
Liberty Mutual Group

PEBELS:

Policy Exposure Based Excess Loss Smoothing

Marquis J. Moehring



Outline

1. Background
2. Goal
3. PEBELS Defined
4. PEBELS Derived (PPR Generalized)
5. Applications
6. Summary

My Challenge

Strong Regional Focus

- State/Program Large Loss Provisions
- Low Credibility
- High Heterogeneity

This Should be Easier

No applicable method in literature

- ILFs for Liability
- ELFs for Workers Compensation
- **Nothing for Commercial Property or Homewners!**

Goal of PEBELS

PEBELS = Property Large Loss Exposure Segmentation

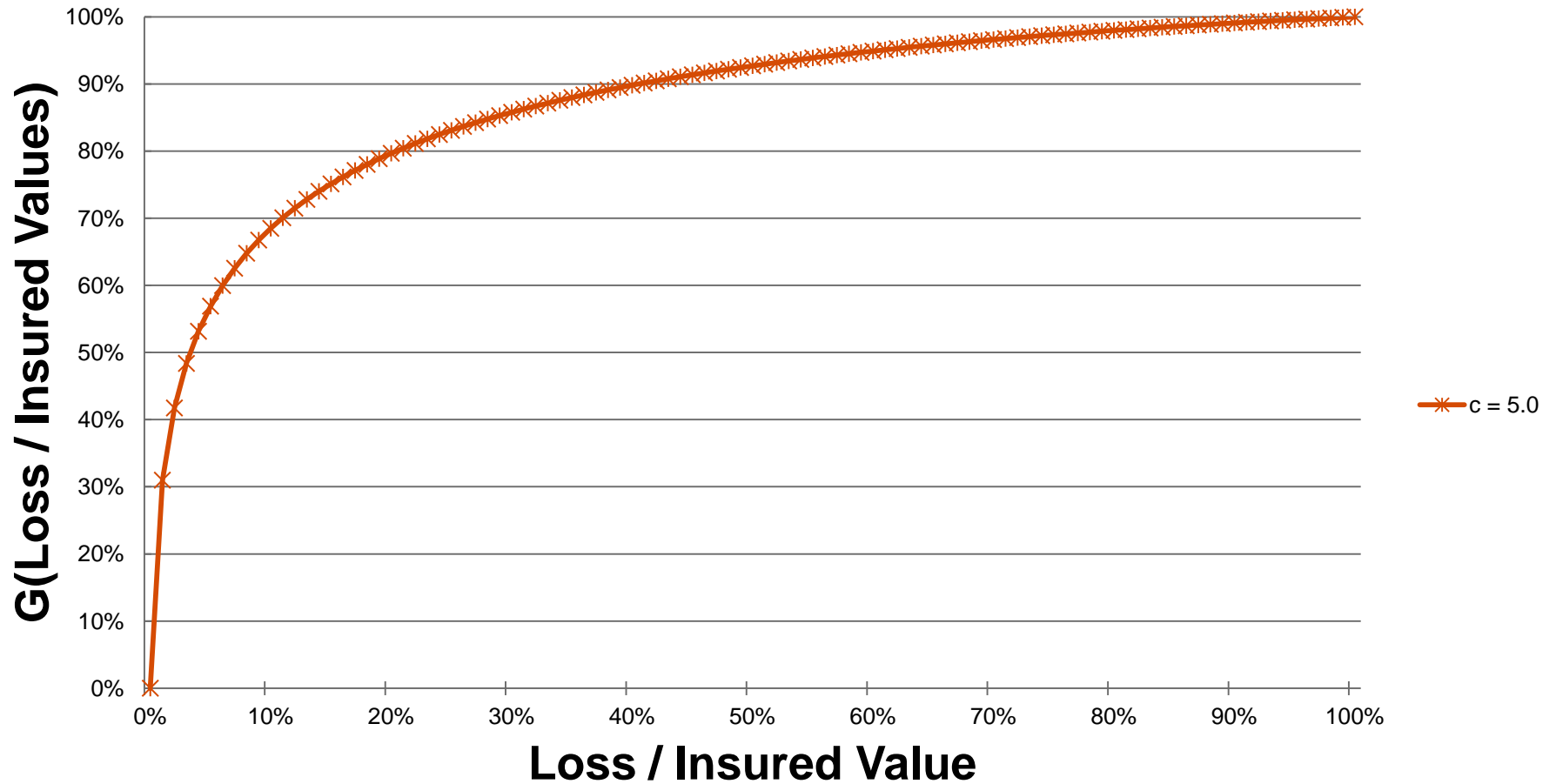
- Meet my challenge
- New applications!
- Deceptively difficult
 - 1) No clear limit
 - 2) Multiple non-linearities
 - 3) Additional nuances
 - 4) Practical considerations

PEBELS Defined

Defined as $PEBEL_i = P_i * ELR_i * EF_i$

- $P_i * ELR_i = E(L_i) = Total Expected Loss$
- $EF_i = G(x_u) - G(x_l) = Percentage of E(L_i) in layer$

Exposure Curve



PEBELS Derived

PEBELS Derived = PPR Generalized

- Classic Reinsurance Per Risk Exposure Rating
- Generalized to contemplate,
 - 1) Policy level heterogeneity
 - 2) Expected loss heterogeneity via ELR_i
 - 3) Loss process heterogeneity via EF_i
 - 4) Historical vs. prospective exposure profiles
 - 5) Credibility

PEBELS Derived

PEBELS Derived = PPR Generalized

- ***Classic Reinsurance Per Risk Exposure Rating***
- Generalized to contemplate,
 - 1) Policy level heterogeneity
 - 2) Expected loss heterogeneity via ELR_i
 - 3) Loss process heterogeneity via EF_i
 - 4) Historical vs. prospective exposure profiles
 - 5) Credibility

Reinsurance Per Risk Exposure Rating

Insured Value Range (\$000s)	Midpoint (\$000s)	Retention as a % of Insured value	Retention + Limit as a % of Insured value	Exposure Factor	Subject Premium	Expected Loss Ratio	Expected Primary Losses	Expected Reinsurer Losses
20-100	60	167%	833%	0%	682,000	65%	443,300	0
100-250	175	57%	286%	26%	161,000	65%	104,650	27,209
250-1,000	625	16%	80%	41%	285,000	65%	185,250	75,953
1,000-2,000	1,500	7%	33%	33%	1,156,000	65%	751,400	247,962
Grand Total					2,284,000	65%	1,484,600	351,124

PEBELS Derived

PEBELS Derived = PPR Generalized

- Classic Reinsurance Per Risk Exposure Rating
- Generalized to contemplate,
 - 1) ***Policy level heterogeneity***
 - 2) Expected loss heterogeneity via ELR_i
 - 3) Loss process heterogeneity via EF_i
 - 4) Historical vs. prospective exposure profiles
 - 5) Credibility

Per Policy Generalization

Insured Value Range (\$000s)	Midpoint (\$000s)	Retention as a % of Insured value	Retention + Limit as a % of Insured value	Exposure Factor	Subject Premium	Expected Loss Ratio	Expected Primary Losses	Expected Reinsurer Losses
20-100	60	167%	833%	0%	682,000	65%	443,300	0
100-250	175	57%	286%	26%	161,000	65%	104,650	27,209
250-1,000	625	16%	80%	41%	285,000	65%	185,250	75,953
1,000-2,000	1,500	7%	33%	33%	1,156,000	65%	751,400	247,962
Grand Total					2,284,000	65%	1,484,600	351,124

PEBELS Derived

PEBELS Derived = PPR Generalized

- Classic Reinsurance Per Risk Exposure Rating
- Generalized to contemplate,
 - 1) Policy level heterogeneity
 - 2) ***Expected loss heterogeneity via ELR_i***
 - 3) Loss process heterogeneity via EF_i
 - 4) Historical vs. prospective exposure profiles
 - 5) Credibility

Heterogeneity Generalization

Insured Value Range (\$000s)	Midpoint (\$000s)	Retention as a % of Insured value	Retention + Limit as a % of Insured value	Exposure Factor	Subject Premium	Expected Loss Ratio	Expected Primary Losses	Expected Reinsurer Losses
20-100	60	167%	833%	0%	682,000	65%	443,300	0
100-250	175	57%	286%	26%	161,000	65%	104,650	27,209
250-1,000	625	16%	80%	41%	285,000	65%	185,250	75,953
1,000-2,000	1,500	7%	33%	33%	1,156,000	65%	751,400	247,962
Grand Total					2,284,000	65%	1,484,600	351,124

Heterogeneity Generalization

$$\underline{PEBEL}_i = P_i * \mathbf{ELR}_i * EF_i$$

- Expected catastrophe loss
- Risk loads
- Rate adequacy

State:	House
X	65.0%
Y	65.0%
Z	40.0%

PEBELS Derived

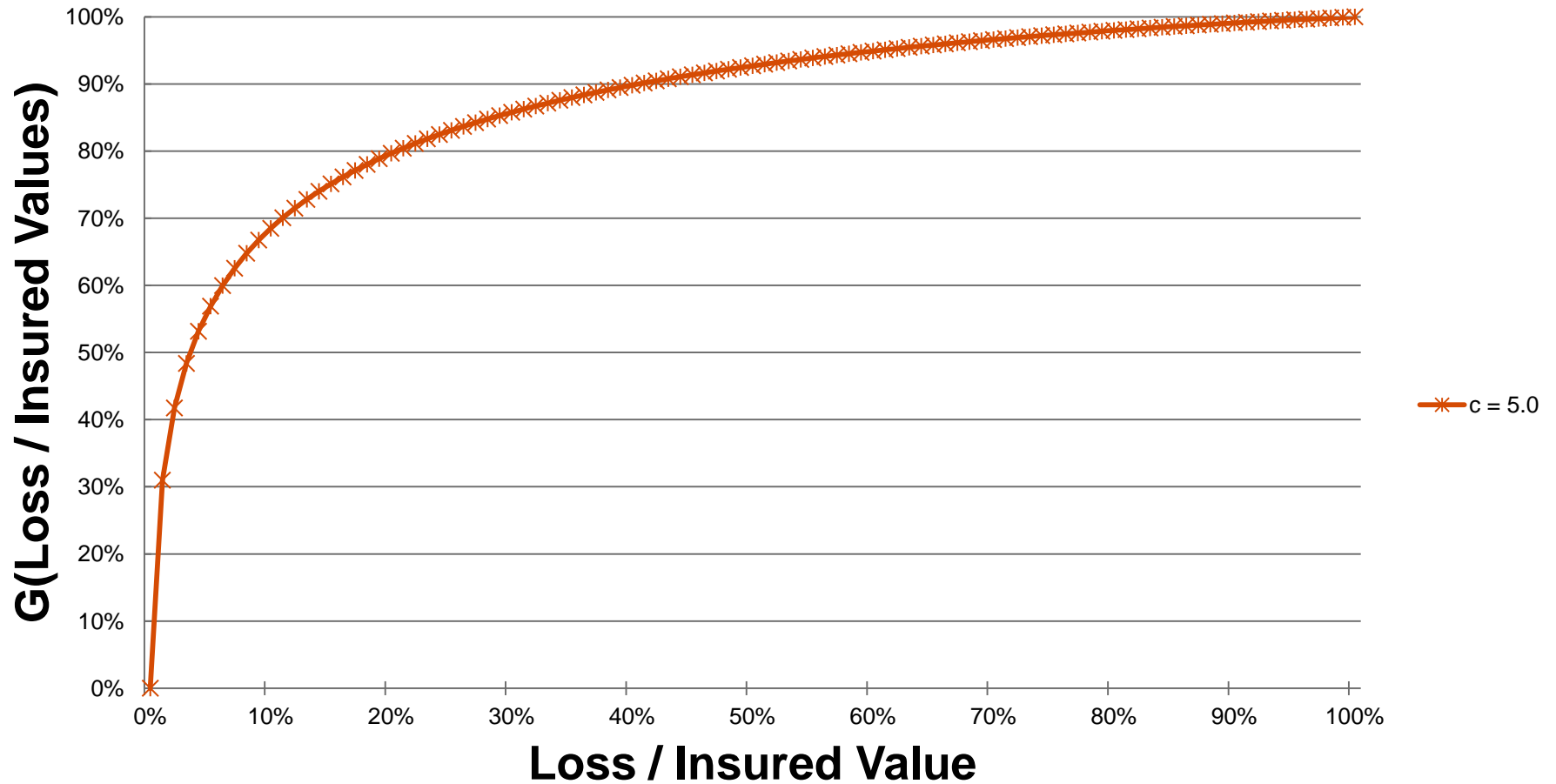
PEBELS Derived = PPR Generalized

- Classic Reinsurance Per Risk Exposure Rating
- Generalized to contemplate,
 - 1) Policy level heterogeneity
 - 2) Expected loss heterogeneity via ELR_i
 - 3) *Loss process heterogeneity via EF_i***
 - 4) Historical vs. prospective exposure profiles
 - 5) Credibility

Heterogeneity Generalization

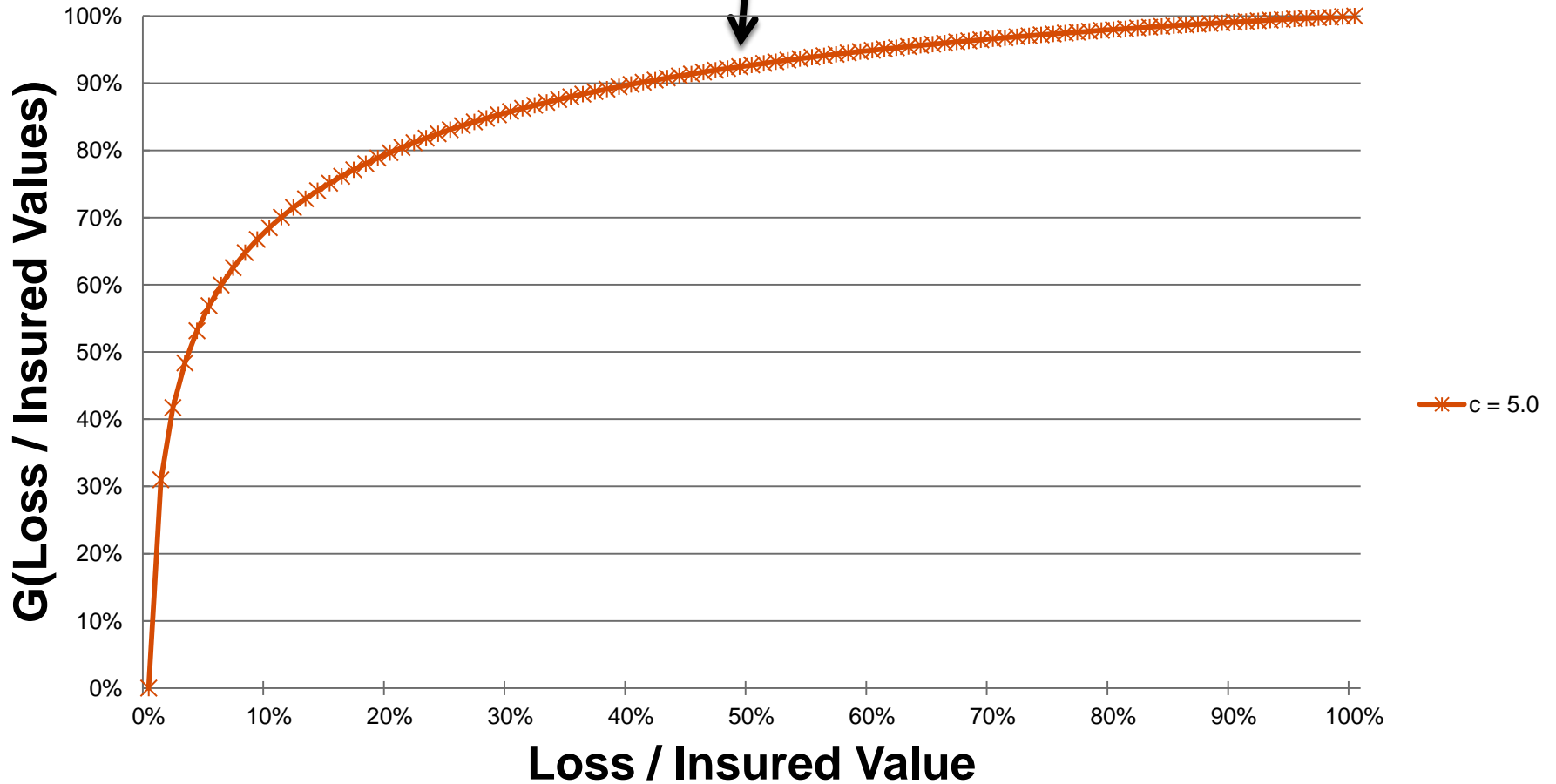
Insured Value Range (\$000s)	Midpoint (\$000s)	Retention as a % of Insured value	Retention + Limit as a % of Insured value	Exposure Factor	Subject Premium	Expected Loss Ratio	Expected Primary Losses	Expected Reinsurer Losses
20-100	60	167%	833%	0%	682,000	65%	443,300	0
100-250	175	57%	286%	26%	161,000	65%	104,650	27,209
250-1,000	625	16%	80%	41%	285,000	65%	185,250	75,953
1,000-2,000	1,500	7%	33%	33%	1,156,000	65%	751,400	247,962
Grand Total					2,284,000	65%	1,484,600	351,124

Exposure Curve



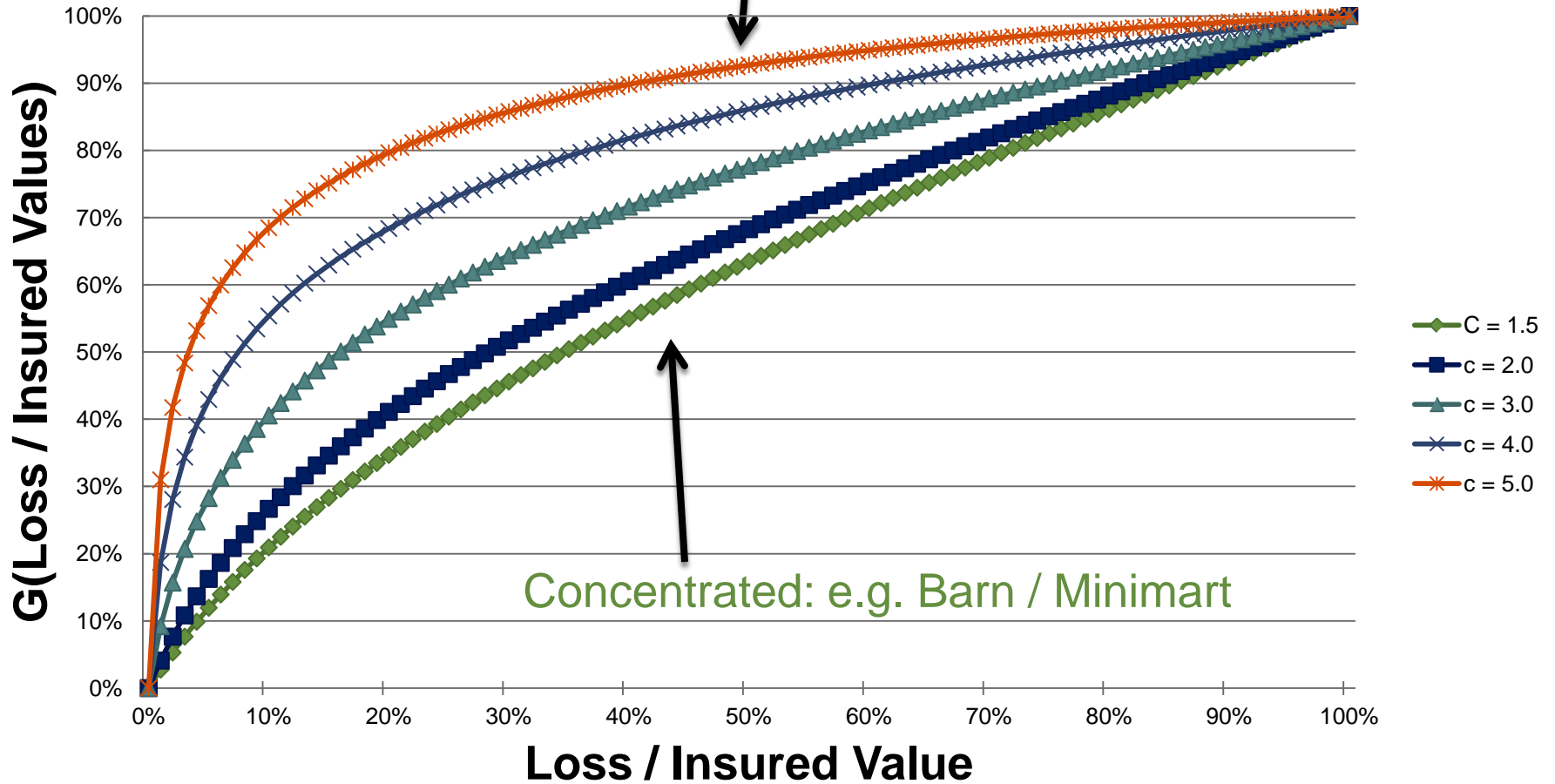
Exposure Curve

Dispersed: e.g. Estate / University Campus



Exposure Curve

Dispersed: e.g. Estate / University Campus



PEBELS Derived

PEBELS Derived = PPR Generalized

- Classic Reinsurance Per Risk Exposure Rating
- Generalized to contemplate,
 - 1) Policy level heterogeneity
 - 2) Expected loss heterogeneity via ELR_i
 - 3) Loss process heterogeneity via EF_i
 - 4) *Historical vs. prospective exposure profiles***
 - 5) Credibility

PEBELS Derived

PEBELS Derived = PPR Generalized

- Classic Reinsurance Per Risk Exposure Rating
- Generalized to contemplate,
 - 1) Policy level heterogeneity
 - 2) Expected loss heterogeneity via ELR_i
 - 3) Loss process heterogeneity via EF_i
 - 4) Historical vs. prospective exposure profiles
 - 5) **Credibility**

Applications

Indications

- Motivated PEBELS
- Allocate large losses to state and program
 - Low credibility
 - High heterogeneity in underlying exposures

Applications

Adjusted Modeled Catastrophe AALs

- Traditionally assume AAL linear with IV
- This contradicts
 - Theory presented
 - Ludwig's study of Hurricane Hugo
- Implies bias between Personal & Commercial
- Can adjust AALs with PEBELS

Applications

Predictive Models

Hypothesize that PEBELS

- More predictive of large loss than IV
- Most predictive for highly skewed perils
- Most predictive in severity/excess models

Applications

Revised Property Per Risk Reinsurance Exposure Rating

Current formulation:

$$NCLL_{\text{Non-Credible Higher Layer}}^{\text{Expected Prospective}} = NCLL_{\text{Credible Lower Layer}}^{\text{Historical}} *$$

$$\frac{PEBEL_{\text{Non-Credible Higher Layer}}^{\text{Prospective}}}{PEBEL_{\text{Credible Lower Layer}}^{\text{Prospective}}}$$

Applications

Revised Property Per Risk Reinsurance Exposure Rating

Proposed formulation:

$$NCLL_{Non-Credible\ Higher\ Layer}^{Expected\ Prospective} = (NCLL_{Credible\ Lower\ Layer}^{Historical})^*$$

$$\left(\frac{PEBEL_{Non-Credible\ Higher\ Layer}^{Historical}}{PEBEL_{Credible\ Lower\ Layer}^{Historical}} \right) * \left(\frac{PEBEL_{Non-Credible\ Higher\ Layer}^{Prospective}}{PEBEL_{Non-Credible\ Higher\ Layer}^{Historical.Annualized}} \right)$$

Summary

PEBELS = Property Large Loss Exposure Segmentation

- Only game in town
- Quantifies messy non-linearities
- Multiple applications
 - Indications
 - Catastrophe Modeling
 - Risk Segmentation



Liberty Mutual[®]

INSURANCE

Historical vs. Prospective

Selecting exposure profile for the application?

Prospective (current inforce)

- Catastrophe modeling
- Reinsurance quotes

Historical (“earned” over experience period)

- Loss ratio ratemaking
- Revised per risk reinsurance exposure rating

Historical vs. Prospective

Loss ratio ratemaking examples

- 1) State in run-off scenario
- 2) State newly entered scenario

Both scenarios lead to skewed state indications

Even small shifts will distort indications

Credibility

Indications example

Layer experience to maximize credibility

Complements

$$1) NCLL_{\$0.1M \text{ to } \$0.5M}^{\text{Historical}} * \frac{PEBEL_{\$0.5M \text{ to } \infty}^{\text{Historical}}}{PEBEL_{\$0.1M \text{ to } \$0.5M}^{\text{Historical}}}$$

$$2) (\text{Direct EP}) * (\text{Reins. Rate}) * (\text{Reinsurer's PLR})$$

Appendix

Misc. Topics

- Exposure curve considerations
- Data limitations and NLE
- Methods in common usage