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Stochastic Loss Reserving with Bayesian MCMC Models

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The CAS Loss Reserve Database Created by Meyers and Shi

With Permission of American NAIC

- Schedule P (Data from Parts 1-4) for several US Insurers
  - Private Passenger Auto
  - Commercial Auto
  - Workers' Compensation
  - General Liability
  - Product Liability
  - Medical Malpractice (Claims Made)
- Available on CAS Website

  http://www.casact.org/research/index.cfm?fa=loss_reserves_data

Illustrative Insurer – Incurred Losses

		Cumulative Incurred Losses										
Premium	AY/Lag	1	2	3	4	5	6	7	8	9	10	Source
5812	1988	1722	3830	3603	3835	3873	3895	3918	3918	3917	3917	1997
4908	1989	1581	2192	2528	2533	2528	2530	2534	2541	2538	2532	1998
5454	1990	1834	3009	3488	4000	4105	4087	4112	4170	4271	4279	1999
5165	1991	2305	3473	3713	4018	4295	4334	4343	4340	4342	4341	2000
5214	1992	1832	2625	3086	3493	3521	3563	3542	3541	3541	3587	2001
5230	1993	2289	3160	3154	3204	3190	3206	3351	3289	3267	3268	2002
4992	1994	2881	4254	4841	5176	5551	5689	5683	5688	5684	5684	2003
5466	1995	2489	2956	3382	3755	4148	4123	4126	4127	4128	4128	2004
5226	1996	2541	3307	3789	3973	4031	4157	4143	4142	4144	4144	2005
4962	1997	2203	2934	3608	3977	4040	4121	4147	4155	4183	4181	2006

Illustrative Insurer – Paid Losses

		Cumulative Paid Losses										
Premium	AY/Lag	1	2	3	4	5	6	7	8	9	10	Source
5812	1988	952	1529	2813	3647	3724	3832	3899	3907	3911	3912	1997
4908	1989	849	1564	2202	2432	2468	2487	2513	2526	2531	2527	1998
5454	1990	983	2211	2830	3832	4039	4065	4102	4155	4268	4274	1999
5165	1991	1657	2685	3169	3600	3900	4320	4332	4338	4341	4341	2000
5214	1992	932	1940	2626	3332	3368	3491	3531	3540	3540	3583	2001
5230	1993	1162	2402	2799	2996	3034	3042	3230	3238	3241	3268	2002
4992	1994	1478	2980	3945	4714	5462	5680	5682	5683	5684	5684	2003
5466	1995	1240	2080	2607	3080	3678	4116	4117	4125	4128	4128	2004
5226	1996	1326	2412	3367	3843	3965	4127	4133	4141	4142	4144	2005
4962	1997	1413	2683	3173	3674	3805	4005	4020	4095	4132	4139	2006

Criteria for a "Good" Stochastic Loss Reserve Model

- Using the upper triangle "training" data, predict the distribution of the outcomes in the lower triangle
  - Can be observations from individual (AY, Lag) cells or sums of observations in different (AY,Lag) cells.

Criteria for a "Good" Stochastic Loss Reserve Model

- Using the predictive distributions, find the percentiles of the outcome data.
- The percentiles should be uniformly distributed.
  - Histograms
  - PP Plots and Kolmogorov Smirnov Tests

Plot Expected vs Predicted Percentiles

KS 95% critical values = 19.2 for n = 50 and 9.6 for n = 200

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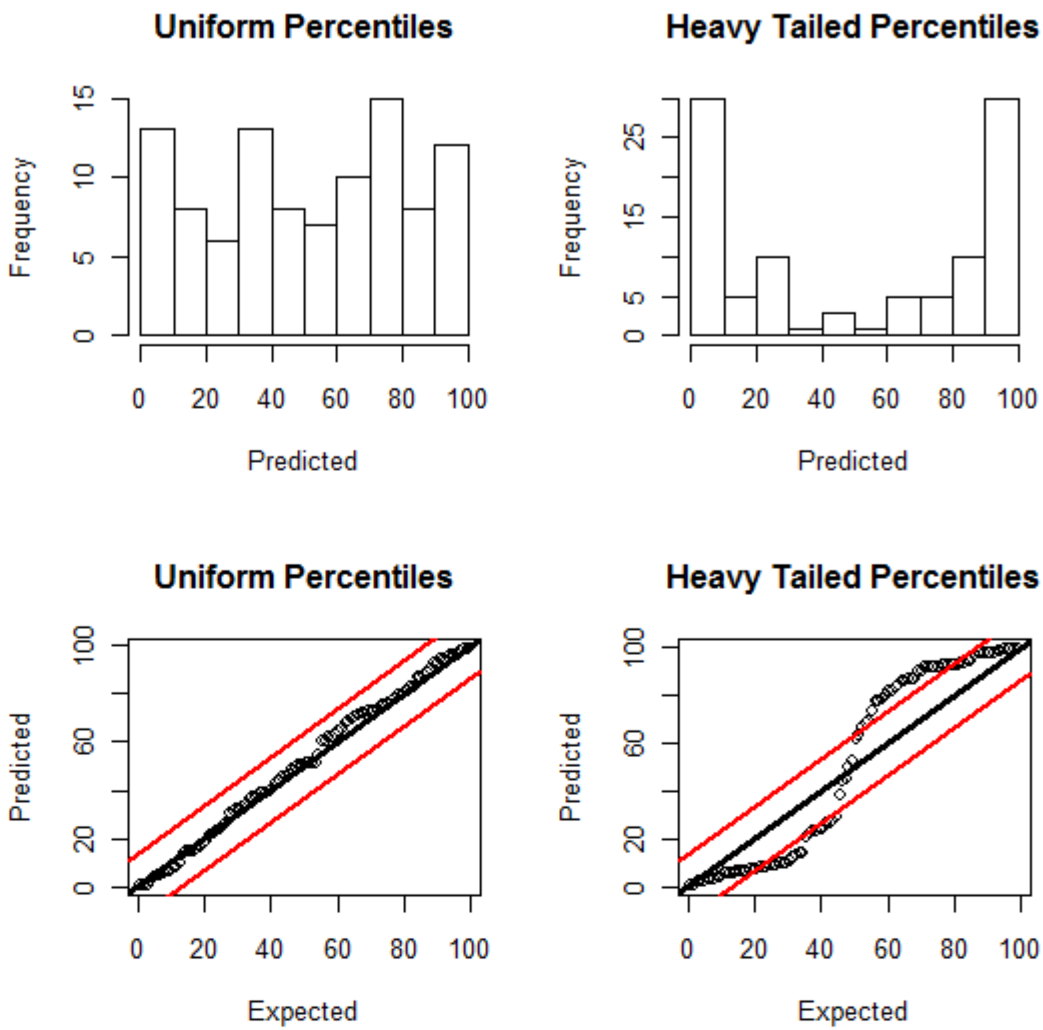
Illustrative Tests of Uniformity



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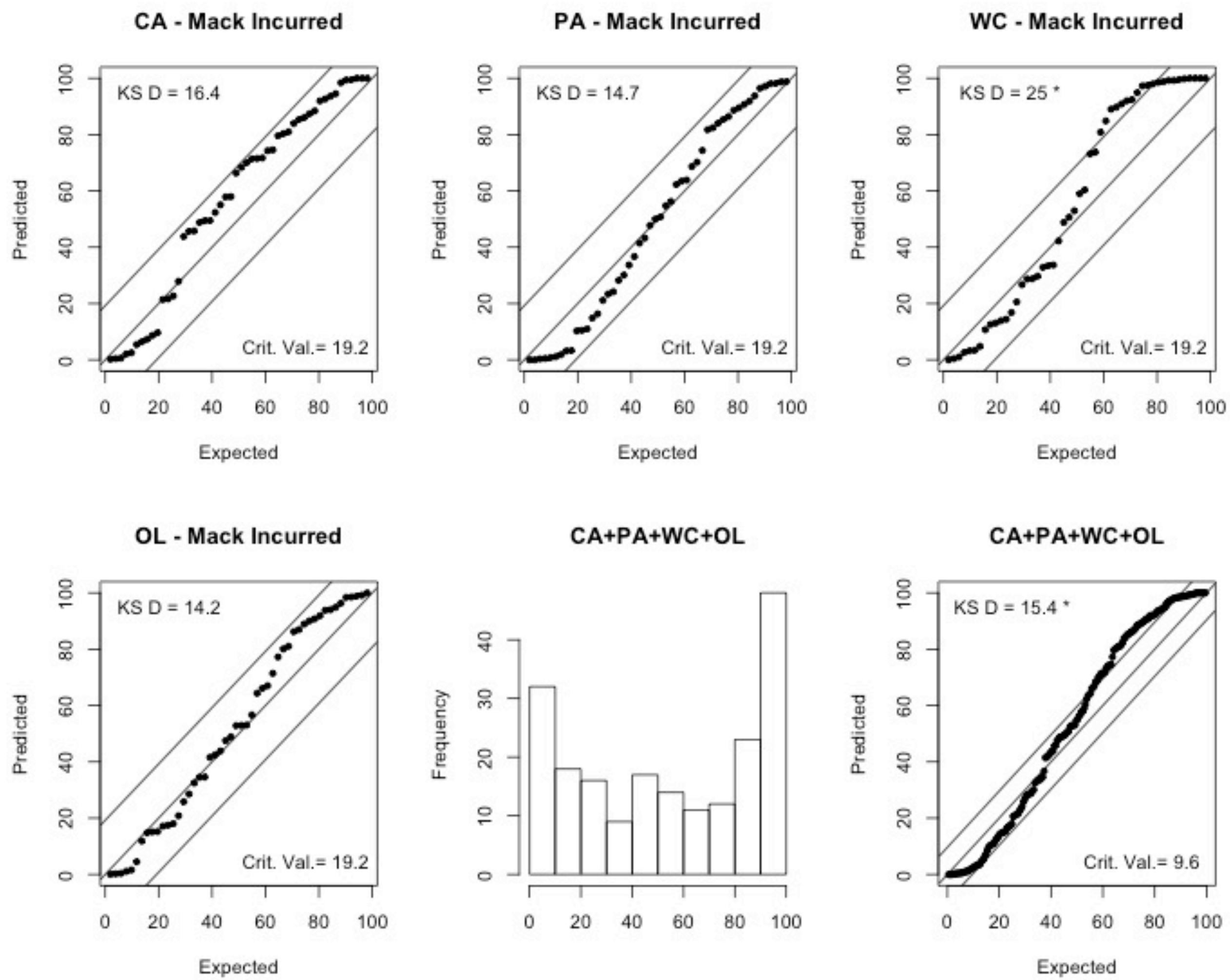
Data Used in Study

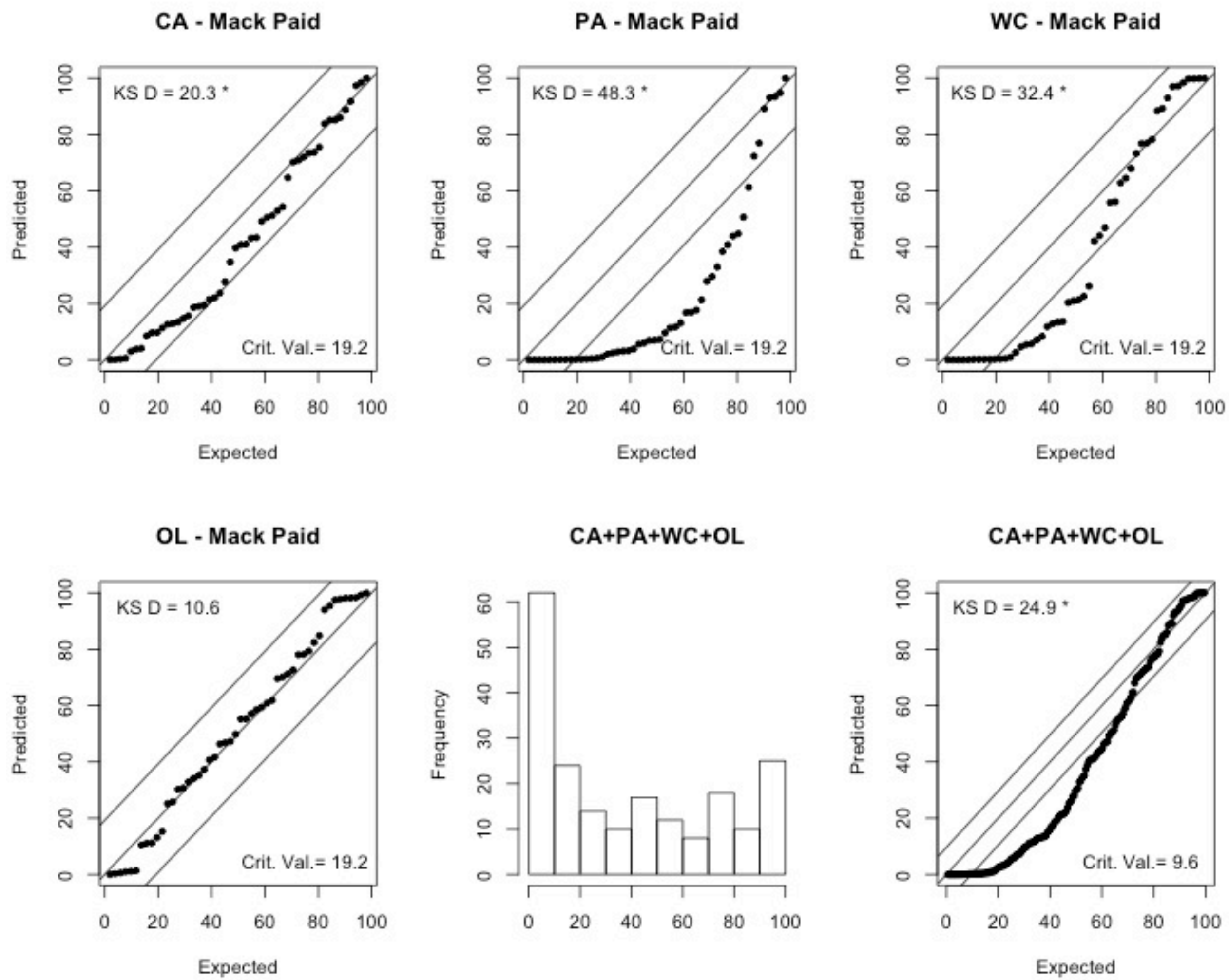
- List of insurers available from me.
- 50 Insurers from four lines of business
  - Commercial Auto
  - Personal Auto
  - Workers' Compensation
  - Other Liability
- Criteria for Selection
  - All 10 years of data available
  - Stability of earned premium and net to direct premium ratio
- Both paid and incurred losses

Test of Mack Model on Incurred Data



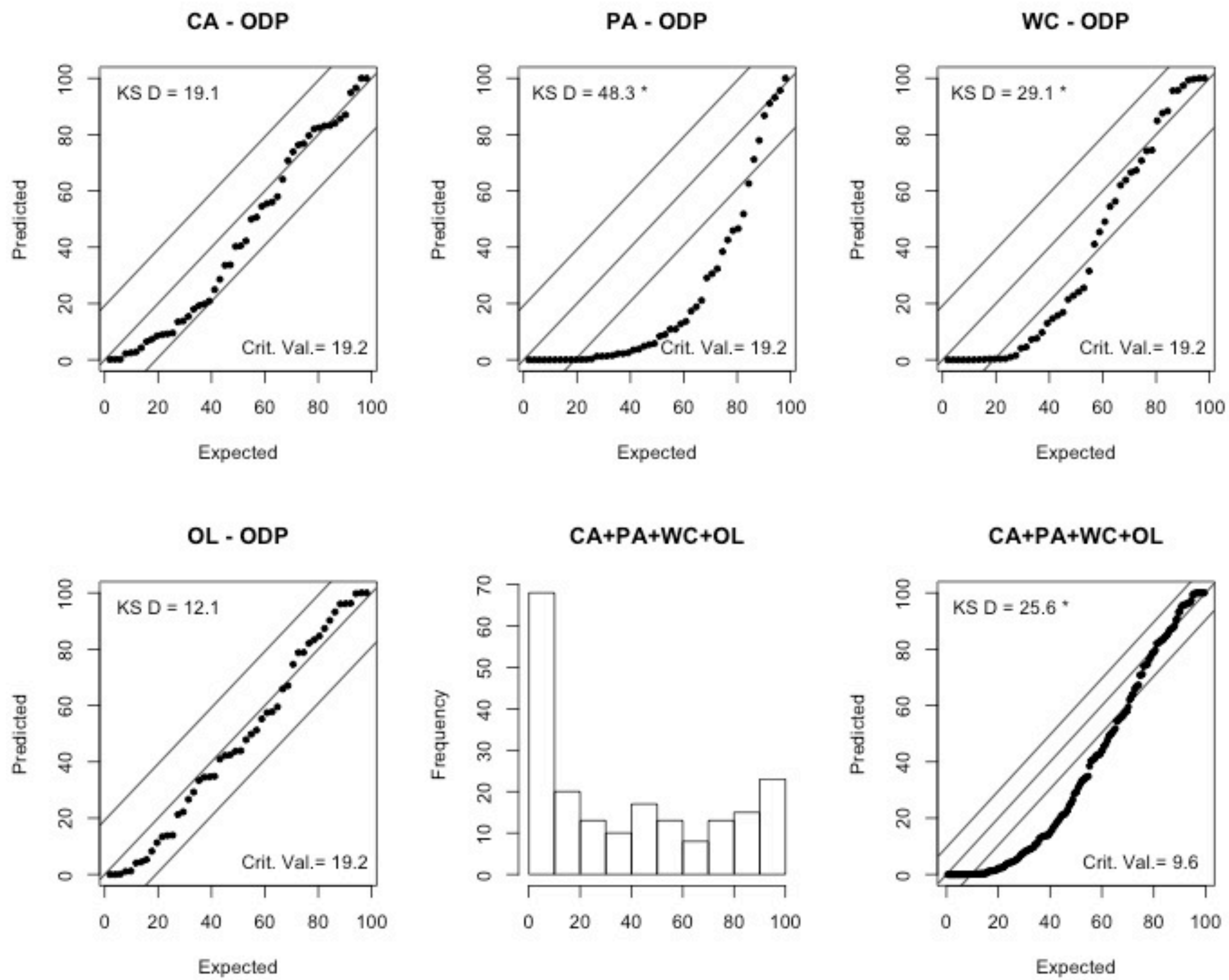
Conclusion – The Mack model predicts tails that are too light.

Test of Mack Model on Paid Data



Conclusion – The Mack model is biased upward.

Test of Bootstrap ODP on Paid Data



Conclusion – The Bootstrap ODP model is biased upward.

Possible Responses to the Model Failures

- The "Black Swans" got us again!
  - We do the best we can in building our models, but the real world keeps throwing curve balls at us.
  - Every few years, the world gives us a unique "black swan" event.
- Build a better model.
  - Use a model, or data, that sees the "black swans."

Proposed New Models are Bayesian MCMC

- Bayesian MCMC models generate arbitrarily large samples from a posterior distribution.
- See the limited attendance seminar tomorrow at 1pm.

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Notation

- w = Accident Year $w = 1,\ldots,10$
- d = Development Year $d = 1,\ldots,10$
- $C_{w,d}$ = Cumulative (either incurred or paid) loss
- $I_{w,d}$ = Incremental paid loss $= C_{w,d} – C_{w-1,d}$

Bayesian MCMC Models

- Use R and JAGS (Just Another Gibbs Sampler) packages
- Get a sample of 10,000 parameter sets from the posterior distribution of the model
- Use the parameter sets to get 10,000, $\sum_{w=1}^{10} C_{wd}$, simulated outcomes
- Calculate summary statistics of the simulated outcomes
  - Mean
  - Standard Deviation
  - Percentile of Actual Outcome

The Correlated Chain Ladder (CCL) Model

- *logelr* ~ uniform(-5,0)
- α_w ~ normal(log(Premium$_w$)+*logelr*,$\sqrt{10}$)
- $\beta_{10} = 0$, β_d ~ uniform(-5,5), for d=1,…,9
- a_i ~ uniform(0,1)
- $\sigma_d = \sum_{i=d}^{10} a_i$ Forces σ_d to decrease as d increases
- $\mu_{1,d} = \alpha_1 + \beta_d$
- $C_{1,d}$ ~ lognormal($\mu_{1,d}$, σ_d)
- ρ_d ~ uniform(-1,1)
- $\mu_{w,d} = \alpha_w + \beta_d + \rho_d \cdot (\log(C_{w-1,d}) - \mu_{w-1,d})$ for w = 2,…,10
- $C_{w,d}$ ~ lognormal($\mu_{w,d}$, σ_d)

Predicting the Distribution of Outcomes

- Use JAGS software to produce a sample of 10,000 $\{\alpha_w\}$, $\{\beta_d\}$, $\{\sigma_d\}$ and $\{\rho\}$ from the posterior distribution.
- For each member of the sample
  - $\mu_{1,10} = \alpha_1 + \beta_{10}$
  - For w = 2 to 10
    - $C_{w,10} \sim \text{lognormal}\,(\alpha_w + \beta_{10} + \rho_d \cdot (\log(C_{w-1,10}) - \mu_{w-1,10})), \sigma_{10})$
  - Calculate $\sum_{w=1}^{10} C_{w,10}$
- Calculate summary statistics, e.g. $E\left[\sum_{w=1}^{10} C_{w,10}\right]$ and $Var\left[\sum_{w=1}^{10} C_{w,10}\right]$
- Calculate the percentile of the actual outcome by counting how many of the simulated outcomes are below the actual outcome.

The First 5 of 10,000 Samples on Illustrative Insurer with $\rho_d = \rho$

Done in JAGS

	MCMC Sample Number				
	1	2	3	4	5
α_1	8.2763	8.2452	8.2390	8.2591	8.2295
α_2	7.8226	7.7812	7.8008	7.8048	7.7810
α_3	8.2625	8.3200	8.2929	8.2883	8.2642
α_4	8.3409	8.3286	8.3539	8.3622	8.3159
α_5	8.2326	8.1166	8.1093	8.1855	8.1523
α_6	8.1673	8.0307	8.0491	8.1727	8.0470
α_7	8.6403	8.4776	8.4113	8.5815	8.4871
α_8	8.2177	8.2488	8.2708	8.0752	8.1763
α_9	8.3174	8.2007	8.2589	8.3744	8.2653
α_{10}	7.4101	8.0036	8.7584	8.4241	8.8420
β_1	-0.5125	-0.5180	-0.6504	-0.4947	-0.7384
β_2	-0.2756	-0.1014	-0.1231	-0.2138	-0.0844
β_3	-0.1271	-0.0313	-0.0622	-0.0758	-0.0498
β_4	-0.1013	-0.0090	0.0165	0.0439	0.0479
β_5	0.0518	-0.0109	0.0060	0.0034	0.0610
β_6	0.0180	0.0885	0.0139	0.0175	0.0709
β_7	0.0105	0.0583	0.0205	0.0427	0.0362
β_8	0.0400	-0.0090	0.0612	0.0444	0.0338
β_9	0.0005	0.0287	0.0419	0.0116	0.0333
β_{10}	0.0000	0.0000	0.0000	0.0000	0.0000
σ_1	0.3152	0.2954	0.3164	0.1895	0.2791
σ_2	0.2428	0.1982	0.2440	0.1858	0.1711
σ_3	0.1607	0.1632	0.2078	0.1419	0.1089
σ_4	0.1245	0.1133	0.0920	0.0842	0.0800
σ_5	0.0871	0.0830	0.0694	0.0747	0.0794
σ_6	0.0733	0.0649	0.0626	0.0508	0.0463
σ_7	0.0324	0.0281	0.0294	0.0368	0.0352
σ_8	0.0279	0.0247	0.0172	0.0270	0.0330
σ_9	0.0171	0.0239	0.0130	0.0267	0.0329
σ_{10}	0.0170	0.0237	0.0105	0.0241	0.0244
ρ	0.1828	0.4659	0.4817	0.1901	0.2155

Done in R

$\mu_{1,10}$	8.2763	8.2452	8.2390	8.2591	8.2295
$C_{1,10}$	3917	3917	3917	3917	3917
$\widetilde{\mu}_{2,10}$	7.8221	7.7942	7.8172	7.8074	7.7904
$\widetilde{C}_{2,10}$	2520	2468	2480	2432	2453
$\widetilde{\mu}_{3,10}$	8.2643	8.3278	8.2924	8.2862	8.2674
$\widetilde{C}_{3,10}$	3893	4190	3939	4090	3802
$\widetilde{\mu}_{4,10}$	8.3414	8.3345	8.3474	8.3679	8.3107
$\widetilde{C}_{4,10}$	4229	4212	4233	4346	4075
$\widetilde{\mu}_{5,10}$	8.2341	8.1219	8.1109	8.1873	8.1527
$\widetilde{C}_{5,10}$	3761	3285	3269	3597	3676
$\widetilde{\mu}_{6,10}$	8.1670	8.0192	8.0400	8.1728	8.0593
$\widetilde{C}_{6,10}$	3450	3127	3120	3552	3196
$\widetilde{\mu}_{7,10}$	8.6365	8.4910	8.4140	8.5819	8.4893
$\widetilde{C}_{7,10}$	5488	4719	4441	5299	4765
$\widetilde{\mu}_{8,10}$	8.2129	8.2340	8.2634	8.0739	8.1720
$\widetilde{C}_{8,10}$	3652	3847	3933	3295	3708
$\widetilde{\mu}_{9,10}$	8.3156	8.2106	8.2655	8.3794	8.2752
$\widetilde{C}_{9,10}$	4112	3538	3949	4426	3914
$\widetilde{\mu}_{10,10}$	7.4112	7.9853	8.7659	8.4271	8.8414
$\widetilde{C}_{10,10}$	1613	3001	6511	4507	6763

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The Correlated Chain Ladder Model Predicts Distributions with Thicker Tails

- Mack uses point estimations of parameters.
- CCL uses Bayesian estimation to get a posterior distribution of parameters.
- Chain ladder applies factors to last ***fixed*** observation.
- CCL uses ***uncertain*** "level" parameters for each accident year.
- Mack assumes independence between accident years.
- CCL allows for correlation between accident years,
  - $Corr[\log(C_{w\text{-}1,\mathrm{d}}),\log(C_{w,d})] = \rho_d$

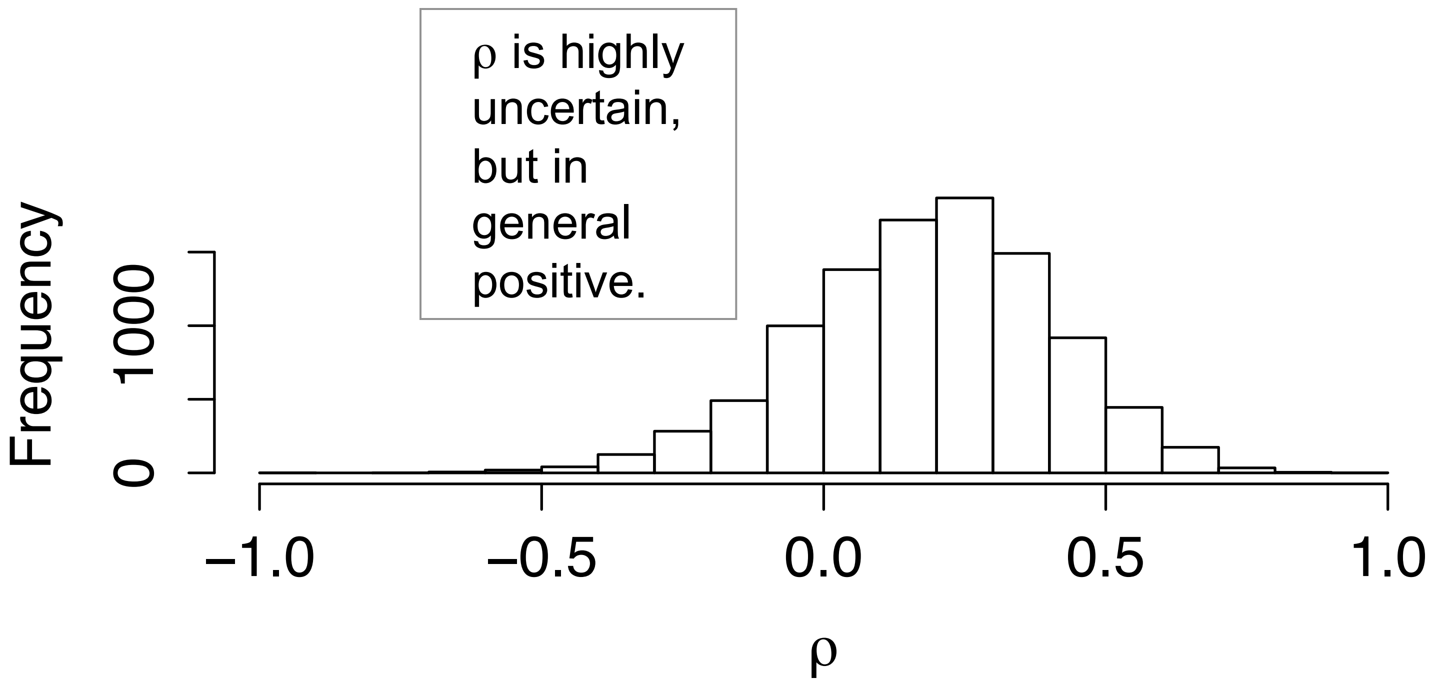
Examine Three Behaviors of ρ_d

1. $\rho_d = 0$ - Leveled Chain Ladder (LCL)

2. $\rho_d = \rho \sim$ uniform (-1,1) (CCL)

3. $\rho_d = r_0 \bullet \exp(r_1 \bullet (d-1))$ (CCL Variable ρ)
   - $r_0 \sim$ uniform (0,1)
   - $r_1 \sim$ uniform $(-\log(10) - r_0, -\log(r_0)/9)$
   - This makes ρ_d monotonic $\in (0,1)$

Case 2 - Posterior Distribution of ρ for Illustrative Insurer



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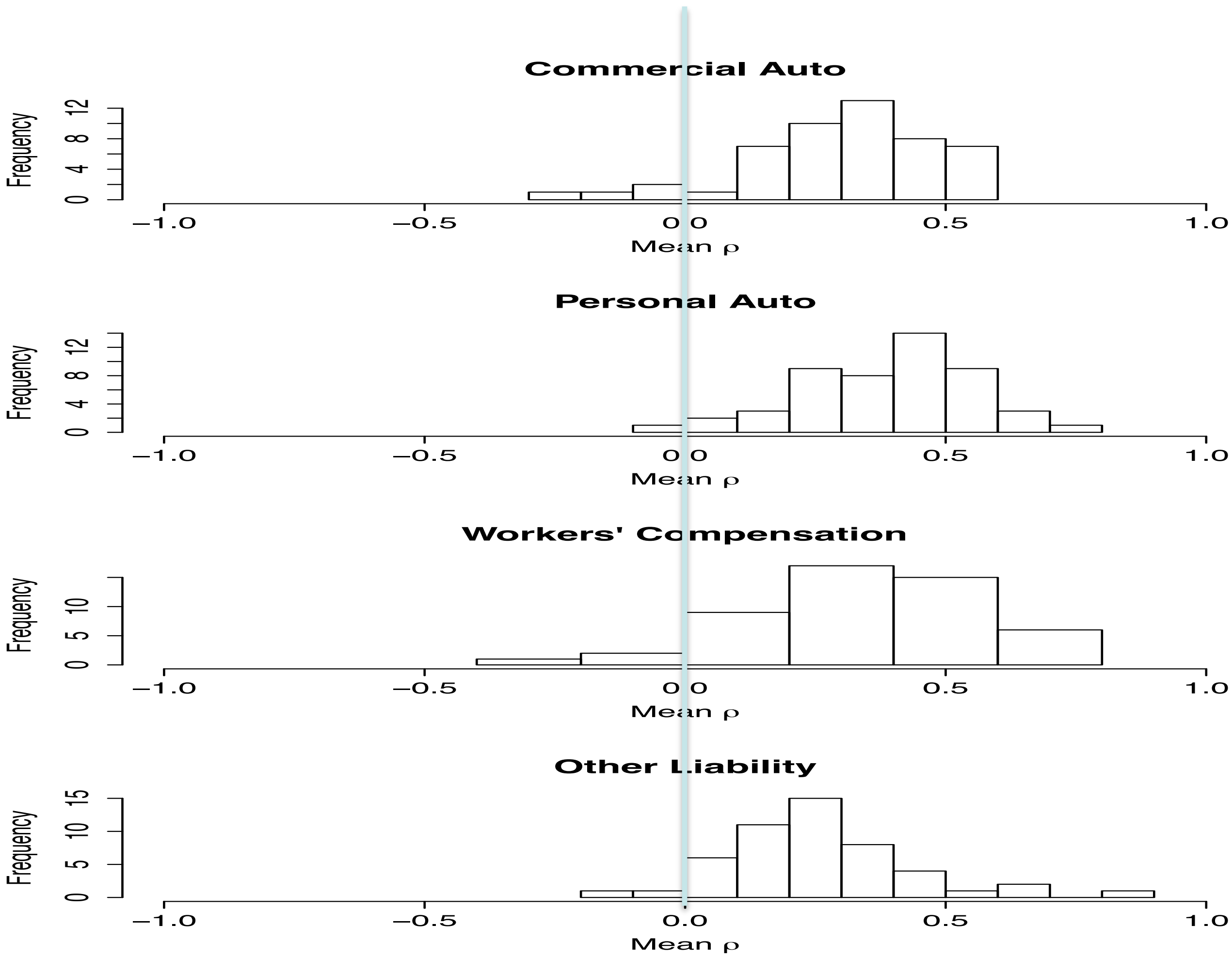
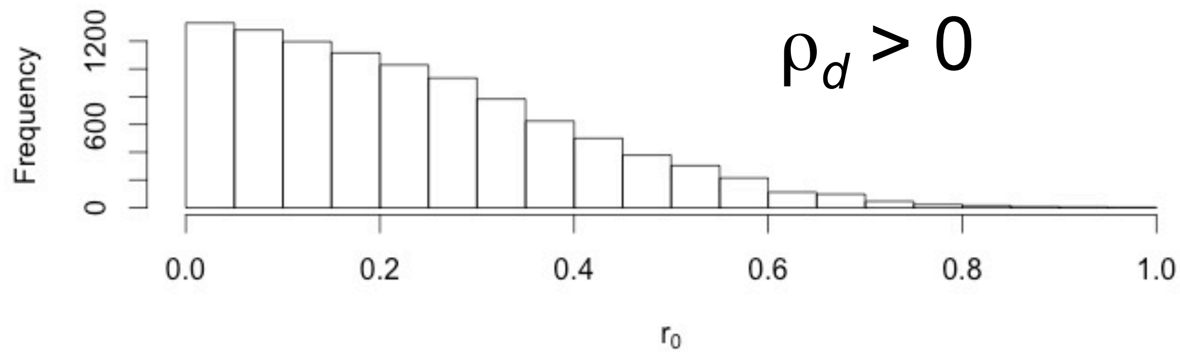
Generally Positive Posterior Means of ρ for all Insurers



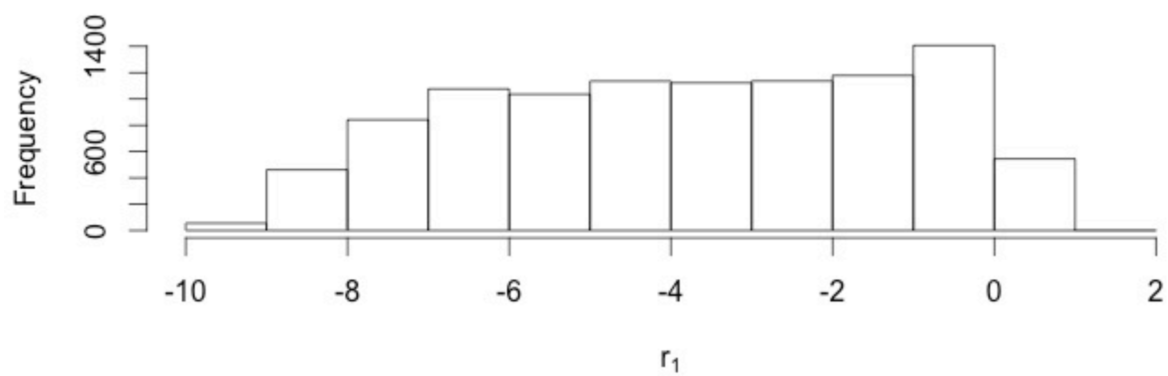
Case 3 - Posterior Distributions of r_0 and r_1 – $\rho_d = r_0 \bullet \exp(r_1 \bullet (d-1))$



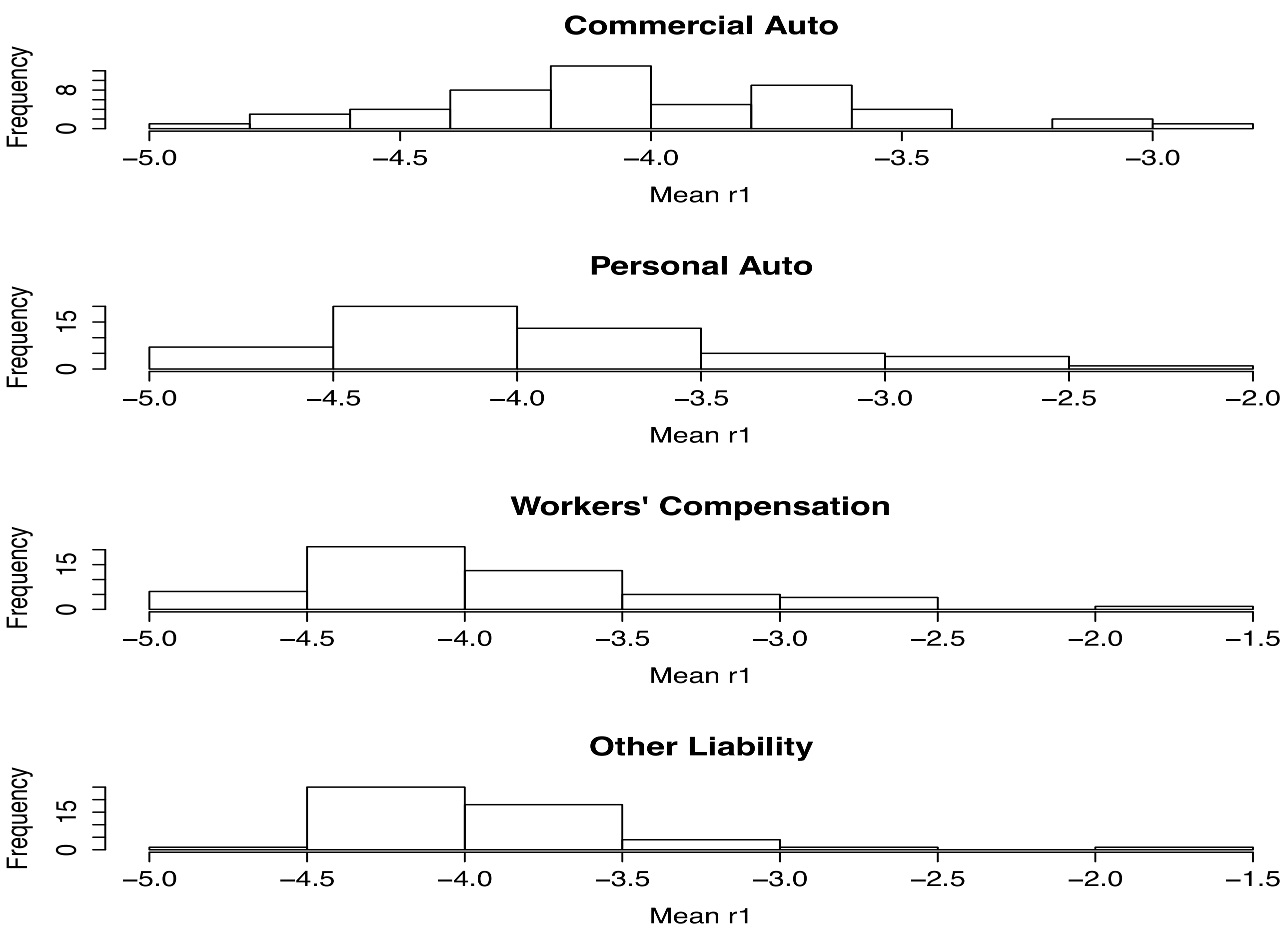
$\rho_d > 0$

Illustrative Insurer

ρ_d is generally monotonic decreasing



Generally Monotonic Decreasing ρ_d for all Insurers



Results for the Illustrative Insured With Incurred Data

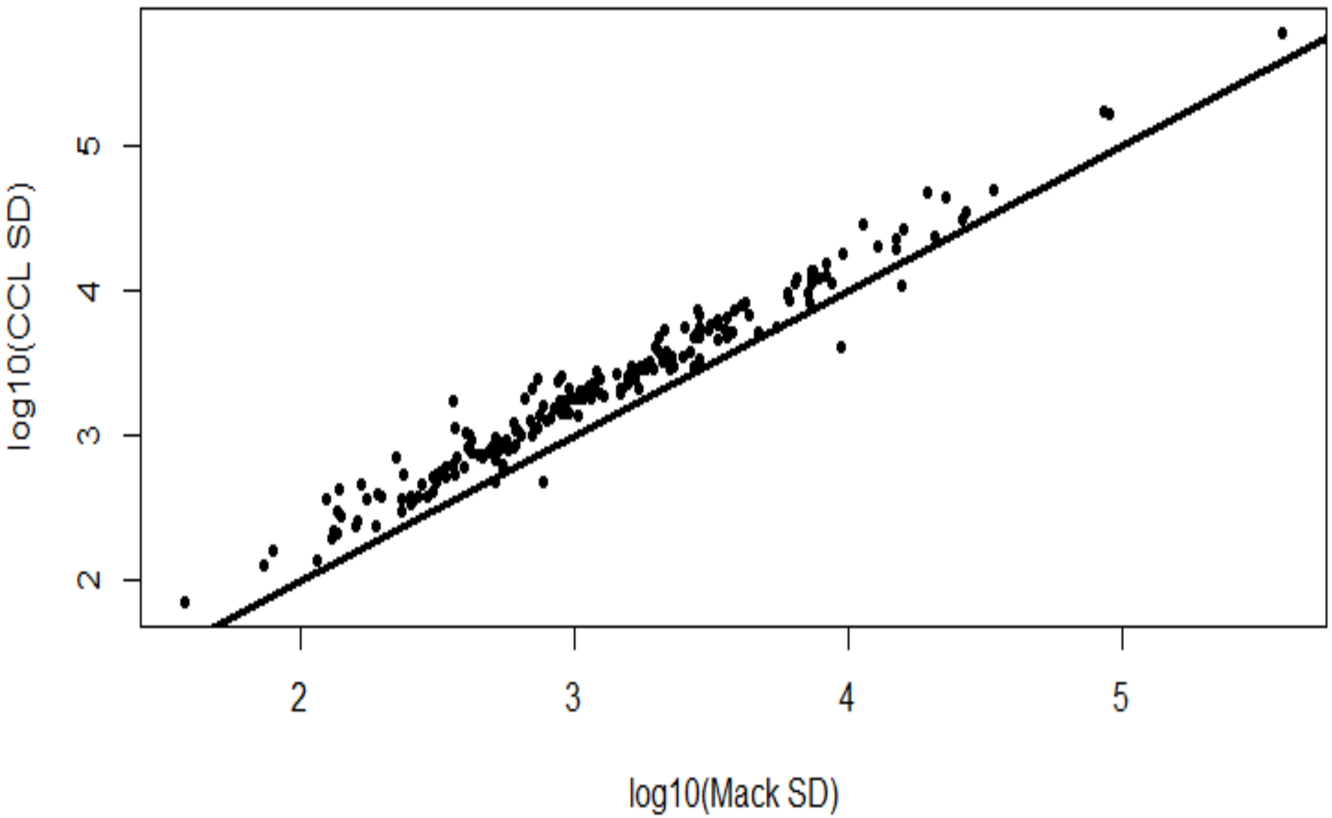
			Mack			LCL		
W	Premium	Estimate	Std Error	CV	Estimate	Std Error	CV	Outcome
1	5812	3917	0	0.000	3917	0	0.000	3917
2	4908	2538	0	0.000	2544	59	0.023	2532
3	5454	4167	3	0.001	4110	106	0.026	4279
4	5165	4367	37	0.009	4307	122	0.028	4341
5	5214	3597	34	0.010	3545	115	0.032	3587
6	5230	3236	40	0.012	3317	132	0.040	3268
7	4992	5358	146	0.027	5315	265	0.050	5684
8	5466	3765	225	0.060	3775	301	0.080	4128
9	5226	4013	412	0.103	4203	561	0.134	4144
10	4962	3955	878	0.222	4084	1157	0.283	4181
Total	52429	38914	1,057	0.027	39116	1551	0.040	40061
Percentile			86.03			76.38		

Results for the Illustrative Insured With Incurred Data

			CCL			CCL Variable ρ		
W	Premium	Estimate	Std Error	CV	Estimate	Std Error	CV	Outcome
1	5812	3917	0	0.000	3917	0	0.000	3917
2	4908	2545	57	0.022	2545	65	0.026	2532
3	5454	4110	113	0.028	4107	116	0.028	4279
4	5165	4314	130	0.030	4306	133	0.031	4341
5	5214	3549	123	0.035	3541	121	0.034	3587
6	5230	3319	146	0.044	3317	141	0.043	3268
7	4992	5277	292	0.055	5290	274	0.052	5684
8	5466	3796	331	0.087	3773	308	0.082	4128
9	5226	4180	622	0.149	4139	593	0.143	4144
10	4962	4155	1471	0.354	4154	1484	0.357	4181
Total	52429	39161	1901	0.049	39090	1898	0.049	40061
Percentile			73.72			75.84		

Rank of Std Errors
Mack < LCL < CCL-VR ≈ CCL-CR

Compare SDs for All 200 Triangles



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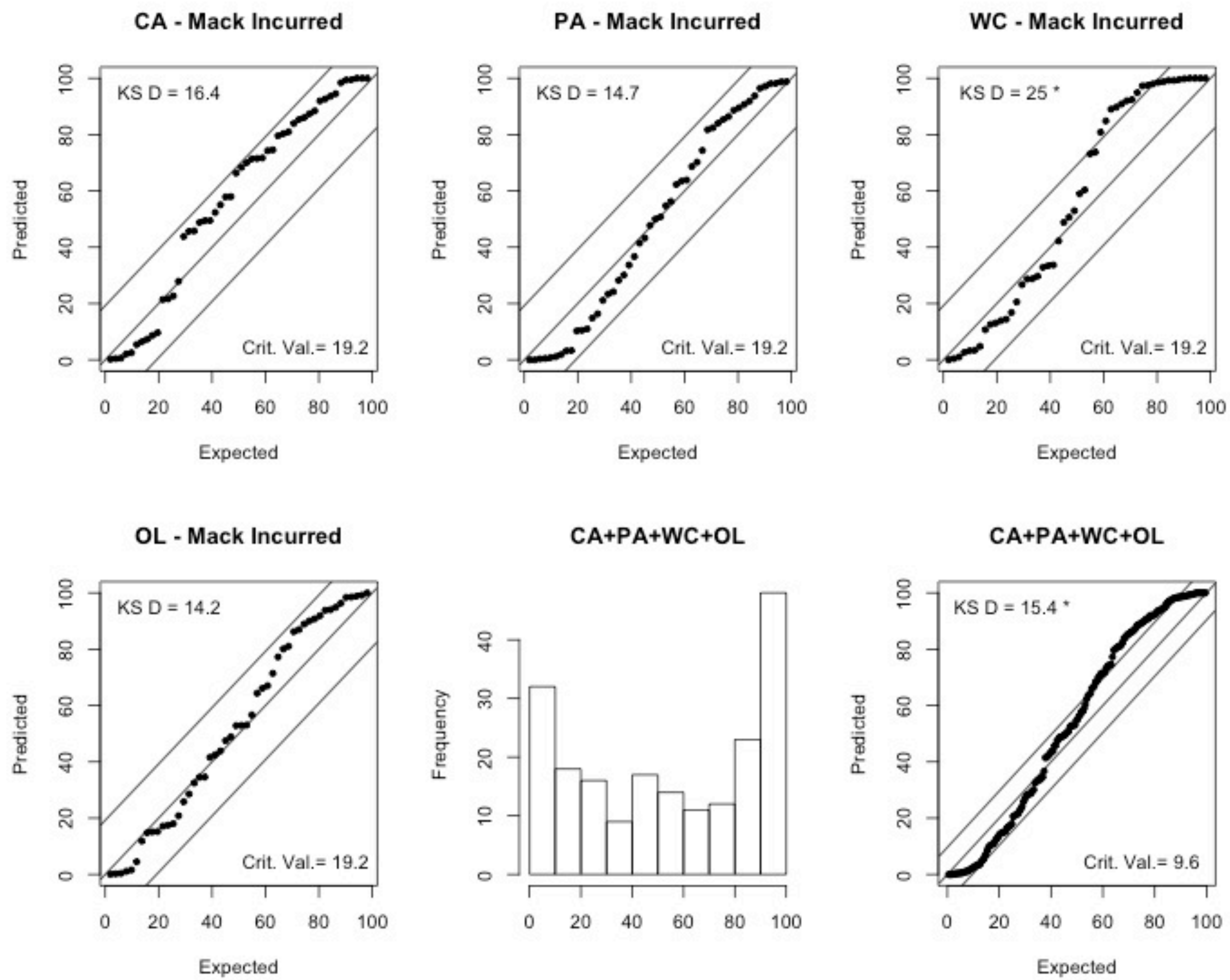
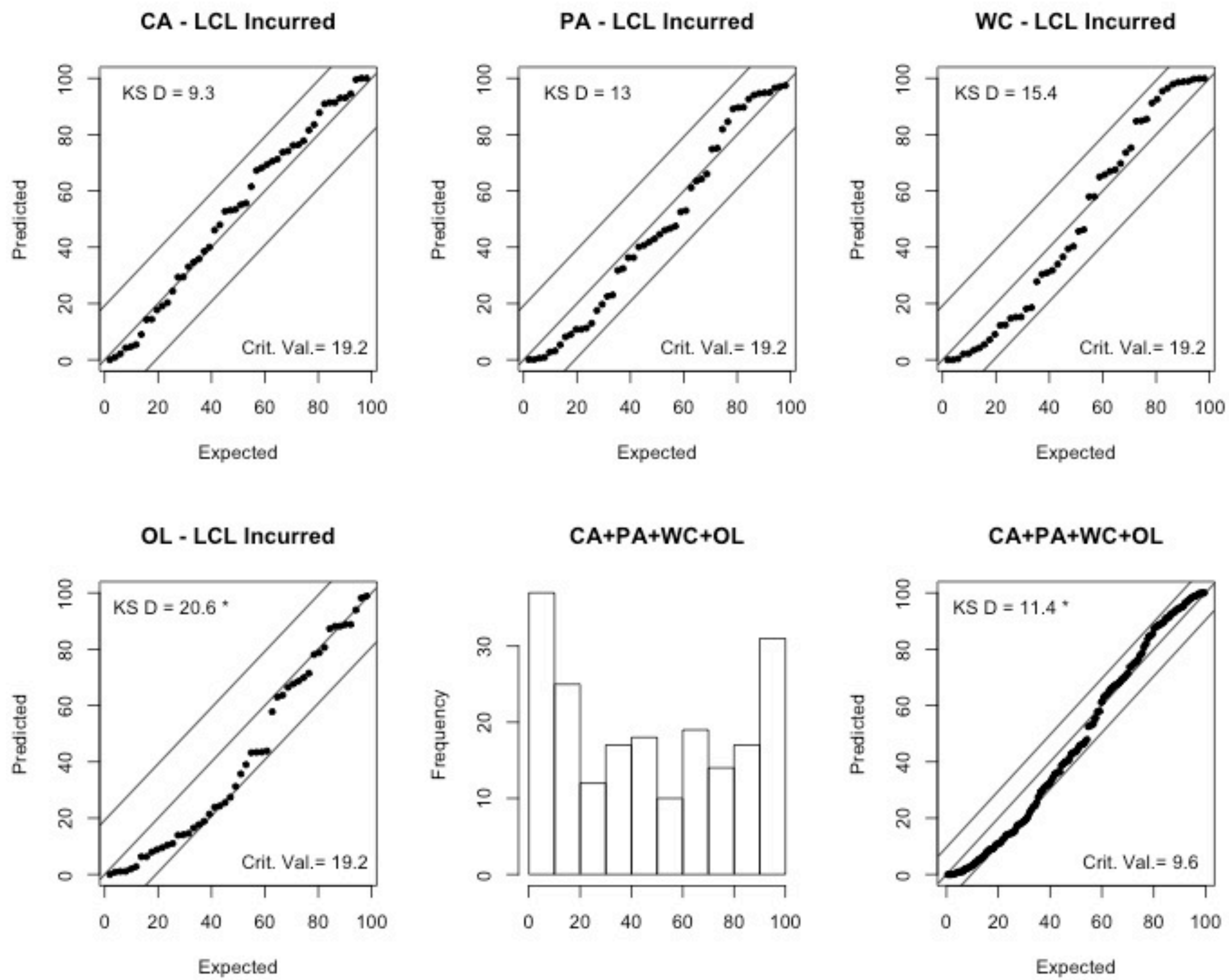
Test of Mack Model on Incurred Data



Conclusion – The Mack model predicts tails that are too light.

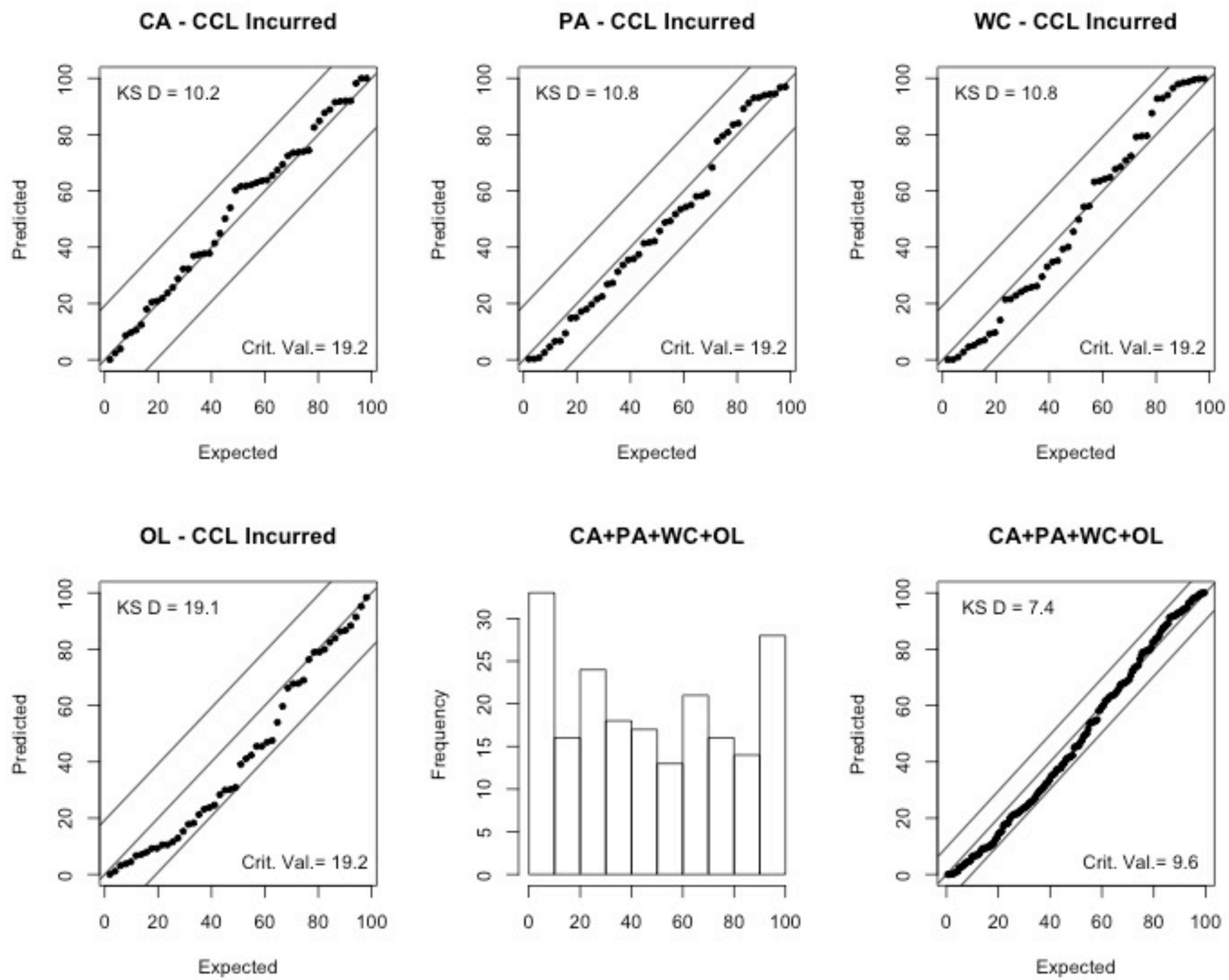
Test of CCL (LCL) Model on Incurred Data $\rho_d = 0$



Conclusion – Predicted tails are too light

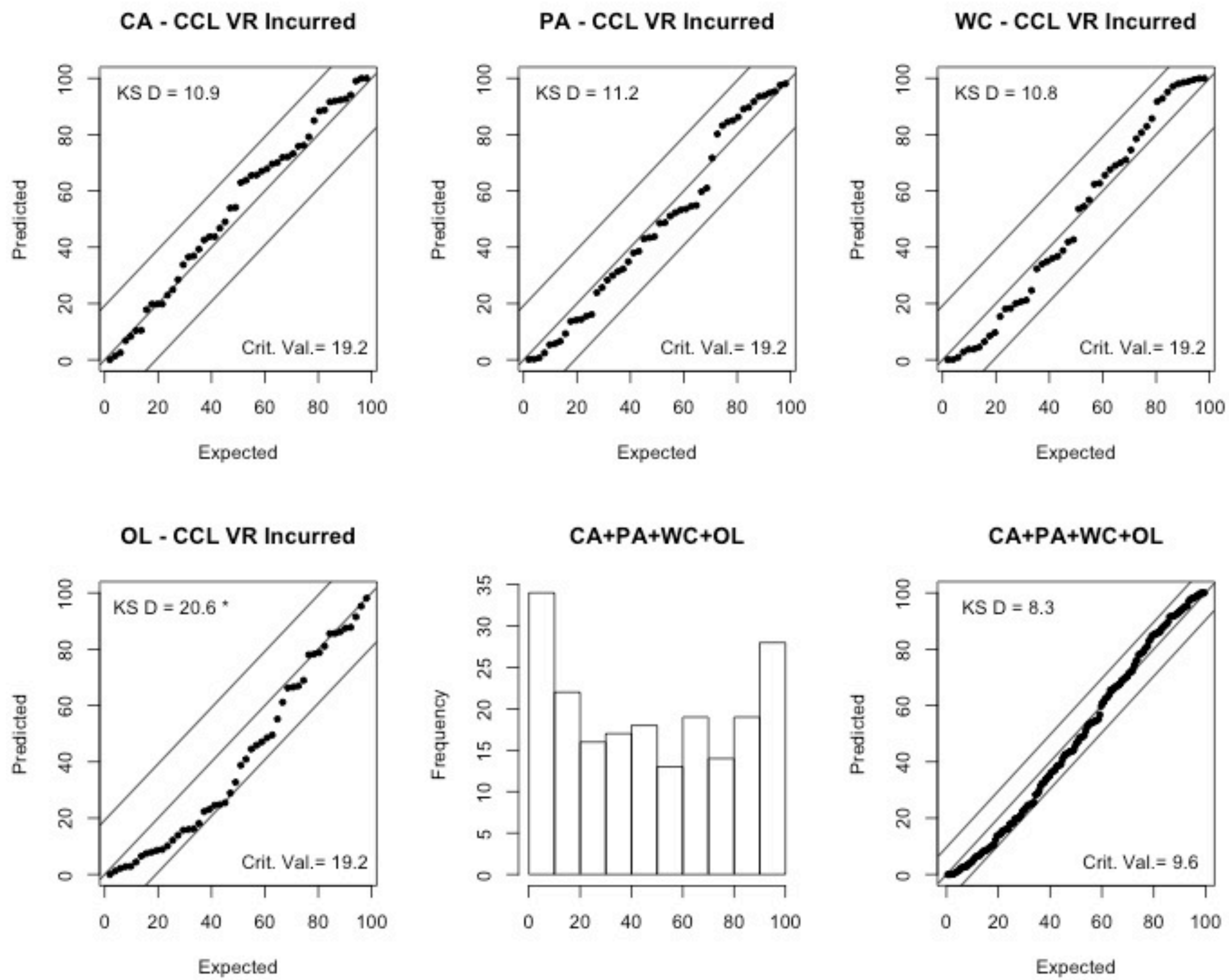
Test of CCL Model on Incurred Data

$\rho_d = \rho$



Conclusion – Plot is within KS Boundaries

Test of CCL Model on Incurred Data Variable ρ_d



Conclusion – Plot is within KS Boundaries

Improvement with Incurred Data

- Accomplished by “pumping up” the variance of Mack model.

What About Paid Data?

- Start by looking at CCL model on cumulative paid data.

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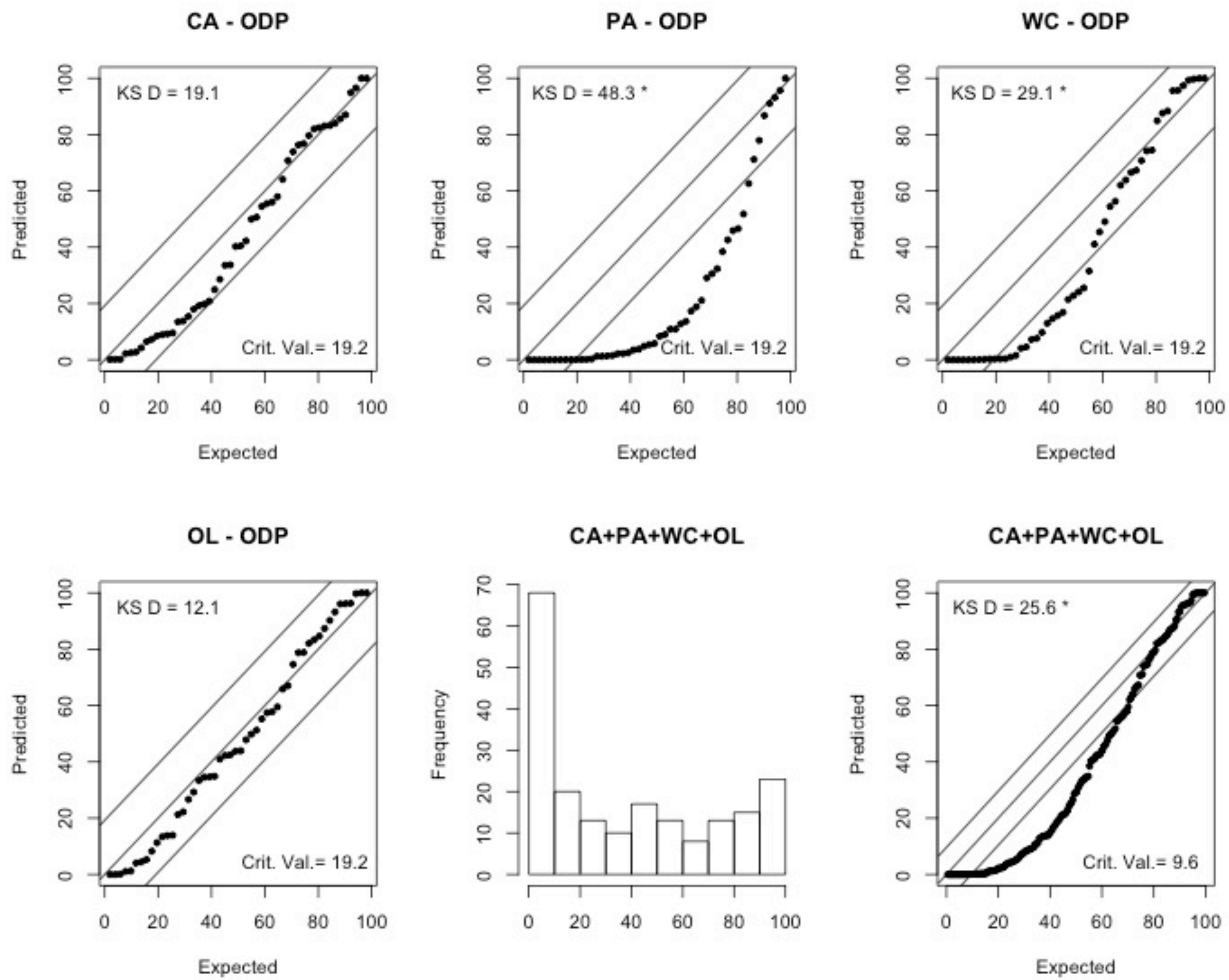
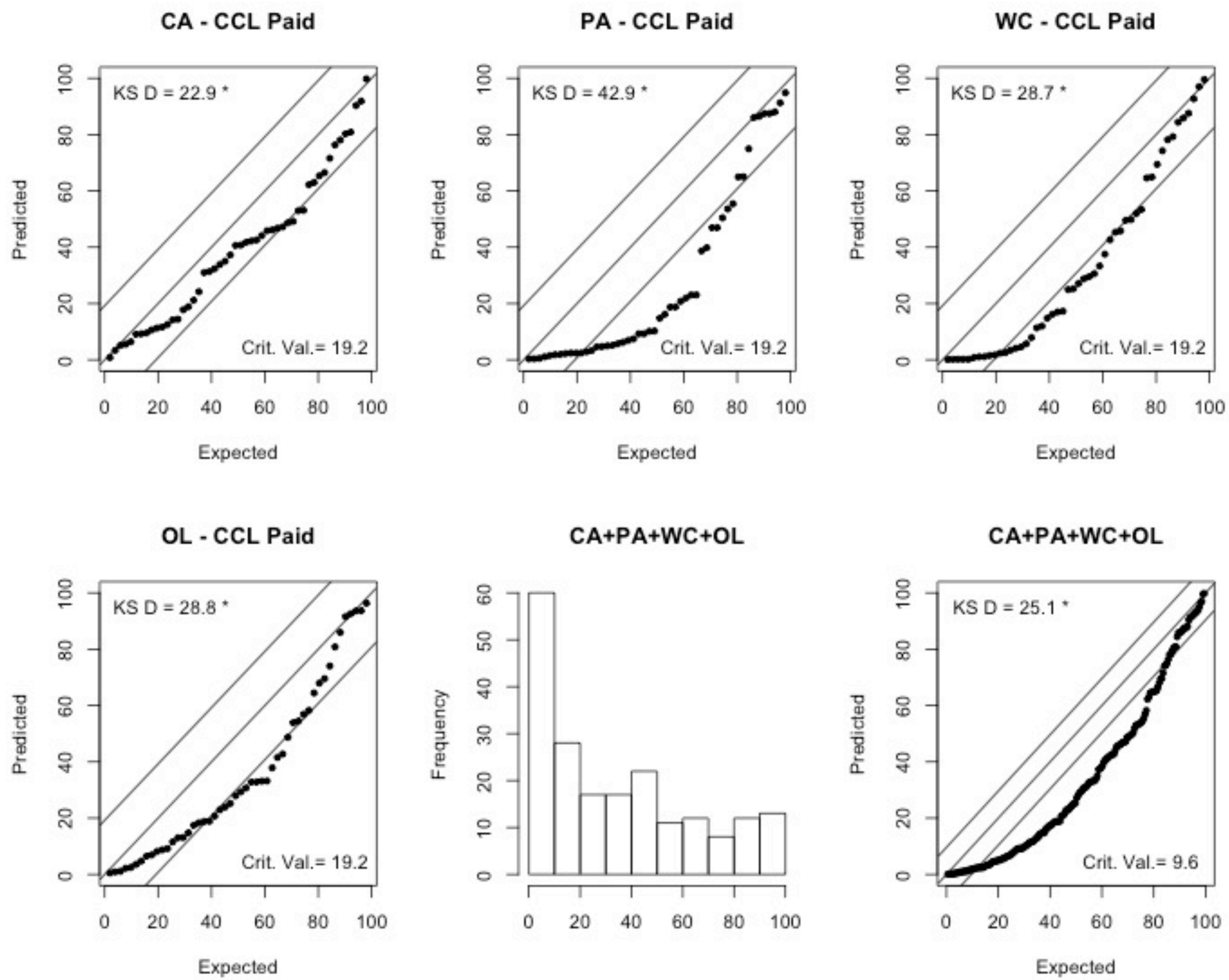
Test of Bootstrap ODP on Paid Data



Conclusion – The Bootstrap ODP model is biased upward.

Test of CCL on Paid Data



Conclusion

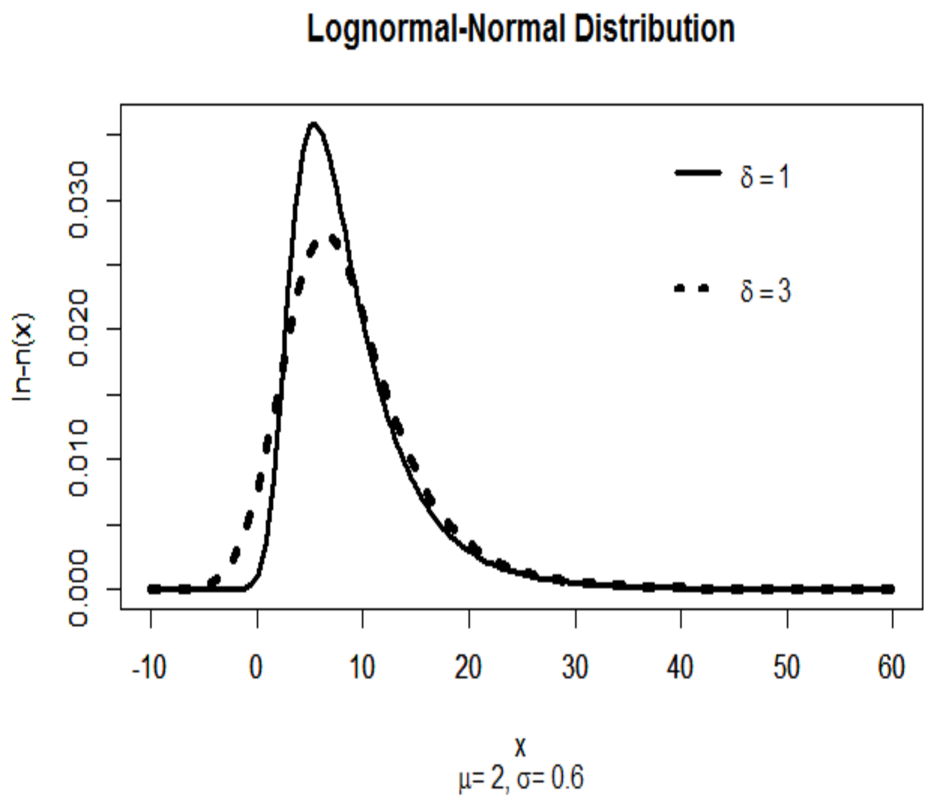
Roughly the same performance as bootstrapping

How Do We Correct the Bias?

- Look at models with payment year trend.
  - Ben Zehnwirth has been championing these for years.
- Payment year trend does not make sense with cumulative data!
  - Settled claims are unaffected by trend.
- Recurring problem with incremental data – Negatives!
  - We need a skewed distribution that has support over the entire real line.

The Lognormal-Normal (ln-n) Mixture

$X \sim \text{Normal}(Z,\delta), \;\; Z \sim \text{Lognormal}(\mu,\sigma)$



The Correlated Incremental Trend (CIT) Model

- $\mu_{w,d} = \alpha_w + \beta_d + \tau \cdot (w + d - 1)$
- $Z_{w,d} \sim \text{lognormal}(\mu_{w,d}, \sigma_d)$ subject to $\sigma_1 < \sigma_2 < \ldots < \sigma_{10}$
- $I_{1,d} \sim \text{normal}(Z_{1,d}, \delta)$
- $I_{w,d} \sim \text{normal}(Z_{w,d} + \rho \cdot (I_{w-1,d} - Z_{w-1,d}) \cdot e^{\tau}, \delta)$

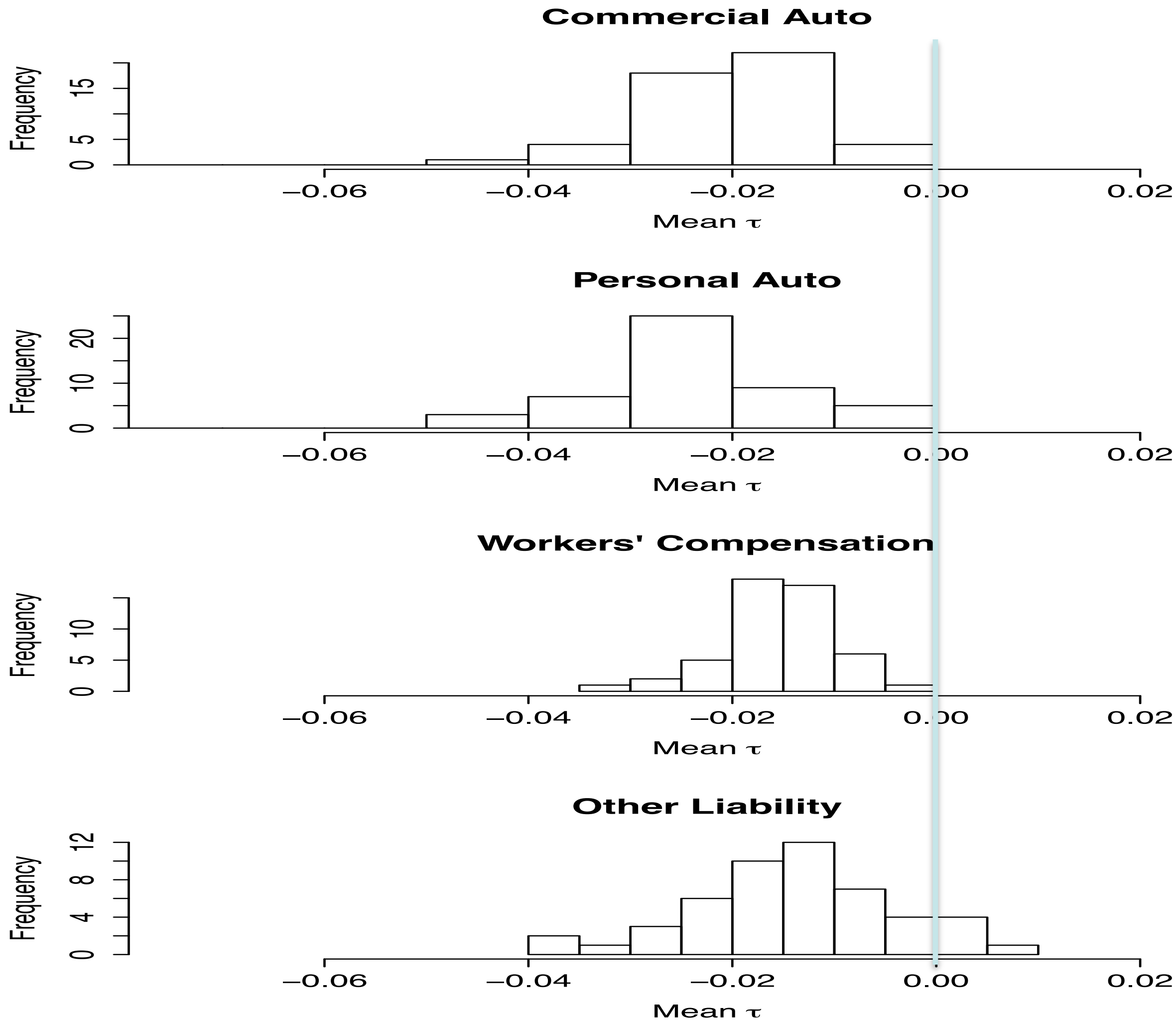
- Estimate the distribution of $\sum_{w=1}^{10} C_{w,10}$

- "Sensible" priors
  - Needed to control σ_d
  - Interaction between τ , α_w and β_d.

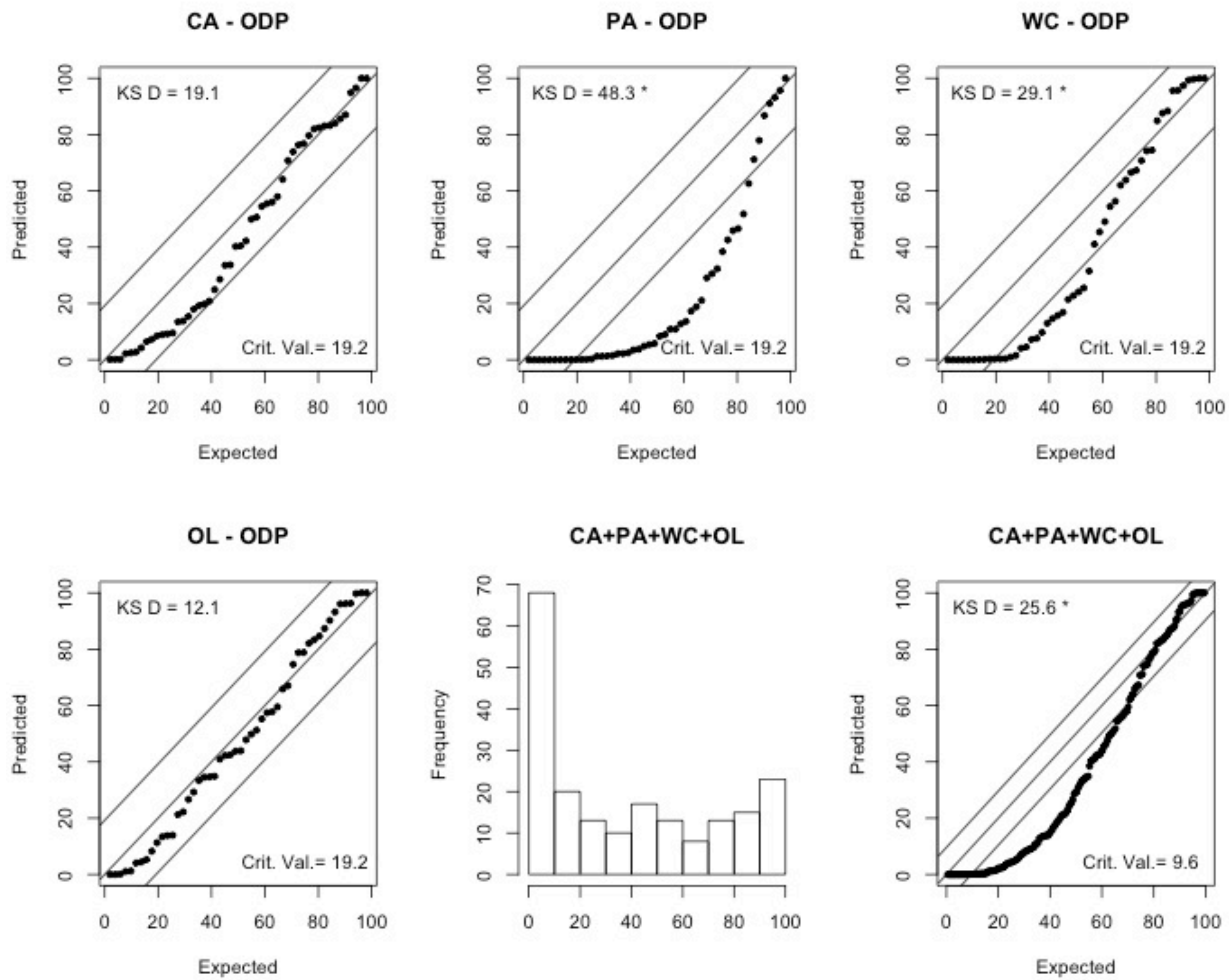
CIT Model for Illustrative Insurer

	CIT				CCL				Outcome
w	$C_{w,10}$	SD	CV		$C_{w,10}$	SD	CV		$C_{w,10}$
1	3912	0	0		3912	0	0.0000		3912
2	2536	5	0.002		2563	110	0.0429		2527
3	4175	11	0.0026		4153	189	0.0455		4274
4	4378	29	0.0066		4320	224	0.0519		4341
5	3539	35	0.0099		3570	207	0.0580		3583
6	3043	105	0.0345		3403	255	0.0749		3268
7	5037	114	0.0226		5207	465	0.0893		5684
8	3501	556	0.1588		3649	467	0.1280		4128
9	3980	710	0.1784		4409	895	0.2030		4144
10	4661	1484	0.3184		5014	2435	0.4856		4139
Total	38763	1803	0.0465		40200	3070	0.0764		40000
Percentile		81.87				51.24			

Posterior Mean τ for All Insurers

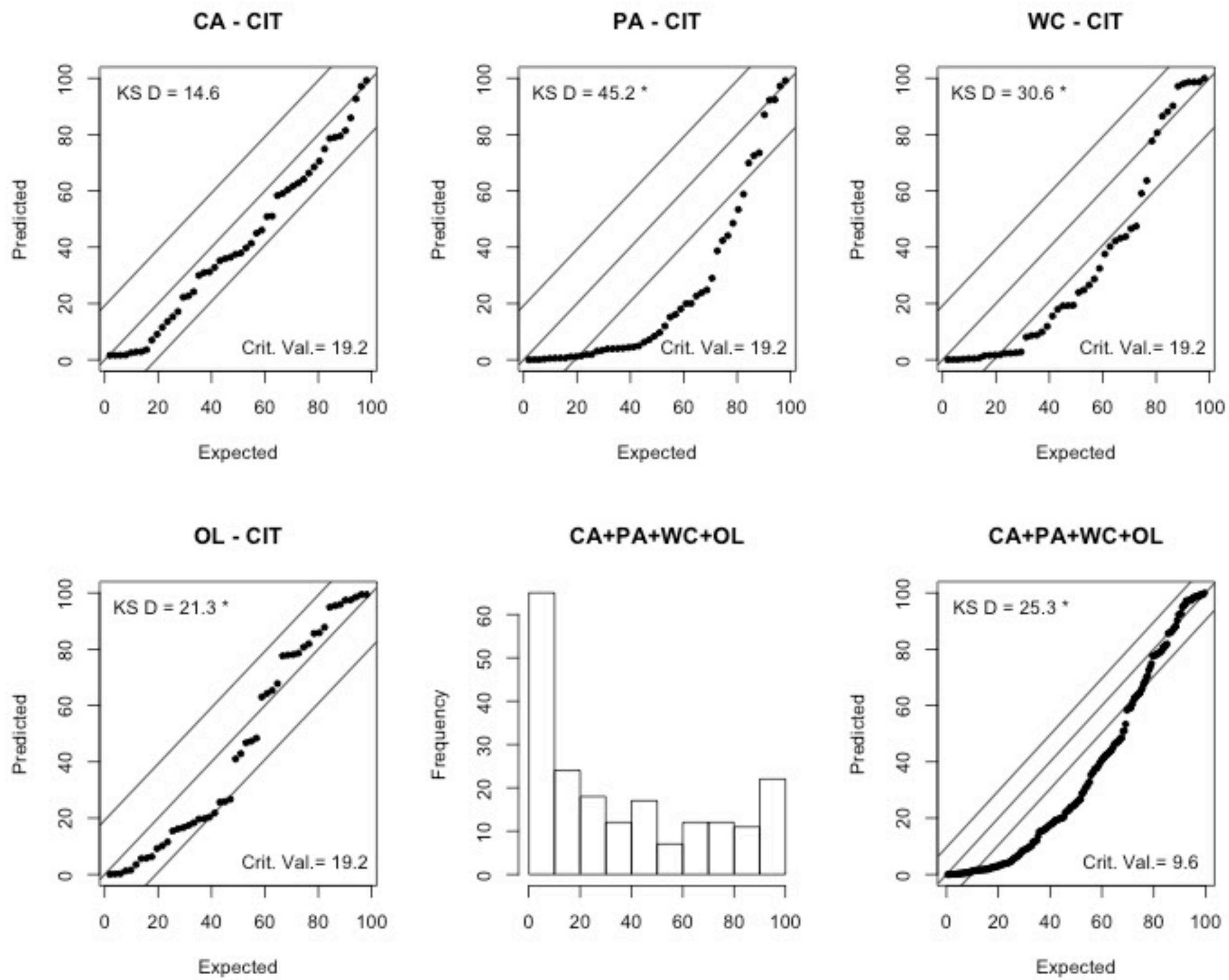


Test of Bootstrap ODP on Paid Data



Conclusion – The Bootstrap ODP model is biased upward.

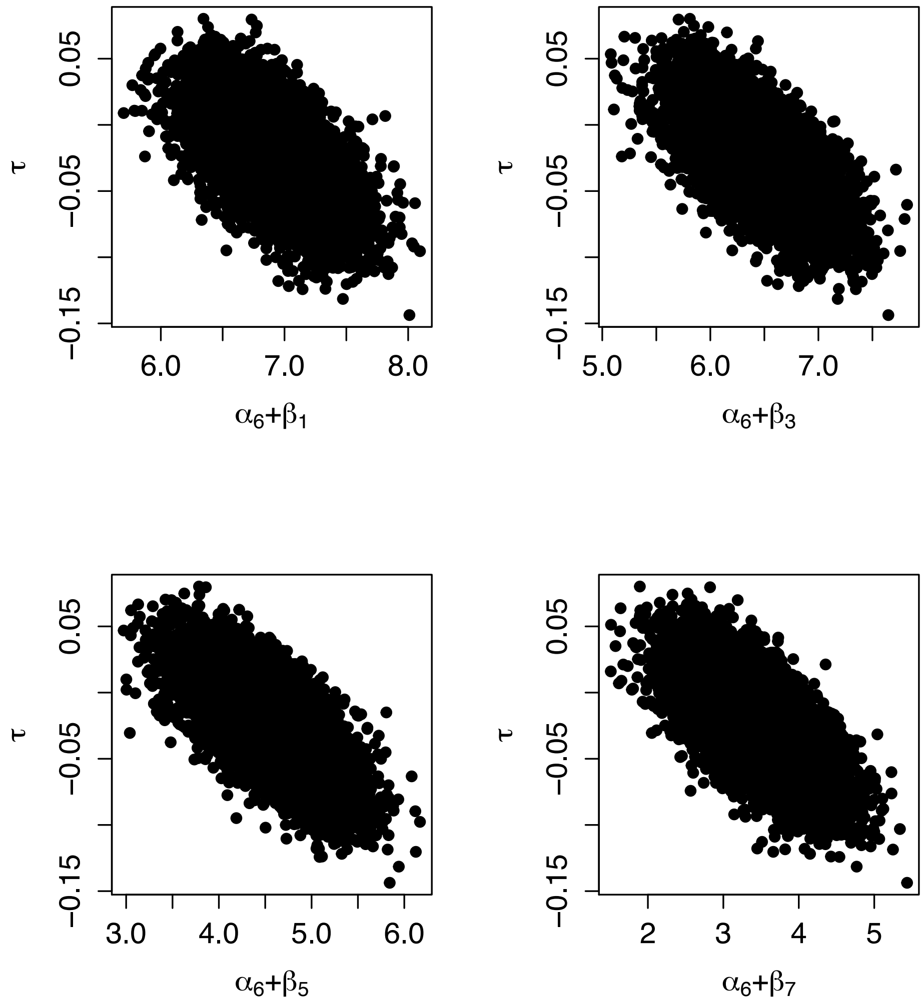
Test of CIT on Paid Data



Better than when ρ = 0 – Comparable to Bootstrap ODP - Still Biased

Why Don't Negative τs Fix the Bias Problem?

Low τ offset by Higher $\alpha + \beta$



The Changing Settlement Rate (CSR) Model

- *logelr* ~ uniform(-5,0)
- α_w ~ normal(log(Premium$_w$)+*logelr*, $\sqrt{10}$)
- $\beta_{10} = 0$, β_d ~ uniform(-5,5), for $d = 1,\ldots,9$
- a_i ~ uniform(0,1)

- $\sigma_d = \sum_{i=d}^{10} a_i$ Forces σ_d to decrease as d increases

- $\mu_{w,d} = \alpha_w + \beta_d \cdot (1-\gamma)^{(w-1)}$ γ ~ Normal(0,0.025)
- $C_{w,d}$ ~ lognormal($\mu_{w,d}$, σ_d)

The Effect of γ

- $\mu_{w,d} = \alpha_w + \beta_d \cdot (1 - \gamma)^{(w - 1)}$
- βs are almost always negative! ($\beta_{10} = 0$)
- Positive γ – Speeds up settlement
- Negative γ – Slows down settlement
- Model assumes speed up/slow down occurs at a constant rate.

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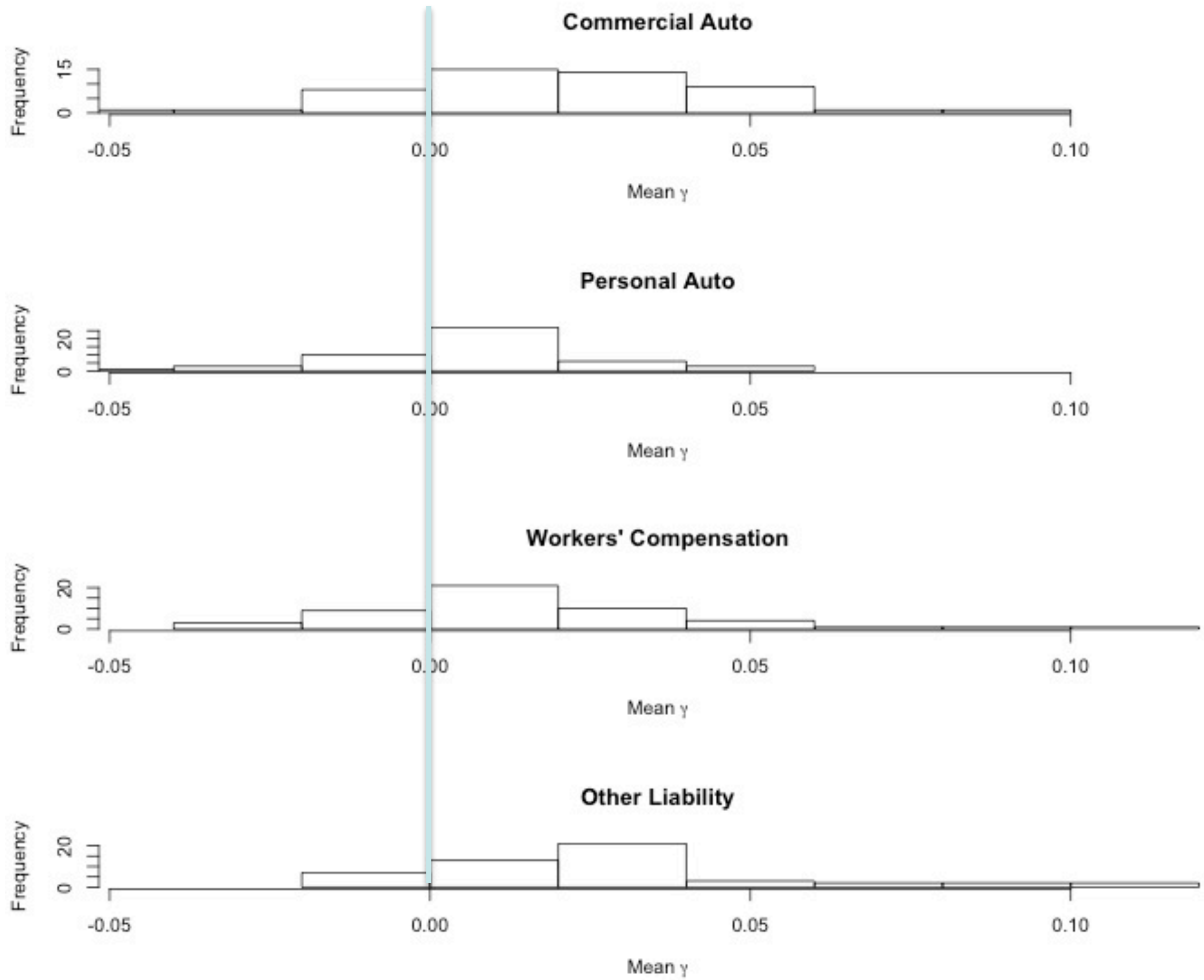
Distribution of Mean γs

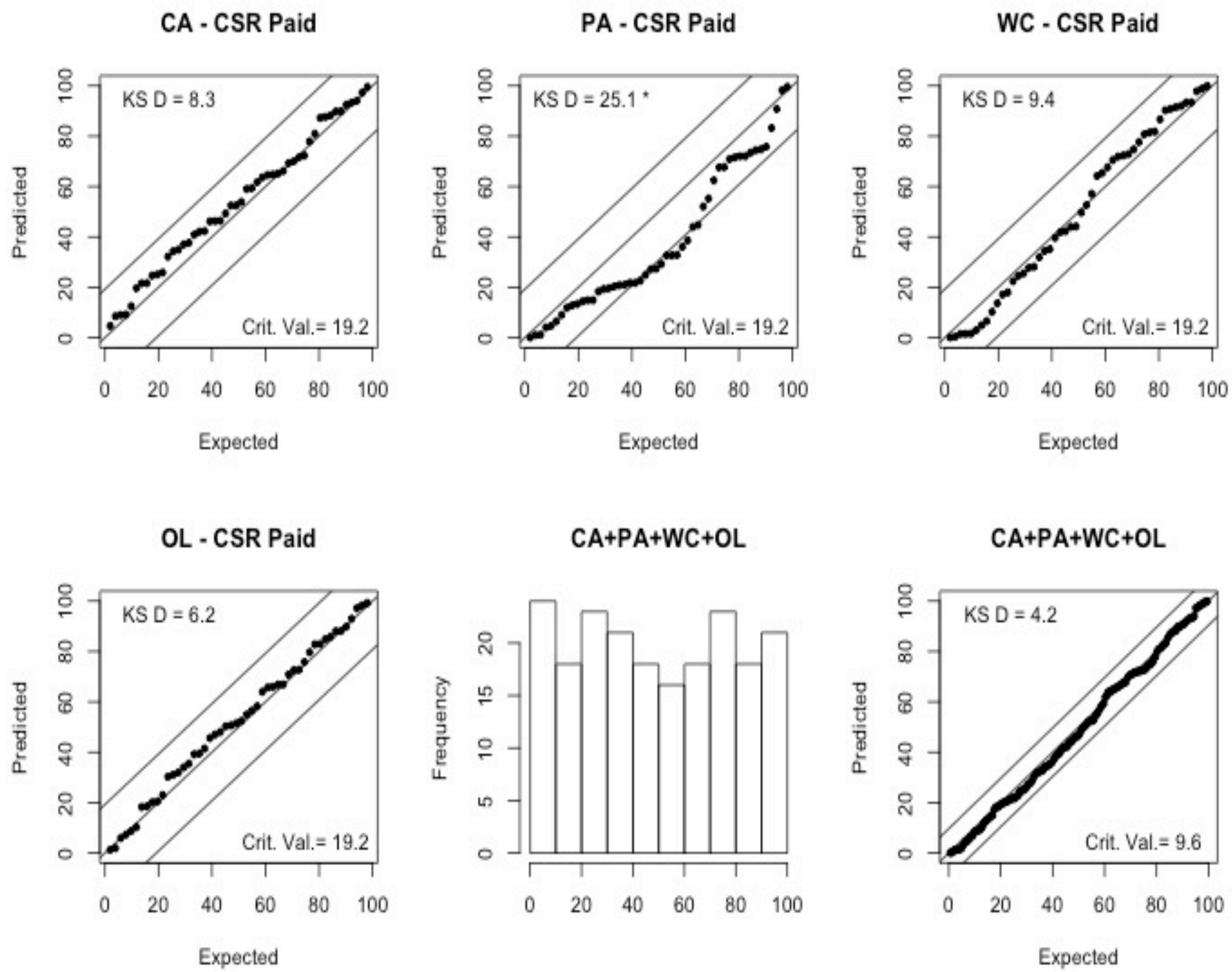


Predominantly Positive γs

CSR Model for Illustrative Insurer

	CIT			CSR			Outcome
w	$C_{w,10}$	SD	CV	$C_{w,10}$	SD	CV	$C_{w,10}$
1	3912	0	0	3912	0	0	3912
2	2539	9	0.0035	2559	103	0.0403	2527
3	4183	21	0.0050	4135	173	0.0418	4274
4	4395	40	0.0091	4285	198	0.0462	4341
5	3553	42	0.0118	3513	180	0.0512	3583
6	3063	101	0.0330	3317	216	0.0651	3268
7	5062	123	0.0243	4967	404	0.0813	5684
8	3512	514	0.1464	3314	402	0.1213	4128
9	4025	707	0.1757	3750	734	0.1957	4144
10	4698	1482	0.3155	3753	1363	0.3632	4139
Total	38942	1803	0.0463	37506	2247	0.0599	40000
Percentile		79.04			87.62		

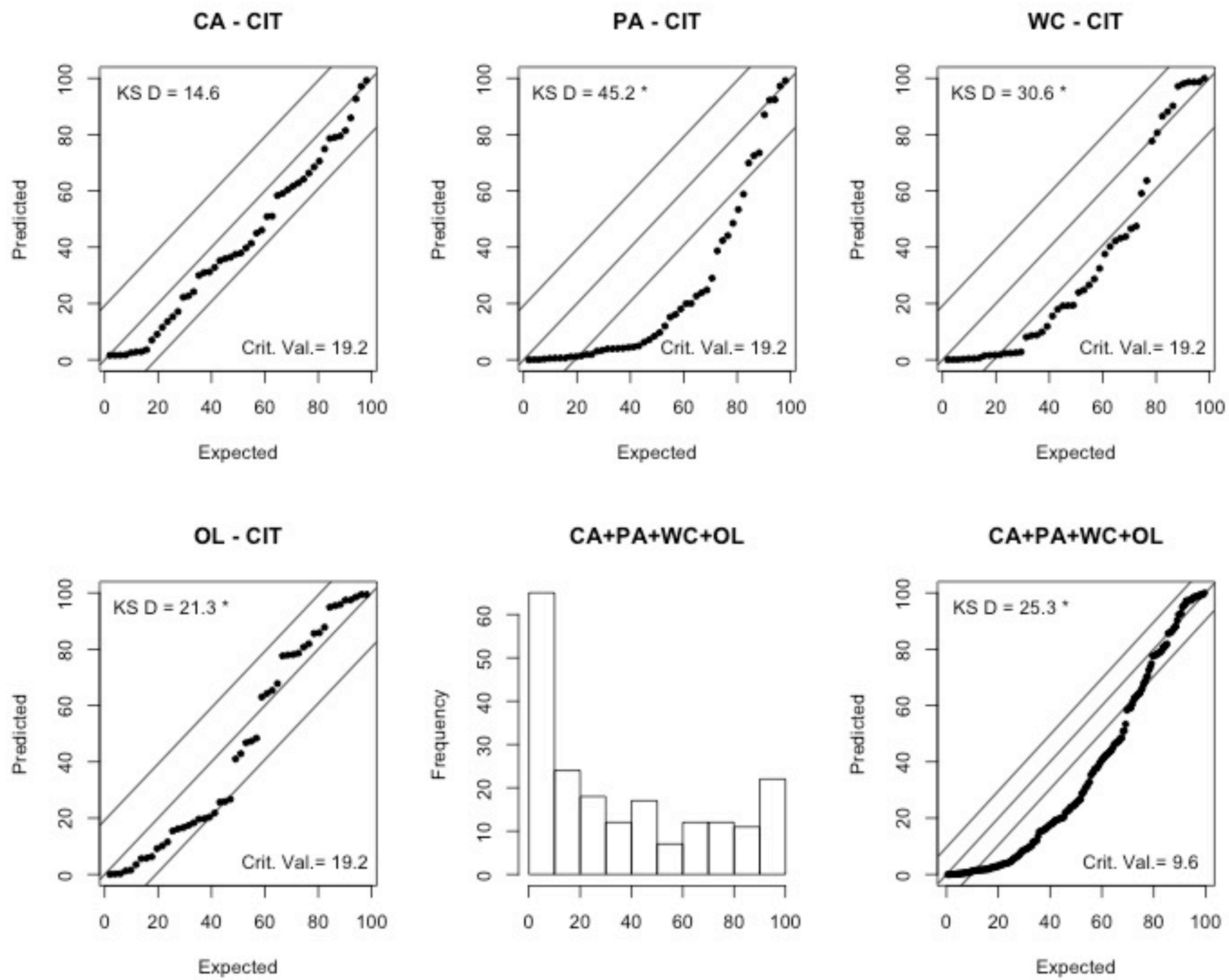
Test of CSR on Paid Data



Conclusion - Much better than CIT

Varying speedup rate???

Test of CIT on Paid Data



Better than when $\rho = 0$ – Comparable to Bootstrap ODP - Still Biased

Calendar Year Risk

Calendar Year Incurred Loss

=

Losses Paid In Calendar Year

+

Change in Outstanding Loss

in Calendar Year

Important in One Year

Time Horizon Risk

- 0 – Prior Year, 1 – Current Year
- IP_1 = Loss paid in current year
- CP_t = Cumulative loss paid through year t
- R_t = Total unpaid loss estimated at time t
- U_t = Ultimate loss estimated at time t

$$U_t = CP_t + R_t$$

Calendar Year Incurred Loss

=

$$IP_1 + R_1 - R_0 = CP_1 + R_1 - CP_0 - R_0 = \mathbf{U_1 - U_0}$$

=

Ultimate at time 1 – Ultimate at time 0

Estimating the Distribution of The Calendar Year Risk

- Given the current triangle and estimate U_0
- Simulate the next calendar year losses
  - 10,000 times
- For each simulation, *j*, estimate U_{1j}
- CCL takes about a minute to run.

10,000 minutes????

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A Faster Approximation

- For each simulation, j
  - Calculate U_{0j} from $\{\alpha, \beta, \rho \text{ and } \sigma\}_j$ parameters
  - Simulate the next calendar year losses CY_{1j}
- Let T = original triangle
- Then for each i
  - Calculate the likelihood

$$L_{ij} = L(T, CY_{1i} | \{\alpha, \beta, \rho \text{ and } \sigma\}_j)$$

Bayes Theorem

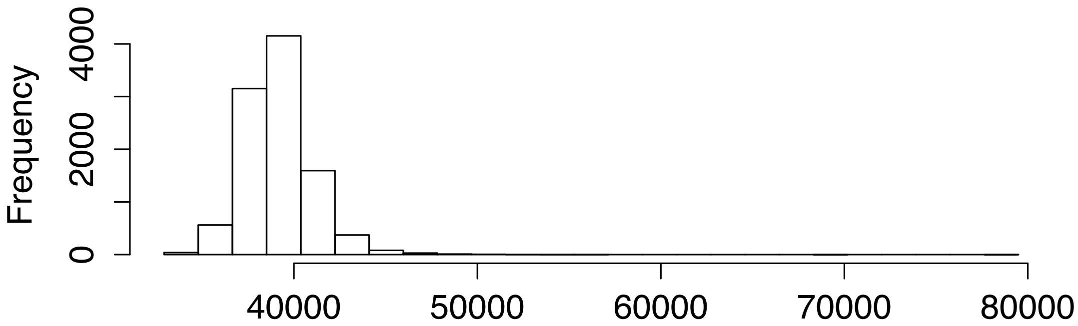
  - Set $p_{ij} = L_{ij} \Big/ \sum_j L_{ij}$ and $\bar{U}_{1i} = \sum_j p_{ij} \cdot U_{0j}$

A Faster Approximation

- $\{\bar{U}_{1i} - U_0\}$ is a random sample of calendar year outcomes.
- Calculate various summary statistics
  - Mean and Standard Deviation
  - Percentile of Outcome (From CCL)

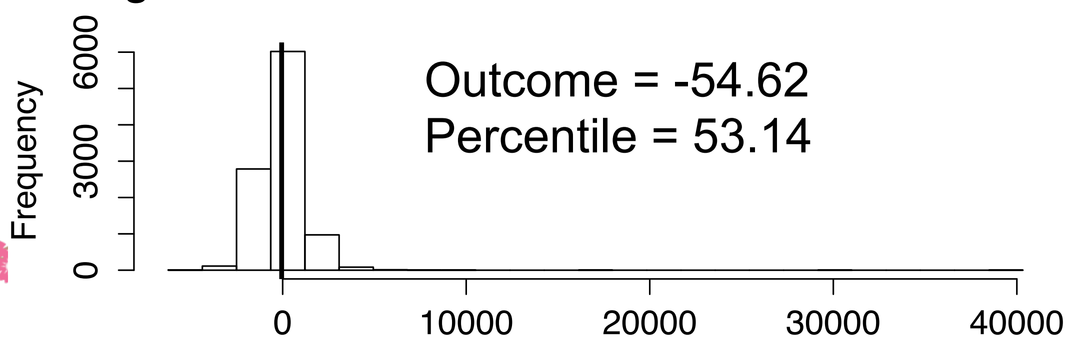
Illustrative Insurer
Constant ρ Model

Figure 1 – 'Ultimate' Incurred Losses at t=0



Mean = 39162   Standard Deviation = 1906

Figure 2 – Next Calendar Year Incurred Losses at t=0



Mean = –56   Standard Deviation = 1248

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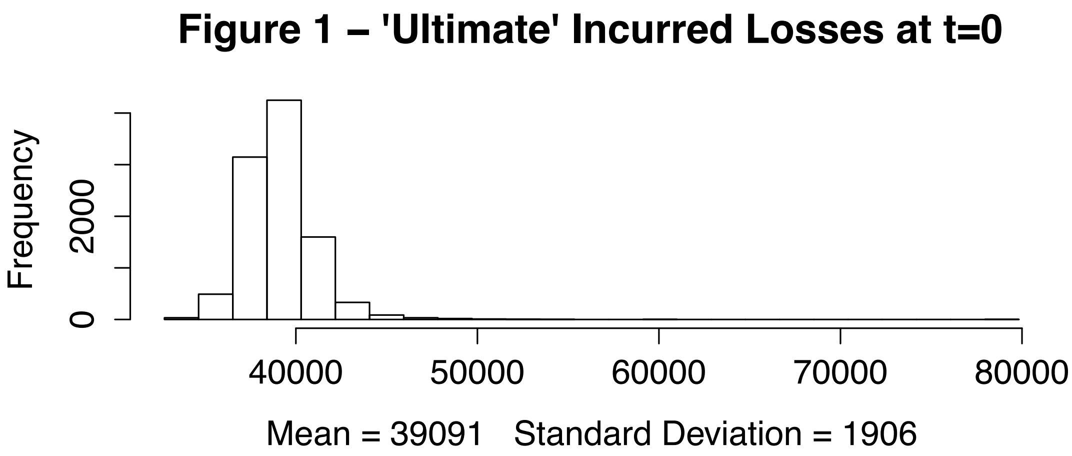
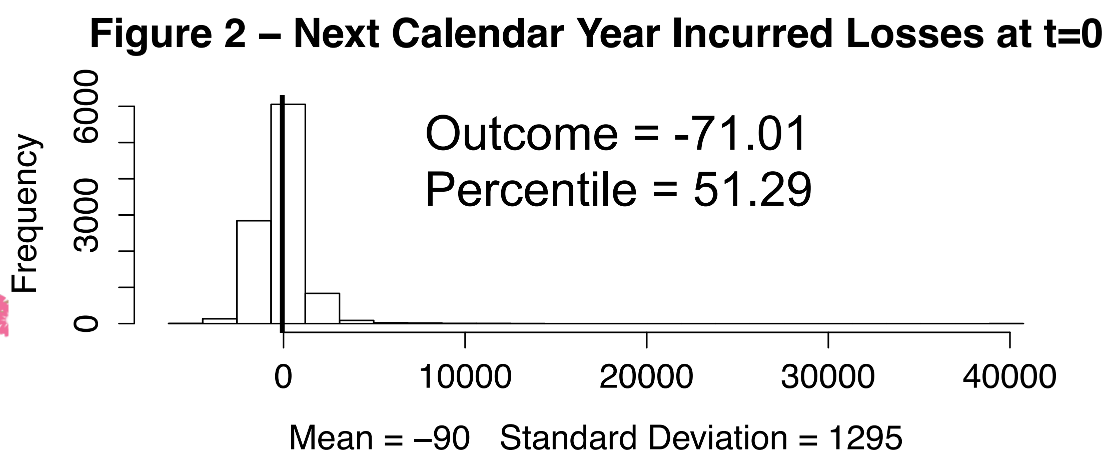
Illustrative Insurer Variable ρ Model





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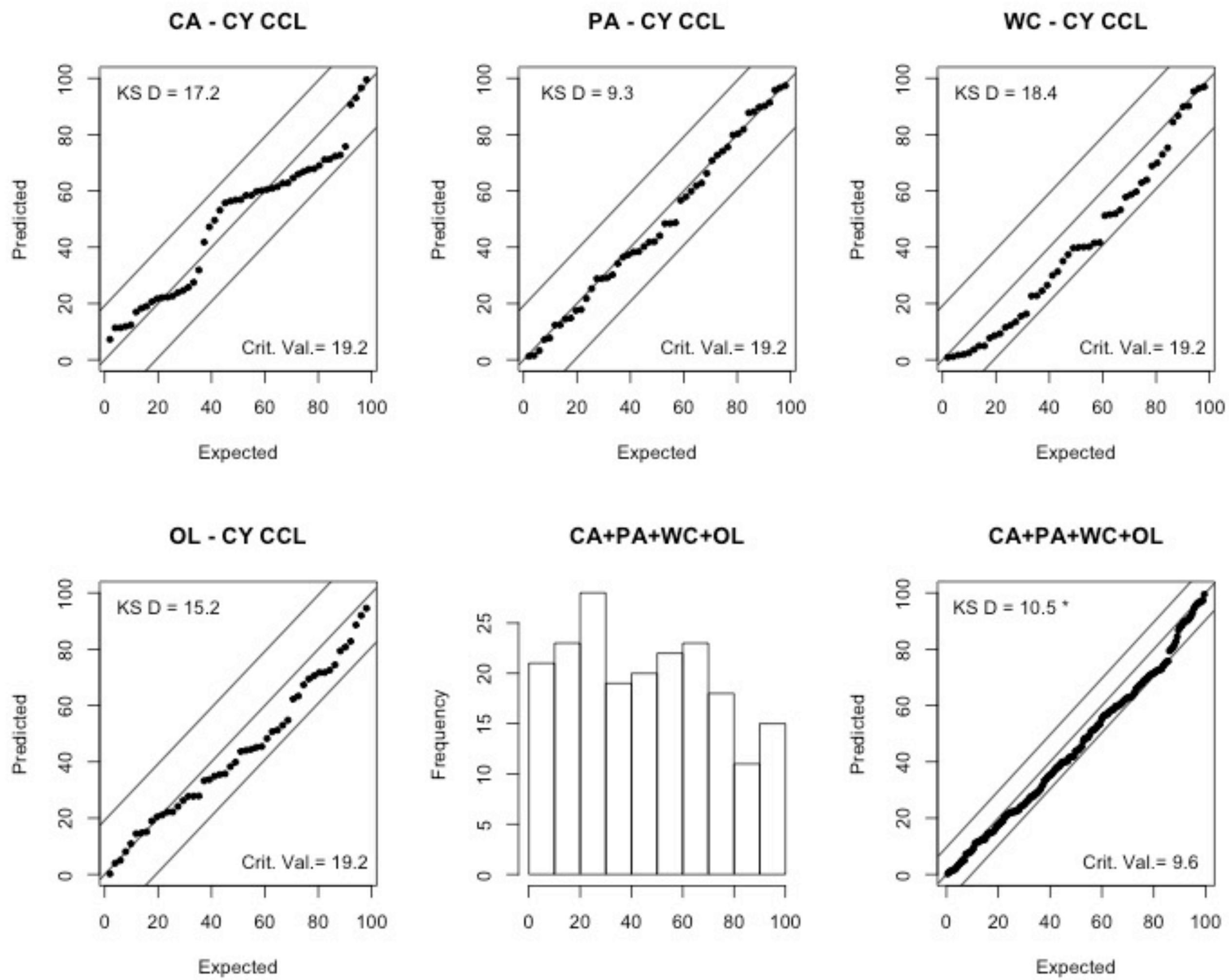
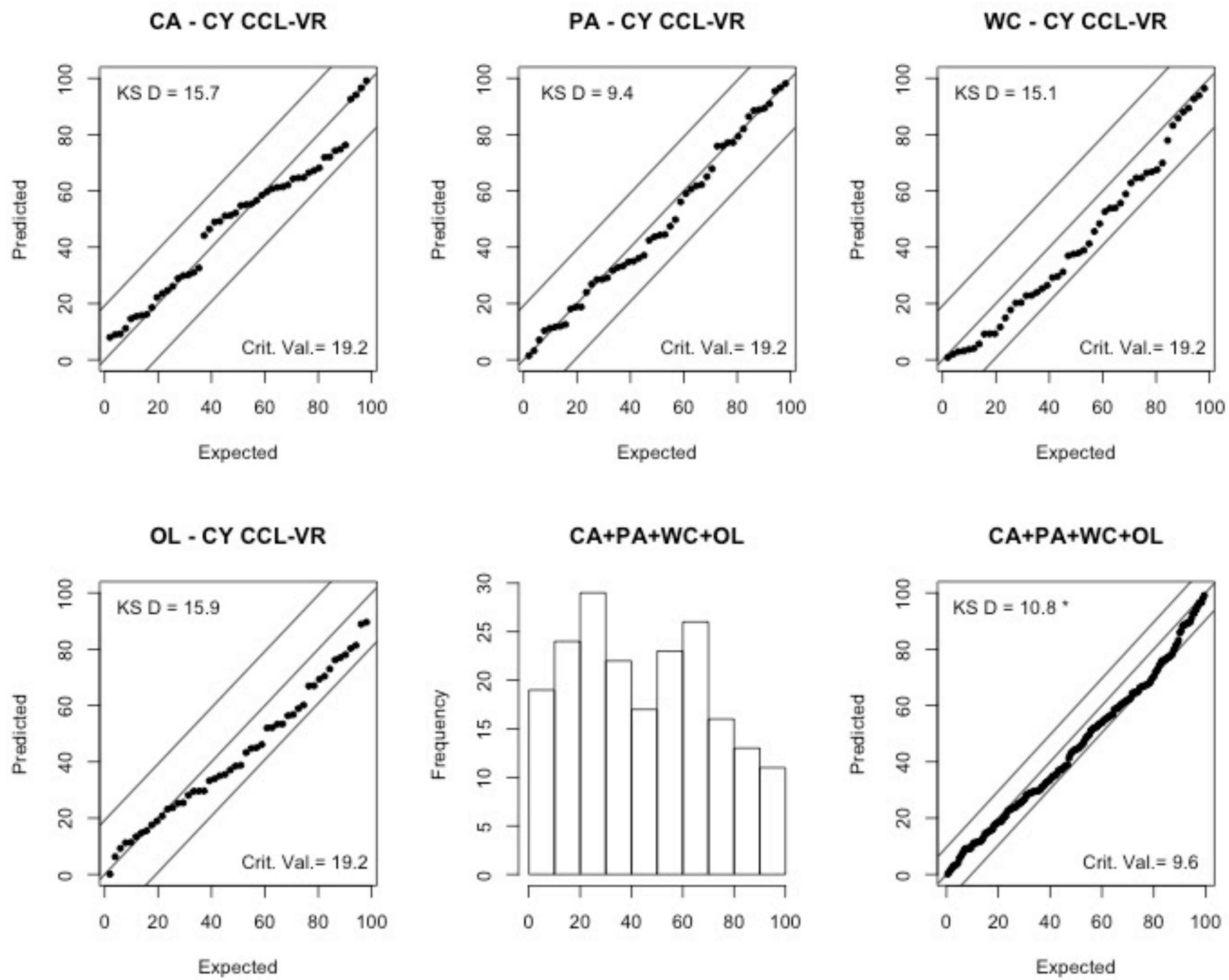
Test of CCL Constant ρ Model
Calendar Year Risk



Test of CCL Variable ρ Model Calendar Year Risk



Short Term Conclusions Incurred Loss Models

- Mack model prediction of variability is too low on our test data.
- CCL model correctly predicts variability at the 95% significance level.
- The feature of the CCL model that pushed it over the top was between accident year correlations.
- CCL models indicate that the between accident year correlation decreases with the development year, but models that allow for this decrease do not yield better predictions of variability.

Short Term Conclusions Paid Loss Models

- Mack and Bootstrap ODP models are biased upward on our test data.
- Attempts to correct for this bias with Bayesian MCMC models that include a calendar year trend failed.
- Models that allow for changes in claim settlement rates work much better.
- *Claims adjusters have important information!*

Short Term Conclusions on Quantifying Calendar Year Risk

- Models with explicit predictive distributions provide a faster approximate way to predict the distribution of calendar year outcomes.
- Even though the original models accurately predicted variability, the variability predicted by the calendar year model was just outside the 95% significance level.

Long Term Recommendations
New Models Come and Go

- Transparency - Data and software released
- Large scale retrospective testing on real data
  - While individual loss reserving situations are unique, knowing how a model performs retrospectively should influence ones choice of models.
- Bayesian MCMC models hold great promise to advance Actuarial Science.
  - Illustrated by the above stochastic loss reserve models.
  - Allows for judgmental selection of priors.