially compares actual loss experience to manual expected losses. The Z_p and Z_e values, which vary by size of risk, determine the credibility assigned to experience. The prospective manual premium for a policy is multiplied by this mod value, which is always positive but may be greater or less than 1.0, as part of premium calculation.

2.1 Quintile Testing the Experience Rating Plan

Risks are sorted by mod value and based on this order split into five quintiles, each containing an equal number of risks. The performance of the ERP is tested by comparing relative pure loss ratios – the ratio of actual losses to expected losses – across the quintiles for the policy year to which the experience mod applies both before and after the mod is applied to manual expected losses. Several adjustments are made to reported actual losses and NCCI manual rates so that losses are on an ultimate basis and exclude both underwriting and loss adjustment expenses. A scale factor is also used to set total modified expected losses equal to total actual losses by risk hazard group within each state. This equalization isolates relative differences between risks, which the mod is designed to address, from issues of aggregate rate adequacy, which are addressed by manual rate levels.

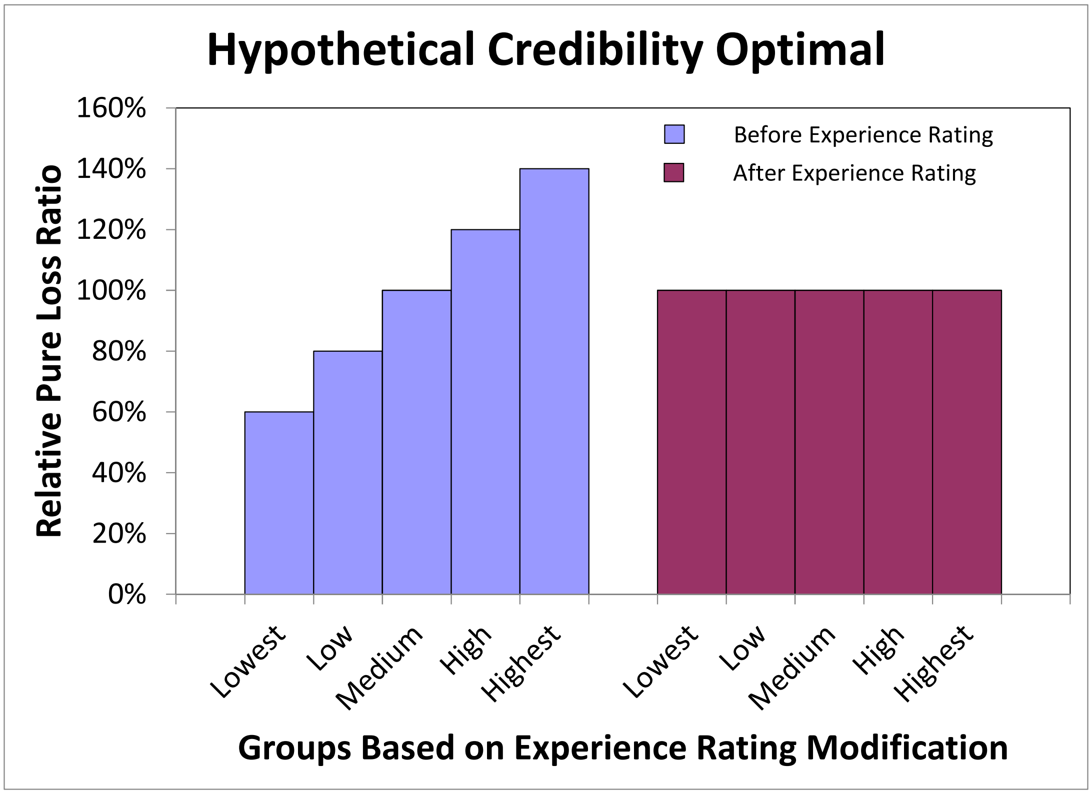
2.2 Lift and Equity

If the ERP can actually differentiate between risks then pure loss ratios calculated from manual rates should increase when moving from lower quintiles to higher quintiles. This increasing slope is called *lift*. The steeper the lift the more value the mod offers in differentiating risks.

Including the mod in the calculation of expected losses should result in nearly equal pure loss ratios, or *equity*, across quintiles if the ERP is working well and there is sufficient data in each quintile. This flatness of the relative modified pure loss ratios reveals how well the mod achieves equity between risks.

Figure 1 displays an idealized hypothetical example. The bars on the left side of the chart demonstrate the concept of lift. The mod is able to differentiate between risks and the slope shows the degree of differentiation between them. If risks were rated only on manual rates then risks in the quintiles to the left would produce more favorable underwriting results.

Figure 1: Experience Rating Plan Displaying Lift and Equity



The second set of bars in Figure 1 demonstrates that the combination of manual rates and the mod is equitable. The underwriting results are equal across the quintiles. Hence underwriting results are the same for risks with different mod values.

Figure 2 displays a hypothetical ERP with considerable lift as seen by the bars on the left side. The five bars on the right side demonstrate that the mod has not fully corrected for predictable differences in manual loss ratios. The rating plan does not charge risks with high mods enough and overcharges risks with lower mods. This inequity is generally the result of not assigning enough credibility to individual risk experience. In contrast, Figure 3 displays a hypothetical ERP that over corrects for predictable differences – this generally results from assigning too much credibility to individual risk experience.

Figure 2: Experience Rating Plan That Undercompensates for Experience

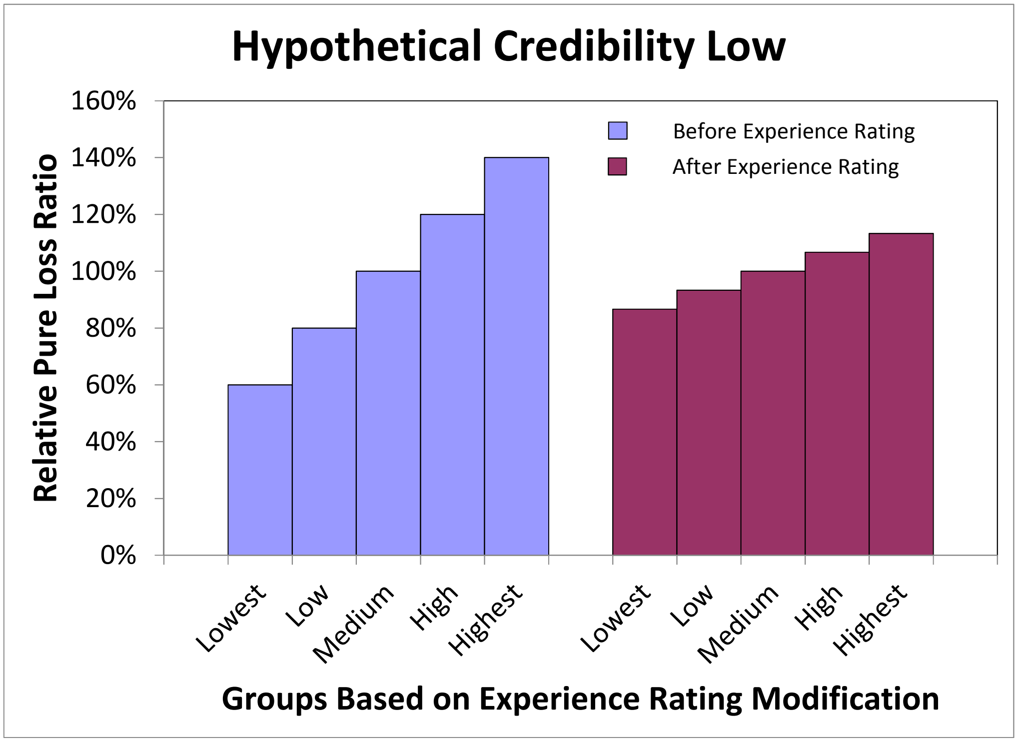
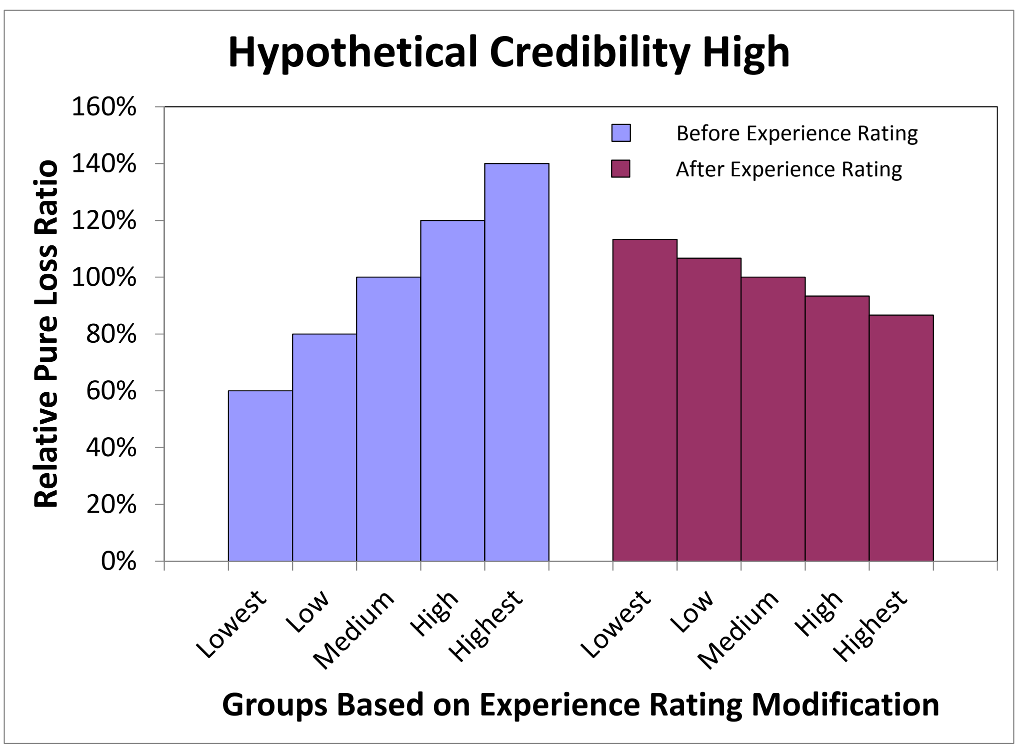


Figure 3: Experience Rating Plan That Overcompensates for Experience



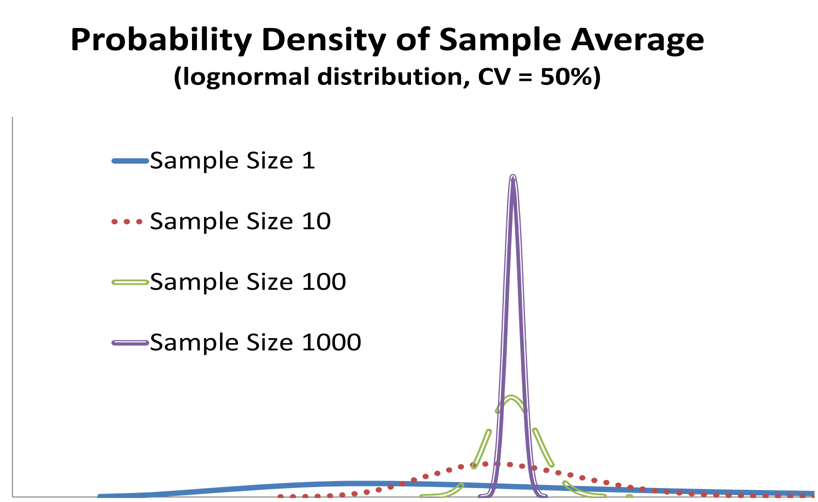
In cases where specific measures are needed to quantify how effectively the ERP is finding lift and achieving equity, the NCCI considers two statistics. The older quintile test statistic is B^*/A^*, where A^* is the variance of the un-modified quintile pure loss ratios and B^* is the variance of the modified quintile pure loss ratios: the variance in the pure loss ratios after application of the modification factors is divided by the variance in the pure loss ratios at manual rates. This traditional statistic measures equity or, perhaps more correctly, the movement towards equity with the ERP. Ideally it should be as close to zero as possible. Note that B^*/A^* would be zero for Figure 1 because B^*, the variance in the modified quintile loss ratios, is zero for this hypothetical example.

The newer quintile test statistic is $\text{sign}(A\text{-}B)\,|A\text{-}B|^{0.5}$, where A and B are equivalent to A^* and B^*, but may be calculated to include some extra variance due to bootstrapping the test, as will be discussed in Section 3.1. This newer statistic measures how effectively the ERP is at finding lift and achieving equitable workers compensation rating. Ideally it should be as large as possible. Using this new test statistic, Figure 1 trumps Figures 2 and 3 because all three have the same value for A but B takes on the smallest possible value of zero for Figure 1.

2.3 Sample Size and the Central Limit Theorem

The Central Limit Theorem says that the sum or average of a large number of independent random variables will be approximately Normal. Even a highly skewed distribution such as the pure loss ratio for an individual risk will tend towards a Normal distribution if an average is computed over many risks. Figure 4 illustrates this concept.

Figure 4: The Central Limit Theorem in Action



To simplify the discussion, assume that pure loss ratios for risks are independently and identically distributed with mean μ and variance σ^2 and that each risk has the same expected loss. σ^2/n is the variance and $\sigma/\sqrt{n}$ is the standard deviation in the overall pure loss ratio for a bin containing n homogeneous risks. As can be seen in Figure 4, the decreasing variance as n increases results in a tighter curve clustered around the expected value.

The practical implication of this is that we expect for both manual and modified pure loss ratios the random observation error will be proportional to $1/\sqrt{n}$. Although the assumptions about homogeneity of risks are far from perfectly met in the real world, the departure will generally not cause this $1/\sqrt{n}$ relationship to lose its practical value.

2.4 Systematic Differences Versus Random Variation

Individual quantiles should contain enough data so that the random variation of the manual pure loss ratios within quantiles is small compared to systematic differences in the underlying expected manual pure loss ratios between quantiles. As another hypothetical example, suppose that risks with mods uniformly distributed on the interval [0.80, 1.00) are compared to risks with mods uniformly distributed on the interval [1.00, 1.20). Figures 5a and 5b show, for interval sample sizes 1 and 100, respectively, hypothetical distributions for manual loss ratios for risks uniformly distributed across these two intervals, assuming individual risk loss ratios are lognormally distributed with mean equal to the mod value and 0.50 standard deviation.

Random Outcomes versus Systematic Differences

Figure 5a

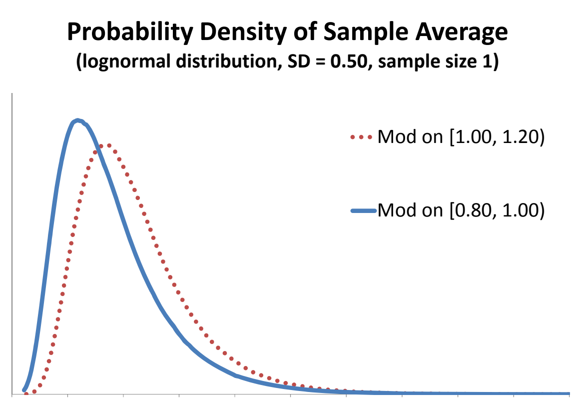
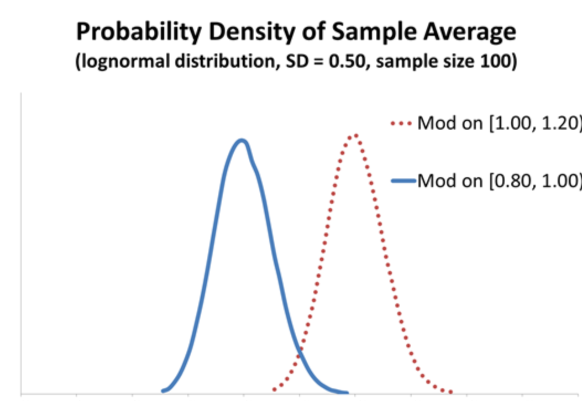


Figure 5b



Note the substantial overlap in the distributions of actual pure loss ratios in the Figure 5a. There is a fair chance that the actual ratio for a risk from [0.80, 1.00) will exceed that for a risk from [1.00, 1.20), which would give misleading results about mod performance. One might conclude that the mod cannot effectively distinguish the loss potential of individual risks. If there are more risks in each interval, as in Figure 5b, then the distinction is almost certainly shown in the observed loss ratios.

The systematic difference between the two previous intervals can be quantified as the differences between their midpoints of 0.90 and 1.10. Assuming that there are enough risks in the intervals so that the resulting distributions are approximately Normal, standard deviations of manual loss ratios are a good way to characterize random variation. The choice of how small the random variation must be compared to the systematic difference is fairly subjective but not impractically ambiguous, as will be demonstrated in the next sections.

2.5 Tradeoffs in Determining the Number of Quantiles

More quantiles provide a more detailed look at how the plan is performing all along the range of mod values. However, more quantiles will increase the random variation within each quantile because a fixed number of risks will be split into fewer risks per quantile. Worse still, more quantiles will simultaneously decrease the systematic differences between adjacent quantiles.

Figure 6: Splitting Into More Intervals

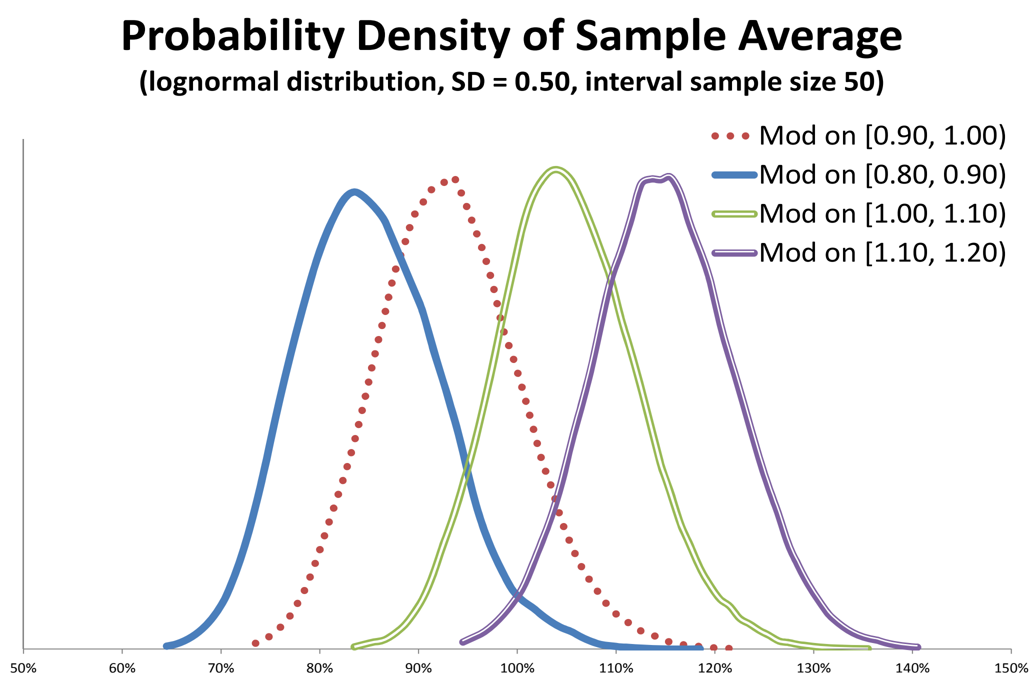


Figure 6 shows an idealized view of the dilemma. Here, we revisit the example from Figure 5b, breaking up the two intervals, each with 100 sampled risks into four intervals, each with 50 sampled risks. First, note that we can safely ignore the contribution of variance of the mod within an interval to the variance of the loss ratio. The variance of the mod within the original 2 intervals of width 0.20 was 0.003 and for the split intervals of width 0.10 was 0.0008, trivial compared to the conditional variance of 0.25 for the loss ratio. So, there will be an increase of about 41% in the standard deviation of the overall loss ratio due to smaller sample size. Simultaneously, the distance between the midpoints of the adjacent intervals has been cut in half. Consequently, the ratio of random variation to systematic variation in Figure 6 is about 282% of what it was in Figure 5b.

2.6 Noise-to-Signal Ratio

It is conceptually useful to think of random variation in observed loss ratios as *noise* and the systematic difference between the means of adjacent bins as *signal*. The ratio of random to systematic variation, that we previously alluded to, is explicitly defined and referred to as the *noise-to-signal ratio* (N/S) in (2.2).

$$\text{N/S} = \frac{\text{Standard deviation of random variations for an interval loss ratio}}{\text{Difference in expected loss ratios between intervals}} = \frac{Noise}{Signal} \tag{2.2}$$

All other things equal this ratio should be as small as possible. Figure 7 graphically illustrates the significance of noise-to-signal ratios using a Normal distribution model.

Figure 7: Noise-to-Signal For Normal Distributions

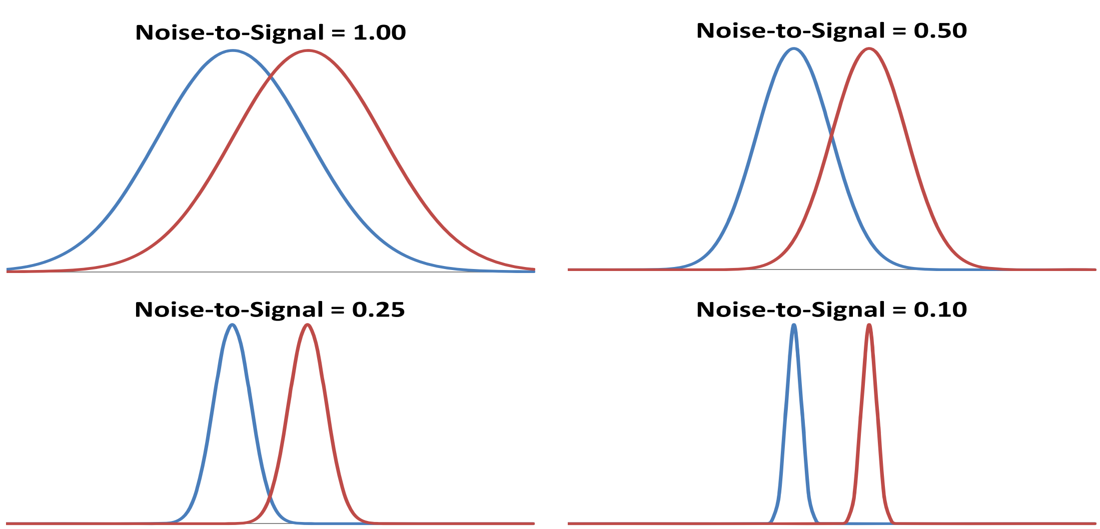


Table 1 shows the probabilities of reversals for a Normal distribution model. By reversal we mean that the observed loss ratio for the higher interval is actually lower than the observed loss ratio for the lower interval.

Table 1: Noise-to-Signal Ratios and Ordering of Pure Loss Ratios

Noise-to-Signal Ratio	Probability of Reversal
1.00	0.2398
0.50	0.0786
0.25	0.0023
0.10	7.69×10^{-13}

A reasonable tolerance for the N/S ratio might be selected at 0.25. So, the "optimal" number of quantiles is beginning to emerge. If we can estimate the N/S ratio as a function of the number of quantiles, then the maximum number of quantiles within our N/S tolerance will be that "optimal" number.

2.7 The Number of Quantiles and Data Requirements

To address the question of the number of quantiles the N/S signal ratio can be estimated by a formula in terms of the following quantities:

b = number of quantiles

σ^2 = variance of the manual pure loss ratio for a single risk

n = number of risks tested

R = a constant corresponding to the "spread" or "variation" of mods

We will assume risks are all the same size. This is a reasonable simplifying starting assumption, but in reality risk sizes and the variances of their loss ratios span across orders of magnitude for the ERP. The resulting formula will be validated, or invalidated, for the general context using empirical data.

The standard deviation for the loss ratio in a single quantile will be $\sigma / \sqrt{n/b} = \sqrt{b}\left(\sigma / \sqrt{n}\right)$. Again, we will ignore variation in the loss ratio due to mod difference within quantiles, as this usually contributes a very small part of the total random variation.

If there are more quantiles then the differences between the expected values for the mods of adjacent quantiles is smaller. If the number of bins is doubled then these differences should be approximately cut in half. A reasonable rule of thumb is that the typical difference is inversely proportional to b, that is equal to $R\ /\ b$.

Putting the pieces above together the N/S ratio formula leads to (2.3).

$$\text{N/S} = \frac{\sqrt{b}(\sigma/\sqrt{n})}{(R/b)} = \frac{\sigma}{R}\left(\sqrt{\frac{b^3}{n}}\right) \tag{2.3}$$

Solving for sample size n leads to (2.4).

$$n = \frac{(\sigma/R)^2}{(\text{N/S})^2} b^3 \tag{2.4}$$

Equation (2.4) shows, among other relations, that the amount of data needed increases as the cube of the number of quantiles: $n \propto b^3$. The ERP is currently tested using a quintile test. A decile test would require 8 times as much data for a comparable N/S ratio. Similiarly, a test with twenty quantiles would require 64 times as much data.

3. RESULTS AND DISCUSSION

3.1 Bootstrapping Empirical Data Demonstrates Effects of Number of Quantiles

To measure the noise associated with the relative pure loss ratios in a quintile test, NCCI bootstraps the underlying data. The data set of risks used for a particular test is resampled with replacement 100 times. Each time the quintile test loss ratios are recalculated. A candlestick chart illustrates the 5th, 25th, 75th, and 95th percentiles of the bootstrapped relative pure loss ratios. The vertical spread of the quintile bars is indicative of the noise in the test and the difference in the vertical location between adjacent candles is indicative of the signal in the test. Consider the following bootstrap quintile and decile tests for policy year 2010:

- Figures 8a and 8b are countrywide, which includes 886,976 individual risks.
- Figures 9a and 9b, are countrywide for risks whose policy period expected pure loss ranges from 1k to 10k, which includes 467,887 individual risks.
- Figures 10a and 10b, are countrywide for risks whose policy period expected pure loss

ranges from 100k to 1m, which includes 18,692 individual risks.

- Figures 11a and 11b, are for a large state, which includes 62,629 individual risks.
- Figures 12a and 12b, are for a small state, which includes 10,943 individual risks.

Figure 8a: Countrywide Quintile Test

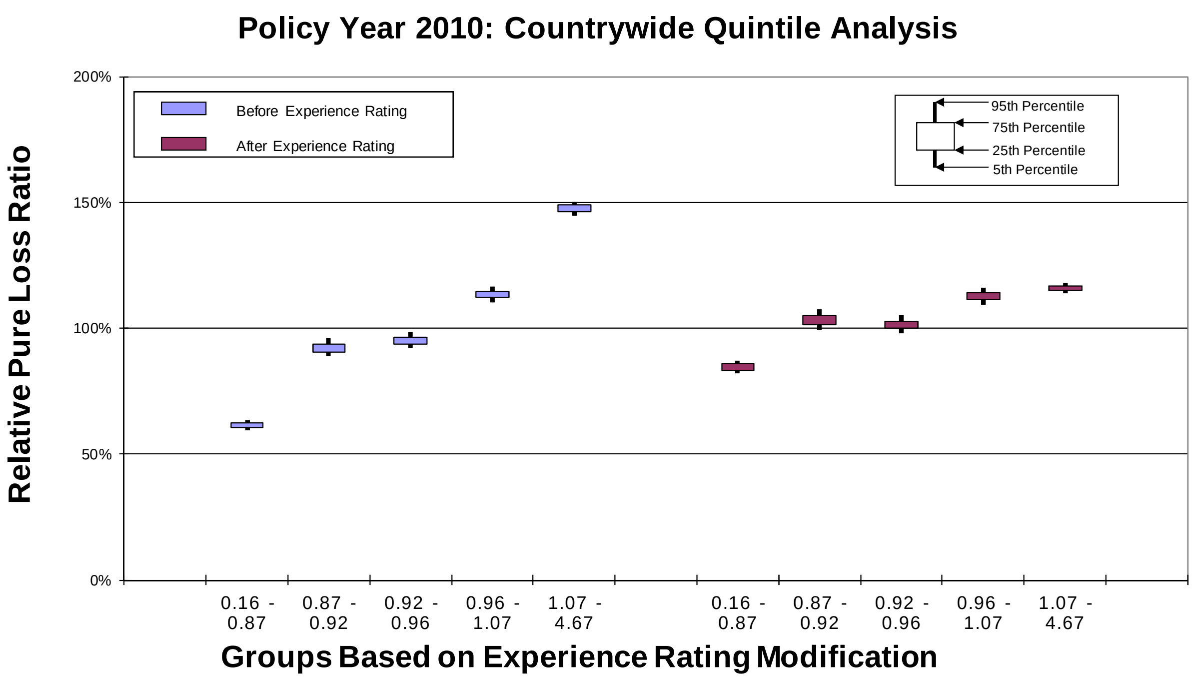
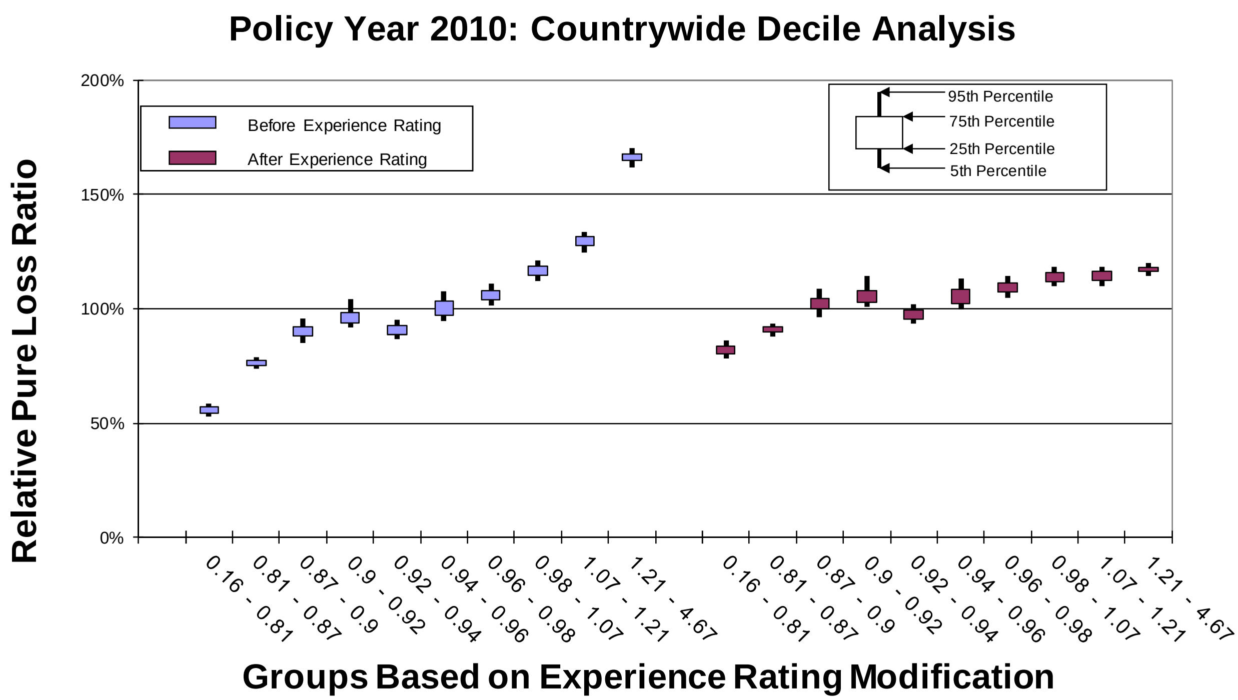


Figure 8b: Countrywide Decile Test



Figures 9a: Countrywide Small Risk Quintile Test

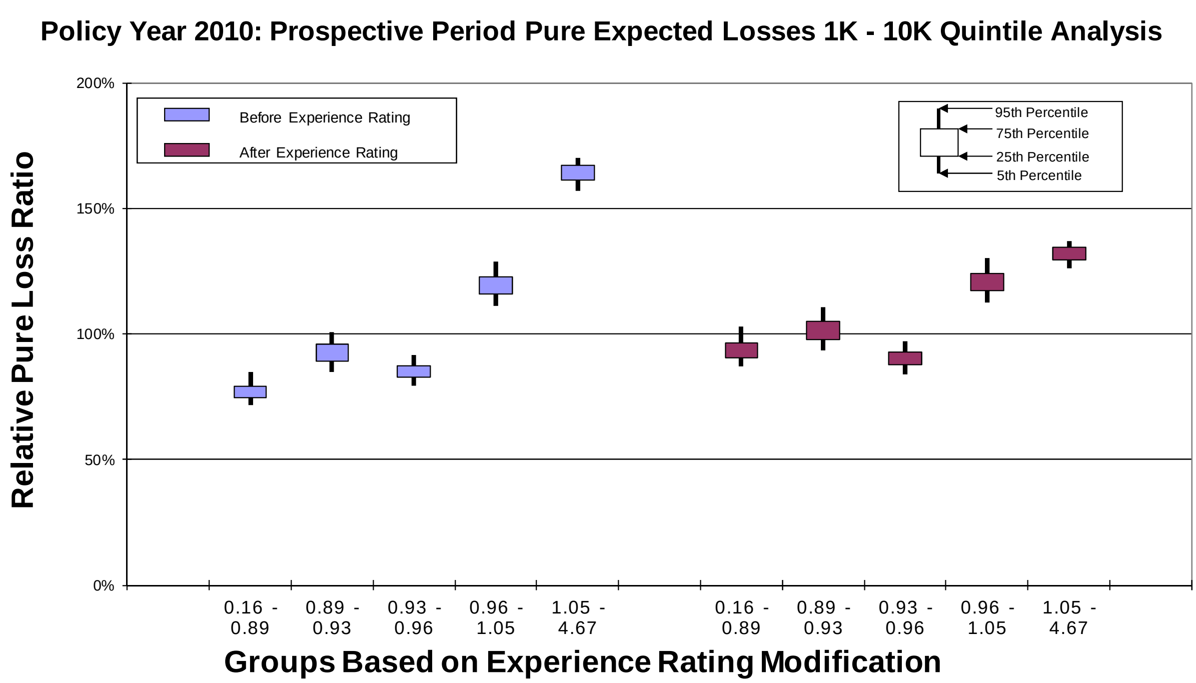
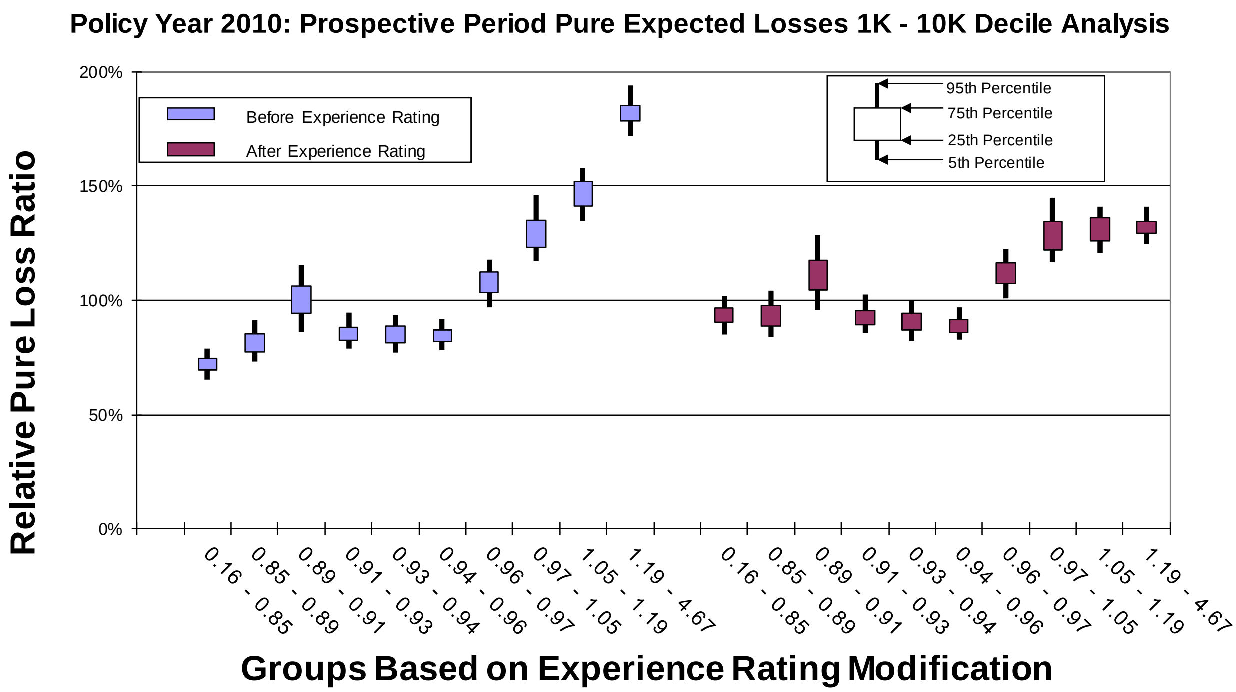


Figure 9b: Countrywide Small Risk Decile Test



Figures 10a: Countrywide Large Risk Quintile Test

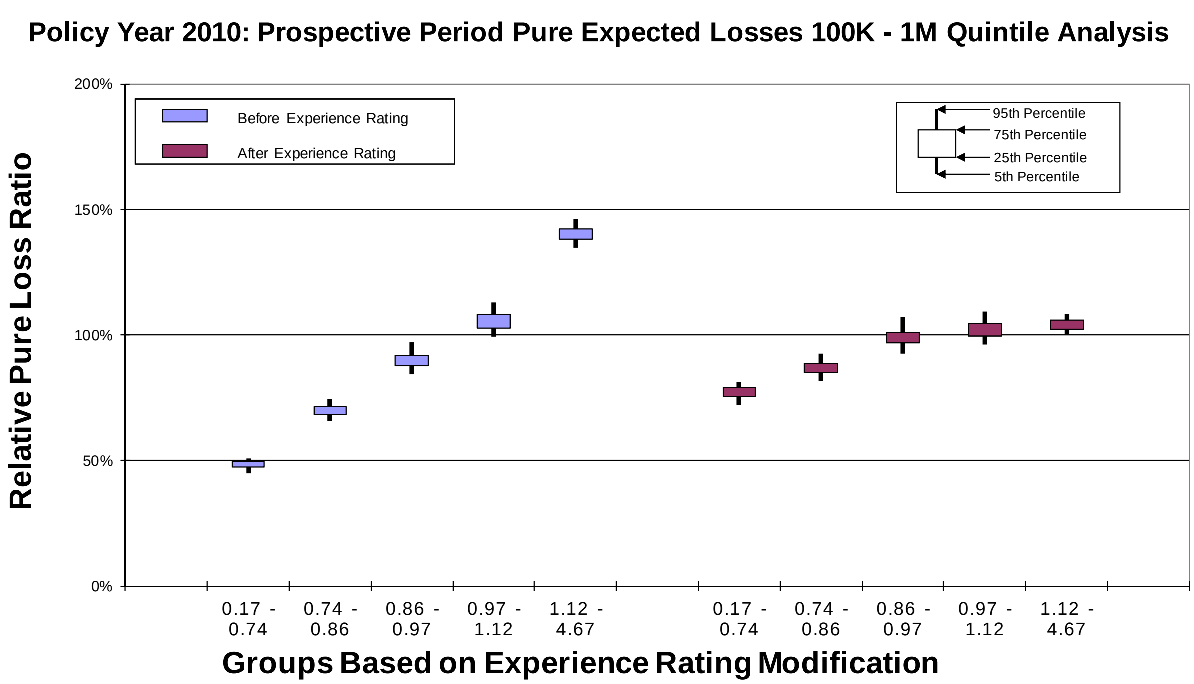
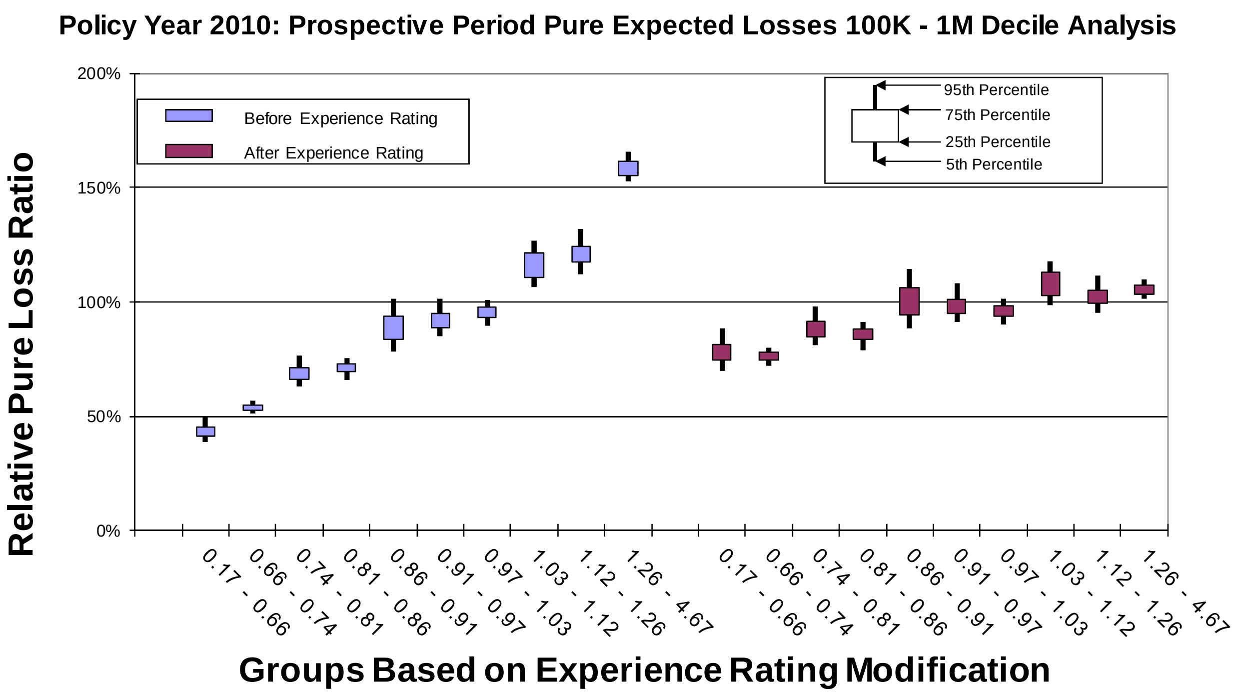


Figure 10b: Countrywide Large Risk Decile Test



Figures 11a: Large State Quintile Test

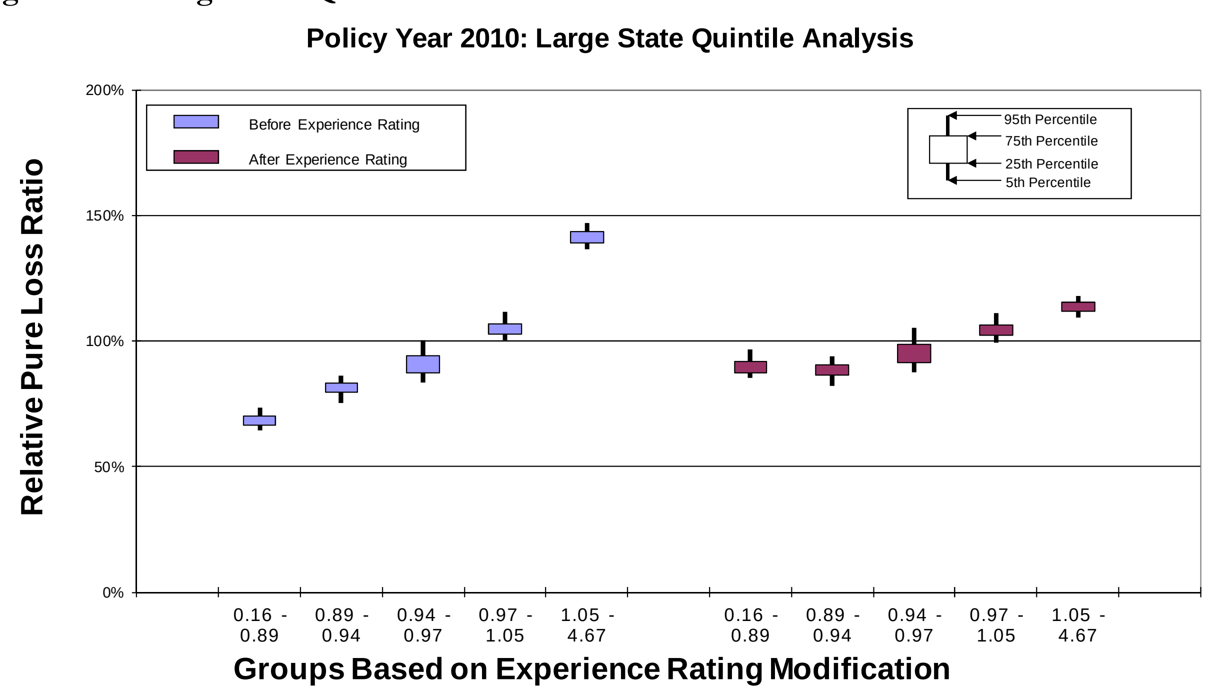
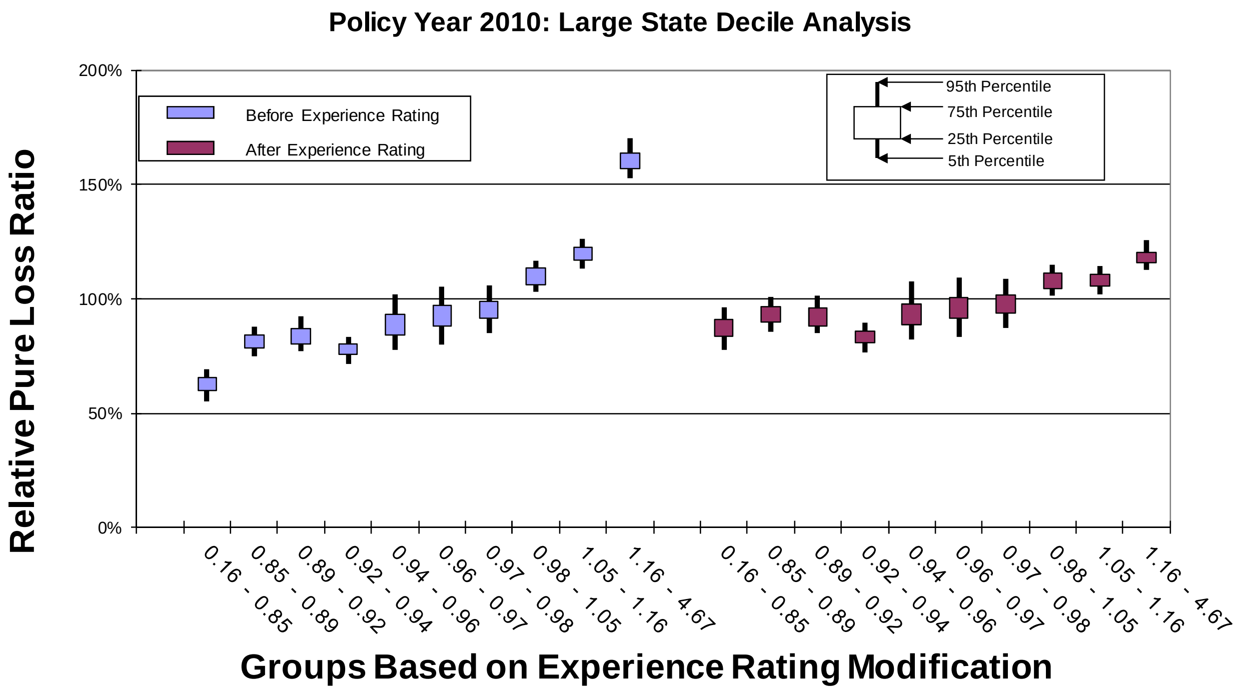


Figure 11b: Large State Decile Test



Figures 12a: Small State Quintile Test

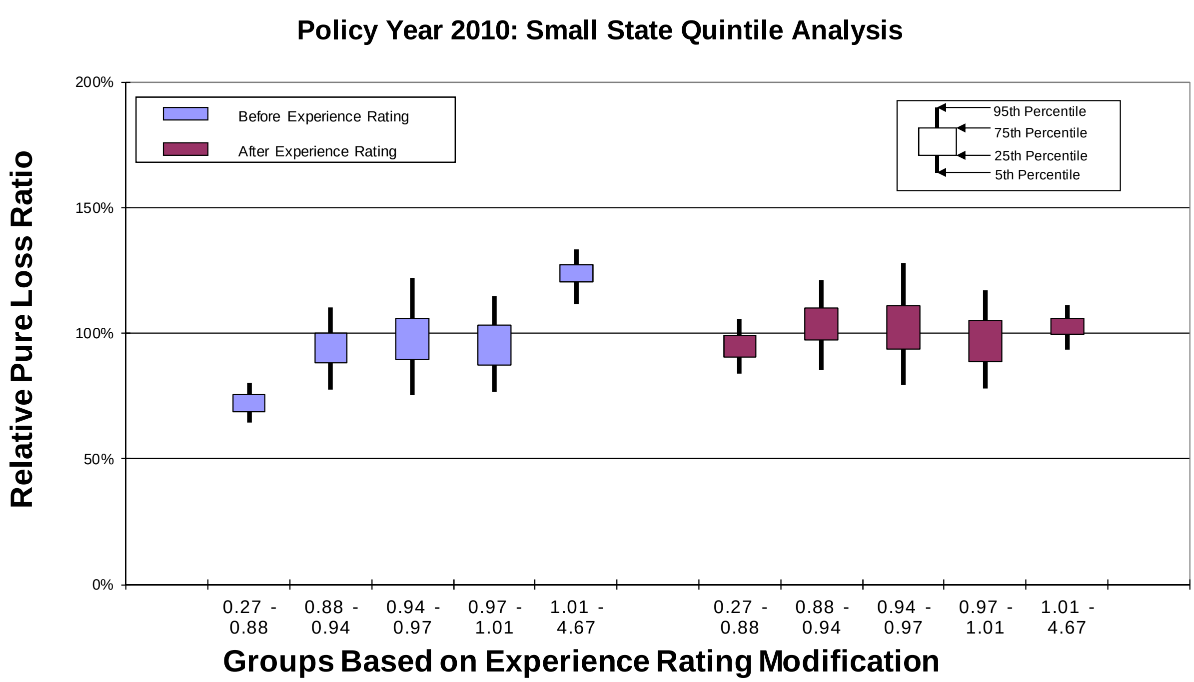
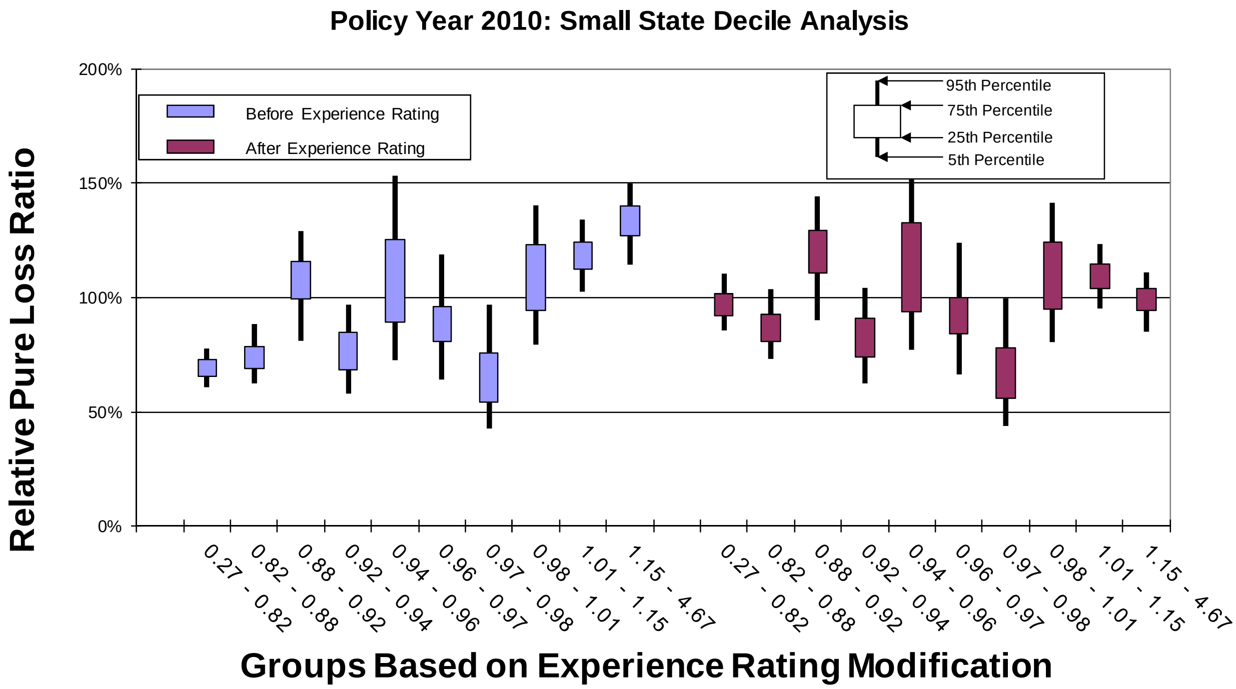


Figure 12b: Small State Decile Test



Comparison between the quintile and decile tests illustrates the three-fold increase in N/S ratio predicted by the model. Since the N/S ratio should also change in proportion to $1/\sqrt{n}$, where n is the number of risks, all other things equal (which they are not), we would expect the N/S to increase going from Figures 8 to Figures 11 to Figures 12. In fact, such a pattern is clearly evident. However, between tests using the same number of quantiles but different data, the random variation in the loss ratio per individual risk may vary, and will certainly decrease going from the small risks in Figures 9 to the large risks in Figures 10. Another thing that can change as the underlying data set changes is the typical signal difference between the quantiles.

The general consistency between the patterns observed in these charts and what we expect from the N/S ratio model provides a reasonable validation of the model as a practical tool.

The slight positive slopes seen in most of the empirical quintile and decile tests for policy year 2010 highlight the need for increased effective credibility that prompted NCCI's increases in the split point beginning in 2013, from \$5,000 to \$10,000 in year one, \$13,500 in year two, and \$15,000 plus two years of inflation adjustment in year three. Further routine increases based on severity indexation will follow.

3.2 Measuring Lift and Equity

At the end of section 2.2, two statistics were introduced: (1) B^*/A^* (smaller is better) is a measure of how effectively the ERP achieves equity, and (2) $\text{sign}(A\text{-}B)|A\text{-}B|^{0.5}$ (larger is better) is a combination measure that increases with more lift, A is larger, and increases with more equity, B is smaller. A^* is the variance of the un-modified pure loss ratios and B^* is the variance of the modified pure loss ratios across the quantile groups. The quantities without the * are similar quantities but may include some additional variance from bootstrapping.

Table 2 displays these statistics for the 2010 policy year data that was used to create the prior ten bootstrapping charts. The first column of numbers, B^*/A^*, shows that the ERP makes considerable progress towards achieving equity because the variance in pure loss ratios is much smaller for the modified pure loss ratios than the un-modified pure loss ratios. For example, the variance in the countrywide modified pure loss ratio quintiles is only 14.9% of the variance in the unmodified quintiles. The second column shows that the ERP is finding lift and moving towards more equitable rating.

Table 2: Statistical Measures of Lift and Equity

		Statistics	
		B^*/A^*	$\text{sign}(A\text{-}B)\lvert A\text{-}B\rvert^{0.5}$
Countrywide	Quintile	0.149	0.261
Countrywide	Decile	0.140	0.265
Countrywide Small Risks	Quintile	0.265	0.272
Countrywide Small Risks	Decile	0.259	0.284
Countrywide Large Risks	Quintile	0.105	0.296
Countrywide Large Risks	Decile	0.107	0.309
Large State	Quintile	0.144	0.232
Large State	Decile	0.150	0.239
Small State	Quintile	0.044	0.157
Small State	Decile	0.474	0.155

3.3 Noise-to-Signal Ratio

The noise-to-signal ratio (N/S) was introduced in equation (2.2) of section 2.6.

$$\text{N/S} = \frac{\text{Standard deviation of random variations for an interval loss ratio}}{\text{Difference in expected loss ratios between intervals}} = \frac{\textit{Noise}}{\textit{Signal}} \tag{2.2}$$

Although an explicit formula for calculating noise-to-signal ratios was presented in equation (2.3), the ratios can also be estimated by bootstrapping empirical data as done in section 3.1. Noise-to-signal ratios corresponding to the bootstrapping results used to create the charts in section 3.1 are displayed in Table 3. As expected, the noise-to-signal ratios are significantly higher for deciles than quintiles. The last column of the table displays the ratio of noise-to-signal ratios for deciles to those of quintiles.

Equation (2.3) shows that N/S $\propto \sqrt{b^3}$ where b is the number of quantiles. Comparing deciles and quantiles with this proportionality yields a value not too far from those in the last column of Table 3.

$$\text{N/S Deciles} \div \text{N/S Quintiles} = \sqrt{10^3} \div \sqrt{5^3} = \sqrt{2^3} = 2.83\ .$$

The theoretical value 2.83 is somewhat greater than values in the table because the experience modification factors spread out in the two tails of the mod distribution. This would not happen if the mods were uniformly distributed over a range.

Table 3: Bootstrapped Estimates of Noise-to-Signal Ratios

	Noise - to - Signal		N/S Decile /
	Quintile	Decile	N/S Quintile
Countrywide (C/W)	0.086	0.229	2.67
C/W $1K - $10K	0.203	0.499	2.46
C/W $100K - $1,000K	0.128	0.354	2.75
Large State	0.192	0.482	2.51
Small State	0.748	1.973	2.64

3.4 Some Hypothetical Examples

Appendix A develops the rule of thumb, shown in (3.1), to estimate σ/R in terms of the credibility Z for an individual risk loss ratio. This is particularly useful, as Z can act as a reasonable measure of risk size, though not on a proportional scale.

$$\frac{\sigma}{R} = \sqrt{\frac{1/Z^2 - 1}{12}} \tag{3.1}$$

However, before progressing too far we must recall that in principle a Z credibility value such as this, although it includes useful information about σ/R, is qualitatively very different from the Z_p and Z_e values found in the experience rating. This Z value would:

1. Estimate the true underlying mean for a single policy year using that policy year's losses, rather than using prior policy years' experience to predict the true mean for a future policy year,
2. Cover all losses unlimited, and
3. Use only one year of losses.

So, much caution must be used in attempting to apply it to the very different situation of the

ERP. Unfortunately, there is no clear way to relate Z to the readily available, but fundamentally very different, Z_p and Z_e. More generally, there is probably no good way to determine such a Z that would directly apply to the context of the NCCI ERP. Statement 1 suggests Z should be higher than Z_p, but 2 and 3 suggest Z should lower than Z_p. Since higher Z implies lower σ/R and hence lower N/S it is prudent to err on the side of a lower Z. So, on balance, it is not unreasonable to speculate that Z should be on the same order as Z_p, but somewhat lower, perhaps $Z \approx Z_p / 2$. Ultimately, any N/S model resulting from whatever relationship we may assume can be validated, or invalidated, using empirical data along the lines we followed in Section 3.1. Table 4 explores what different values for Z, n, and b imply for the N/S ratio.

Table 4: Noise-to-Signal By Z Credibility

Noise to Signal <= 0.25 shaded

Z Credibility = 50%

	Sample Size-->				
Quantiles	100	1,000	10,000	100,000	1,000,000
2	0.14	0.04	0.01	0.00	0.00
5	0.56	0.18	0.06	0.02	0.01
10	1.58	0.50	0.16	0.05	0.02
20	4.47	1.41	0.45	0.14	0.04
100	50.00	15.81	5.00	1.58	0.50

Z Credibility = 25%

	Sample Size-->				
Quantiles	100	1,000	10,000	100,000	1,000,000
2	0.32	0.10	0.03	0.01	0.00
5	1.25	0.40	0.13	0.04	0.01
10	3.54	1.12	0.35	0.11	0.04
20	10.00	3.16	1.00	0.32	0.10
100	111.80	35.36	11.18	3.54	1.12

Z Credibility = 10%

	Sample Size-->				
Quantiles	100	1,000	10,000	100,000	1,000,000
2	0.81	0.26	0.08	0.03	0.01
5	3.21	1.02	0.32	0.10	0.03
10	9.08	2.87	0.91	0.29	0.09
20	25.69	8.12	2.57	0.81	0.26
100	287.23	90.83	28.72	9.08	2.87

Z Credibility = 5%

	Sample Size-->				
Quantiles	100	1,000	10,000	100,000	1,000,000
2	1.63	0.52	0.16	0.05	0.02
5	6.45	2.04	0.64	0.20	0.06
10	18.23	5.77	1.82	0.58	0.18
20	51.58	16.31	5.16	1.63	0.52
100	576.63	182.35	57.66	18.23	5.77

The formulas for Z_e and Z_p vary by state and over time, according to a fairly complicated formula that is a function of experience period expected losses, rather than policy period pure expected losses. However, the values in Table 4 would be roughly in the ballpark for recent years.

The conjecture $Z \approx Z_p / 2$ together with Table 5 suggest that Z would be around 3% to 20% for Figures 9 and around 40% to 45% for Figures 10.

Table 5: Approximate Recent ERP Credibility By Risk Size

Policy Period Pure Premium	Approximate Recent ERP Credibility Z_p	Z_e
1,000	5%	0%
10,000	40%	2%
100,000	80%	10%
1,000,000	90%	40%

Next recall that Figure 9 had a sample size approaching half a million risks and Figure 10 had a sample size a bit under 20,000. From Table 4 we can see that both Figures 9 and 10 would be expected to be well within the acceptable N/S for the quintile. The deciles test would be expected to be around the maximum N/S ratio. This is roughly the situation we see in the charts and therefore $Z \approx Z_p / 2$, although not founded in any sort of solid mathematics or logic, is still empirically validated to be in the ballpark and therefore practically useful within broad limits.

4. CONCLUSIONS

The number of quantiles selected for a meaningful test of predictive performance of the NCCI Experience Rating Plan is constrained by the ratio of noise-to-signal. If this ratio is not kept below a reasonable threshold, which is subjective but can be sensibly selected somewhere in the neighborhood of 0.25, the results of the quantile test will be unclear. In a sense the "optimal" number of quantiles is the largest number that produces a N/S ratio under this threshold. The N/S ratio is proportional to the standard deviation of observed loss ratios for individual risks and the 1.5 power of the number of quantiles. The N/S ratio is inversely proportional to the variation in mod values and the square root of the number of risks in the data. Consequently, the data required to maintain a given N/S ratio is proportional to the cubic power of the number of quantiles. This huge data penalty in test resolution for increasing the number of quantiles explains the use of a relatively small number of quantiles, exactly five in the quintile test, for testing the NCCI Experience Rating Plan. These and other implications of this N/S ratio can be demonstrated consistently for both empirical tests of the ERP and hypothetical examples.

Appendix A

A Connection Between Noise-to-Signal Ratio and Credibility

Suppose a single credibility Z value, which can be any value in (0%, 100%) not necessarily based on any sound credibility model, is used on the total unlimited policy year loss ratio L to estimate a non-predictive individual risk modification factor. That is, a risk's actual loss ratio in a single year is used to estimate its own true mean loss ratio for that same year. The sample variance in such a mod would be (A.1).

$$\begin{aligned}
&\frac{1}{n-1}\sum_{i=1}^{n}[Z\,L_i + (1-Z)\overline{L} - (Z\,\overline{L} + (1-Z)\overline{L})]^2 \\
&= \frac{Z^2}{n-1}\sum_{i=1}^{n}(L_i - \overline{L})^2 \\
&= Z^2\hat{\sigma}_L^2
\end{aligned} \tag{A.1}$$

where $\hat{\sigma}_L^2$ is the actual sample variance of the observed loss ratios. The remaining or "random" part of the sample variance is (A.2).

$$\left(1 - Z^2\right)\hat{\sigma}_L^2 \tag{A.2}$$

Although a quantile test would be meaningless in this non-predictive situation, we can estimate a ratio σ / R in the N/S formula (2.3). (A.2) can be used as an estimate of σ^2 and (A.1) can be used to derive an estimate for *R*. As a simplification, assume that mods are effectively uniformly distributed across an interval of width *R*. For a uniform distribution the difference between the means of mods in adjacent quantiles, or signal, where mods are split into *b* quantiles would be R / b. This is the key property of R as used in (2.3). Equating the variance expression for a uniform distribution with (A.1) leads to (A.3).

$$\frac{R^2}{12} = Z^2\hat{\sigma}_L^2 \tag{A.3}$$

This would lead to (A.4).

$$\frac{\sigma}{R} = \frac{\sqrt{(1 - Z^2)\ \hat{\sigma}_L^2}}{\sqrt{12\, Z^2 \hat{\sigma}_L^2}} = \sqrt{\frac{1/Z^2 - 1}{12}} \qquad \text{(A.4)}$$

Assuming a uniform distribution of mods (A.4) corresponds implicitly to (A.5).

$$R = \sqrt{12}\ \sigma_{Mod} \qquad \text{(A.5)}$$

(A.5) will certainly not hold true in general, but it is worth noting how it compares to a decile test of hypothetical mods lognormally distributed around mean 1.00 with standard deviation 0.10, as shown in Table A1. (A.5) predicts that *R* would be 0.346 and the difference between adjacent quantiles would be 0.035 in this situation.

Table A1: Differences between decile means for a lognormal distribution with mean 1.00 and standard deviation 0.10

Decile	Mean	Difference
1st	0.836	
2nd	0.897	0.061
3rd	0.930	0.033
4th	0.957	0.027
5th	0.983	0.025
6th	1.008	0.025
7th	1.034	0.027
8th	1.065	0.030
9th	1.104	0.040
10th	1.186	0.082

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Abbreviations and notations

C/W, countrywide
ERP, experience rating plan
Mod, experience modification factor
NCCI, National Council on Compensation Insurance
N/S, noise-to-signal ratio
A, A^*, variance of un-modified quintile pure loss ratios
B, B^*, variance of modified quintile pure loss ratios
b, number of quantiles
L, unlimited policy year loss ratio for a risk
n, number of risks
R, spread in modification factor values
σ^2, variance in pure loss ratio for one risk
$\hat{\sigma}_L^2$, actual sample variance of observed loss ratios
Z_p, primary credibility for an experience rated risk
Z_e, excess credibility for an experience rated risk
Z, credibility for an individual risk

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