Practical Aspects of Mortality Improvement Modeling

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Actuaries' Club of the Southwest 2014 Fall Meeting

SCOR Global Life

Presentation Outline

- Insurance vs. Population Data
- Consideration for Smoking Trends
- Methodologies
- Mortality Improvement Examples

Insurance
vs.
Population Data

Insurance Data – 2001 VBT Committee Report

- Male select vs. ultimate period

Implied Annual Mortality Improvement – SOA Male Experience (1985-90 to 1990-95)							
Issue Age	**Duration 1**	**Duration 5**	**Duration 10**	**Duration 20**		**Attained Age**	**Ultimate**
15	2.7%	2.9%	2.4%	-2.6%		25	4.0%
25	5.0	2.0	0.4	-2.1		35	-2.7
35	5.4	3.4	2.6	2.0		45	-1.0
45	8.4	5.5	1.8	-0.3		55	1.5
55	3.1	6.4	1.9	2.2		65	0.7
65	9.1	0.7	2.1	1.1		75	1.7
75	0.5	-0.4	1.2	-2.6		85	0.9

Insurance Data – 2001 VBT Committee Report

- Female select vs. ultimate period

Implied Annual Mortality Improvement – SOA Female Experience (1985-90 to 1990-95)							
Issue Age	**Duration 1**	**Duration 5**	**Duration 10**	**Duration 20**		**Attained Age**	**Ultimate**
15	-1.5%	5.0%	4.9%	-1.6%		25	5.8%
25	1.7	6.3	-2.4	1.3		35	-2.1
35	2.9	2.9	3.9	0.3		45	1.3
45	1.7	3.3	3.2	-0.9		55	-0.8
55	-1.1	1.3	3.7	-0.7		65	-1.1
65	-2.6	3.5	-2.4	-0.2		75	-1.1
75	-0.4	0.3	2.6	1.0		85	-0.5

Comparison of SOA Ultimate Table Rates

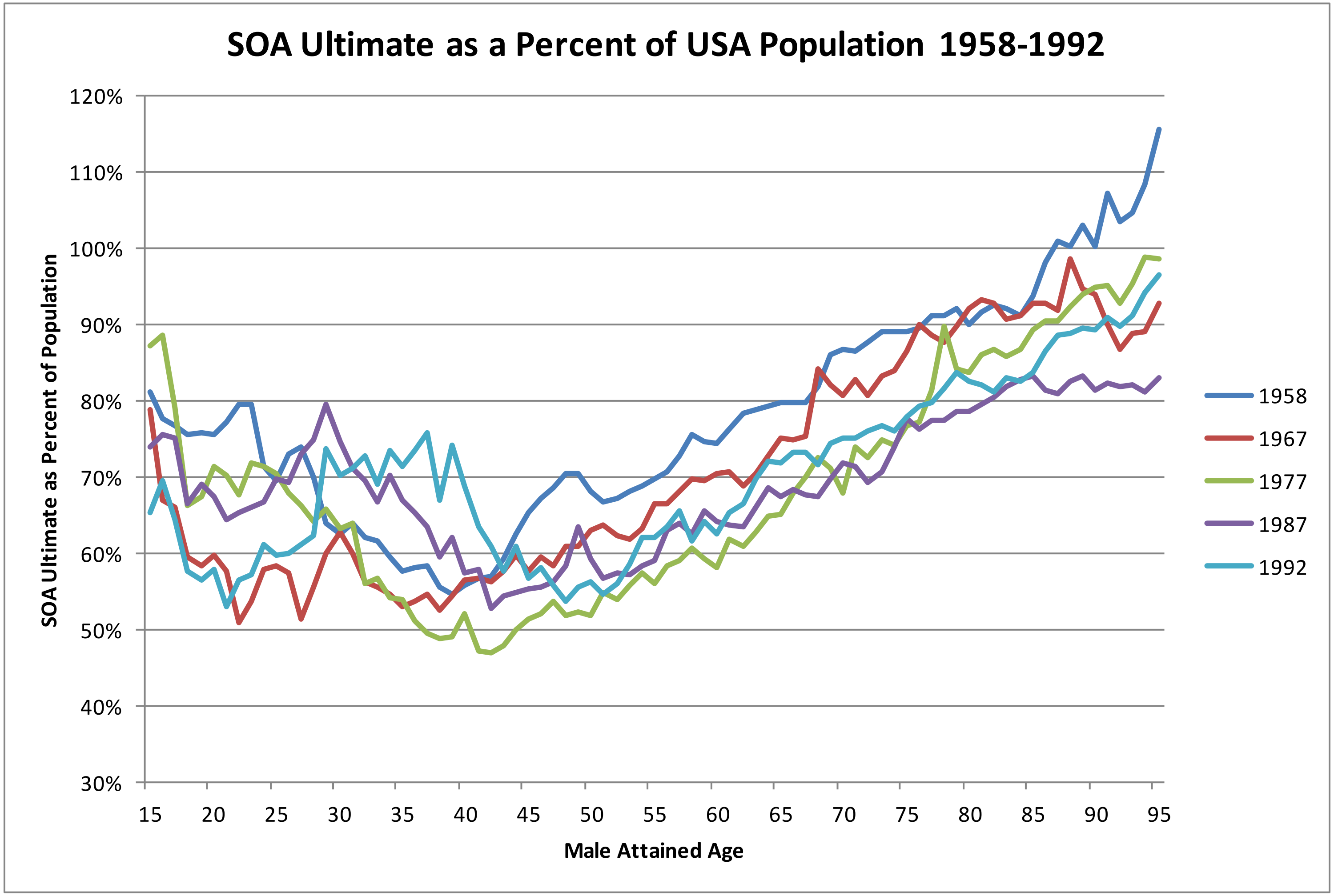
Male Mortality Rates

Age	57-60	65-70	75-80	85-90	90-95
20-29	1.31	1.11	1.32	1.20	1.01
30-39	1.45	1.46	1.21	1.58	1.81
40-49	3.92	3.60	2.59	2.38	2.48
50-59	10.91	10.02	7.20	6.37	5.72
60-69	27.50	25.71	19.28	16.76	16.05
70-79	63.03	61.04	49.41	42.98	40.16
80-89	148.16	139.97	119.54	105.69	103.89

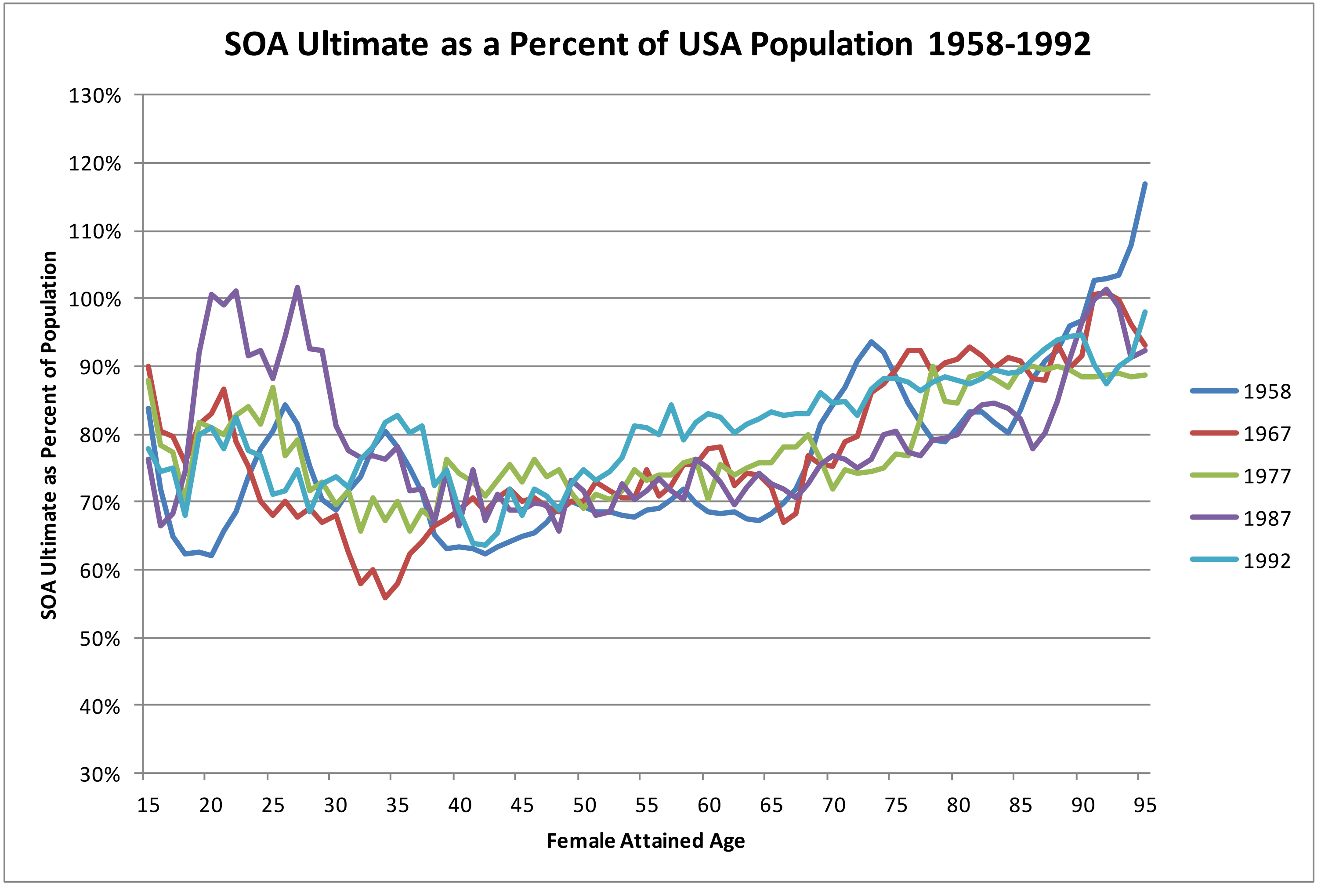
Female Mortality Rates

Age	57-60	65-70	75-80	85-90	90-95
20-29	0.59	0.57	0.53	0.57	0.42
30-39	1.10	0.95	0.78	0.74	0.77
40-49	2.33	2.43	2.08	1.56	1.46
50-59	5.62	5.48	4.75	4.16	4.28
60-69	13.65	12.54	10.87	10.04	10.76
70-79	41.84	38.03	27.79	25.33	26.45
80-89	109.24	104.10	83.22	73.17	73.87

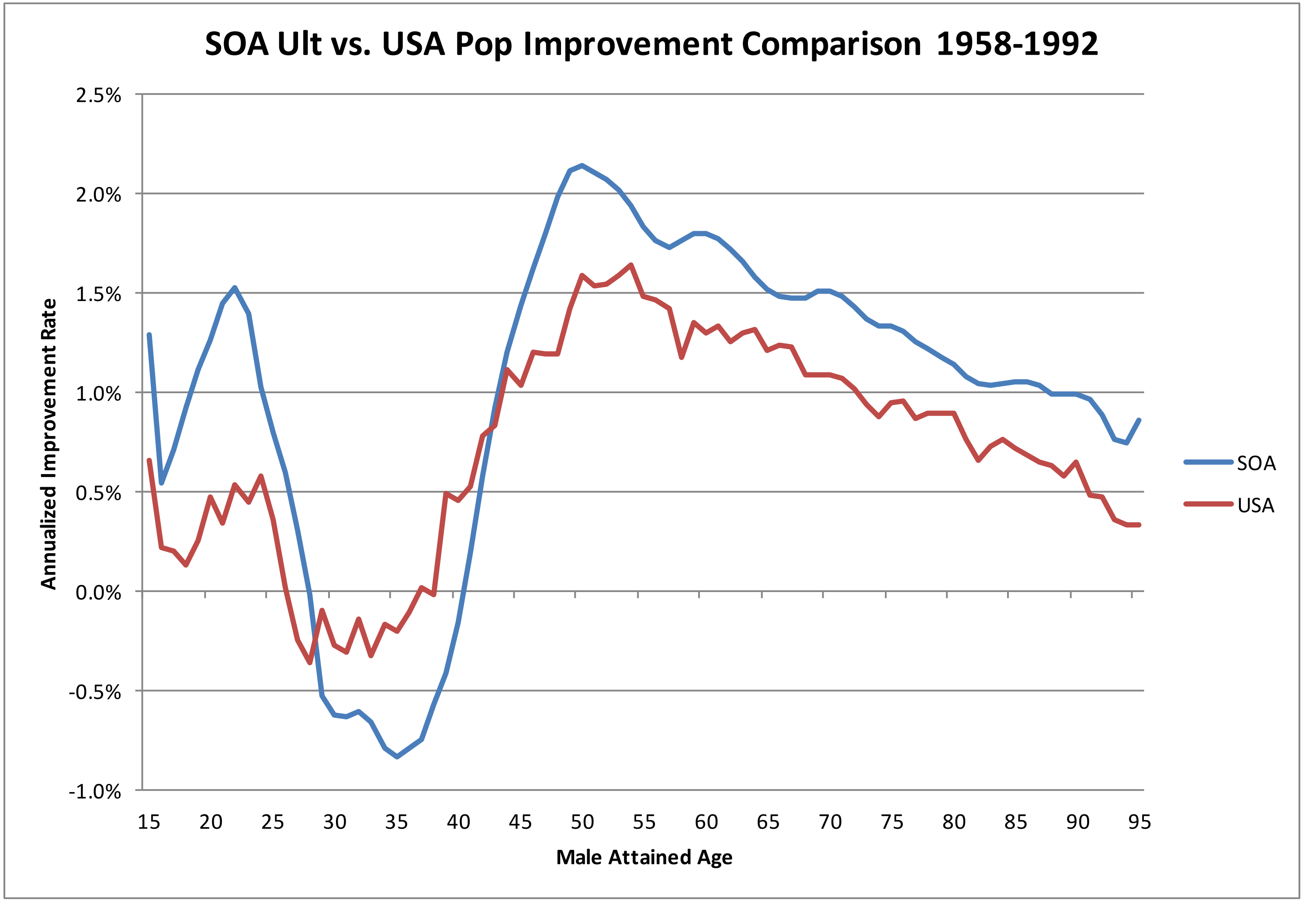
Comparison of SOA Ultimate to Population – Male



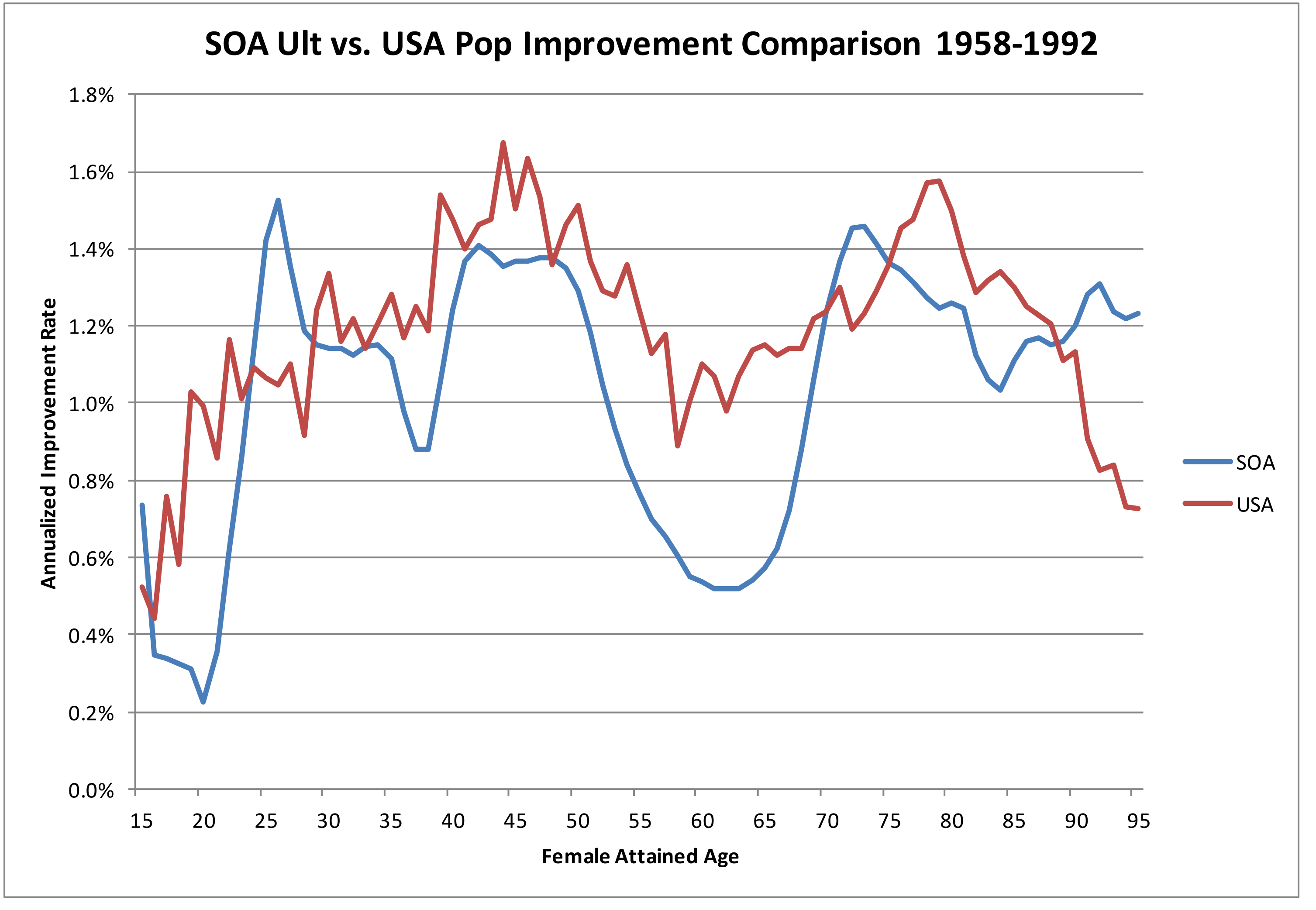
Comparison of SOA Ultimate to Population – Female



Comparison of SOA Ultimate to Population – Male

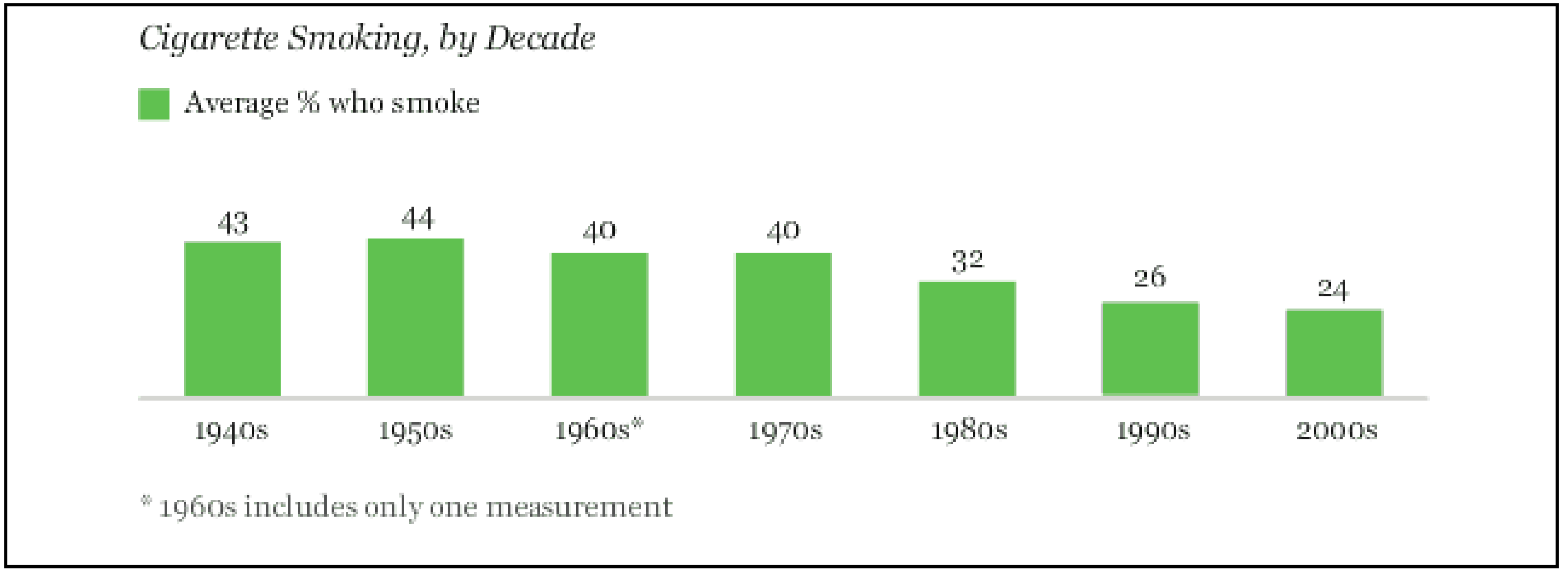


Comparison of SOA Ultimate to Population – Female



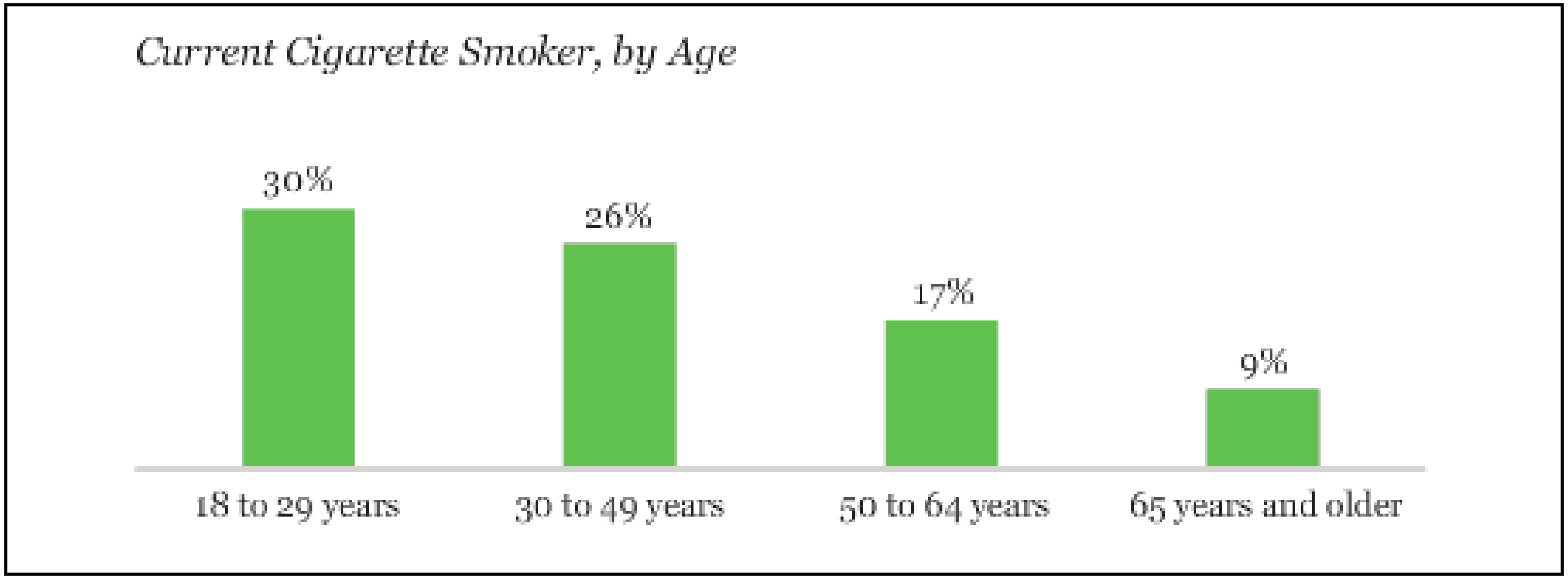
Consideration for Smoking Trends

US Population Historical Smoking Trends



Source: Gallop Poll - July 24, 2008; *U.S. Smoking Rate Still Coming Down*

US Population Current Smoking Trends by Age



Source: Gallop Poll - July 24, 2008; *U.S. Smoking Rate Still Coming Down*

Smoking Adjusted Improvement Rates

- How much improvement is due to reduced smoking?
- Example for male ages 40-50
- Constant S/N ratio shouldn't really be constant
- 25% of annual improvement could be from S/N changes

Year	%Smoker	U.S. Pop Male Mort Ages 40-50	Improvement AG Factor Since 1946	Tillinghast S/N Ratio	Implied NS Mort	Improvement NS Factor Since 1946	Implied SM Mort	Improvement SM Factor Since 1946
1946	43.0%	0.00729	1.000	2.35	0.00461	1.000	0.00922	1.000
1955	44.0%	0.00614	0.842	2.35	0.00385	0.835	0.00770	0.835
1965	40.0%	0.00607	0.832	2.35	0.00394	0.854	0.00788	0.854
1975	40.0%	0.00541	0.743	2.35	0.00352	0.762	0.00703	0.762
1985	32.0%	0.00424	0.582	2.35	0.00296	0.642	0.00592	0.642
1995	26.0%	0.00435	0.596	2.35	0.00322	0.698	0.00644	0.698
2004	24.0%	0.00367	0.504	2.35	0.00277	0.601	0.00555	0.601
1946-2004 Annualized Improvement Rate			1.2%			0.9%		0.9%

Methodologies

Methodologies to Analyze Mortality Improvement

- *Lee-Carter*
  - Pro: Widely used by biostatisticians
  - Con: Overly complex and difficult to explain to laymen

- *Use raw mortality rates*
  - Pro: Produces a mean improvement rate and a standard deviation
  - Con: Uses raw mortality rates and makes no attempt to smooth or trend the data

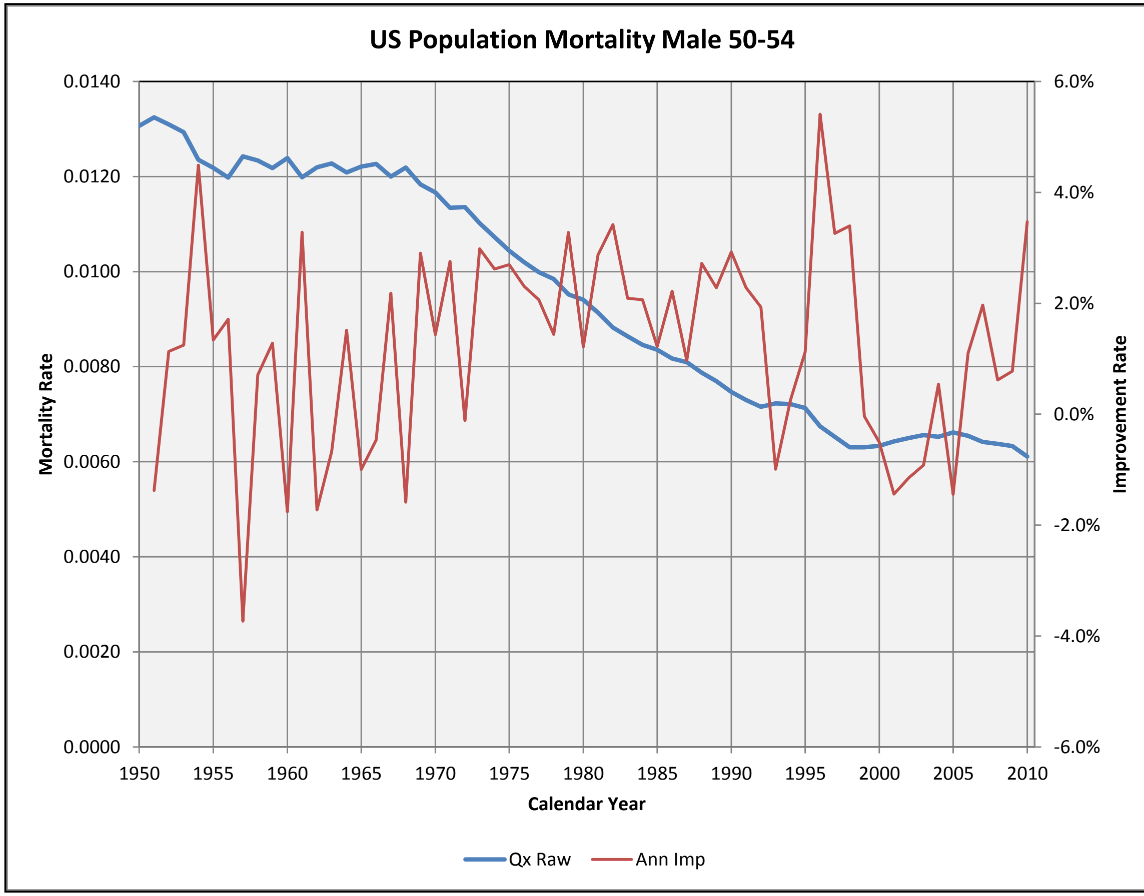
- *Create a regression model from the raw rates*
  - Pro: Impact of anomalous values (or outliers) is minimized and thus may represent a better view of mortality trends
  - Con: Cannot be used to calculate a standard deviation for the dataset

Lee-Carter

- $\ln(mx,t) = a_x + (b_x)(k_t) + \varepsilon_{x,t}$
  - $m_{x,t}$ is central death rates at age x in year t
  - k_t is the index of mortality change
  - a_x and b_x are the age specific constant vectors
  - $\varepsilon_{x,t}$ is the residual error term with mean 0 and variance σ_ε^2
- Normalization
  - a_x = average of $\ln(m_{x,t})$
  - b_x sum to 1
  - k_t sum to 0
- Two stage approach to fitting the model
  1. Singular value decomposition applied to matrix of $[\ln(m_{x,t}) – a_x]$ to obtain estimates of b_x and k_t
  2. Time series of k_t is re-estimated so total number of deaths in model matches total number of actual deaths
- Annual Improvement rate $a_{x,t} \sim 1 – \exp[b_x * (k_{t+1} – k_t)]$

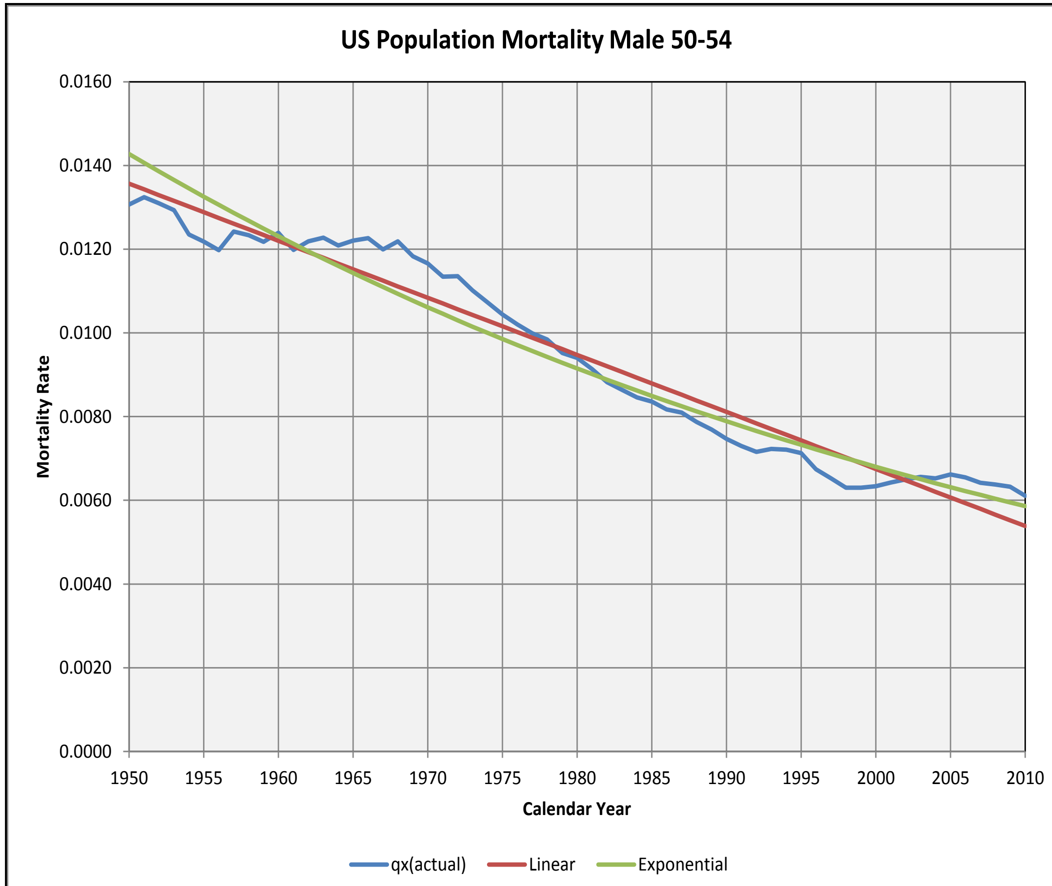
Use Raw Mortality Rates

	Mean	1.24%
	Stdev	1.80%
	CLT Stdev	0.23%
Year	Qx Raw	Ann Imp
1950	0.013065	
1951	0.013245	-1.4%
1952	0.013095	1.1%
1953	0.012932	1.2%
1954	0.012351	4.5%
1955	0.012185	1.3%
1956	0.011977	1.7%
1957	0.012423	-3.7%
1958	0.012335	0.7%
1959	0.012177	1.3%
1960	0.012391	-1.8%
1961	0.011984	3.3%
1962	0.012191	-1.7%
1963	0.012274	-0.7%
1964	0.012088	1.5%
1965	0.012208	-1.0%
1966	0.012265	-0.5%
1967	0.011997	2.2%
1968	0.012187	-1.6%
1969	0.011834	2.9%
1970	0.011663	1.4%



Create a Regression Model

		Linear	Exponential
	m	-0.00014	0.98528
	b	27.940%	5.1695E+10
	Ann'l Imp	1.53%	1.47%
Year	qx(actual)	qx(trend)	qx(trend)
1950	0.013065	0.013566	0.014277
1951	0.013245	0.013430	0.014067
1952	0.013095	0.013294	0.013860
1953	0.012932	0.013157	0.013656
1954	0.012351	0.013021	0.013455
1955	0.012185	0.012885	0.013257
1956	0.011977	0.012748	0.013061
1957	0.012423	0.012612	0.012869
1958	0.012335	0.012476	0.012680
1959	0.012177	0.012339	0.012493
1960	0.012391	0.012203	0.012309
1961	0.011984	0.012067	0.012128
1962	0.012191	0.011930	0.011949
1963	0.012274	0.011794	0.011774
1964	0.012088	0.011658	0.011600
1965	0.012208	0.011521	0.011430
1966	0.012265	0.011385	0.011261
1967	0.011997	0.011249	0.011096
1968	0.012187	0.011112	0.010932
1969	0.011834	0.010976	0.010771
1970	0.011663	0.010840	0.010613



Long-Term Improvement Using the Central Limit Theorem

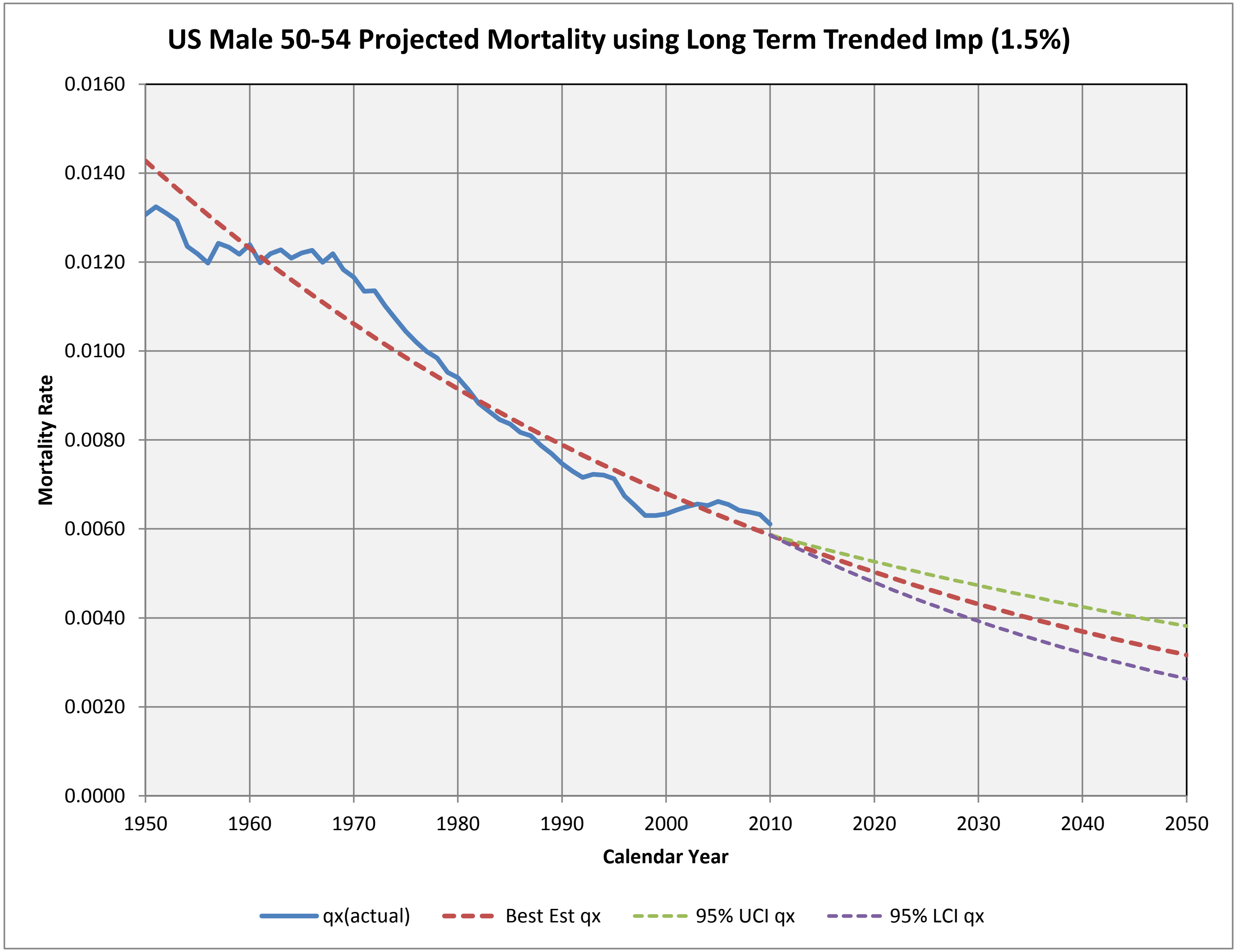
- It is important to understand that the standard deviation we have calculated represents the fluctuation in <u>yearly</u> improvement rates.

- In projecting future mortality, we need to calculate the fluctuation in the <u>long-term mean</u> of improvement rates.

- We use the Central Limit Theorem to determine the standard deviation of the mean of our historical sample dataset from the standard deviation of the annual improvement rates.

- Std dev (imp rate means) = std dev (dataset imp rates) / SQRT(dataset size)

Projecting Mortality Rates

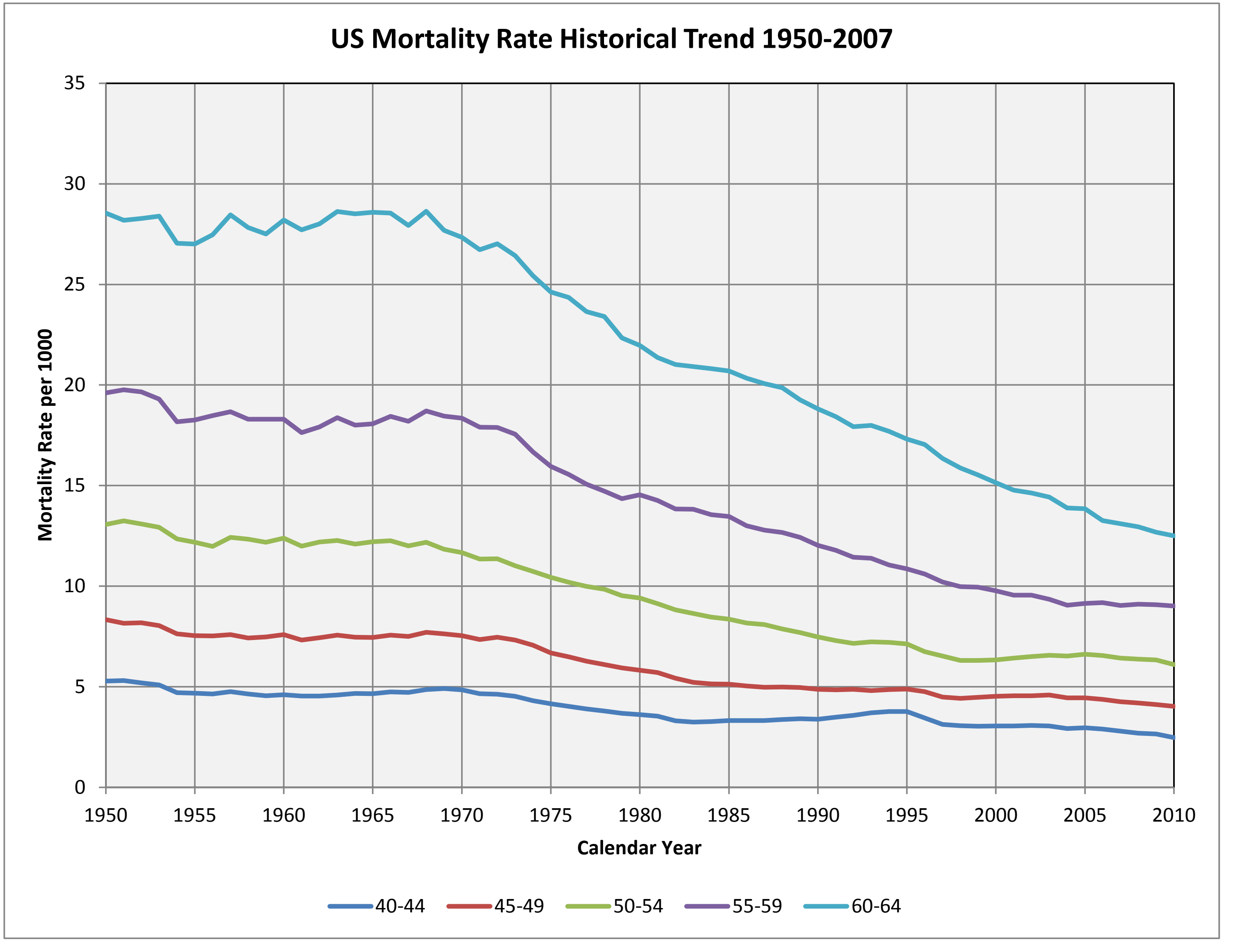


Choosing Appropriate Historical Periods

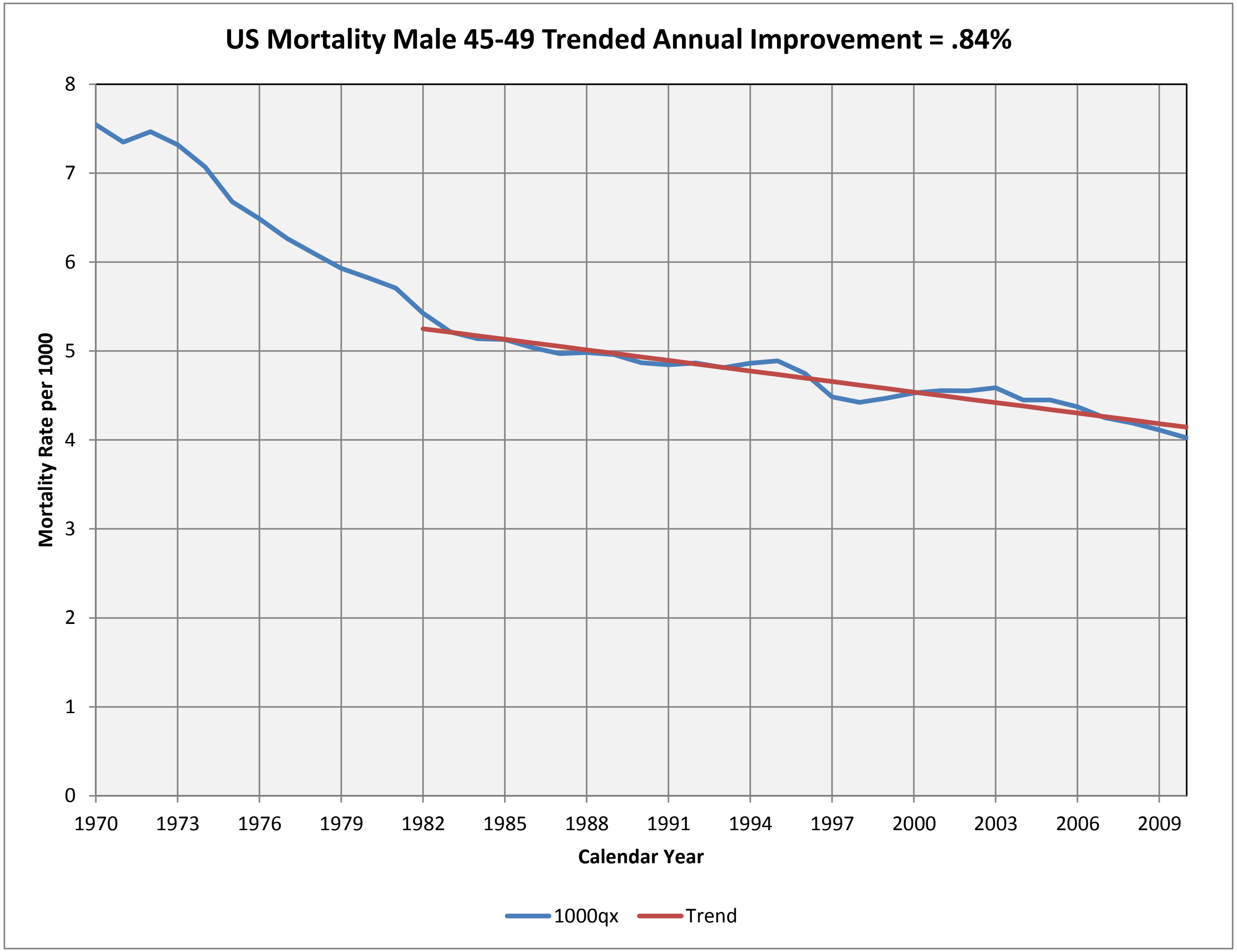
- In determining average historical improvement rates, it is important to use only the most appropriate time periods from the available dataset.
- We begin by looking at the pattern of mortality rates since 1950 by age group and gender.
- A year in which a significant and permanent change occurred in the pattern for a specific age group and gender may be used to censor the data prior to that year.
- However, care is always taken to ensure that we are using a reasonable number of data points.
- For example, a change that occurred in 2003 would not normally warrant excluding prior data without a sufficiently strong rationale.

Examples

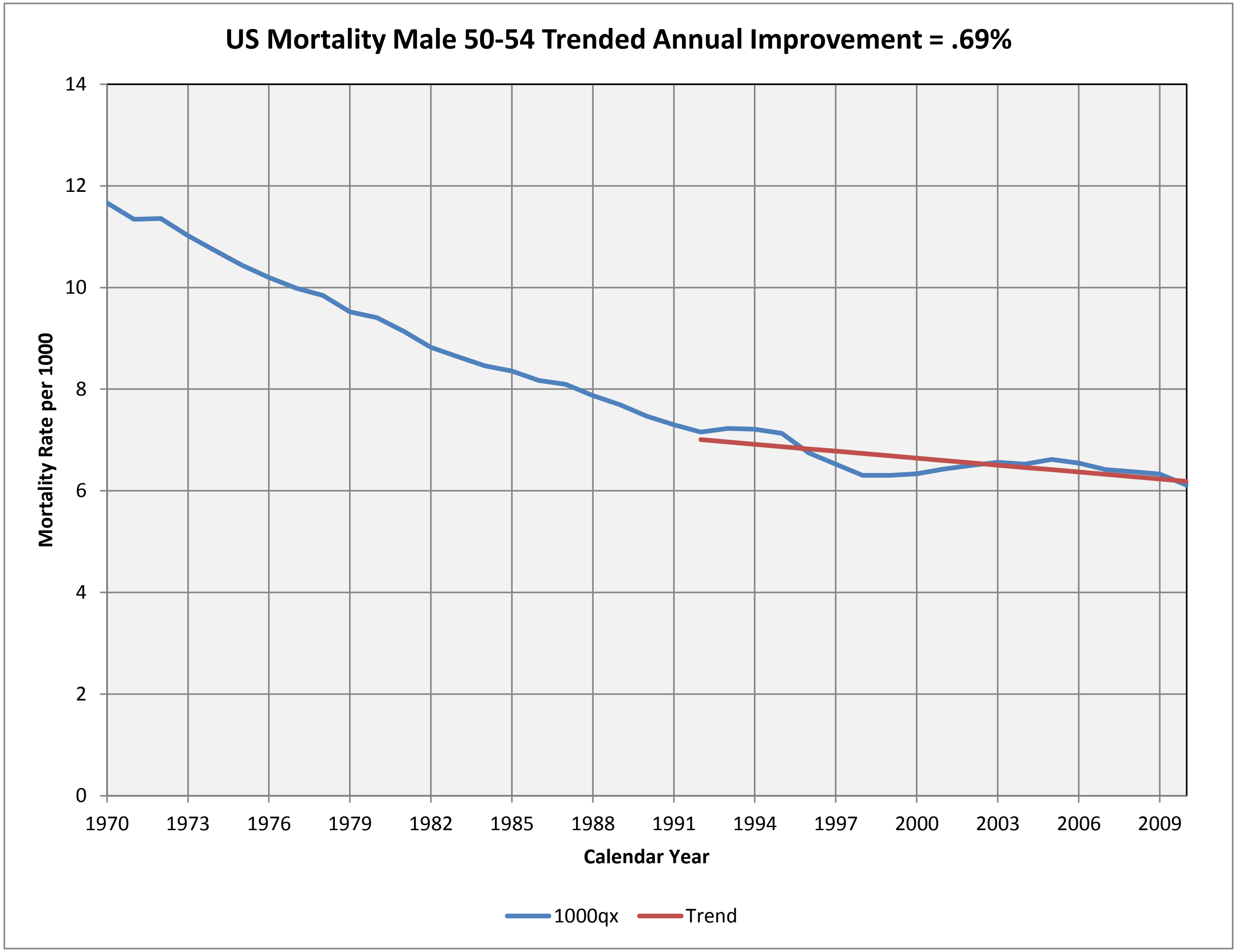
US Population – Males



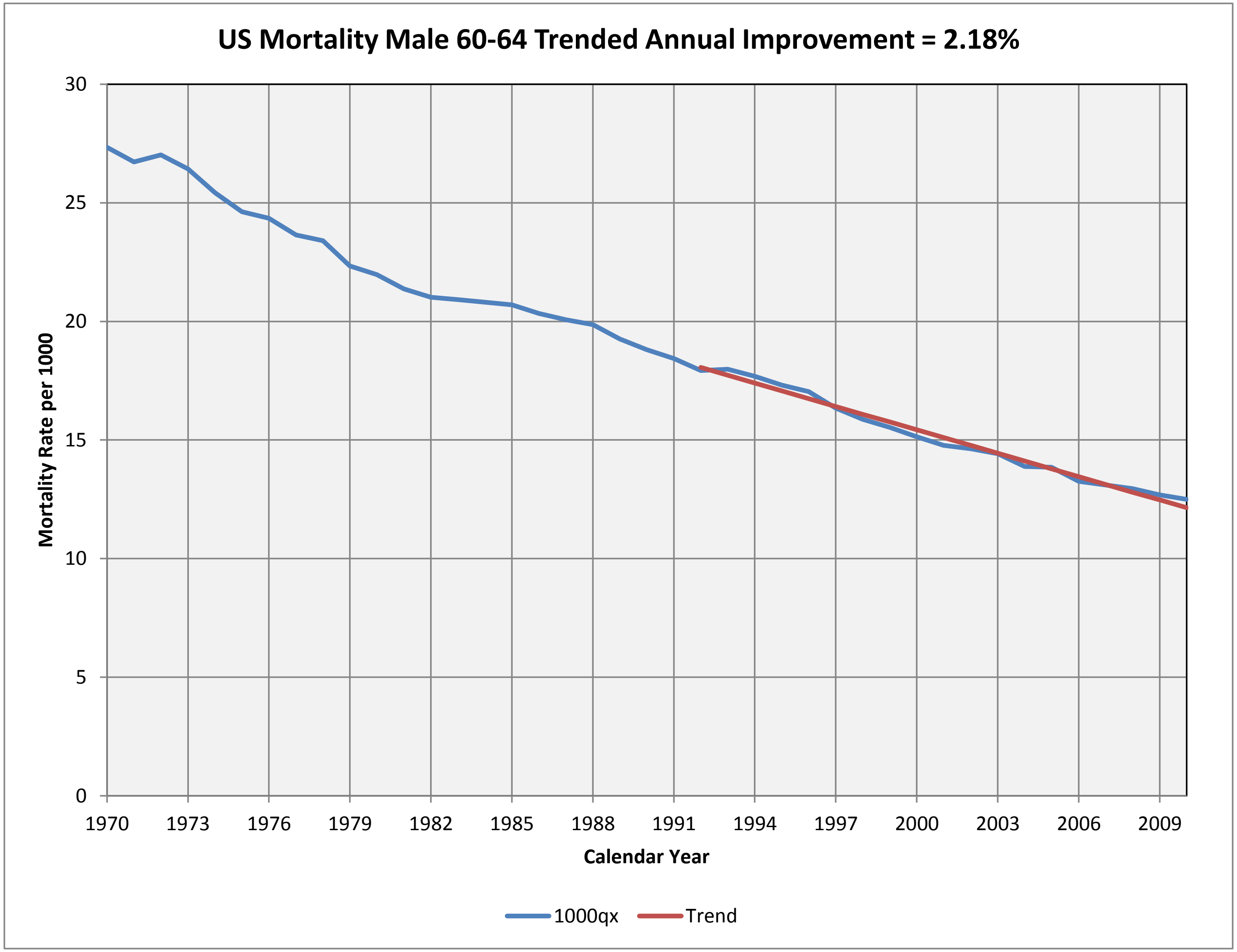
US Population – Males



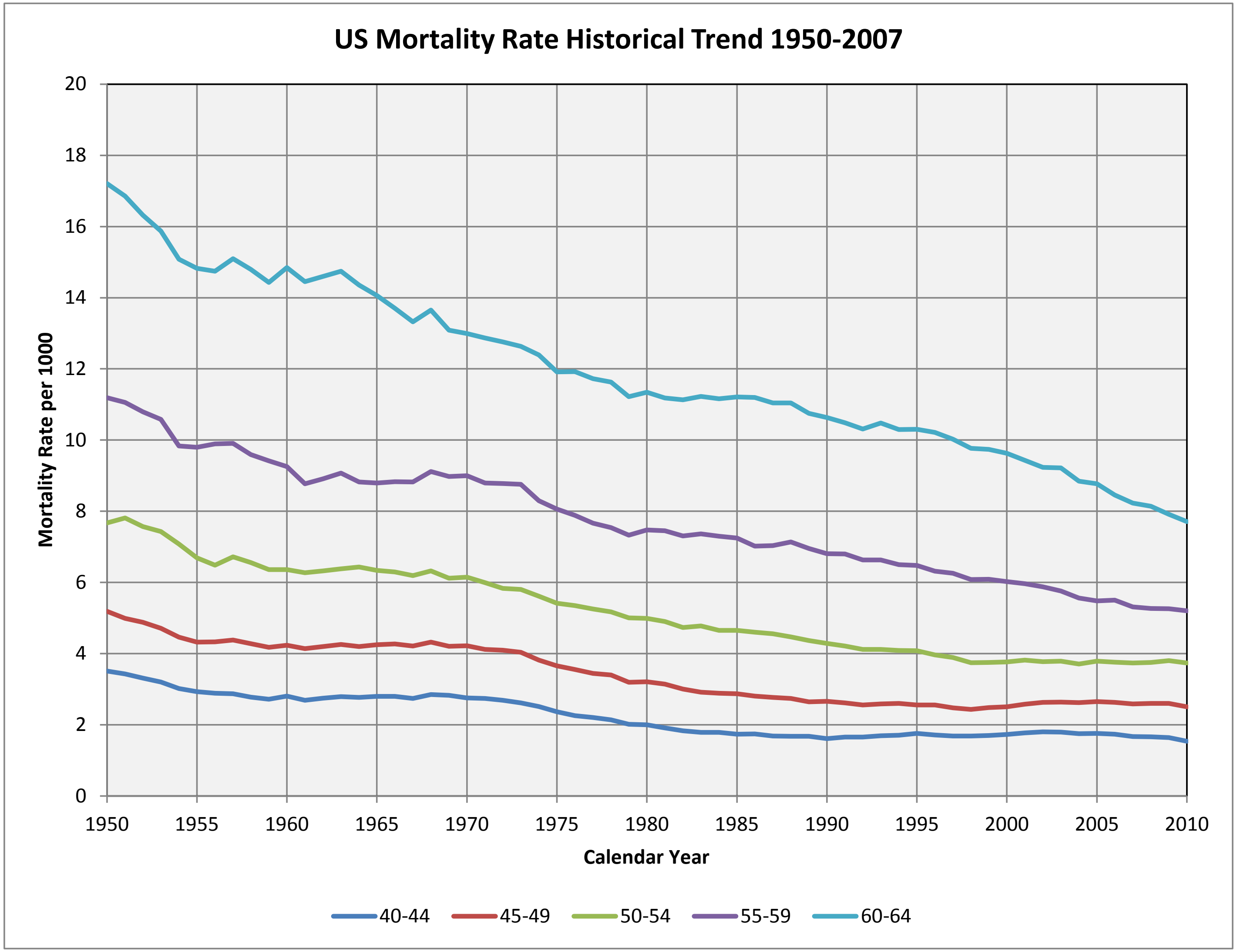
US Population – Males



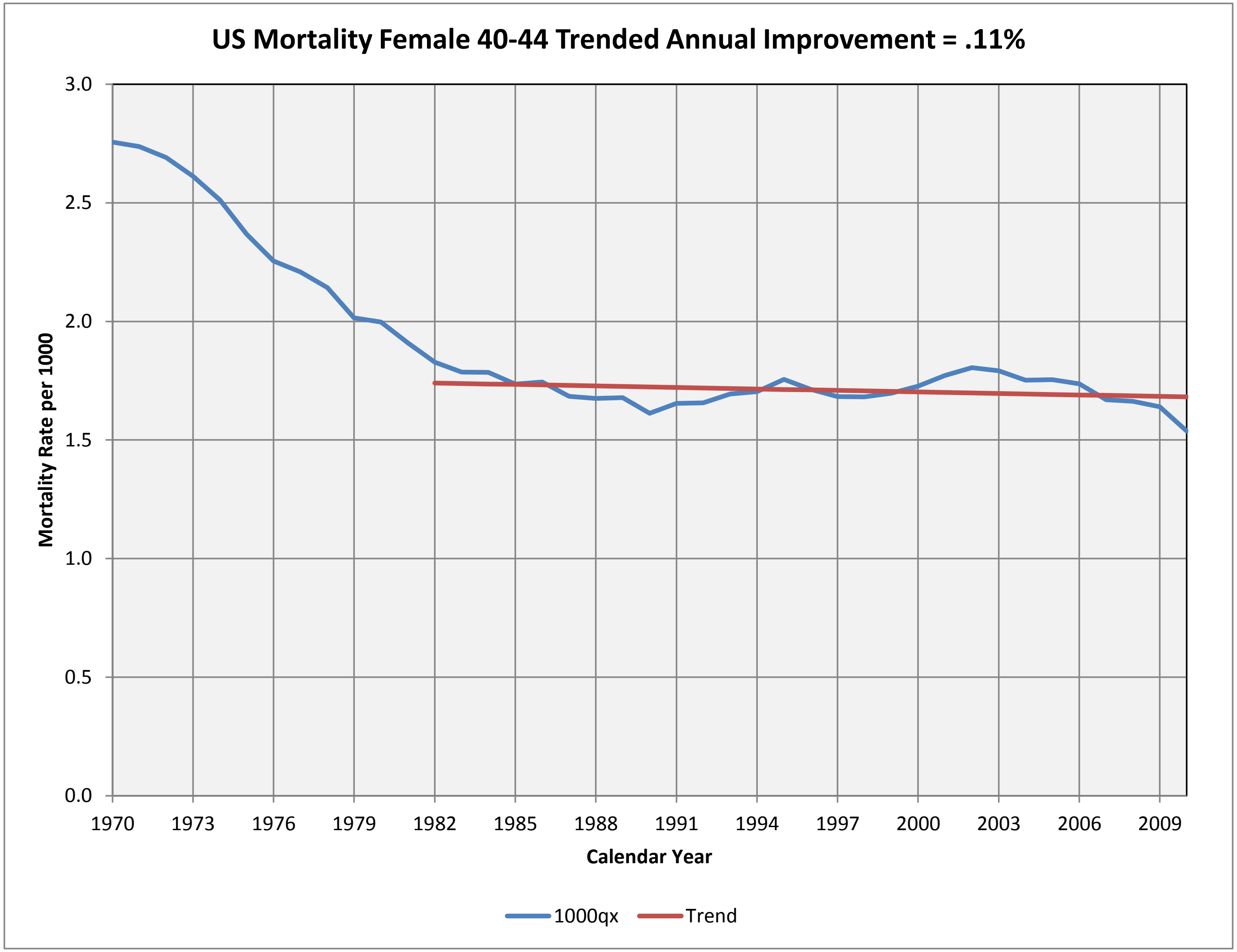
US Population – Males



US Population – Females



US Population – Females



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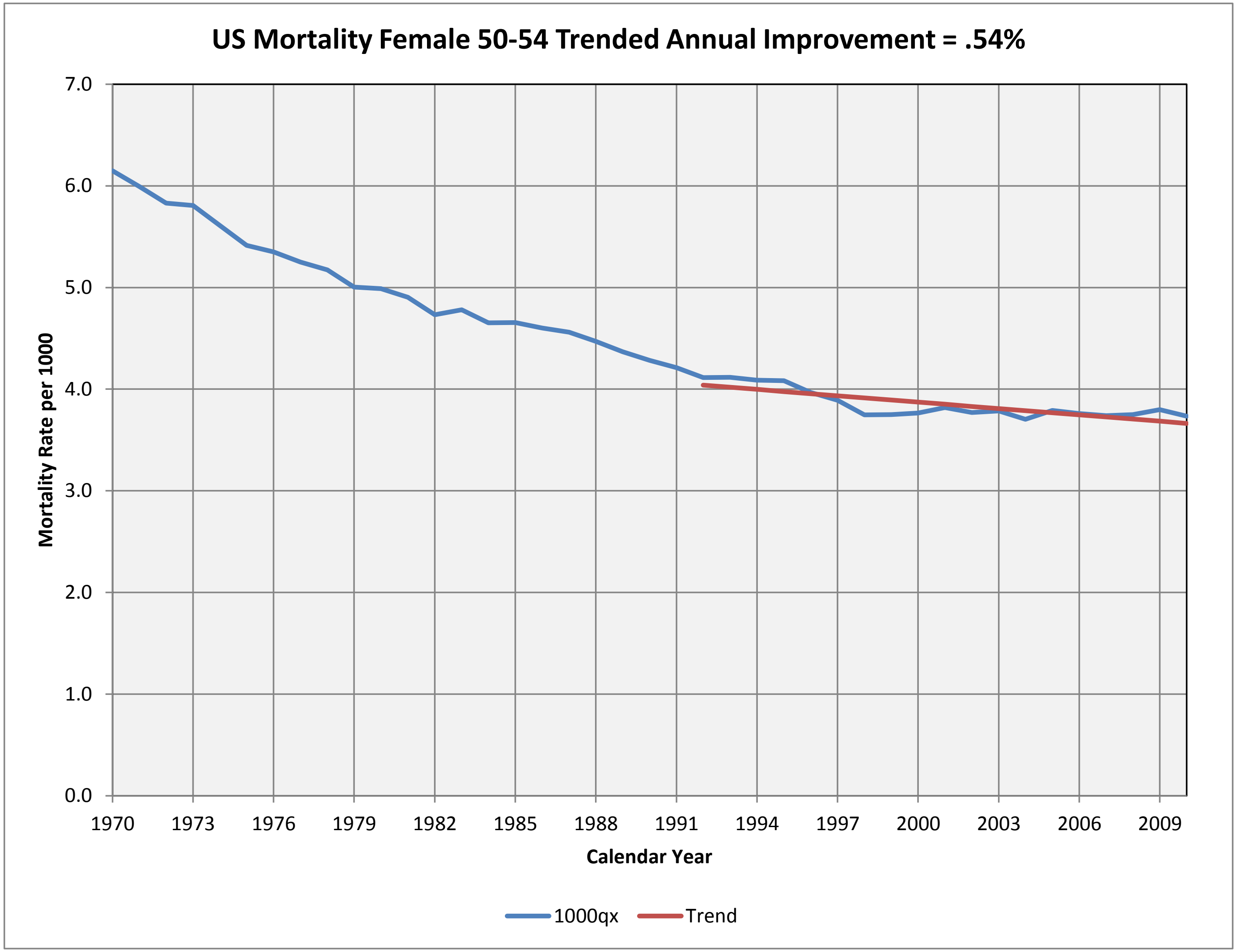
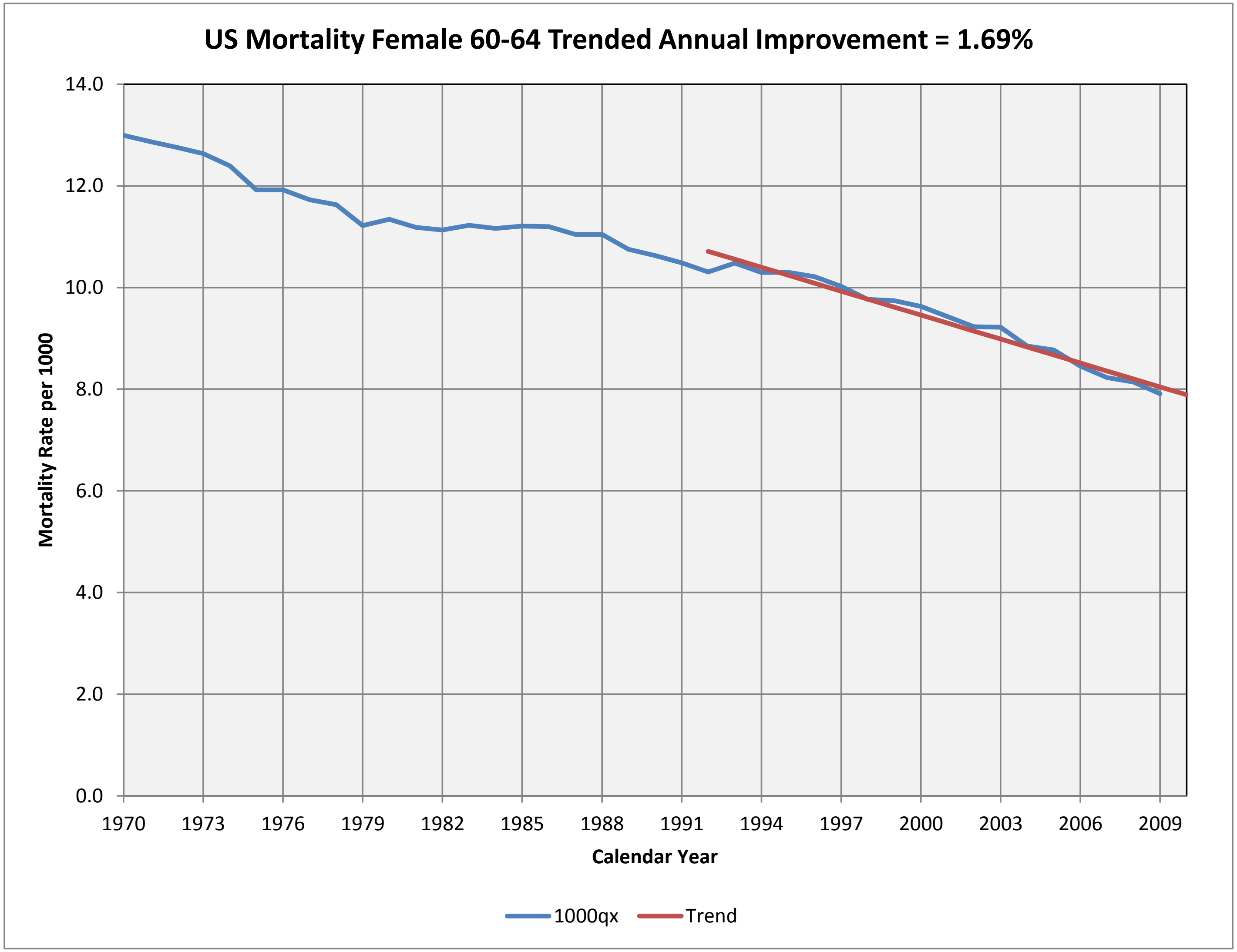
US Population – Females



US Population – Females



Mortality Experience: The Funnel Effect

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Defining the Problem

- Companies with very similar underwriting practices, guidelines, preferred criteria, and marketing strategies often have very different experience.
- Even after normalizing for underwriting mortality class distributions and other identifiable characteristics, credible actual-to-expected ratios for these supposedly similar companies can differ significantly.

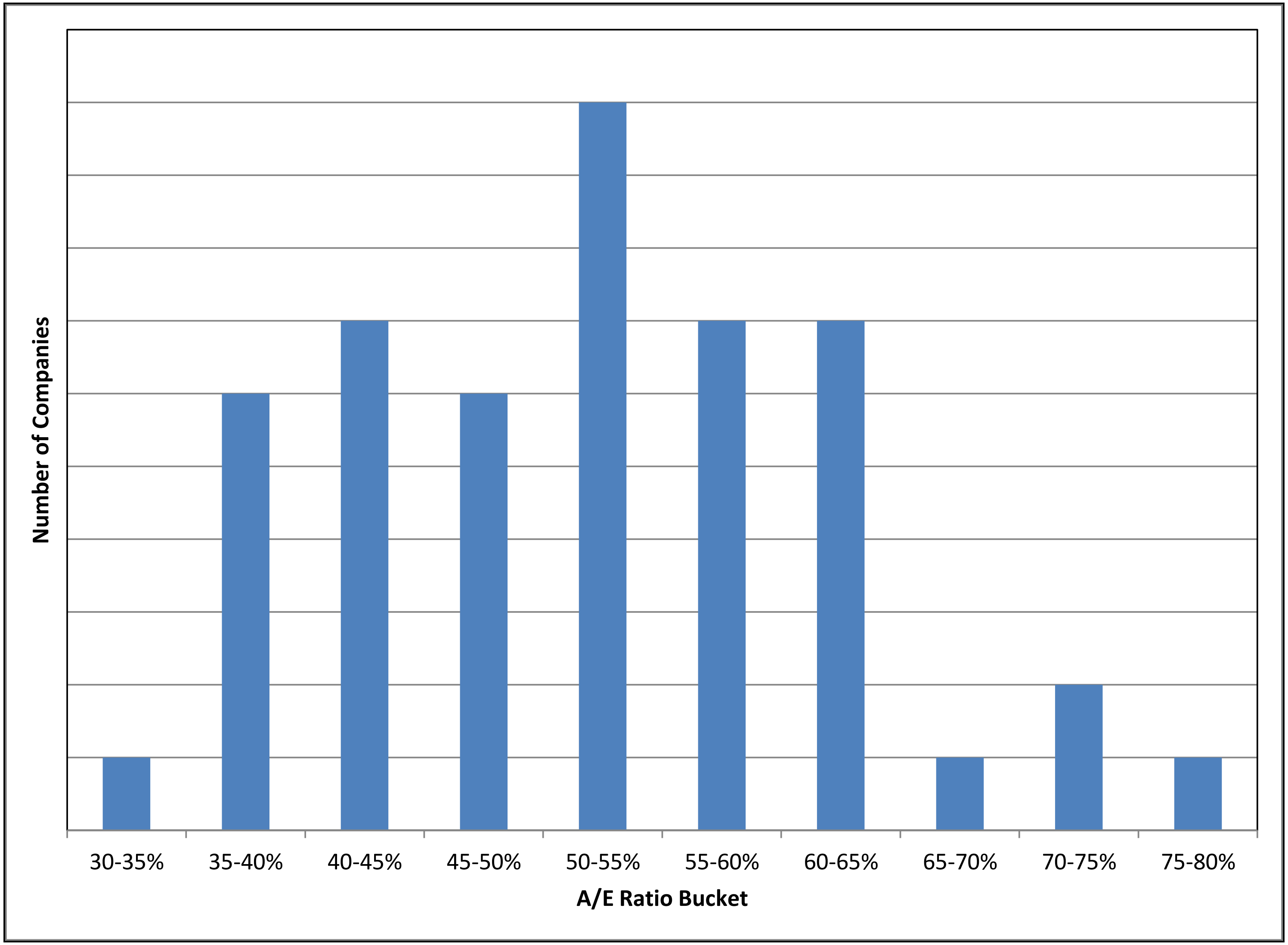
- “The Funnel Effect”
  - A company’s mortality experience is partially determined by the population “funneled” to it via distribution channels and market forces.
  - Even though a company’s underwriting process selects and segments this applicant pool, if a company’s funnel draws from a population having worse/better than average mortality, such mortality deviations will permeate the company’s segmented experience due to unspecified, but relevant, population characteristics.

- Let’s take a look at some SCOR reinsurance experience…

Company A/E Ratio Distribution

- SCOR reinsurance experience database
- Exposure years 2004-2011
- Original face amounts $100,000 and above
- Filter on 2, 3, 4, 5, and 6 nontobacco class systems
- Actual to expected ratios by amount based upon SOA 2001 VBT
- Companies with 35 or more claims

Company A/E Ratio Distribution



Defining the Experiment

- The funnel effect implies that a company's early duration mortality experience does not converge at some point to an industry average as measured by, for example:
  - Society of Actuaries Inter-company study
  - Reinsurer's combined experience table

- The experiment was designed to see if a company's mortality remained stable over durational time.
  - Did a company with high early duration mortality also have high mortality in later durations?
  - Did a company with low early duration mortality have low mortality in later durations?

Defining the Experiment

- An ideal experiment would look at current early duration actual-to-expected (A/E) ratios for a wide variety of companies and then follow these closed blocks of business for the next 30+ years to see if the initial A/E ratios hold steady into the future (all else being equal).
  - This would provide good evidence that individual company experience does not converge to a common level.

- Unfortunately, I did not have the luxury of waiting this long for results!
  - Instead, using information from a large industry mortality study, I compared today's recent experience among companies for policies issued during 1980-84, 1985-89, 1990-94, 1995-99, and 2000-04.
  - This allowed me to view A/E ratio trends by company for durations 1-5, 6-10, 11-15, 16-20, and 21-25.

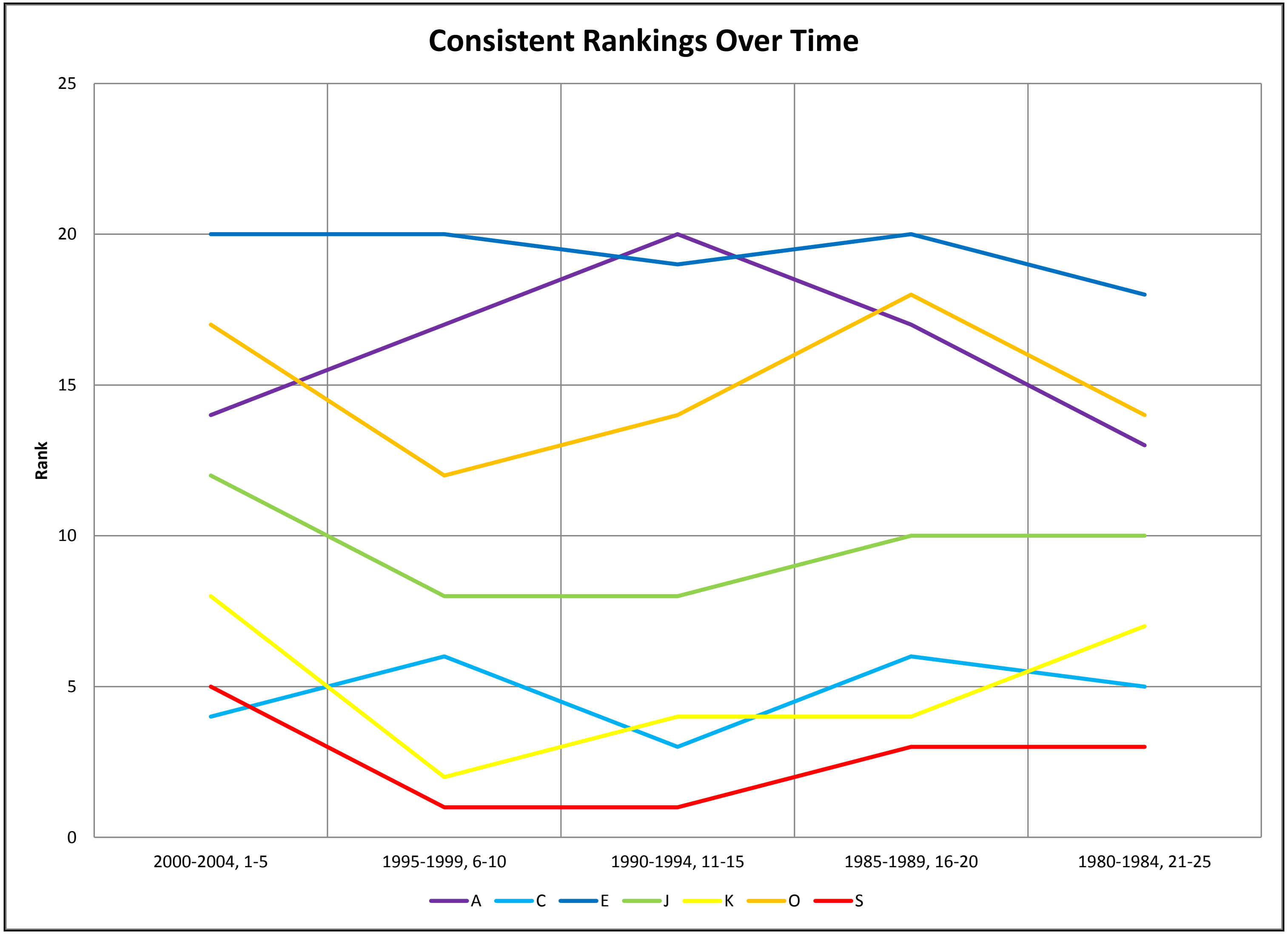
Defining the Experiment

- This form of the experiment is far from perfect due to marketplace evolution over the issue periods surveyed.
- Elements such as target market, product characteristics, distribution channels, underwriting philosophy, company reputation, and mergers/acquisitions could have affected historical mortality experience.
- The data was filtered as much as possible to compensate for these items.

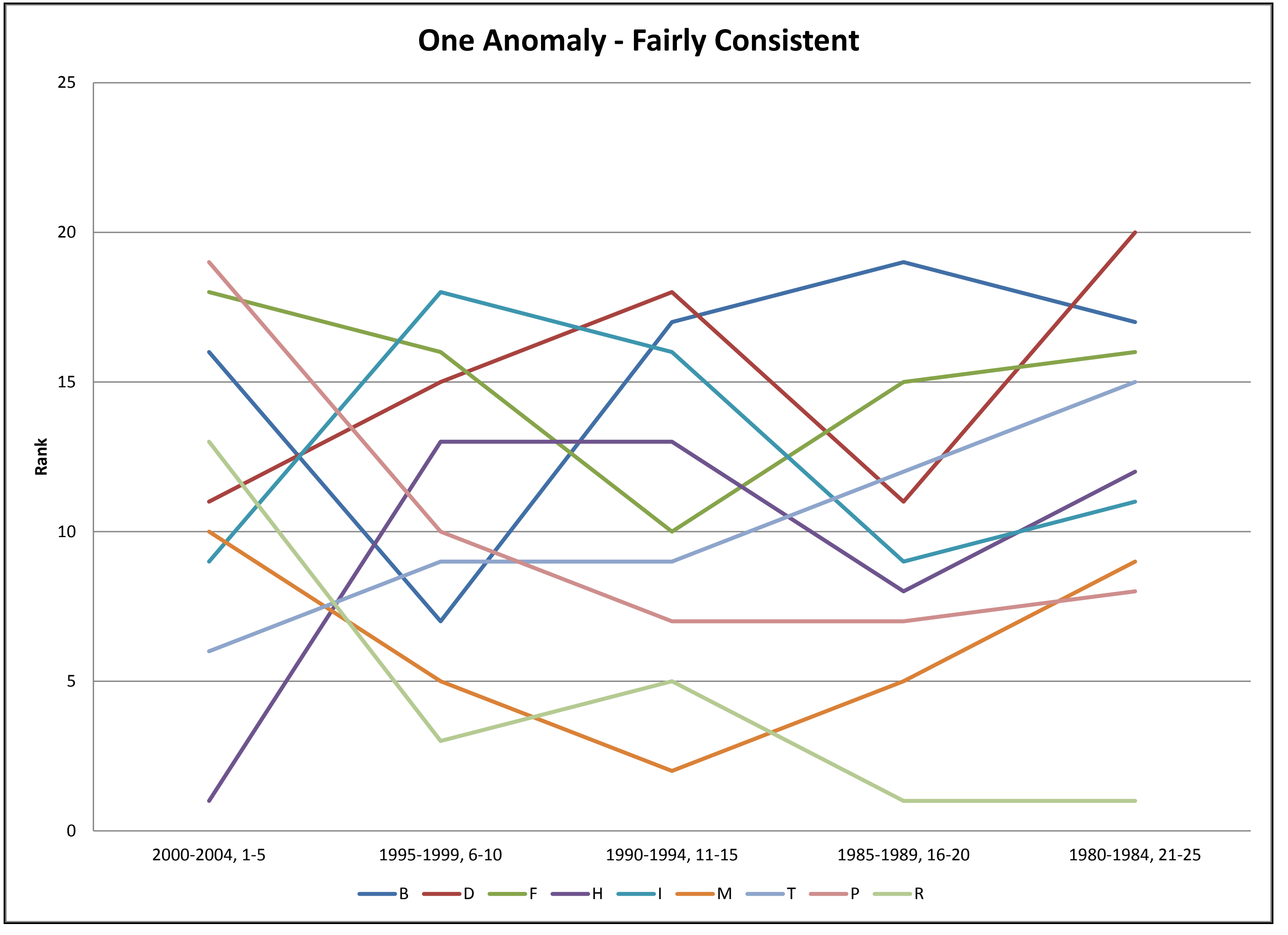
Preliminary Analysis

- Data obtained from 20 companies' experience.
- The analysis entailed ranking the company A/E ratios (2008 VBT) from lowest (1) to highest (20) for each of the five issue era periods.
- Results for 7 companies appeared to have very stable rankings from period to period.
- An additional 9 companies had rankings that were reasonably stable (one anomalous period).
- The final 4 companies had rankings that varied from period to period.

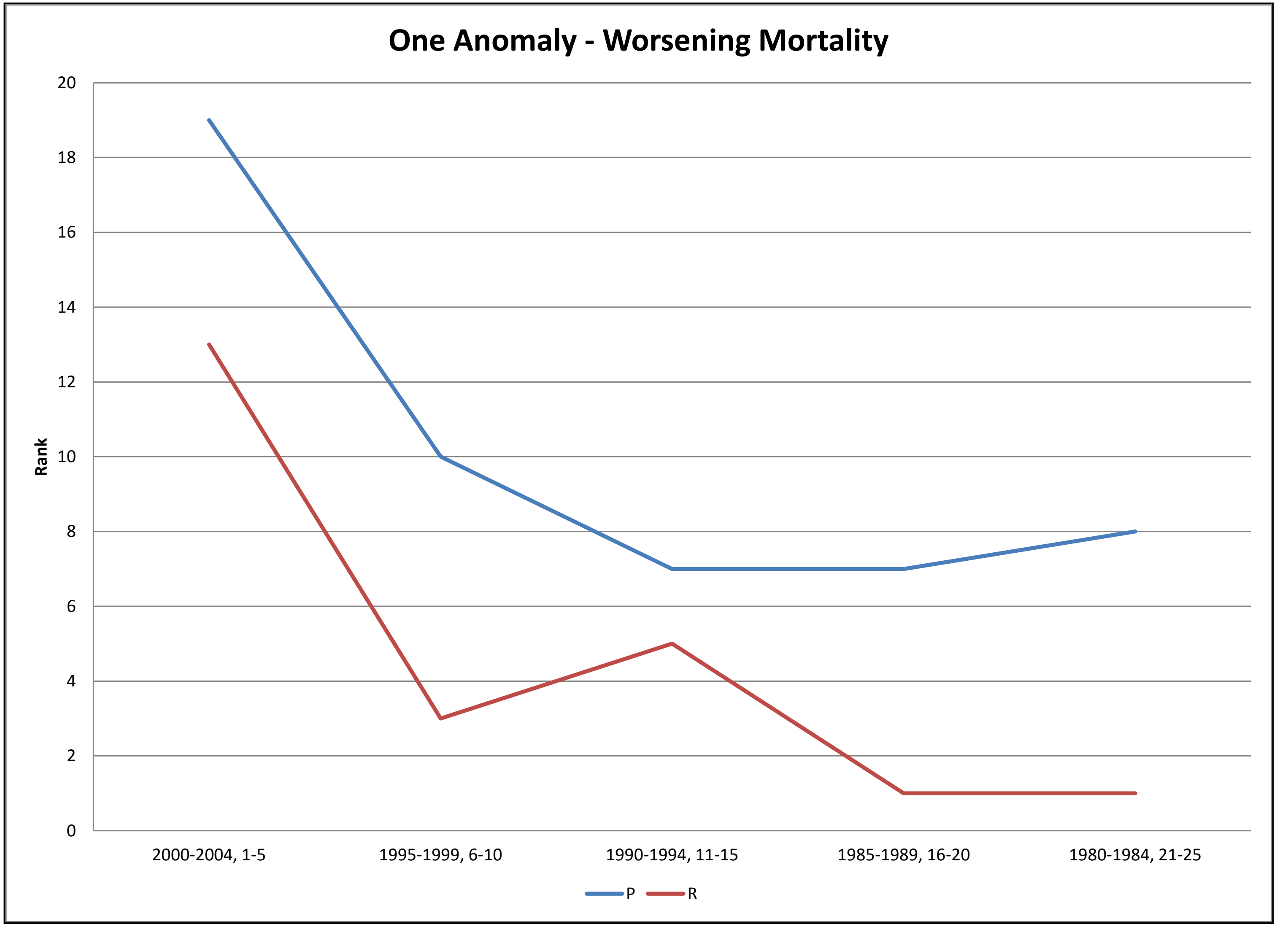
Consistent Mortality Rank



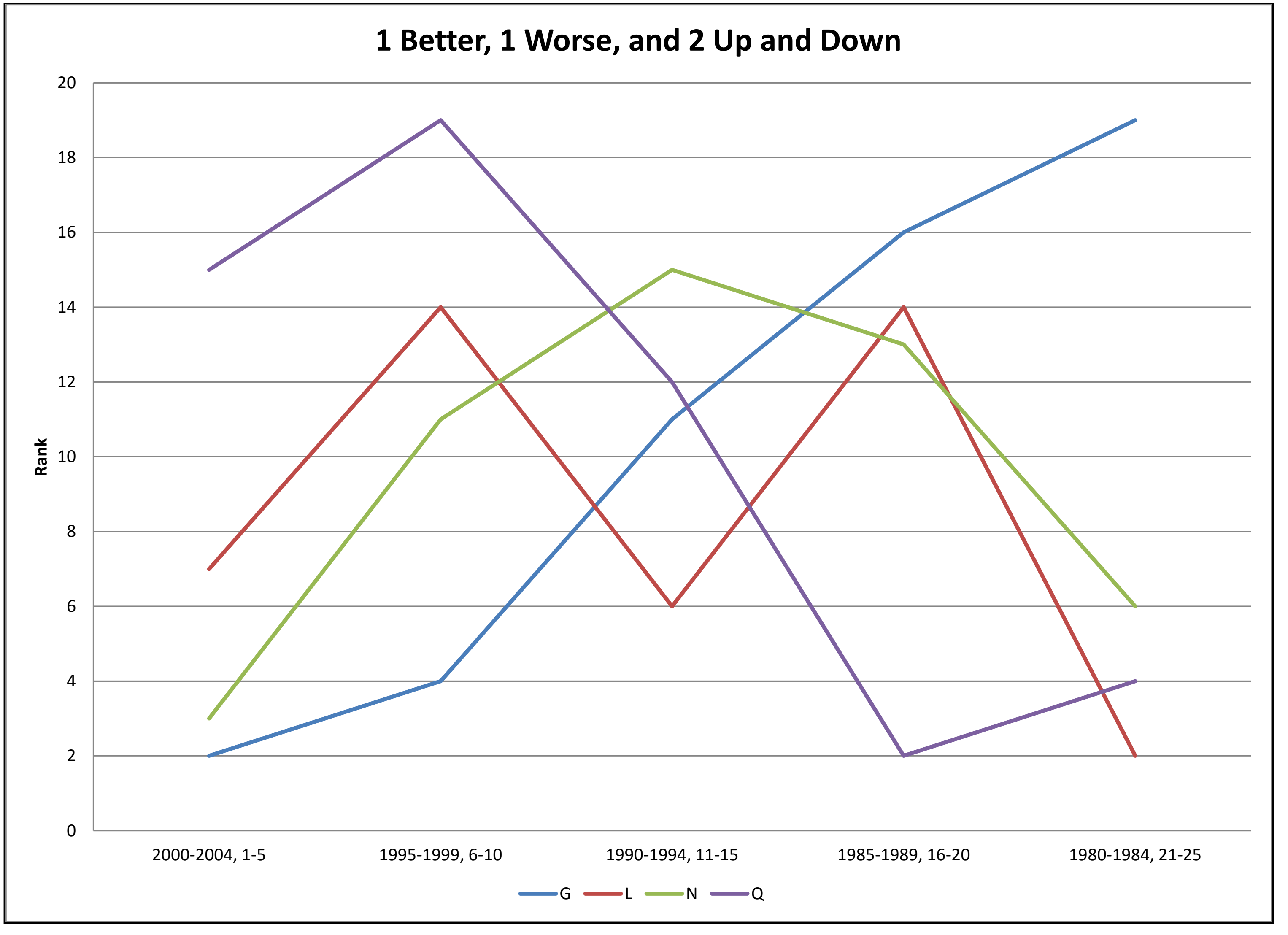
One Anomaly


One Anomaly - Fairly Consistent
25
20
15
10
5
0
Rank
2000-2004, 1-5
1995-1999, 6-10
1990-1994, 11-15
1985-1989, 16-20
1980-1984, 21-25
B
D
F
H
I
M
T
P
R

One Anomaly


One Anomaly - Worsening Mortality
Rank
20
18
16
14
12
10
8
6
4
2
0
2000-2004, 1-5
1995-1999, 6-10
1990-1994, 11-15
1985-1989, 16-20
1980-1984, 21-25
P
R

Outliers



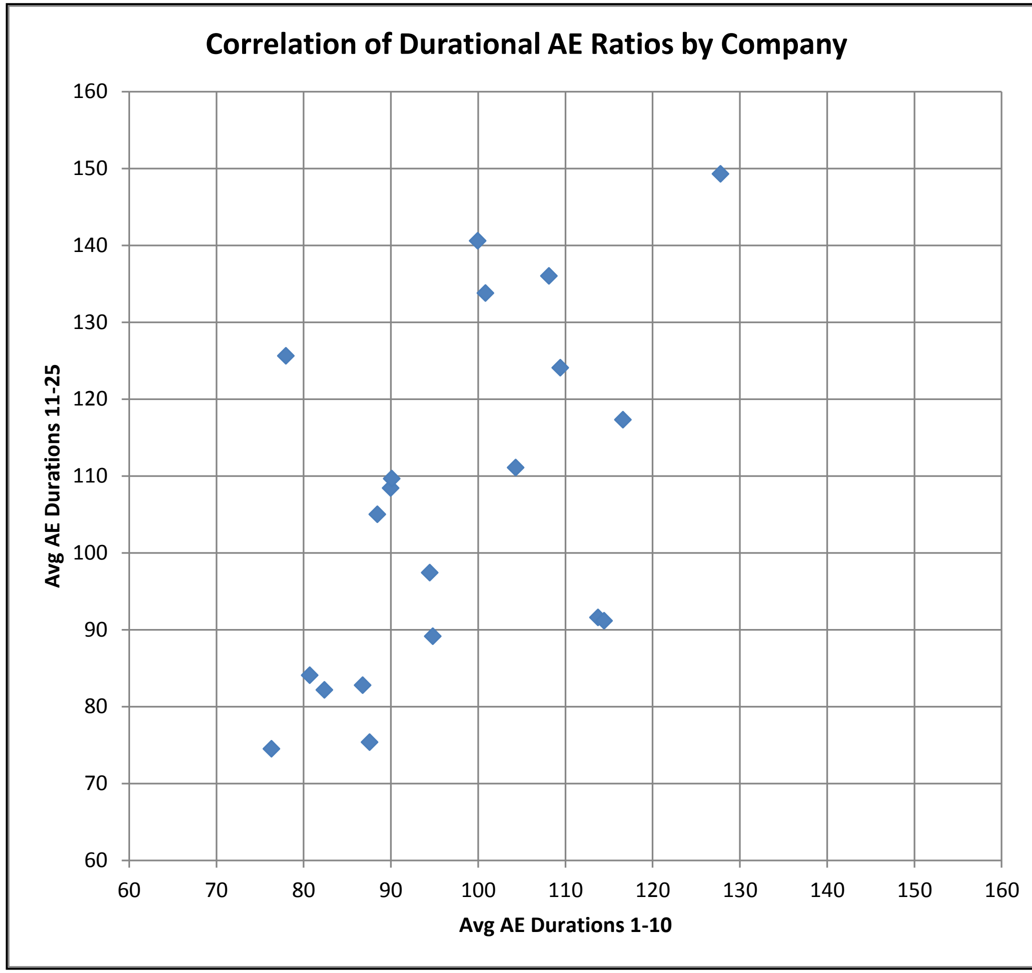
1 Better, 1 Worse, and 2 Up and Down
Rank
20
18
16
14
12
10
8
6
4
2
0
2000-2004, 1-5
1995-1999, 6-10
1990-1994, 11-15
1985-1989, 16-20
1980-1984, 21-25
G
L
N
Q

Further Analysis

- These preliminary results were promising since they showed that many companies have maintained their relative mortality position in the marketplace over the past 25 to 30 years.
  - However, the question still persisted as to whether the A/E ratios used to rank the companies remained reasonably stable over that time period.
- The problem I was trying to solve was:
  - Is a company’s early duration mortality experience predictive of later duration mortality?
  - Can pricing actuaries be confident that overall A/E ratios derived from a client’s experience study covering, say, the first 8-10 durations predict later duration A/E ratios?
- To provide an answer to this question, I used the A/E ratio data from the 20 companies and averaged the ratios for durations 1-10 (issue years 1995-2004) and for durations 11-25 (issue years 1980-1994).

Early Duration vs. Late Duration A/E Ratios

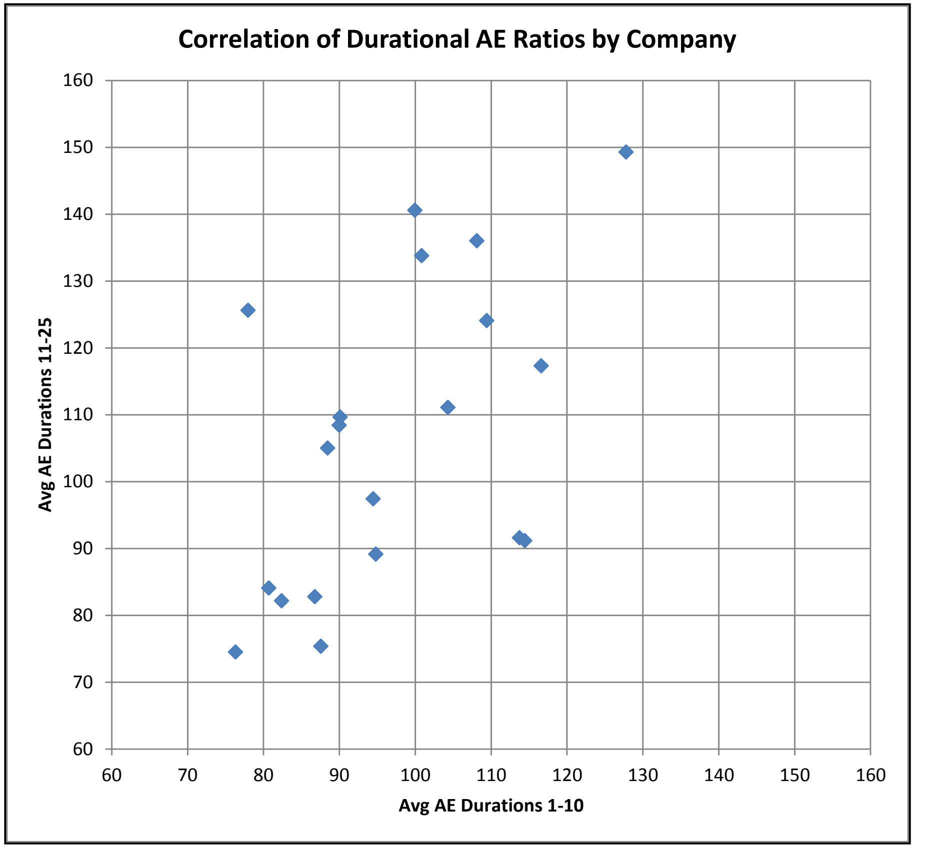
	Average A/E Ratios (%)	
	Durations	Durations
Company	01-10	11-25
A	108.1	136.0
B	100.0	140.6
C	82.4	82.2
D	100.9	133.8
E	127.8	149.3
F	116.6	117.3
G	78.0	125.6
H	88.5	105.0
I	104.3	111.1
J	94.5	97.4
K	80.7	84.1
L	94.8	89.1
M	86.8	82.8
N	90.0	108.4
O	109.4	124.1
P	113.8	91.6
Q	114.4	91.1
R	87.6	75.4
S	76.3	74.5
T	90.1	109.7



Analyzing the A/E Ratios

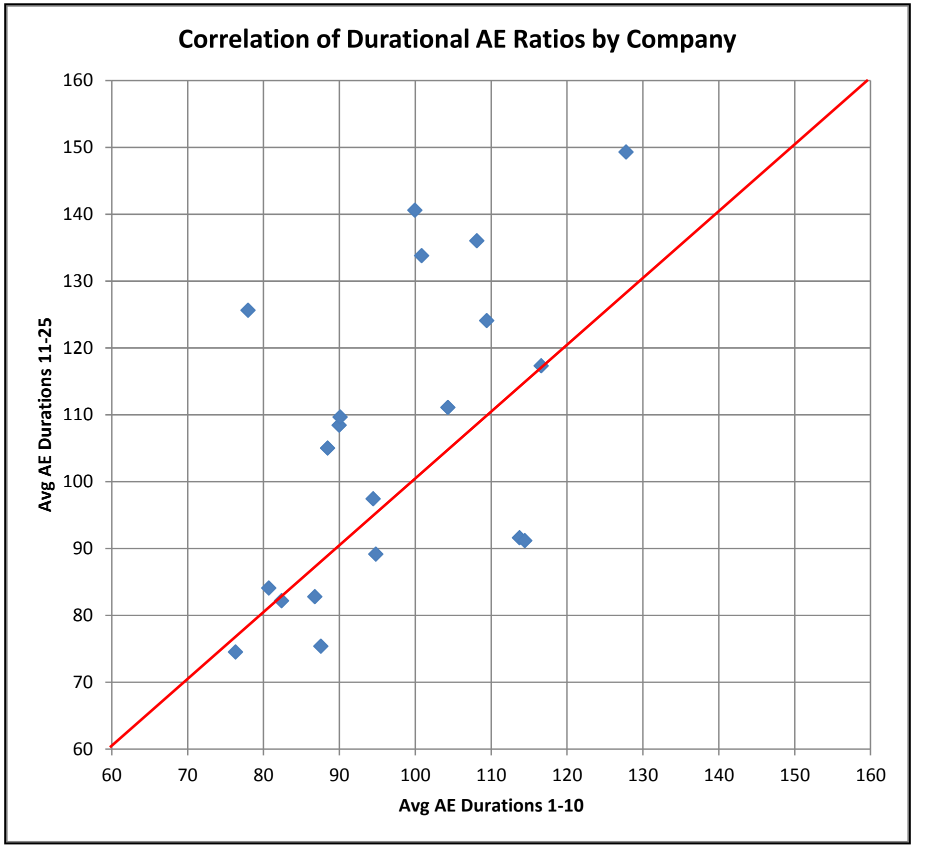
- In statistics, the Pearson product-moment correlation coefficient is a measure of the linear dependence between two variables.
  - Values can range between +100% percent and −100%.
  - 100% is total positive correlation,
  - 0% is no correlation,
  - −100% is total negative correlation.

- $$r = \frac{1}{n-1} \sum_{i=1}^{n} \left(\frac{X_i - \bar{X}}{s_X} \right) \left(\frac{Y_i - \bar{Y}}{s_Y} \right)$$



Analyzing the A/E Ratios

- If our predictions of duration 11-25 A/E ratios based upon duration 1-10 A/E ratios were absolutely perfect, all of the data points would fall along the diagonal red line and would produce a correlation coefficient of 100%.
- In reality, the data shows a correlation of around 54%, which indicates a fairly strong positive linear relationship.



What Does it All Mean?

- In general, companies with lower than average A/E ratios for business issued today tend to have lower than average A/E ratios for business issued 10 years ago, 15 years ago, 20 years ago, and so forth. The same holds for companies with higher than average A/E ratios.

- While not conclusive, I believe the results provide some evidence that the level of a company's early duration experience is predictive of the level of their later duration experience and will not necessarily grade back to an industry average as a block ages.

- A company can make some improvement in its mortality experience by refining underwriting and marketing practices, but as long as it is "fishing in the same pond," better bait will not necessarily attract better fish.

What Causes the Funnel Effect?

- The Short Answer:
  - I DON'T KNOW!

- The Long Answer:
  - Socio-economic factors may play a bigger part in mortality experience than we traditionally thought.

Socio-economic Factors: A Selection Hypothesis

- Variables from the group of socio-economic measures are candidates to describe and account for some of the differences in mortality experience.

- While likely not directly responsible for the mortality differences, they are proxies for certain behaviors and dynamics on the individual level that can influence mortality significantly.

- Many of these socio-economic measures are easier to record and analyze than some complex individual behavior patterns.

Can We Test the Hypothesis?

- We need a data set that includes:
  - Traditional life insurance selection parameters
    - Health history
    - Biometrics
    - Lab results
    - Tobacco use
  - Socioeconomic measures
    - Income, education, ethnicity, marital status and others
  - Mortality feedback
    - Significant and complete enough to be credible
    - Detailed with date of death and cause of death

Using NHANES as a Data Source

- NHANES database
  - Survey designed to measure the health and nutritional status of children/adult US population conducted periodically since the 1960's
  - Consists of detailed questions, physical exams and extensive laboratory testing
  - Overall >6000 variables measured in continuous NHANES
  - Data is available freely for download, extensively documented
  - Mortality follow-up is available for participants through year 2004 as of year-end 2006.
- Underwriting NHANES to simulate an insured population
  - Limit to adult applicants (Age 18+)
  - Use the data that 'duplicates' the typical information a US life insurance company would obtain (extensive health questions, exam, labs)
  - Classify tobacco use the way a typical life insurance company would (self reported use plus cotinine testing)
  - Underwrite 'applicants' towards a 'likely std' / 'likely substd' category

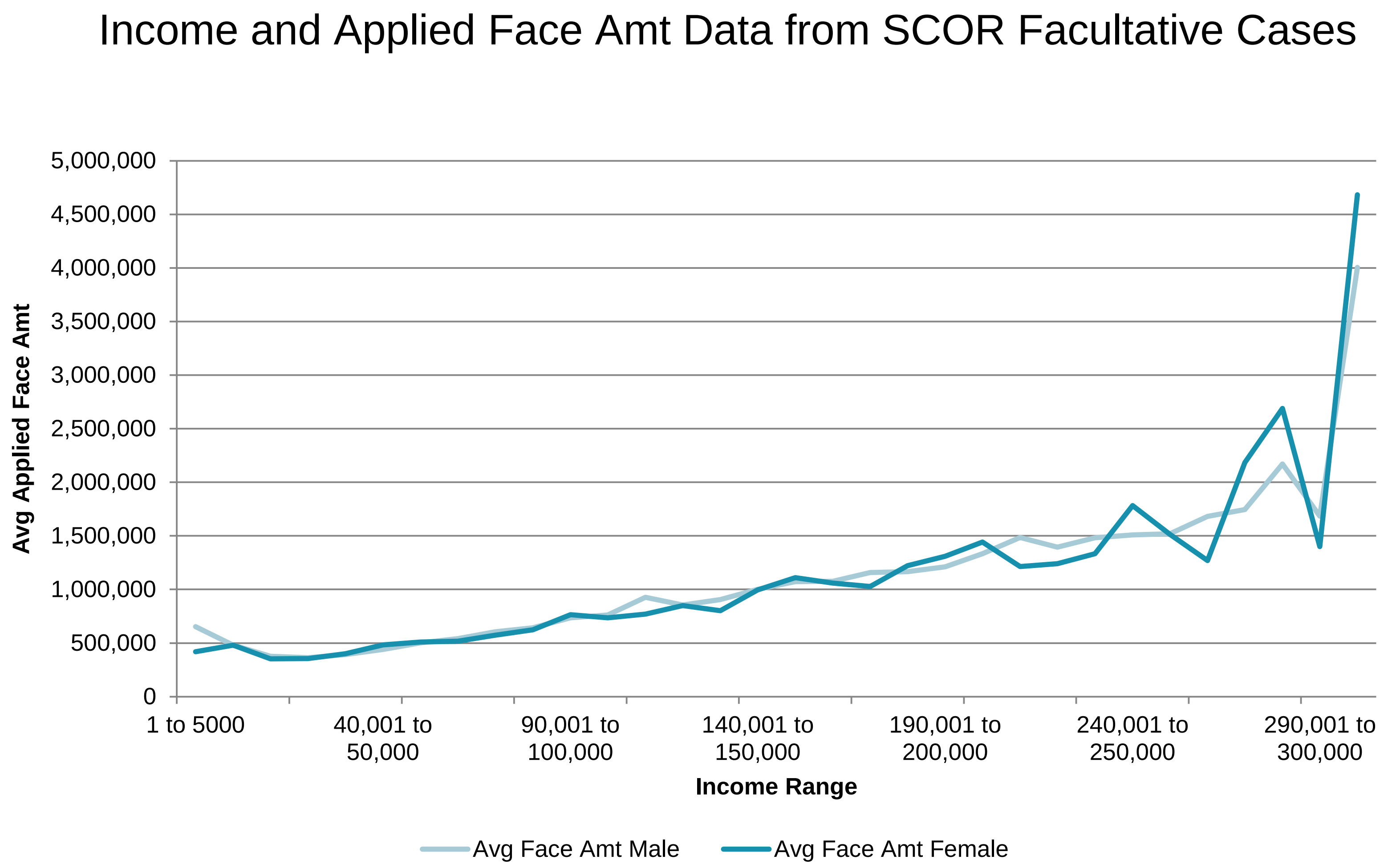
The NHANES Mortality Study

- Traditional life insurance mortality study
- Calculate A/E ratios taking age, gender, duration, tobacco status into account
- Express results in terms of Social Security annual tables
- Combine with all available measures (health history, biometric, labs, socio-economic, cause of death)

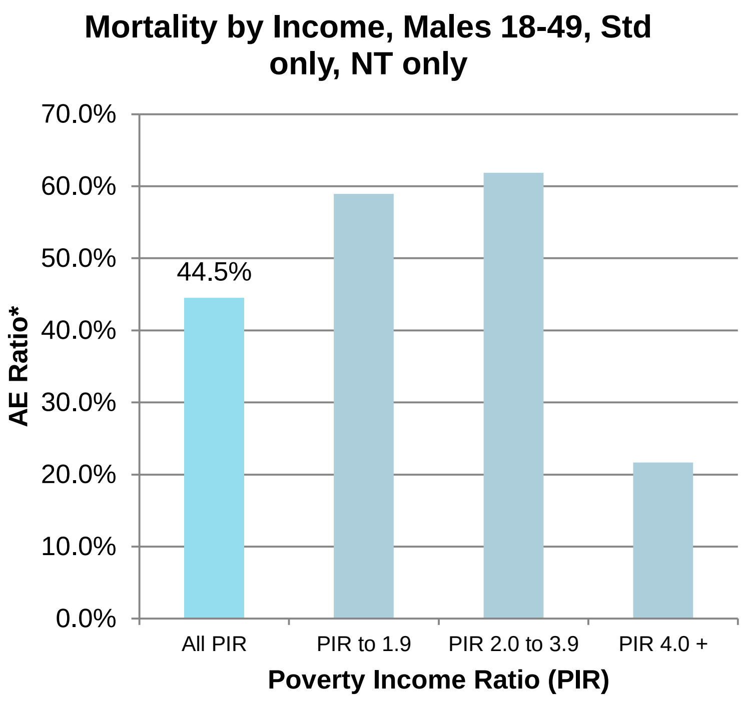
Typical Socio-economic Measures

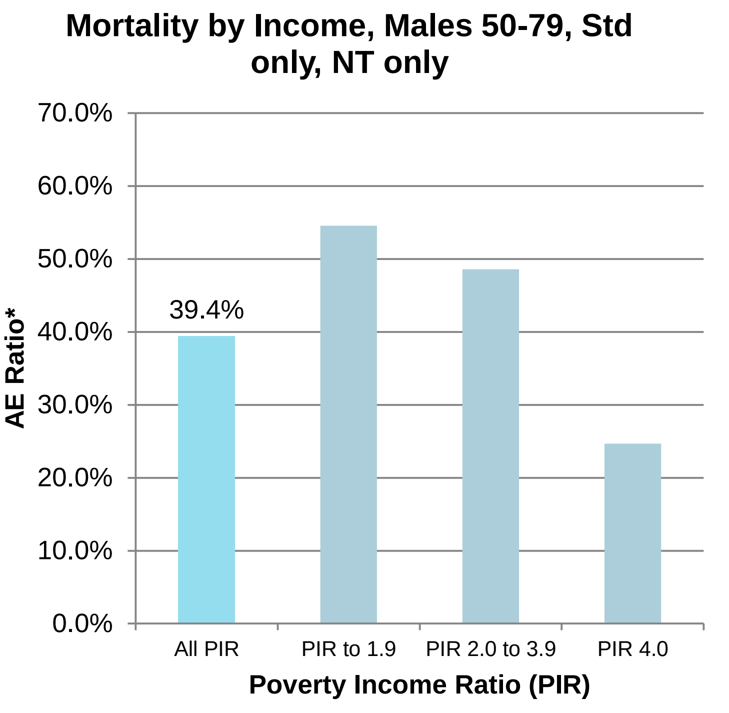
- Income
- Educational achievement
- Profession / industry
- Marital status
- Geography

Face Amount as a Socio-economic Measure



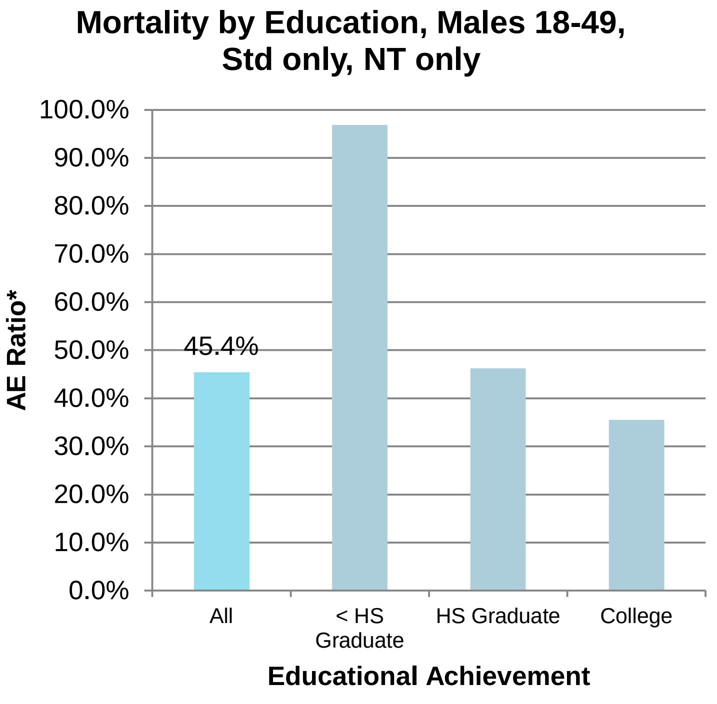
Mortality Outcomes by Income

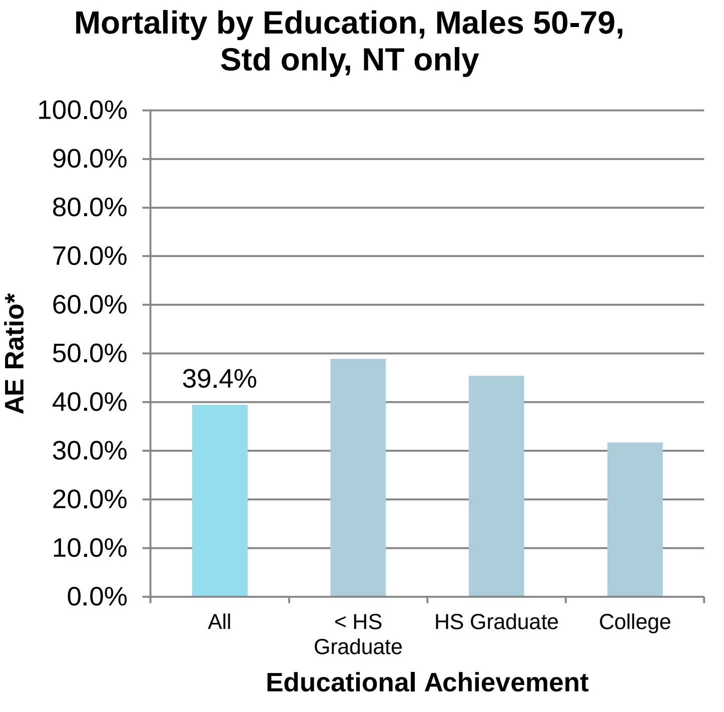




*Expected basis: Social Security annual tables

Mortality Outcomes by Educational Achievement





*Expected basis: Social Security annual tables

Conclusion / Summary

- Even after controlling for age, gender, health history and tobacco use, certain socio-economic measures remain predictive of differences in mortality outcomes.

- In the life insurance context, face amounts and income are closely and predictably linked.

- Differences in socio-economic mix by face amount range may contribute more to mortality differences than individual underwriting selection.

- Applying similar individual underwriting to applicant groups of different socio-economic mix is unlikely to result in comparable mortality outcomes.

- While often unsuitable for use as primary individual selection parameters, socio-economic measures can aid in describing overall target groups for certain products more precisely and result in products that are more appropriately structured.

The Reality of Preferred Risk Classification

- The theory
  - Classification accurately system identifies health characteristics of potential insureds
  - Insureds with similar health profiles are grouped together into underwriting classes

- The reality
  - This system is far from perfect!
  - Demarcation of risks is not clean
  - System produces a very fuzzy boundary that puts many insureds into the wrong underwriting class

The Reality of Preferred Risk Classification

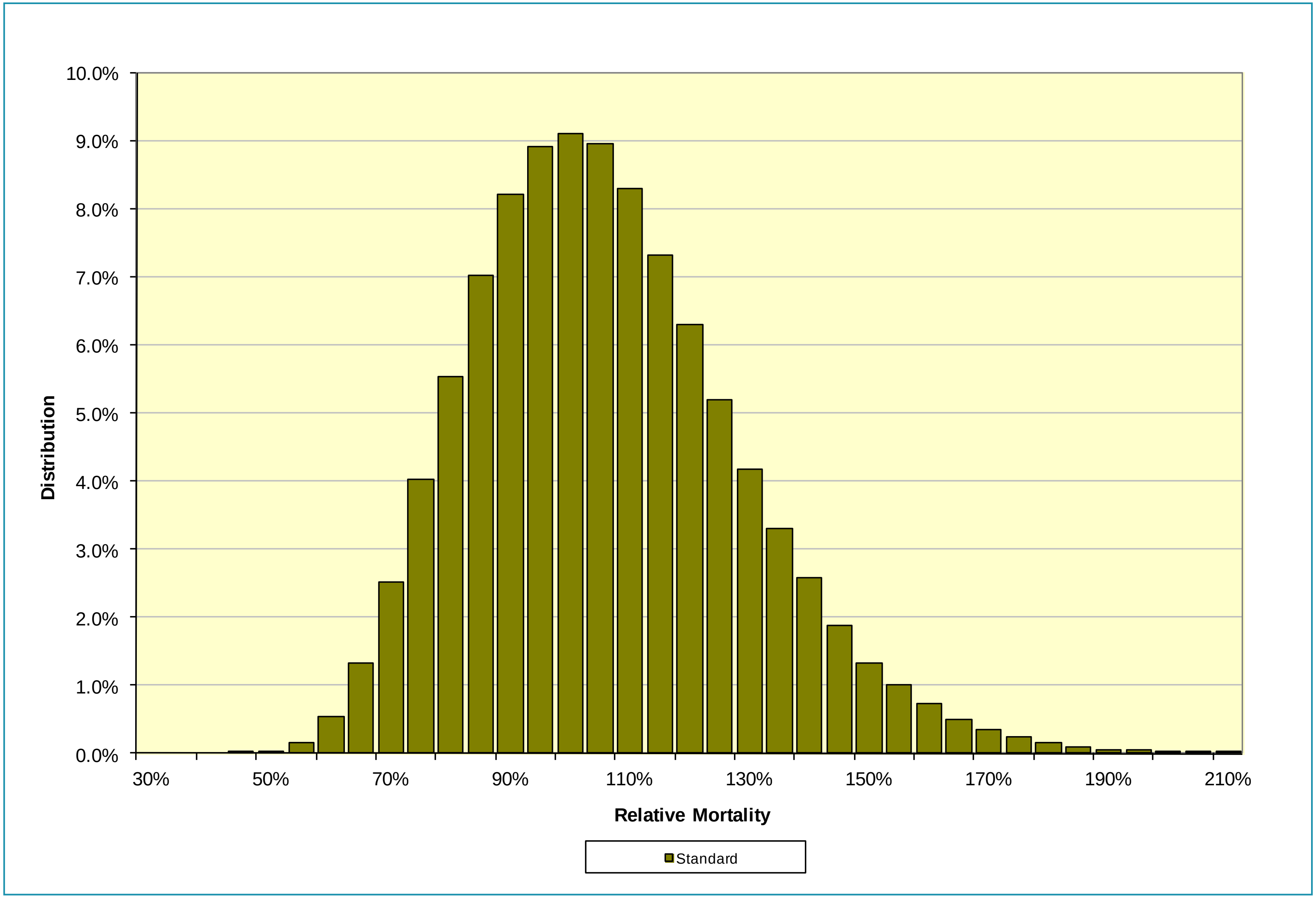
- Cox Proportional Hazards Model
  - Model is used very frequently in clinical research studies
  - Analyzes relative mortality among groups having different medical conditions

- My model
  - Created from a database of approximately 435,000 recently underwritten lives
  - Indicators for age, gender, and smoking status
  - Values for build, blood pressure, total cholesterol, and HDL ratio
  - Model was tested and validated using data from SCOR's proprietary mortality experience database

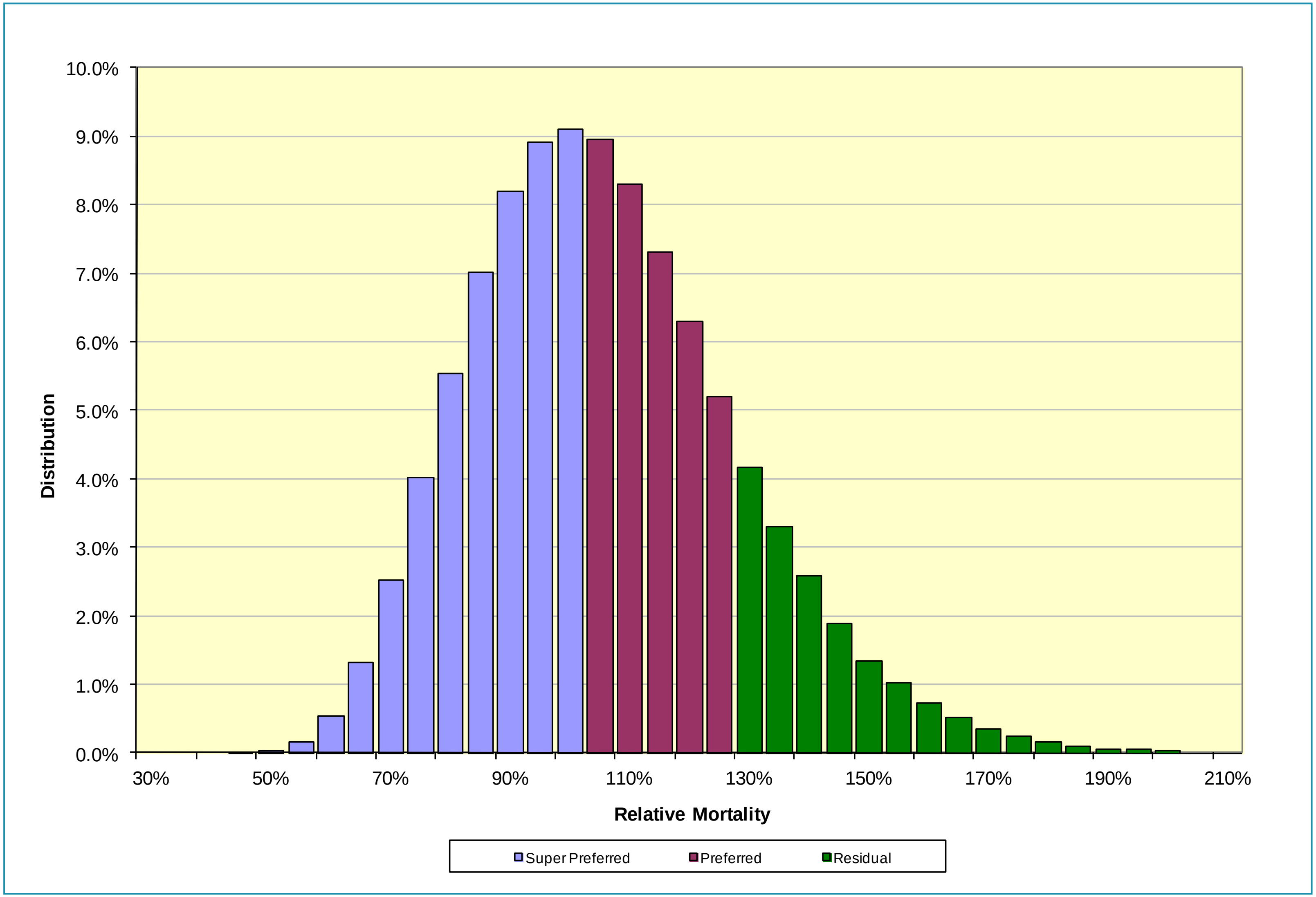
Illustrative Extract from Model Input / Output

record	Age	Gender	Height	Weight	Build	Nicotine	Chol	HDL	Sys BP	Dia BP	CPHM
11581959	20	M	71	181	108%	N	174	5.4	112	62	93%
11581975	22	M	71	190	111%	N	168	5.4	126	76	121%
11581985	28	M	79	205	93%	N	156	3.0	130	80	105%
11581988	32	F	63	139	109%	N	142	3.2	90	66	64%
11581993	33	M	72	182	99%	N	254	4.8	116	72	105%
11581994	34	M	69	215	127%	N	145	4.5	106	74	95%
11581996	35	F	65	145	108%	N	165	3.7	110	60	82%
11581998	33	M	70	215	124%	N	208	3.8	122	76	118%
11582002	23	M	69	142	87%	N	157	3.5	112	72	80%
11582012	22	M	67	137	90%	N	143	4.0	90	70	62%
11582031	27	F	64	150	117%	N	167	3.2	110	82	96%
11582035	26	F	69	158	107%	N	203	2.9	102	80	83%
11582042	25	M	71	220	127%	N	131	3.0	126	66	106%
11582044	23	F	69	160	109%	N	180	2.6	130	70	107%
11582045	32	F	63	122	96%	N	128	3.3	111	83	85%
11582046	32	F	64	123	95%	N	170	4.0	96	64	68%
11582047	33	F	66	136	100%	N	177	3.0	118	72	91%
11582048	26	F	63	125	100%	N	140	2.7	104	76	75%
11582058	25	M	67	224	145%	N	209	4.0	124	82	141%
11582068	29	F	68	140	98%	N	176	2.9	108	65	76%
11582070	33	M	76	158	77%	T	265	4.4	120	72	97%
11582074	34	F	63	160	125%	N	164	4.0	104	70	89%
11582076	22	M	69	153	94%	N	162	2.8	122	70	89%

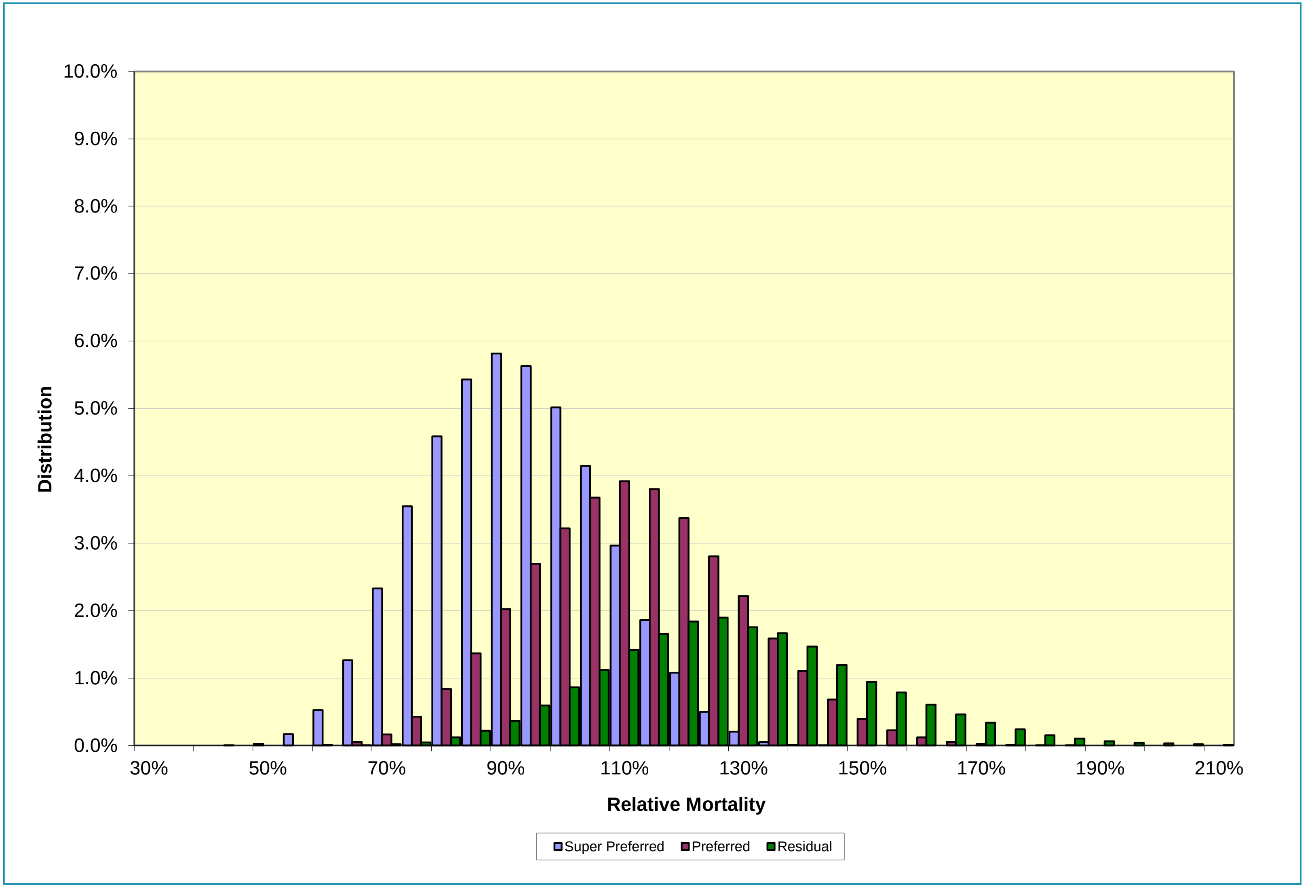
Mortality Distribution – All Lives Combined



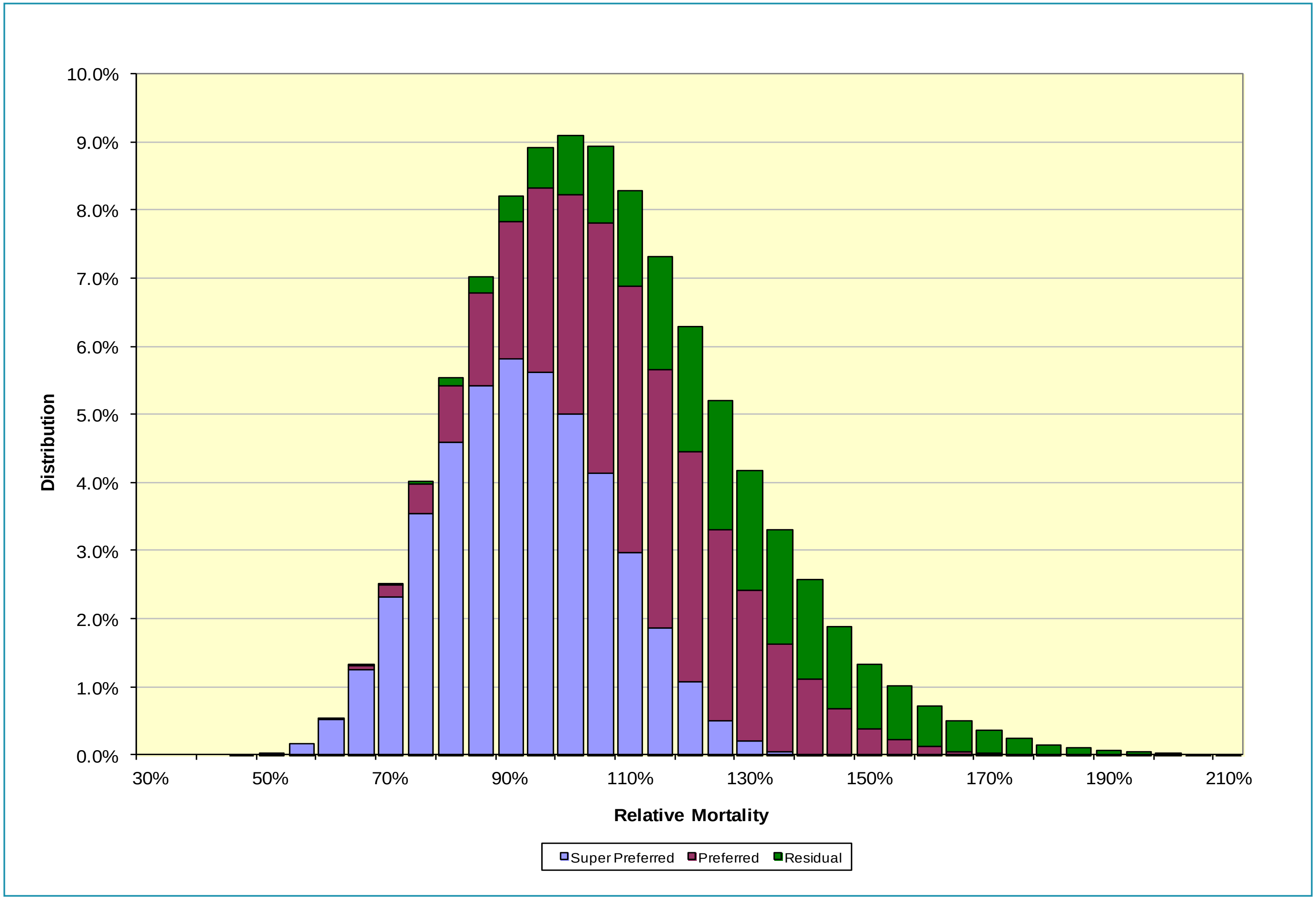
Theoretical Mortality Distribution by Underwriting Class



Actual Mortality Distribution by Underwriting Class



Actual Mortality Distribution by Underwriting Class



Comments About the Results

- To be fair, the majority of today's knock-out classification methods vary criteria values by age groups and include motor vehicle and personal/family history indicators

- More companies are using debit/credit classification systems that try to fairly balance positive and negative risk factors

- These enhancements tend to lessen the mortality overlaps, but certainly will not eliminate them entirely

Thank You!