PBGC PIMS Peer Review Data Input Assessment

Observations and Conclusions
December 21, 2021

Buck Team

Stuart Schulman
FSA, EA, MAAA, FCA, CFA
Principal, Wealth Practice

Christopher Teh
FSA, EA, MAAA, FCA, CFA
Director, Wealth Practice

David Harwood
EA, MAAA, FCA
Principal, Wealth Practice

Rebecca Reynolds
ASA, EA, MAAA
Director, Wealth Practice

Matthew DeWitt
Senior Consultant,
Wealth Practice

Ronald Thompson
Senior Consultant,
Wealth Practice

Table of Contents

Table of Contents (continued)

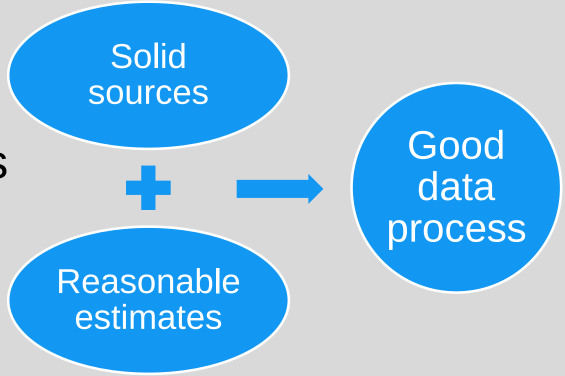
Executive Summary

Executive Summary – What Did Buck Do?

Independent Analysis for Single-Employer (SE) and Multiemployer (ME) Plans

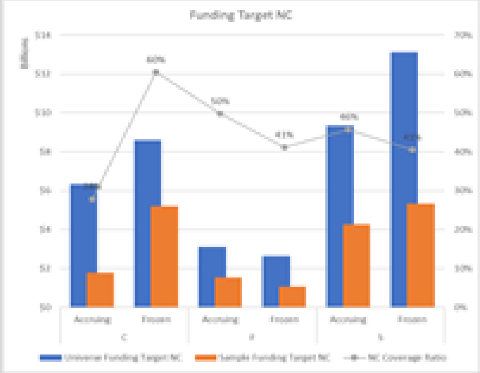
Review SE & ME PIMS Data Inputs

- Processes followed
- Data sources
- Estimation techniques
- Assumption modeling



Review SE & ME PIMS Sampling Methods

- Distribution analysis
- Coverage analysis
- Historical claims



Review SE & ME PIMS Calibration Methods

- Assess current methodologies
- Cause for calibration
- Reasonable approach
- Reasonable alternatives

Review ME PIMS Zone Status Data

- Process followed
- Data sources
- Reasonable alternatives

Executive Summary – What Did Buck Do?

The review focused on the processes followed for preparing the input datasets used for participant, plan, and plan sponsor data. Buck was also asked to review several calibration estimates used within the models.

Our review covered nearly 100 files, including data and modeling manuals, along with biweekly meetings with PRAD to review the modeling process across a period of 7 months.

Data Inputs & Process

- Methodology to Select Input Data for SE Plans
- Development of Plan Participant Profiles
- Data Input Items from Form 5500
- Availability of Form 5500 Data
- Plan Status, Benefit Design and Features
- Plan Sponsor's Financial Information to Determine Future Bankruptcies
- Economic and Regulatory Inputs
- PBGC Asset, Liability and Premium
- Zone Status Availability for ME Plans
- Standard Data Input Assessment for ME Plans

Calibration Process

- Sample Plans/Firms to the SE Universe
- Plan Benefits
- Cashflows for ME Plans

Develop Recommendations

- Focused on items that may enhance the collection of plan, participant, and plan sponsor data
- Focused on assumptions and methods that may enhance processes and projections results

Executive Summary – What Has Buck Observed?

Overall, the PBGC approach for data inputs to SE PIMS and ME PIMS is reasonable and should produce reasonable forecasts of the SE and ME systems. We have identified a few areas where processes could be refined to improve the projection methodology.

Generally, our findings show that expanding datasets and incorporating additional information that is generally available as part of the annual actuarial valuation, particularly plan cash flows, will lead to improvements in modeling.

Executive Summary – Key Recommendations

Electronic submission of the projected benefit cashflows for both SE and ME Plans

Maintain current sampling methods for SE PIMS but consider strategically adjusting input data to refine modeling, such as increasing specific industry or plan grouping representation

Expand ME PIMS with assumptions and plan specific data from applications submitted for Special Financial Assistance and latest Zone Status certifications provided by the IRS

Monitor ongoing behavior of SE and ME plan sponsors and adjust modeling as needed for recent legislative and industry changes

Key Recommendations

Key Recommendations

Plan Specific Cash Flows

Consider electronic submission of the projected benefit cashflows for both SE and ME Plans

- Cash flows are now generally available from annual actuarial valuation processing and can be provided annually.
- Leading actuarial valuation software is designed to generate cash flows, which will minimize any additional burden on plan sponsors.
- This will help:
  - Validate the cashflows generated by PIMS
  - Adjust the cashflows of the guaranteed benefits in PIMS
  - Confirm whether the interest rate sensitivities of the sample plans are reasonable (convexity and duration)
  - Adjust any future benefits payment patterns in PIMS, as needed
  - Reduce number of calibration steps
  - By offering transparency of financial implications of holding a Plan, and assisting all stakeholders in the understanding of managing pension risks

Key Recommendations

SE Modeling Inputs & Methods

Maintain current SE sampling methods but consider strengthening areas

- Analysis indicated the SE sampling methods are well aligned relative to the universe of plans measured on a liability basis.
- Increase areas of coverage as indicated by the analysis to enhance overall modeling and refine the results.
  - Consider increasing representation of Small Plans (less than $200M in Funding Target Liability) and Underfunded Plans (assets < liability)
    - Potential bundling approach of Small Plans as a new sample
    - Potential adjustment handled and analyzed outside of PIMS
  - Consider increasing Normal Cost coverage
  - Consider periodic review of industries, specifically to identify distressed industries, and potentially include industry weighting
- Sample of 500 plans should be reviewed regularly to ensure reasonable representation.

Key Recommendations

SE Modeling Inputs & Methods – Funding Target Liability Coverage

Small Plans are underrepresented in the Sample, which may understate impact of future accruals on PBGC liability.

Table displays the funding target liability and coverage ratios stratified by Funding Target Range.

- Sample covers 55.6% of universe liability.
- Big Plans (≥$1B) have good coverage.
- Small Plans (<$200M) have low coverage.
  - $4B of $242B, or 1.7%
- 12% of universe liability is in Small Plans.
- Historically, Small Plans account for 98% of all defaults and 29% of termination liability. Consider bundling plans to address representation for this group.
- Broader liability coverage may be achieved by targeting the $200M and $400M ranges.

FT Range	Universe Funding Target Liability	Sample Funding Target Liability	FT Ratio	FT Ratio / Total FT Ratio (55.6%)
$0M - $199.99M	241,998,163,719	4,035,146,680	1.7%	3.1%
$200M - $399.99M	123,728,948,862	11,430,753,451	9.2%	16.5%
$400M - $599.99M	103,937,312,041	35,072,495,135	33.7%	60.6%
$600M - $799.99M	69,169,716,550	31,493,193,236	45.5%	81.8%
$800M - $999.99M	59,705,689,093	29,035,510,295	48.6%	87.4%
$1B or more	1,375,229,615,453	986,746,423,349	71.8%	129.1%
Grand Total	1,973,769,445,718	1,097,813,522,146	55.6%	N/A

Key Recommendations

SE Modeling Inputs & Methods – Funding Target Normal Cost Coverage

Normal Cost for Small Plans is underrepresented in the Sample.

Table displays the funding target normal cost and coverage ratios stratified by Funding Target Range.

- Sample covers 44.9% of universe normal cost.
- Big Plans have good coverage.
- Small Plans have low coverage.
  - $73M of $8B, or 0.9%
- Although we believe the PBGC can withstand exposure of expected defaults for Small Plans, low coverage of normal cost may have projection implications.
- Broader normal cost coverage may be achieved by targeting the $200M and $400M ranges.

FT Range	Universe Funding Target NC	Sample Funding Target NC	NC Ratio	NC Ratio / Total NC Ratio (44.9%)
$0M - $199.99M	8,036,555,458	72,954,741	0.9%	2.0%
$200M - $399.99M	2,544,047,372	185,255,040	7.3%	16.3%
$400M - $599.99M	2,489,976,480	692,602,995	27.8%	61.9%
$600M - $799.99M	1,541,036,474	666,678,648	43.3%	96.4%
$800M - $999.99M	974,420,570	422,379,448	43.3%	96.4%
$1B or more	27,172,139,412	17,165,782,378	63.2%	140.8%
Grand Total	42,758,175,766	19,205,653,250	44.9%	N/A

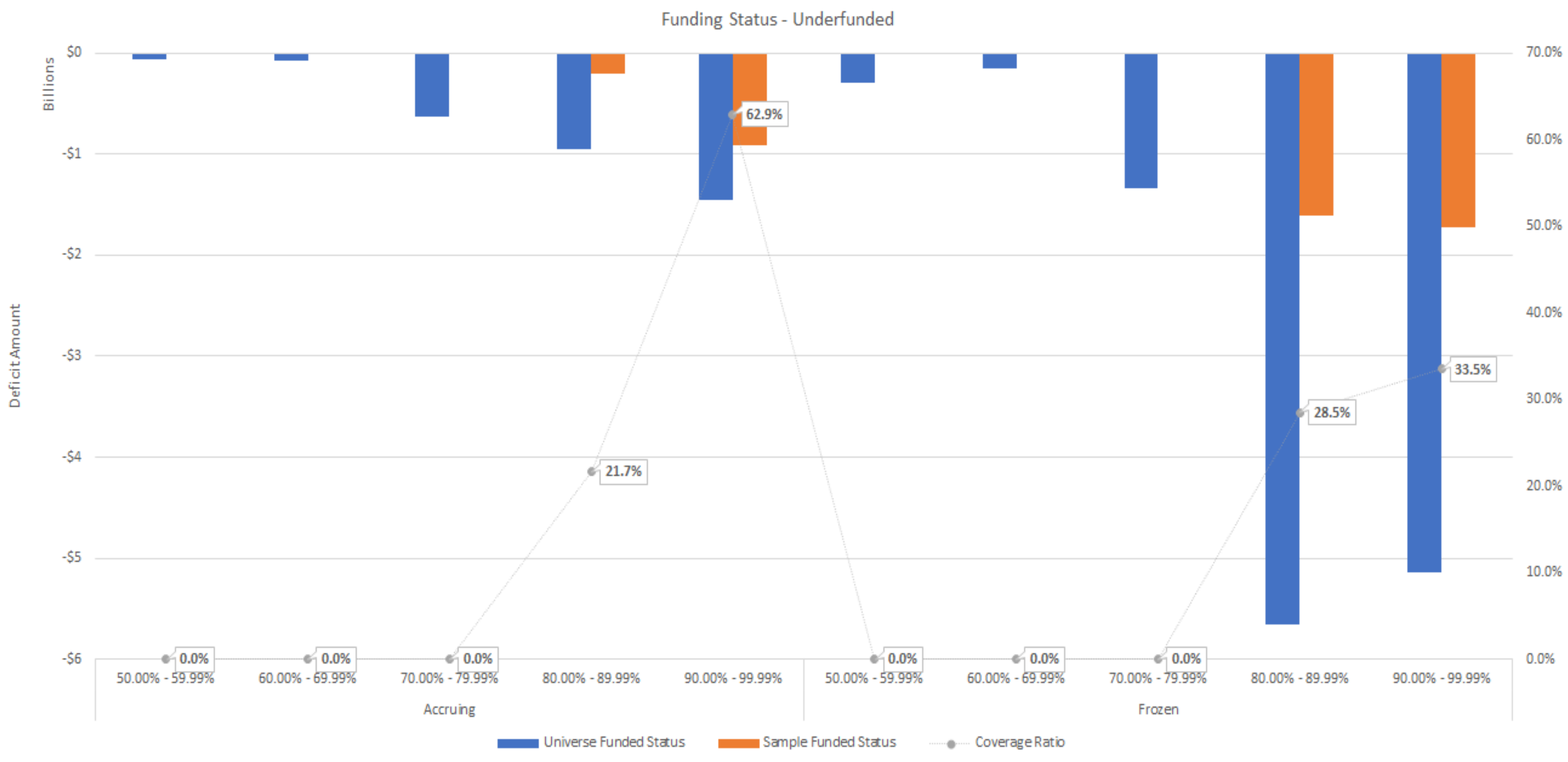
Key Recommendations

SE Modeling Inputs & Methods – Underfunded Plan Coverage

Plans with funded ratios of 50.00%-79.99% are underrepresented in the Sample.

The chart depicts the funded status amount for underfunded plans by funded status range and plan operating status. The gray line is coverage ratio.

- Sample covers 28% of universe underfunded/deficit liability.
- In general, we see low coverage across the ranges – just one coverage ratio above 50%.
- Aggregate Deficit Amount:
  - Universe -$15.8B
  - Sample -$4.5B



Key Recommendations

SE Modeling Inputs & Methods – Industry Coverage

Manufacturing and others are well represented in the Sample, while Health Care and other sectors are underrepresented.

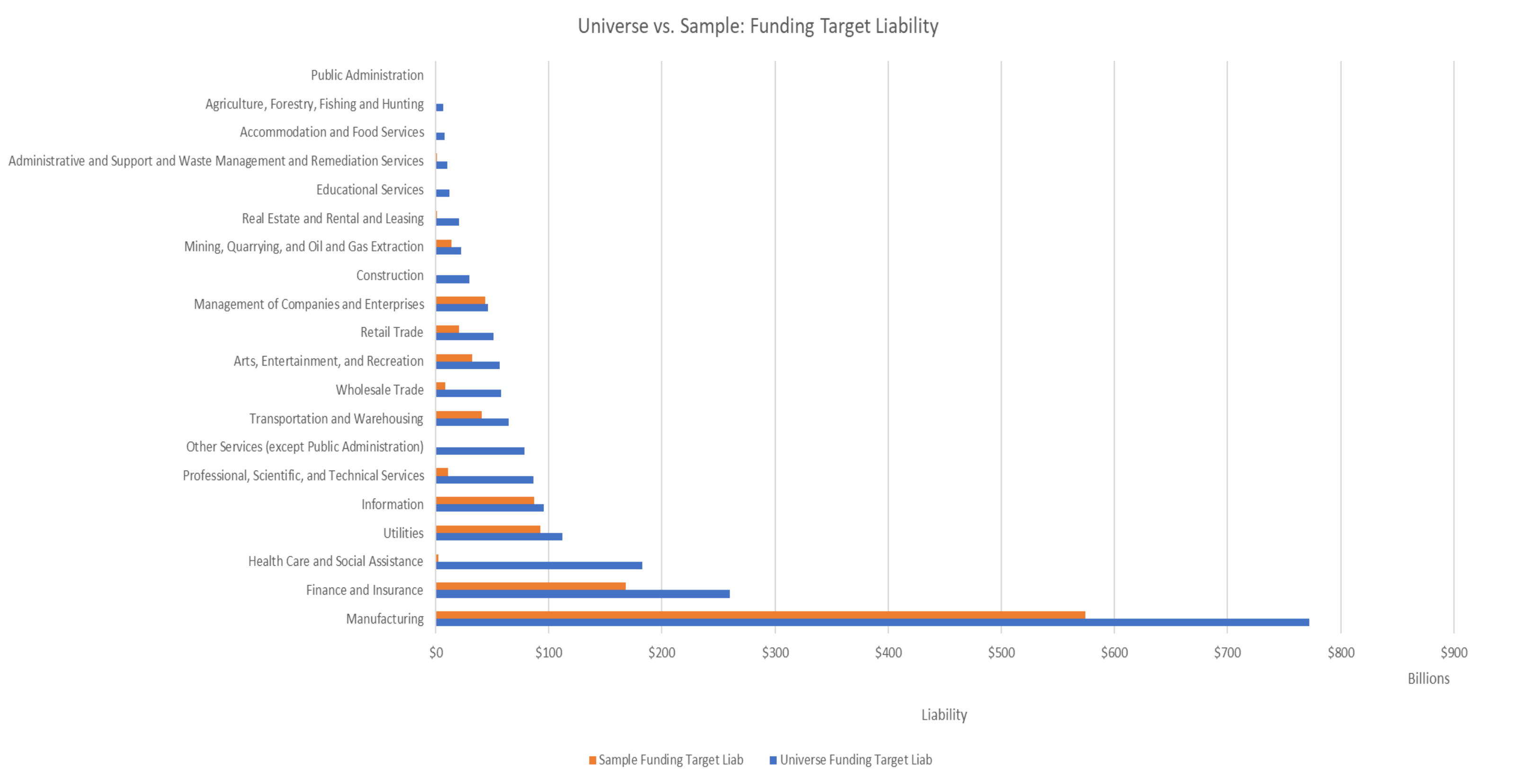
The chart depicts the funding target liability amounts by **industry** for the sample vs. universe datasets.

Good coverage: Manufacturing (74%), Finance (65%), Utilities (82%), Information (91%), Transportation (64%), Arts (55%), and Management (95%).

Low coverage: Health Care and Social Assistance.

No coverage: Other Services, Construction, Accommodation, Agriculture, Public Administration.

Representation can be meaningful as plan sponsors of different industries may have different propensity for bankruptcy.



Key Recommendations

ME Data Availability

Consider expanding the sample of ME data used in the model

- Consider reflecting Zone Status information from available IRS certification submissions by plan actuaries to reflect the latest information.
  - Review to consider reasonability of projections from ME PIMS.
- Consider utilizing all the data items to enhance ME PIMS projection model for approximately 250 plans that will be made available soon to the PBGC from the Special Financial Assistance (SFA) applications.
  - Utilize the application information to refine current methodologies and/or utilize the actual data instead of sample data, if feasible.
  - Consider more direct focus on modeling plans that narrowly miss eligibility for SFA or are denied approval and may be in trouble.

Key Recommendations

Plan Behavior Monitoring – SE PIMS

Consider the ongoing legislative environment and how the behavior of plan sponsors will impact modeling

- Based on current observations, consider the following updates to reflect American Rescue Plan Act (ARP) of 2021 for SE plans:
  - May need to incorporate ARP inputs for plans electing to implement fresh-start 15-year amortization in 2019-2022
  - Contribution patterns in the short-term and long-term may change:
    - Plan sponsors who elected ARP to lower minimum required contribution (MRC), may only pay the new, lower MRC
    - Additional interest rate relief under the Infrastructure Investment and Jobs Act may change contribution patterns for an extended period
  - Plans in distress are the most likely to elect immediate relief and represent the greatest risk to the PBGC

Key Recommendations

Plan Behavior Monitoring – ME PIMS

Consider the ongoing legislative environment and how the behavior of plan sponsors will impact modeling

- Based on current observations, consider the following updates to reflect ARP and SFA for ME plans:
  - — Consider creating a probability of electing SFA based on comments and feedback on the interim rules published July 2021.
    - Commenters indicate possible hesitation for plans that received MPRA benefit suspensions to elect SFA relief because of potential conflicts in fiduciary responsibility to their active and retiree populations.
    - We believe it is not certain that plans that applied for MPRA relief will elect SFA and recommend allowing for this possible behavior.

Methodology to Select Input Data for SE PIMS

Methodology to Select Input Data for SE PIMS

Our Understanding

- Once plan is identified for inclusion to sample plans dataset (sample), it generally stays in the group unless access to data is impaired.
- PRAD receives funding data, representing the dataset for all plans (universe), in the form of a table matrix grouped by funded status ranges (excluding Airline & Auto Plans).
- Sample is grouped by funded status ranges in accordance with universe.
- Weight factors are developed by computing the **funding target liability** ratio, universe to sample, across the funded status ranges.
- These weight factors are used later in the SE PIMS projections to scale up.

Methodology to Select Input Data for SE PIMS

Our Hypothesis on Effect of Sampling Techniques for Modeling

At first glance, the current approach appears limited by focusing only on one metric, funded status, to group the plans; and one metric, Funding Target Liability, to develop weight factors. Using only the funded status metric may result in plans with different key features being grouped together – specifically, plans with different benefit structures and operating status (e.g., frozen versus ongoing). Similarly, focusing only on accrued liability could result in suboptimal modeling of the aggregate normal cost, which has implications for projections.

We would expect to find comparisons in our analysis when grouping and measuring the liability. We will assess the hypothesis by substituting different metrics for grouping and measuring.

Methodology to Select Input Data for SE PIMS

Summary of Methods

To confirm this hypothesis, two analytical techniques are used in this analysis:

- Percent Distribution: Used to assess alignment – weight to column total
- Quantitative Relation: Used to assess coverage – ratio of sample to universe

Additional groupings considered:

- Benefit type: C-Cash balance; F-Flat; S-Salaried
- Plan operating status: Ongoing or Frozen
- Industry

Measures summarized are:

- Schedule SB Funding Target Liability (FT)
- Schedule SB Funding Target Liability Normal Cost (FTNC)
- Participants
- Plans

Source Data: ‘SE Plans Bundle 2018PY_rev’ with minor adjustments as instructed by PRAD

Methodology to Select Input Data for SE PIMS

Summary of Methods (continued)

Key Measurements for the Analysis:

“**Well Aligned**” – two metrics are within 5%

“Good Coverage” – sample to universe ratio is greater than or equal to 50%. If coverage is less than 25%, results may be skewed due to maximum applied weighting factor of “4x” under the current methods.

Methodology to Select Input Data for SE PIMS

Summary of Methods (continued)

Funding Target Liability

Funding Target Liability Range Analyzed:

$0-$1B+ in $200M increments

Funding Target Normal Cost

Funding Target Normal Cost Range Analyzed:

$0-$1B+ in $200M increments

Funded Status Percentage (MVA / FT Liability)

Funding Range Analyzed:

50%-150%+ in 10% increments

Small Plans

Funding Target Liability < $200M

Big Plans

Funding Target Liability ≥ $1B

Distribution Analysis

Methodology to Select Input Data for SE PIMS

Summary of Analysis

- This section examines the current SE PIMS methodology by comparing the **distribution** of the SE sample and universe datasets.
- The measures summarized are:
  - Plan counts
  - Participant Counts
  - Funding Target Liability
- Groupings are by:
  - Benefit Type
  - Operating Status
  - Industry
- Stratified by funded status ranges

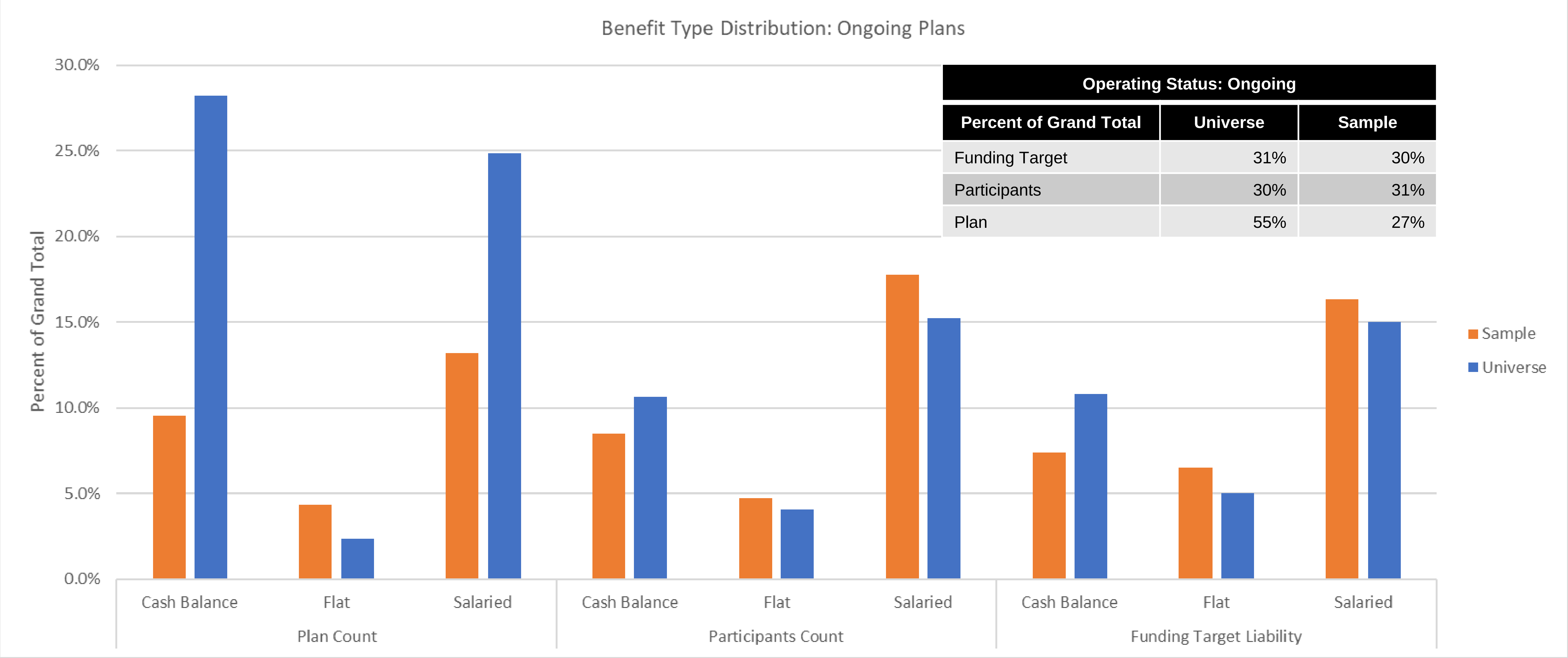
Distribution of the Universe Dataset by Operating Status and Benefit Type

Operating Status	Plan Count	Participant Count	Funding Target Liability
Ongoing	**55.4%**	**29.9%**	**30.8%**
C – Cash Balance	28.2%	10.7%	10.8%
F – Flat Benefit	2.3%	4.1%	5.0%
S – Salaried Benefit	24.8%	15.2%	15.0%
Frozen	**44.6%**	**70.1%**	**69.2%**
C – Cash Balance	14.8%	27.4%	29.5%
F – Flat Benefit	4.3%	8.0%	7.7%
S – Salaried Benefit	25.5%	34.7%	32.1%
Grand Total	**100.0%**	**100.0%**	**100.0%**

Note: Totals may not add due to rounding.

Methodology to Select Input Data for SE PIMS

Summary of Analysis (continued)



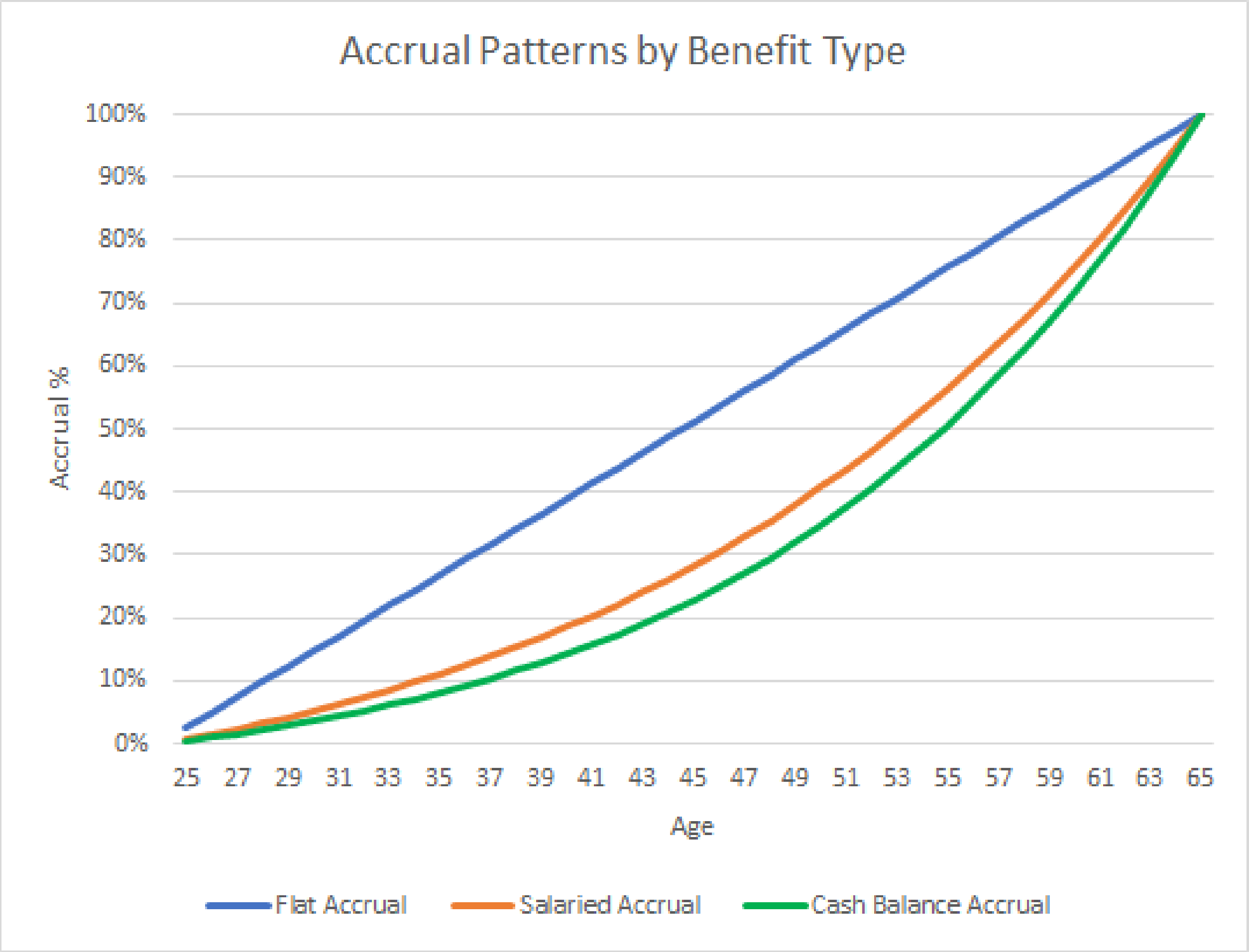
Operating Status: Ongoing		
Percent of Grand Total	**Universe**	**Sample**
Funding Target	31%	30%
Participants	30%	31%
Plan	55%	27%

Methodology to Select Input Data for SE PIMS

Summary of Analysis (continued)

<u>Key Features</u>

- **Benefit Type**: Alignment improves the representative projections for several reasons: benefit accrual patterns differ; benefit rights and features differ. Different future accrual patterns may impact future exposure for PBGC.
  - Projection results would be more predictive if future accruals are modeled as reasonably as possible.
  - Cash balance plans have a higher propensity for paying lump sums.
- **Operating Status**: Key concern is for accruing plans.
- **Funded Status**: Are the poorly funded plans well represented?
- **Industry**: Analyze distribution across distressed vs. healthy industries, which is useful in bankruptcy analysis.



Methodology to Select Input Data for SE PIMS

Distribution of Participants and Plans

The tables display counts and the percent of total for the sample and universe datasets.

- **Participants** are well aligned across operating status and benefit type.
- **Plans** display misalignment for ongoing cash balance and salaried plans. Flat plans are well aligned and not overrepresented.

	By Participants				
Operating Status	**Ongoing**			**Frozen**	
Benefit Type	**Cash Balance**	**Flat**	**Salaried**	**N/A**	**Total**
Sample (counts)	955,906	536,202	2,005,386	7,785,518	11,283,012
Sample (weights)	8.5%	4.8%	17.8%	69.0%	100.0%
Universe (counts)	2,513,602	958,763	3,601,154	16,573,071	23,646,590
Universe (weights)	10.6%	4.1%	15.2%	70.1%	100.0%

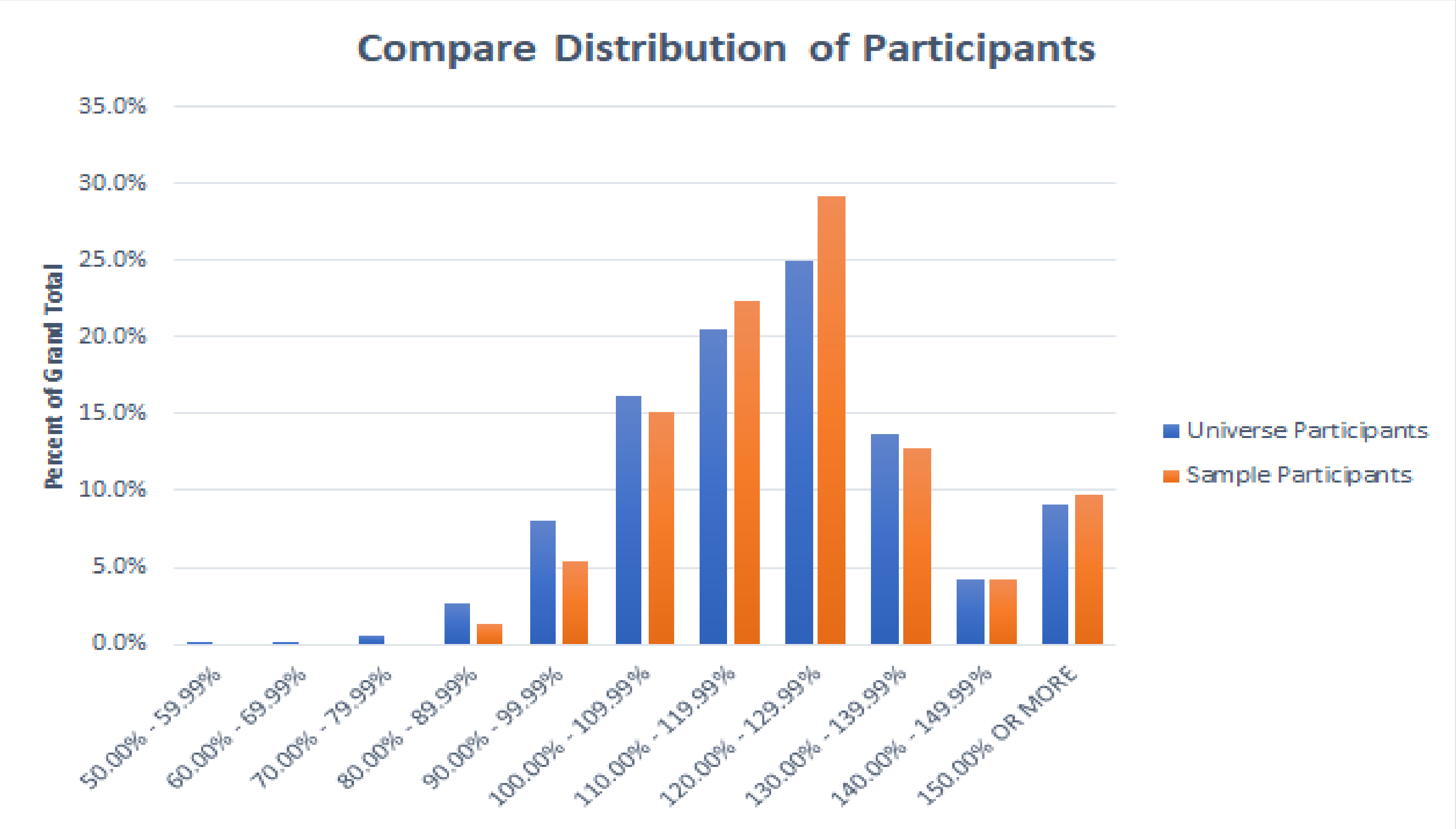
	By Plans				
Operating Status	**Ongoing**			**Frozen**	
Benefit Type	**Cash Balance**	**Flat**	**Salaried**	**N/A**	**Total**
Sample (counts)	42	19	58	318	437
Sample (weights)	9.6%	4.3%	13.3%	72.8%	100.0%
Universe (counts)	6,082	518	5,394	10,277	22,271
Universe (weights)	27.3%	2.3%	24.2%	46.1%	100.0%

Note: Totals may not add due to rounding.

Methodology to Select Input Data for SE PIMS

A closer look at the participant distribution reveals a well aligned sample. A general observation is that participants in underfunded plans are not well represented.

Funded Status Range	Sample Participants	Universe Participants
50.00% - 59.99%	0	17,080
60.00% - 69.99%	0	11,525
70.00% - 79.99%	0	126,287
80.00% - 89.99%	147,261	634,566
90.00% - 99.99%	609,842	1,902,704
100.00% - 109.99%	1,705,761	3,809,602
110.00% - 119.99%	2,515,728	4,855,741
120.00% - 129.99%	3,287,940	5,892,086
130.00% - 139.99%	1,443,710	3,239,290
140.00% - 149.99%	479,838	1,001,009
150.00% or more	1,092,932	2,156,700
Grand Total	11,283,012	23,646,590



Methodology to Select Input Data for SE PIMS

Funding Target Liability Distribution

Sample vs. Universe

The table displays the funding target liability distribution.

- The sample and universe distributions are well aligned.
- Sample has no representation for plans less than 80% funded.
  - From a liability perspective, this is a small group in the universe.

Funded Status Range	Universe Funding Target Liability	Sample Funding Target Liability
50.00% - 59.99%	0.0%	0.0%
60.00% - 69.99%	0.0%	0.0%
70.00% - 79.99%	0.4%	0.0%
80.00% - 89.99%	2.4%	1.2%
90.00% - 99.99%	8.2%	6.4%
100.00% - 109.99%	17.5%	18.4%
110.00% - 119.99%	20.9%	22.9%
120.00% - 129.99%	25.6%	28.3%
130.00% - 139.99%	13.7%	13.1%
140.00% - 149.99%	3.7%	2.9%
150.00% or more	7.5%	6.8%
Grand Total	100.0%	100.0%

Note: Totals may not add due to rounding.

Methodology to Select Input Data for SE PIMS

Funding Target Liability Distribution (continued)

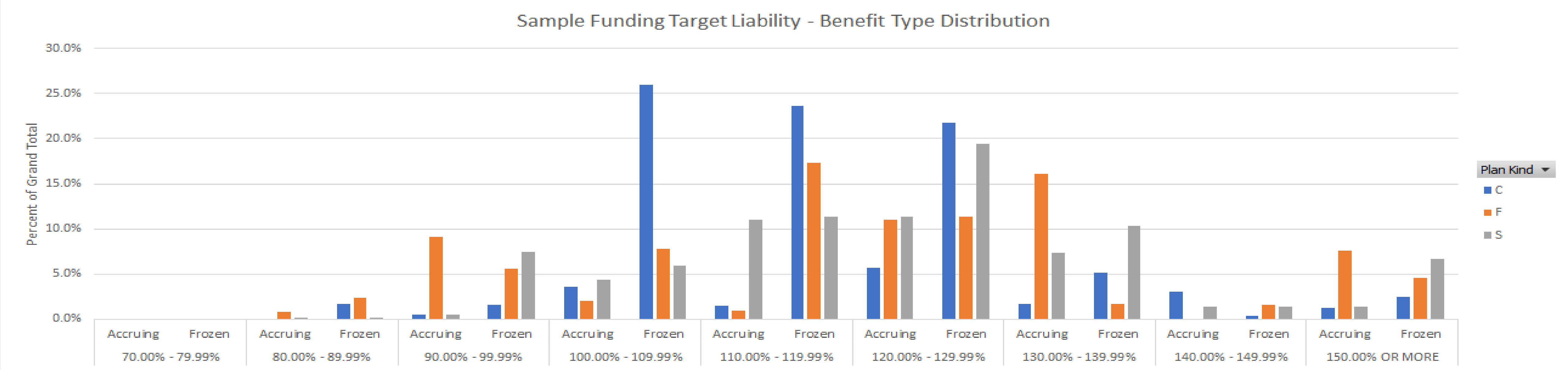
Exhibit 1

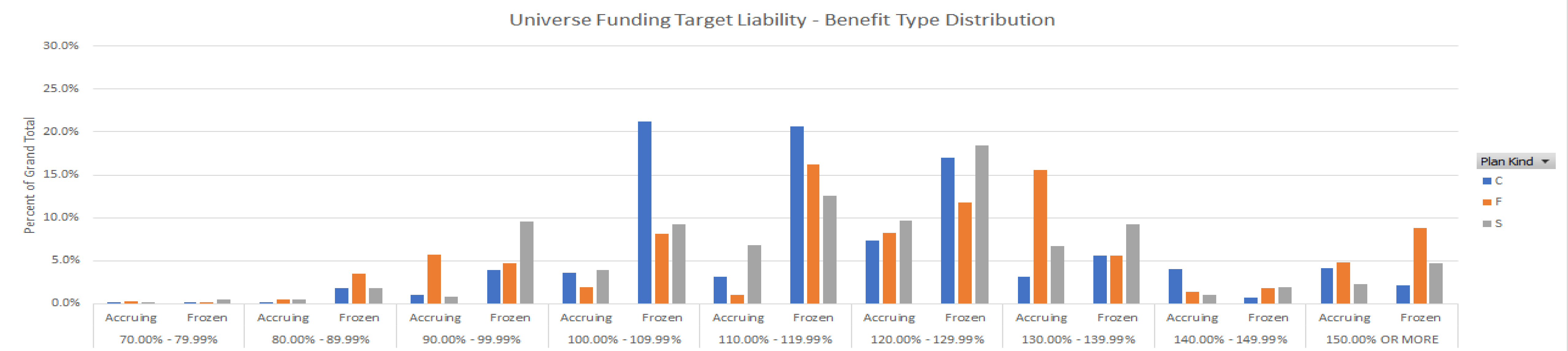
- **Background:**
  - On the following slide, Exhibit 1 depicts the distribution of Funding Target liability across **benefit type and operating status**. The top chart represents the sample, and the bottom represents the universe.
  - Although not shown, the universe has three bands that are not represented in sample plans (Less than 40%, 50%-60%, and 60%-70%), which were filtered out for comparison purposes. From a liability perspective, this is a small group in the universe.
- **Observations:**
  - Sample liability distribution by benefit type generally aligns with universe.
  - Flat benefit type is not overrepresented.
  - Liability distribution by operating status aligns within tolerance (the ongoing cohort aligns better than the frozen cohort).
  - The 70%-79.99% range is not represented in sample.

Exhibit 1:

C – Cash Balance, F – Flat, S – Salaried

Universe $1,974B. Sample $1,098B





Methodology to Select Input Data for SE PIMS

Funding Target Liability Distribution (continued)

Operating Status: Ongoing

The table displays the funding target liability distribution for **ongoing** plans.

As illustrated, the sample and universe distributions are well aligned.

Funded Status Range	Universe Funding Target Liability	Sample Funding Target Liability
Ongoing	30.8%	30.2%
50.00% - 59.99%	0.0%	0.0%
60.00% - 69.99%	0.0%	0.0%
70.00% - 79.99%	0.1%	0.0%
80.00% - 89.99%	0.4%	0.1%
90.00% - 99.99%	1.6%	1.7%
100.00% - 109.99%	3.5%	3.7%
110.00% - 119.99%	4.6%	5.6%
120.00% - 129.99%	8.6%	8.9%
130.00% - 139.99%	6.4%	6.2%
140.00% - 149.99%	2.3%	1.9%
150.00% or more	3.3%	2.2%

Note: Totals may not add due to rounding.

Methodology to Select Input Data for SE PIMS

Funding Target Liability Distribution (continued)

Operating Status: Frozen

The table displays the funding target liability distribution for **frozen** plans.

As illustrated, the sample and universe distributions are aligned although not as aligned as ongoing plans.

Funded Status Range	Universe Funding Target Liability	Sample Funding Target Liability
Frozen	69.2%	69.8%
50.00% - 59.99%	0.0%	0.0%
60.00% - 69.99%	0.0%	0.0%
70.00% - 79.99%	0.3%	0.0%
80.00% - 89.99%	2.0%	1.1%
90.00% - 99.99%	6.7%	4.7%
100.00% - 109.99%	13.9%	14.7%
110.00% - 119.99%	16.3%	17.4%
120.00% - 129.99%	17.0%	19.3%
130.00% - 139.99%	7.3%	6.9%
140.00% - 149.99%	1.4%	1.0%
150.00% or more	4.2%	4.6%

Note: Totals may not add due to rounding.

Methodology to Select Input Data for SE PIMS

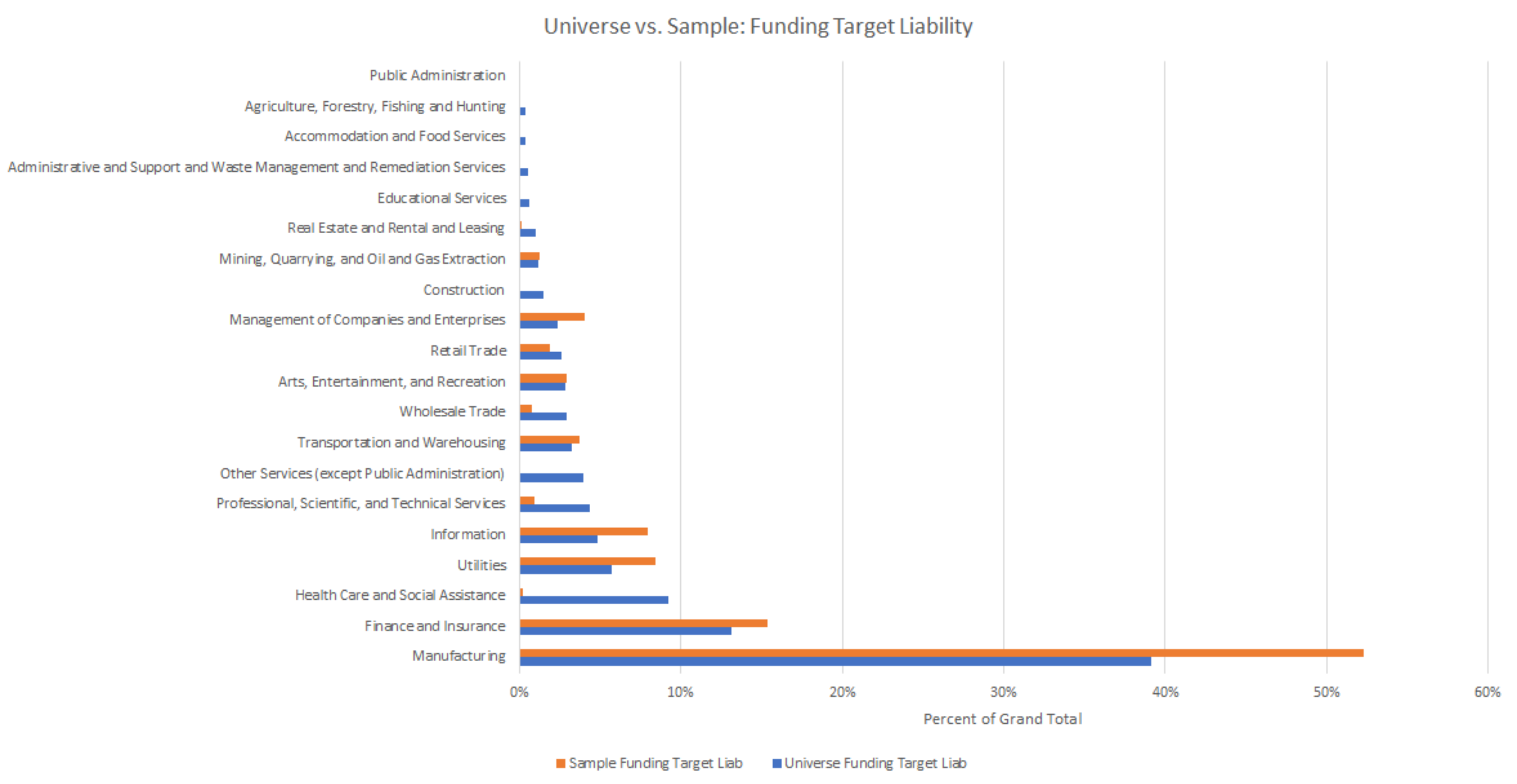
Funding Target Liability Distribution (continued)

Industry:

The chart depicts the funding target liability distribution by **industry** for the sample vs. universe datasets.

The chart shows misalignment across various industries, and several industries have no representation in sample.

Representation can be meaningful as plan sponsors of different industries may have different propensity for bankruptcy.



Methodology to Select Input Data for SE PIMS

Funding Target Normal Cost Distribution

Sample vs. Universe

The table displays the funding target normal cost distribution by operating status.

- The sample and universe distributions are well aligned.
- Sample has no representation for plans less than 80% funded.
  - Aggregate NC of $606M, of $42.8B

Funded Status Range	Universe Funding Target Normal Cost		Sample Funding Target Normal Cost	
Plan Operating Status	**Accruing**	**Frozen**	**Accruing**	**Frozen**
50.00% - 59.99%	0.0%	0.0%	0.0%	0.0%
60.00% - 69.99%	0.0%	0.0%	0.0%	0.0%
70.00% - 79.99%	0.1%	0.1%	0.0%	0.0%
80.00% - 89.99%	0.5%	1.5%	0.1%	0.9%
90.00% - 99.99%	2.3%	6.1%	1.4%	3.5%
100.00% - 109.99%	4.8%	9.6%	4.2%	10.5%
110.00% - 119.99%	7.0%	12.2%	7.0%	14.7%
120.00% - 129.99%	10.9%	11.6%	11.6%	14.5%
130.00% - 139.99%	9.6%	9.2%	8.2%	10.2%
140.00% - 149.99%	3.1%	1.6%	3.5%	0.9%
150.00% or more	4.8%	4.9%	3.5%	5.2%
Subtotals	43.2%	56.8%	39.5%	60.5%

Note: Totals may not add due to rounding.

Methodology to Select Input Data for SE PIMS

Distribution Analysis Summary

Wrap-up

What have we learned?

Distributions of participants are well aligned while plans are not as well aligned.

Participants in underfunded plans are not well represented.

Better alignment measuring funding target liability.

When compared by benefit type and operating status, distributions align well within tolerance.

Misalignment across various industries.

Several industries have no representation in sample.

Methodology to Select Input Data for SE PIMS

Distribution Analysis Summary

Benefit Type:
- The distributions are within tolerance when measuring both funding target liability and participants.
- Distributions do not align well on plan count basis. We see no improvement gained by adding benefit type measures to development of the weight factors given current system constraints.

Operating Status:
- The normal cost distributions align across operating status, but there was concern about optimization of normal cost for accruing plans.
- Although the alignment is within tolerance (sample 39.5% and universe 43.2% for accruing plans), there can be improvement, which may be achieved by strategically adding plans to sample.

Funded Status:
- Underfunded plans (i.e., less than 100%) are not well represented in the sample based on the analysis.
- Plans less than 80% funded are not well represented, and as shown in the Historical Claims section, most defaults are comprised of underfunded plans.
- Consider including additional weight factors. Alternatively, since the current model groups by funded status, adding plans may suffice.

Industry:
- There is misalignment across various industries, and several industries have no representation in sample.
- We recommend periodic reviews of industry alignment with a focus on distressed industries. Modeling improvements may be gained by including industry in the development of the weight factors. PRAD should consider if adding industries with no coverage is warranted.

Coverage Analysis

Methodology to Select Input Data for SE PIMS

Summary of Analysis

- This section examines the current SE PIMS methodology by inspecting the **coverage** of the SE sample dataset to universe.
- The measures summarized are:
  - Plan counts
  - Participant Counts
  - Funding Target Liability
- Groupings are by:
  - Benefit Type
  - Operating Status
  - Industry
- Stratified by funding target liability ranges
- Key Features are the same as Distribution Analysis
- Bundling Process: develop distinct scale-weights for a targeted cohort, potentially aggregate small plans enhance the representation

Distribution of the Universe Dataset by Operating Status and Benefit Type

Operating Status	Plan Count	Participant Count	Funding Target Liability
Ongoing	**11,994**	**7,073,519**	**608,319,290,053**
C – Cash Balance	6,082	2,513,602	213,471,081,670
F – Flat Benefit	518	958,763	98,476,577,248
S – Salaried Benefit	5,394	3,601,154	296,371,631,135
Frozen	**10,277**	**16,573,071**	**1,365,450,155,665**
C – Cash Balance	3,435	6,475,802	581,484,905,917
F – Flat Benefit	993	1,882,204	151,135,216,907
S – Salaried Benefit	5,849	8,215,065	632,830,032,841
Grand Total	**22,271**	**23,646,590**	**1,973,769,445,718**

Methodology to Select Input Data for SE PIMS

Plan Counts

Table displays plan counts and coverage ratios stratified by Funding Target Range.

- Sample covers 2.0% of universe plans.
- Big Plans (funding target liability ≥ $1B) have good coverage.
- Small Plans (funding target liability < $200M) have low coverage.
  - 41 of 21,106, or 0.2%
- 95% of universe plans are Small Plans.
  - A bundling approach could be used to better represent this group, particularly for accruing plans.
- Broader plan coverage may be achieved by targeting the $200M and $400M ranges.

FT Range	Universe Plans	Sample Plans	Plan Ratio
$0M - $199.99M	21,106	41	0.2%
$200M - $399.99M	439	38	8.7%
$400M - $599.99M	211	71	33.6%
$600M - $799.99M	99	45	45.5%
$800M - $999.99M	67	33	49.3%
$1B or more	349	209	59.9%
Grand Total	22,271	437	2.0%

Methodology to Select Input Data for SE PIMS

Participant Counts

Table displays participant counts and coverage ratios stratified by Funding Target Range.

- Sample covers 47.7% of universe participants.
- Big Plans have good coverage.
- Small Plan participants have low coverage.
  - 76K of 4M, or 1.8%
- 18% of universe participants are in Small Plans.
  - A bundling approach could be used to better represent this group, particularly for accruing plans.
- Broader participant coverage may be achieved by targeting the $200M and $400M ranges.

FT Range	Universe Participants	Sample Participants	Participant Ratio
$0M - $199.99M	4,213,536	76,374	1.8%
$200M - $399.99M	1,920,828	186,829	9.7%
$400M - $599.99M	1,410,275	532,699	37.8%
$600M - $799.99M	908,997	436,391	48.0%
$800M - $999.99M	750,995	312,355	41.6%
$1B or more	14,441,959	9,738,364	67.4%
Grand Total	23,646,590	11,283,012	47.7%

Methodology to Select Input Data for SE PIMS

Funding Target Liability Coverage

Table displays the funding target liability and coverage ratios stratified by Funding Target Range.

- Sample covers 55.6% of universe liability.
- Big Plans have good coverage.
- Small Plans have low coverage.
  - — $4B of $242B, or 1.7%
- 12% of universe liability is in Small Plans.
- Historically, Small Plans account for 98% of all defaults and 29% of termination liability. Consider bundling plans to address representation for this group.
- Broader liability coverage may be achieved by targeting the $200M and $400M ranges.

FT Range	Universe Funding Target Liability	Sample Funding Target Liability	FT Ratio	FT Ratio / Total FT Ratio (55.6%)
$0M - $199.99M	241,998,163,719	4,035,146,680	1.7%	3.1%
$200M - $399.99M	123,728,948,862	11,430,753,451	9.2%	16.5%
$400M - $599.99M	103,937,312,041	35,072,495,135	33.7%	60.6%
$600M - $799.99M	69,169,716,550	31,493,193,236	45.5%	81.8%
$800M - $999.99M	59,705,689,093	29,035,510,295	48.6%	87.4%
$1B or more	1,375,229,615,453	986,746,423,349	71.8%	129.1%
Grand Total	1,973,769,445,718	1,097,813,522,146	55.6%	N/A

Methodology to Select Input Data for SE PIMS

Funding Target Liability Coverage (continued)

Industry:

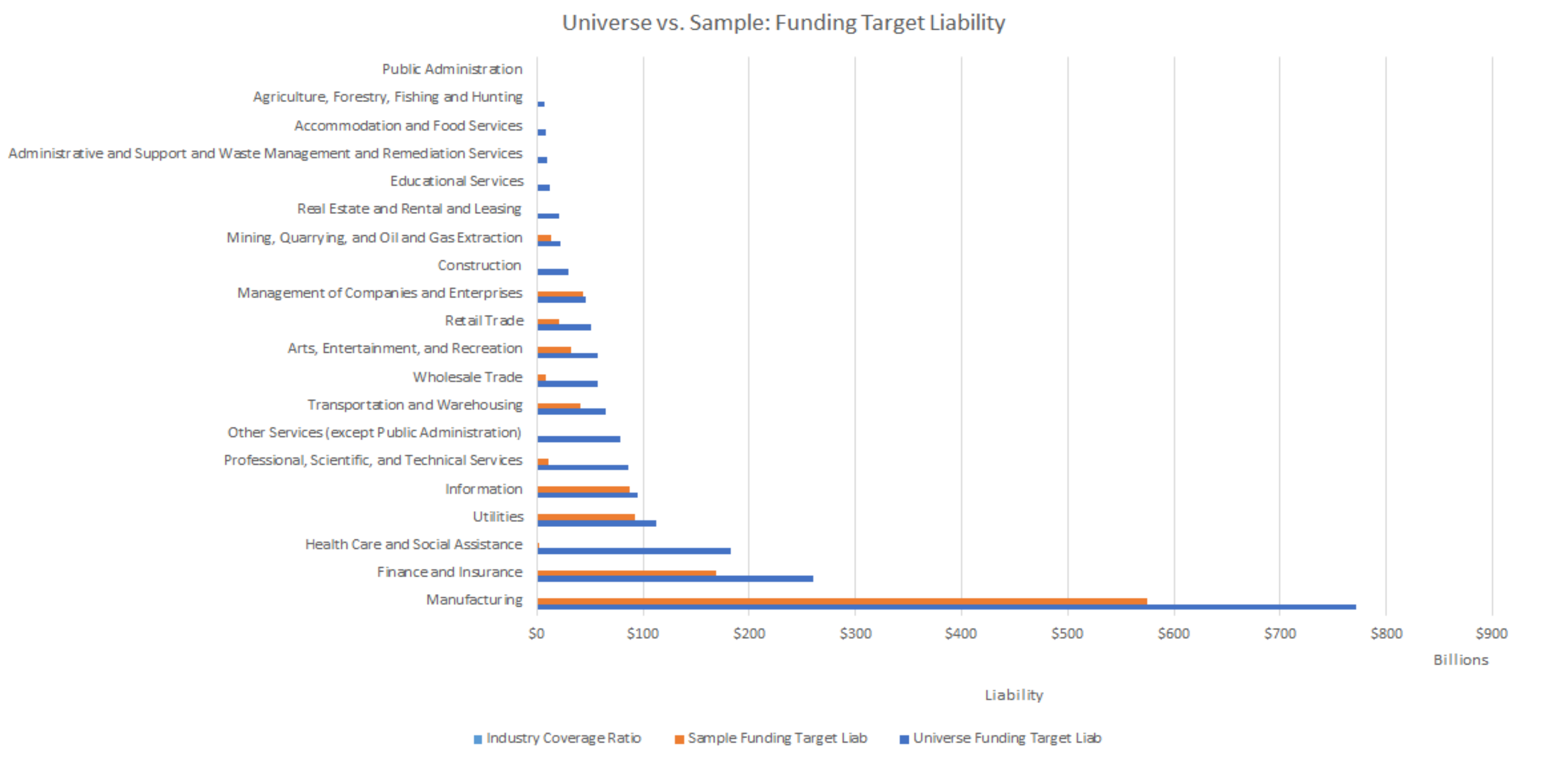
The chart depicts the funding target liability coverage by **industry** for the sample vs. universe datasets.

Good coverage: Manufacturing (74%), Finance (65%), Utilities (82%), Information (91%), Transportation (64%), Arts (55%), Management (95%).

Low coverage: Health Care and Social Assistance.

No coverage: Other Services, Construction, Accommodation, Agriculture, Public Administration.

Representation can be meaningful as plan sponsors of different industries may have different propensity for bankruptcy.

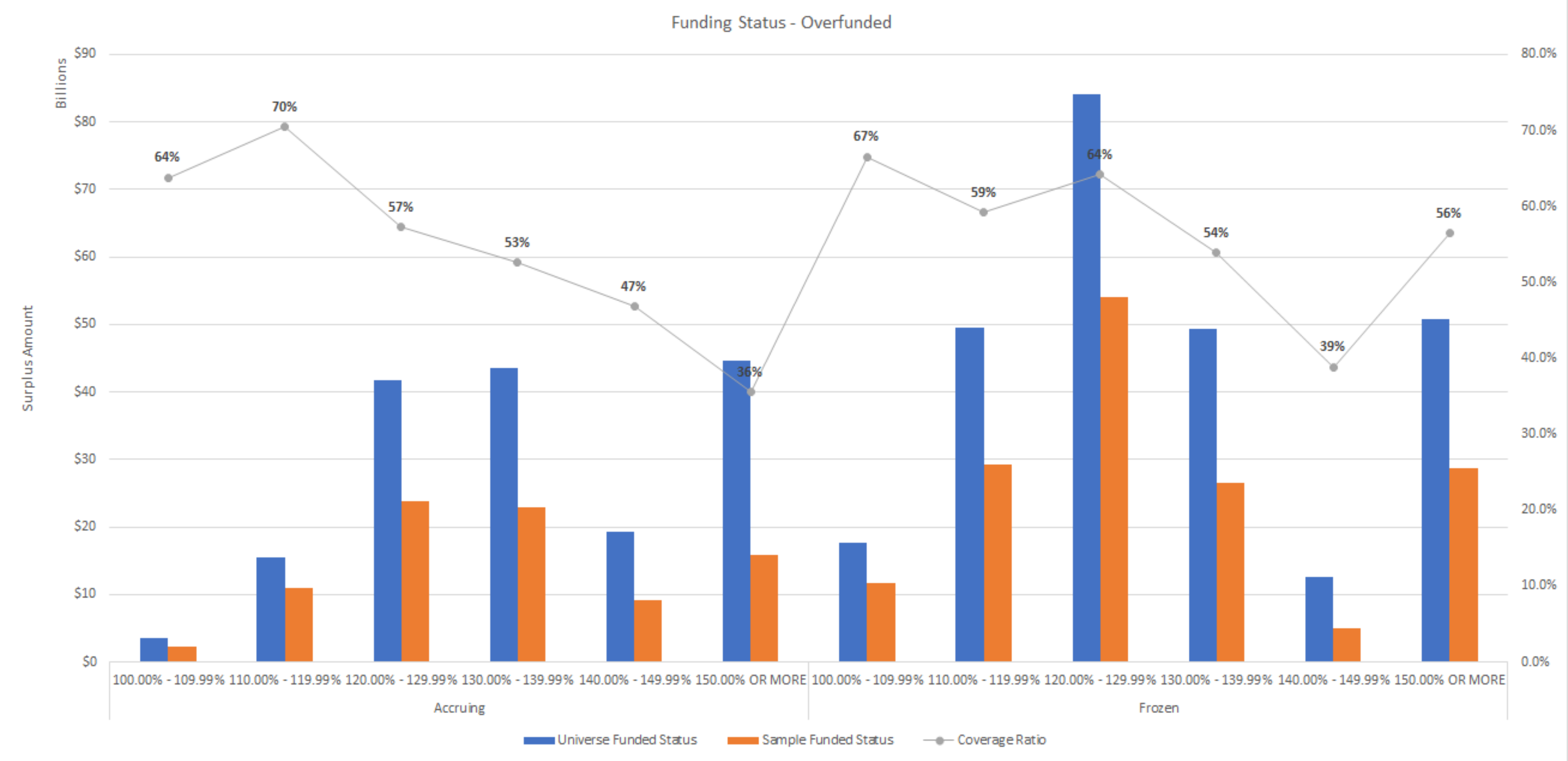


Methodology to Select Input Data for SE PIMS

Funded Status – Overfunded

The chart depicts the aggregate funded status amount for overfunded plans by funded status range and plan operating status. The gray line is coverage ratio.

- Sample covers 56% of universe overfunded/surplus liability.
- In general, we see good coverage across the ranges – just three coverage ratios below 50%.
- Surplus Amount:
  - Universe $432.0B
  - Sample $239.9B

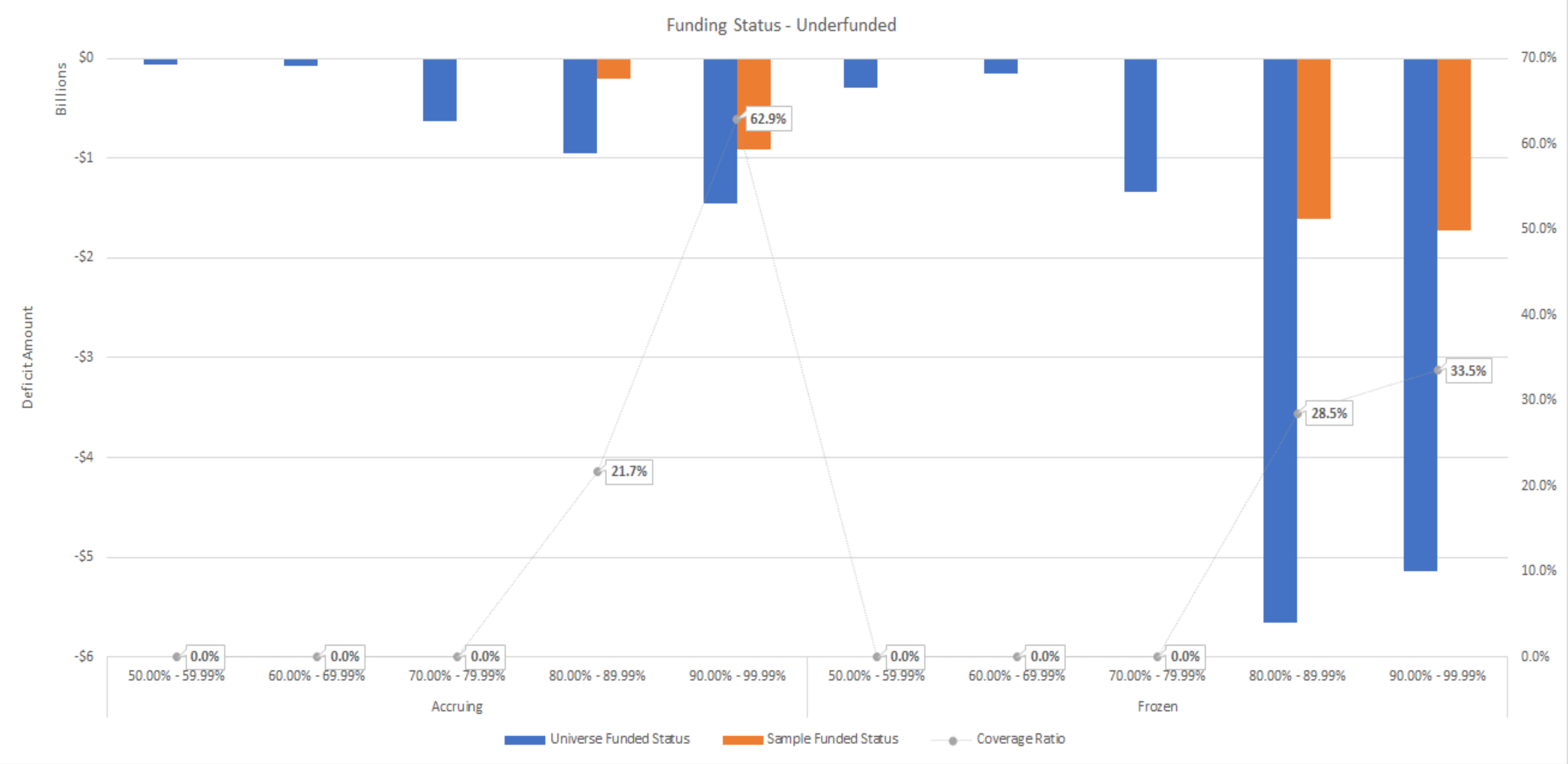


Methodology to Select Input Data for SE PIMS

Funded Status – Underfunded

The chart depicts the funded status amount for underfunded plans by funded status range and plan operating status. The gray line is coverage ratio.

- Sample covers 28% of universe underfunded/deficit liability.
- In general, we see low coverage across the ranges – just one coverage ratio above 50%.
- Aggregate Deficit Amount:
  - Universe -$15.8B
  - Sample -$4.5B



Methodology to Select Input Data for SE PIMS

Funding Target Normal Cost

Table displays the funding target normal cost and coverage ratios stratified by Funding Target Range.

- Sample covers 44.9% of universe normal cost.
- Big Plans have good coverage.
- Small Plans have low coverage.
  - $73M of $8B, or 0.9%
- Although we believe the PBGC can withstand exposure of expected defaults for Small Plans, low coverage of normal cost may have projection implications.
- Broader normal cost coverage may be achieved by targeting the $200M and $400M ranges.

FT Range	Universe Funding Target NC	Sample Funding Target NC	NC Ratio	NC Ratio / Total NC Ratio (44.9%)
$0M - $199.99M	8,036,555,458	72,954,741	0.9%	2.0%
$200M - $399.99M	2,544,047,372	185,255,040	7.3%	16.3%
$400M - $599.99M	2,489,976,480	692,602,995	27.8%	61.9%
$600M - $799.99M	1,541,036,474	666,678,648	43.3%	96.4%
$800M - $999.99M	974,420,570	422,379,448	43.3%	96.4%
$1B or more	27,172,139,412	17,165,782,378	63.2%	140.8%
Grand Total	42,758,175,766	19,205,653,250	44.9%	N/A

Methodology to Select Input Data for SE PIMS

Funding Target Normal Cost (continued)

A closer look at the "$1B or more" cohort from the previous slide – *the group is further stratified by normal cost ranges*.

- Sample covers 63.2% of universe normal cost for Big Plans.
- This view shows the $600M-$799.99M range has no coverage and there is only one plan in the universe in this range.
- Higher normal cost coverage may be achieved by including the one plan in the $600M-$799.99M range in the sample.

FTNC Range	Universe FTNC	Sample FTNC	NC Ratio
FT: $1B or more	27,172,139,412	17,165,782,378	63.2%
NC: $0M - $199.99M	14,572,422,735	8,810,653,195	60.5%
NC: $200M - $399.99M	5,911,272,958	3,707,113,603	62.7%
NC: $400M - $599.99M	3,258,672,457	2,829,193,106	86.8%
NC: $600M - $799.99M	738,425,900	0	0.0%
NC: $800M - $999.99M	2,691,345,362	1,818,822,474	67.6%

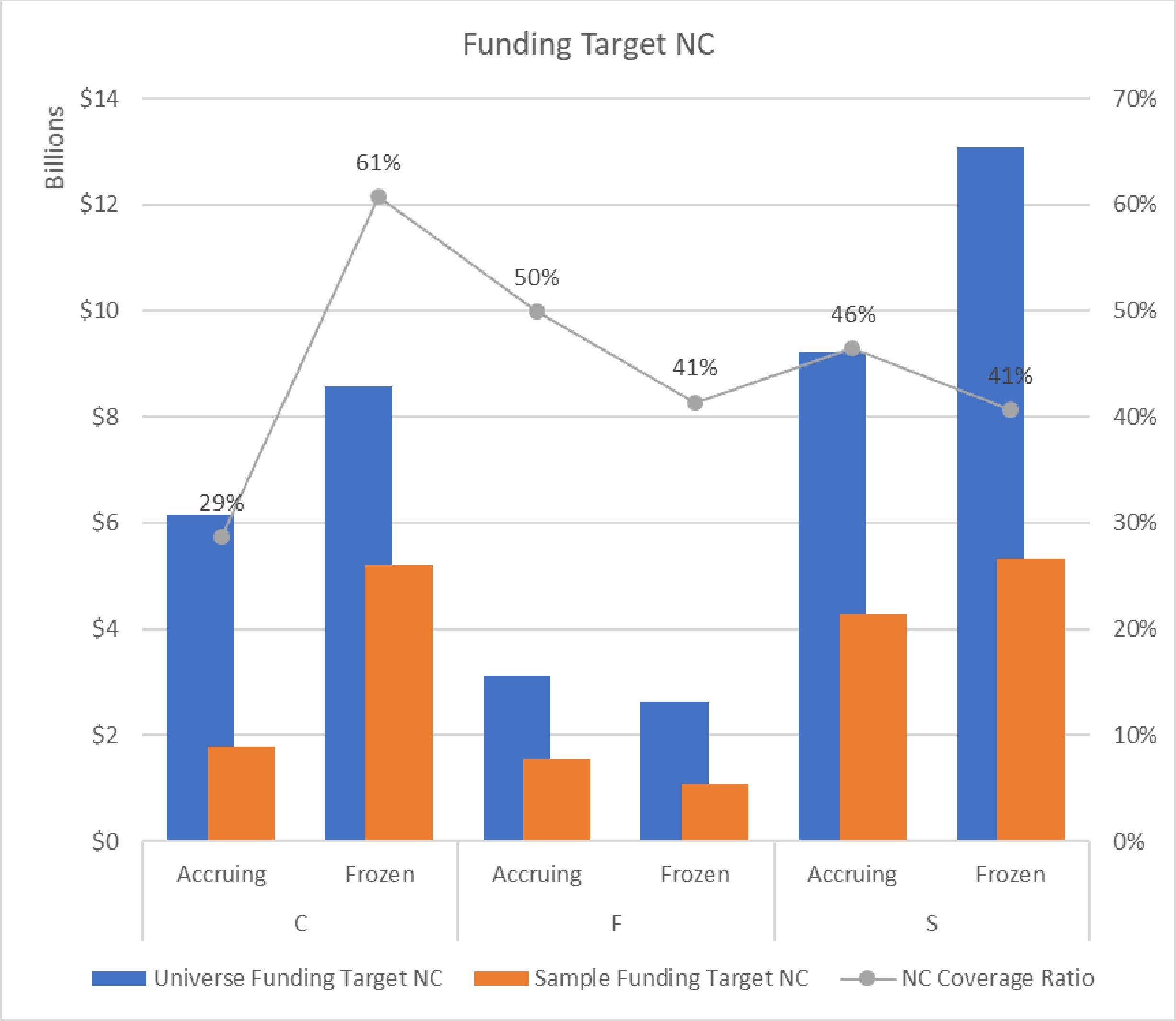
Methodology to Select Input Data for SE PIMS

Funding Target Normal Cost (continued)

Operating Status	Universe	Sample	Coverage %
Accruing	$18.5B	$7.6B	41%
Frozen	$24.3B	$11.6B	48%
Total	$42.8B	$19.2B	45%

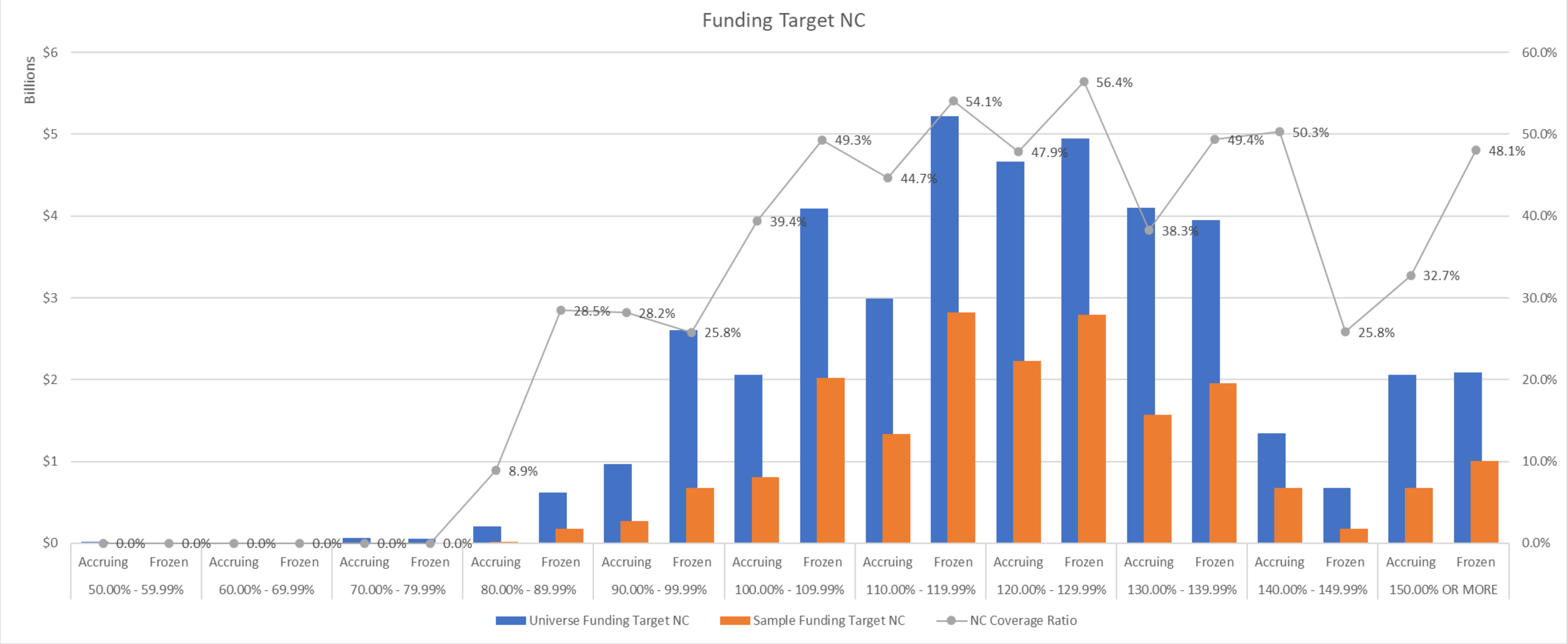
The chart depicts normal cost by benefit type (C – Cash Balance, F – Flat Benefit, S – Salaried Benefit).

- Gray line represents the coverage ratio.
- Coverage ratios are below 50% for most accruing cohorts, net coverage for the cohort is 41%. Moderate coverage.
- Accruing Cash Balance plans have the lowest coverage at 29%.
- Flat benefit types are not overrepresented.
- Since data source is from the Schedule SB, the NC for the frozen cohort is assumed to be the expense load, or the plan could be partially frozen but indicated as frozen on the Form 5500 filing.



Methodology to Select Input Data for SE PIMS

Funding Target Normal Cost (continued)



Sample Plans Dataset Coverage of the SE Universe

56% Funding Target Liability	**45%** Funding Target Normal Cost	**72%** Liability Coverage – Big Plans
2% Liability Coverage – Small Plans	**48%** Participants	**2%** Plans

Methodology to Select Input Data for SE PIMS

Coverage Analysis Summary

Wrap-up

What have we learned?

Moderate participant coverage may impact projection estimates that rely on participant counts – PBGC premiums.

Small Plans and underfunded plans have low coverage.

Good coverage of funding target liability.

Sample covers 56% of universe liability.

Big Plans have good liability coverage: 72%.

Moderate coverage of normal cost.

Sample covers 45% of universe normal cost.

Medium alignment across benefit type.

Expand coverage by adding more sample plans from the "$400M or less" FT Range.

Methodology to Select Input Data for SE PIMS

Coverage Analysis Summary

Benefit Type and Operating Status:

- We used normal cost to inspect the coverage for both features. Sample reasonably covers the normal cost.
- Without modifying the current model, the sample can be improved by strategically adding plans based on observations from this study and internal goals.
- Consider targeting ongoing cash balance plans since that group has the lowest NC coverage.

Funded Status:

- On average, funded status shows good coverage; however overfunded plans have good coverage, while underfunded plans have low coverage.
- The magnitude of the funded status deficit amount is relatively small when compared to that of the surplus amount.
- Without modifying the current model, the sample can be improved by strategically adding plans.

Industry:

- We observed good coverage for top 10 industries with largest proportion of liability except for: Health Care, Professional, Scientific, and Technical Service, Other Services, Wholesale Trade.
- We recommend periodic reviews of industry alignment with a focus on distressed industries. Modeling improvements may be gained by including industry in the development of the weight factors. PRAD should consider if adding industries with no coverage is warranted.

Historical Claims Analysis

Methodology to Select Input Data for SE PIMS

Historical PBGC Claims

YEAR OF TERMINATION	TERMINATION LIABILITY	PARTICIPANTS	PLAN COUNT
1970 - 1979	$461,332,272	88,516	629
1980 - 1989	$3,624,991,132	237,387	1,153
1990 - 1999	$7,343,681,939	394,807	1,140
2000 - 2009	$77,909,321,960	1,311,047	1,312
2010 - 2019	$22,986,057,930	399,358	774
2020 or later	$4,711,001,305	58,115	33
Grand Total	$117,036,386,538	2,489,230	5,041

Methodology to Select Input Data for SE PIMS

Historical PBGC Claims (continued)

Historical claims data, from 1974 to current, were analyzed.

- Dataset included plan names, participant counts, liability, and assets **as of date of termination**.
- The table displays plan and participant counts for terminated plans grouped by funded status ranges.
- 91% of terminated plans were underfunded (e.g., funded status less than 100%).

Funded Status Range	Plan Count	Participants
Less than 40%	8	1,259
50.00% - 59.99%	2,776	1,330,849
60.00% - 69.99%	621	498,617
70.00% - 79.99%	445	272,449
80.00% - 89.99%	335	179,463
90.00% - 99.99%	380	97,870
100.00% - 109.99%	270	87,532
110.00% - 119.99%	57	5,389
120.00% - 129.99%	45	2,935
130.00% - 139.99%	21	8,051
140.00% - 149.99%	16	967
150.00% or more	67	3,849
Grand Total	5,041	2,489,230

Methodology to Select Input Data for SE PIMS

Historical PBGC Claims (continued)

Historical claims data, from 1974 to current, was analyzed. Dataset included plan names, participant counts, liability, and assets **as of date of termination.**

- The table displays plan and participant counts for terminated plans grouped by funded status ranges.
- Funded status less than 80% at termination:
  - 76% of plans
  - 84% of participants
  - 87% of termination liability
- Funded status greater than, or equal, 100% at termination:
  - 9% of plans
  - 4% of participants
  - 2% of termination liability
- 91% of terminated plans were underfunded.

Funded Status Range	Termination Liability (TL)	Plan Count	Participants
Less than 40%	$0	8	1,259
50.00% - 59.99%	$64,212,059,247	2,776	1,330,849
60.00% - 69.99%	$22,324,628,568	621	498,617
70.00% - 79.99%	$15,128,038,603	445	272,449
80.00% - 89.99%	$10,696,521,954	335	179,463
90.00% - 99.99%	$2,529,856,367	380	97,870
100.00% - 109.99%	$1,782,492,160	270	87,532
110.00% - 119.99%	$48,606,616	57	5,389
120.00% - 129.99%	$25,574,623	45	2,935
130.00% - 139.99%	$259,892,746	21	8,051
140.00% - 149.99%	$6,801,641	16	967
150.00% or more	$21,914,013	67	3,849
Grand Total	$117,036,386,538	5,041	2,489,230

Methodology to Select Input Data for SE PIMS

Historical PBGC Claims (continued)

Zoom in on Small Plans and Big Plans at termination using the FT Ranges.

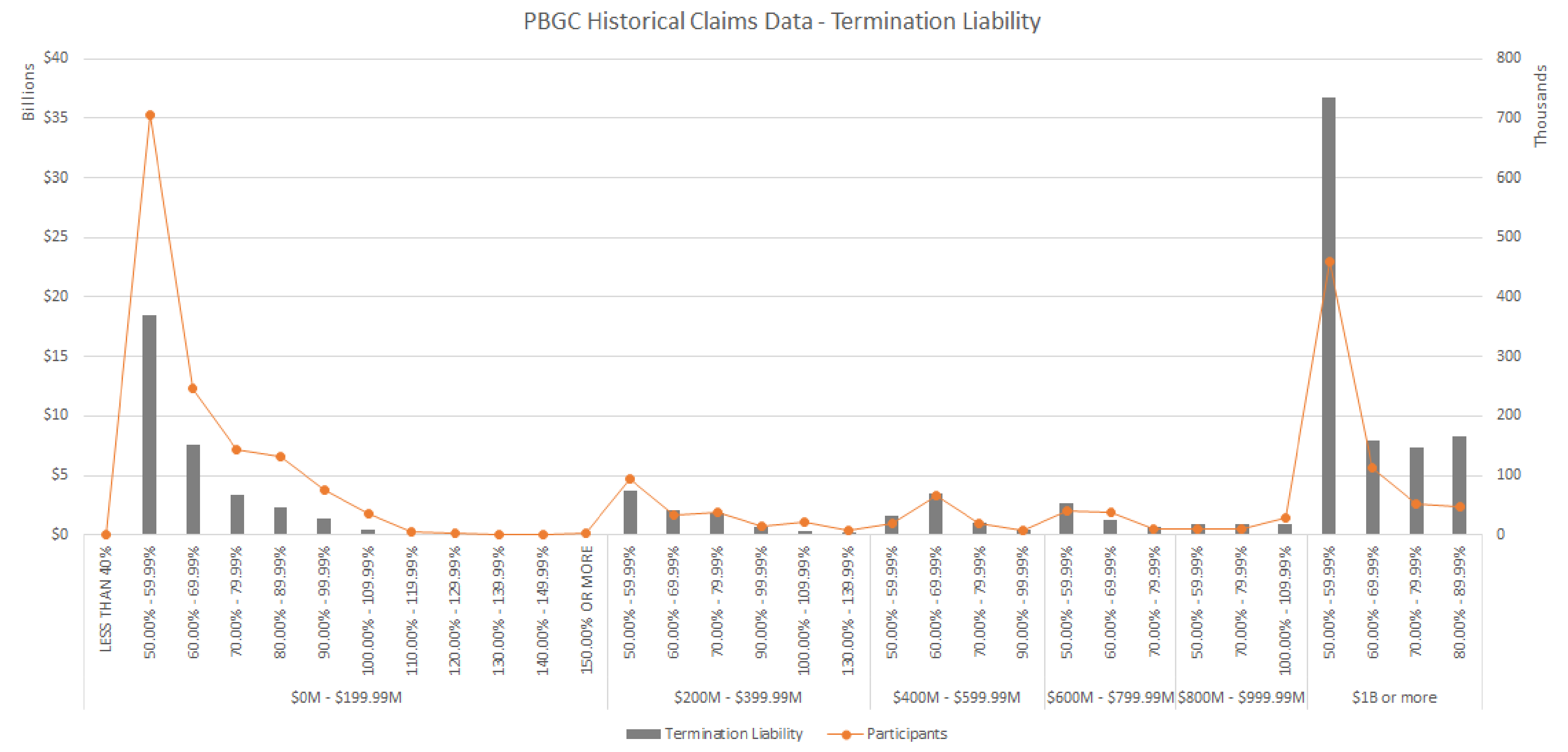
- Data is stratified by funded status ranges.
- Small Plans make up,
  - 98% of terminated plans
  - 54% of participants
  - 29% of Termination Liability (TL)
- Big Plans make up,
  - 0.5% (23 plans) of terminated plans
  - 27% of participants
  - 52% of Termination Liability (TL)

TL & FUNDED STATUS RANGE	TL	PLAN COUNT	PARTICIPANTS
TL: $0M - $199.99M	**$33,739,339,943**	**4,964**	**1,353,554**
Less than 40%	$0	8	1,259
50.00% - 59.99%	$18,504,547,154	2,741	706,010
60.00% - 69.99%	$7,561,972,722	602	246,537
70.00% - 79.99%	$3,355,761,510	432	142,588
80.00% - 89.99%	$2,349,325,934	331	130,888
90.00% - 99.99%	$1,355,138,280	377	75,195
100.00% - 109.99%	$504,766,013	268	36,875
110.00% - 119.99%	$48,606,616	57	5,389
120.00% - 129.99%	$25,574,623	45	2,935
130.00% - 139.99%	$4,931,437	20	1,062
140.00% - 149.99%	$6,801,641	16	967
150.00% or more	$21,914,013	67	3,849
TL: $1B or more	**$60,357,776,098**	**23**	**672,820**
50.00% - 59.99%	$36,749,148,282	13	459,798
60.00% - 69.99%	$7,903,061,216	3	112,643
70.00% - 79.99%	$7,358,370,580	3	51,804
80.00% - 89.99%	$8,347,196,020	4	48,575
Grand Total (All Plans, See Prior Page)	$117,036,386,538	5,041	2,489,230

Methodology to Select Input Data for SE PIMS

Historical PBGC Claims (continued)

- Chart depicts termination liability at date of termination.
- Orange line is participant counts.
- Grouped by Funded Status range within FT Range.
- Small Plans and Big Plans have historically seen most of the action.



Methodology to Select Input Data for SE PIMS

Bringing It All Together:

Our analysis shows that the current sampling method generates good coverage and well aligned distributions compared to the universe when measured on a liability basis. This finding meets expectations since the methods center on the liability.

There are some areas that may be considered for improvement: Small Plans, underfunded plans, and normal cost. Small Plans and underfunded plans are not well represented, and the normal cost is covered at less than 50%. Based on historical claims data, Small Plans and underfunded plans make up most defaults and the aggregate termination liability is significant (28%).

In our hypothesis we questioned if using different groupings and measures would show varied results. The analysis shows that when the basis is changed to plans, misalignment and lower coverage is observed across benefit type, operating status and industry. The analysis also shows that while the current grouping approach does create 'blind spots' by using only liability for weights, the net result is generally sufficient and reasonable.

We do not foresee significant improvements to projections from including additional plan distinctions in the development of the weight factors.

Additionally, given current system limitations around configuring plan provision details, any improvements gained by rebalancing on benefit type, participant, or plan basis, may be limited. Deficiencies shown for operating status and industry can be addressed by strategically adding plans and do not warrant direct changes to the weight factors.

Methodology to Select Input Data for SE PIMS

Key Recommendations:

Maintain current SE sampling methods but consider strengthening areas

- Analysis indicated the SE sampling methods are well aligned relative to the universe of plans measured on a liability basis.
- Increase areas of coverage as indicated by the analysis to enhance overall modeling and refine the results.
  - Consider increasing representation of Small Plans (less than $200M in Funding Target Liability) and Underfunded Plans (assets < liability)
    - Potential bundling approach of Small Plans as a new sample
    - Potential adjustment handled and analyzed outside of PIMS
  - Consider increasing Normal Cost coverage
  - Consider periodic review of industries, specifically to identify distressed industries, and potentially include industry weighting
- Sample of 500 plans should be reviewed regularly to ensure reasonable representation.

Statement of Objectives from Scope of Services

Development of Plan Participant Profiles

Our Understanding

&

Observations

- We understand that the PBGC uses the age/service matrix to create the grouped active data population.
- PIMS estimates the age/benefit distribution of the inactive population by performing a 100-year projection of the current active population and then scales the counts to the actual inactive count and then scales benefits to match the initial liabilities.
- There are multiple calibration factors used to align the sample plan's Schedule SB initial liabilities by status and normal costs.
  - Two sets of calibration factors are used for active liabilities:
    - "Retrospective" calibration factor to align the initial funding target
    - "Prospective" calibration factor to align the initial target normal cost
  - PIMS also uses separate calibration factors for the initial deferred vested and retiree liabilities.

Development of Plan Participant Profiles

Recommendations

- Consider requesting cash flows, which are now generally available from annual actuarial valuation processing and can be provided annually.
- Leading actuarial valuation software is designed to generate cash flows, which will minimize any additional burden on plan sponsors.
- This will help:
  - Validate the cashflows generated by PIMS
  - Adjust the cashflows of the guaranteed benefits in PIMS
  - Confirm whether the interest rate sensitivities of the sample plans are reasonable (convexity and duration)
  - Adjust any future benefits payment patterns in PIMS, as needed
  - Reduce number of calibration steps
  - By offering transparency of financial implications of holding a Plan, and assisting all stakeholders in the understanding of managing pension risks

Standard Data Input Assessment of SE PIMS

Our Understanding

&

Observations

- The data used in PIMS comes from the following sources:
  - Census file, plan provisions, and valuation assumptions are collected via government filings and summarized by a contractor
  - Firm data used to estimate bankruptcy probabilities is sourced from CompuStat
  - Capital market assumptions are collected from Ibbotson Associates
  - Summary of Findings (see Appendix A):

Source of Data Fields	Percentage
Not Used	48%
Sourced from Filing and Attachments	18%
Sourced from Third Party Providers	10%
Produced by PRAD	9%
Prescribed	3%
Estimated	3%

Standard Data Input Assessment of SE PIMS

Recommendations

- Consider deleting data fields that are not used to create efficiencies and avoid errors.
- Consider expanding service brackets of the Schedule SB matrix to improve PIMS census file:
  - Ungroup after an agreed upon service amount
  - Ungroup after an agreed upon age
- Consider incorporating firm financial information from PBGC 4010 filings for privately held companies with large, underfunded plans in the sample data.
- Consider updating RP-2014 based mortality tables to Pri-2012 based mortality tables to align with most recent tables published by the SOA.

Standard Data Input Assessment of SE PIMS

Recommendations (continued)

- PIMS only values single life annuity form of payment, assumes annual payment, and assumes all participants are male.
  - Consider adding male/female percentage assumption to account for longer life expectancy of females.
  - Consider making joint and survivor annuity assumption to reflect beneficiary life expectancy.
- Consider requesting the following attachment in the Schedule SB to improve the quality of the inactive file used in PIMS:
  - An attachment with the average age and average benefit amounts for terminated vested participants, retirees, and beneficiaries.
    - This information is readily available in actuarial valuation reports.
    - Can assist with calibration of projected inactive cash flows.

Data Input Items from Form 5500 Used to Develop Expected Cash Flows

Our Understanding

&

Observations

- Same process is used for grouped (non-seriatim) data for SE and ME.
- PBGC has opted to maintain the Actuarial Services Division's assumptions for SE.
- Data to generate expected cash flows comes from Form 5500 Filings via PIMS Data Entry Program, or DEP, (combination of automated and manual data entry) as well as actuarial valuation reports (AVRs).
- Plan is currently condensed down to three participants – one active, one deferred vested, and one retiree:
  - Based on average age of each group from AVRs
  - Retiree monthly benefit reported from AVRs
  - Active and deferred vested monthly benefits are determined based on liability, average age, and assumed retirement age

Data Input Items from Form 5500 Used to Develop Expected Cash Flows

Recommendations

- To ensure accurate cash flows, consider requesting SE projected cash flows be electronically submitted as part of the Schedule SB and/or PBGC filing, as mentioned earlier.
- If requesting cash flows is not feasible, consider adding more representative participants to allow for cash flows to be less concentrated in the mid-term time horizon and achieve improved accuracy overall – primarily for deferred vested participants.
  - In the current model used to estimate short-term and long-term cash flows, distribution of ages is not extensive.
  - Consider using three representative deferred vested participants (rather than just one) to scale cash flows – average age and average age +/- a specified number of years.

Availability of Form 5500 Data and Adjustments to Create a Uniform Data Set

Our Understanding

&

Observations

- Form 5500 data items including the Schedule SB are two to three years old and compiled by the DEP, which includes automated and manual entry by a third-party contractor.
- For non-seriatim data, PIMS starting liabilities, asset values and census information are projected forward from the Form 5500 snapshot date to the current PIMS projection date using deterministic assumptions based on known economic impact.
- We understand that the starting position is treated as follows:
  - If plan year begins January 1, Schedule SB data is as of January 1.
  - If plan year begins between January 1 and June 30, Schedule SB data is treated as January 1 plan year beginning in the *current* calendar year.
  - If plan year begins between July 1 and December 31, Schedule SB data is treated as January 1 plan year beginning in *following* calendar year (but using *current* year regulations).

Availability of Form 5500 Data and Adjustments to Create a Uniform Data Set

Recommendations

- Consider using the latest PBGC filing information with more recent liability, asset values, and census count information to adjust projected starting point liabilities, if available. Continue to use timing adjustments for non-calendar plans as needed.
- Consider updates to reflect American Rescue Plan (ARP) for FY 2021:
  - May need to incorporate ARP inputs for plans electing to implement fresh-start 15-year amortization in 2019-2022.
  - Contribution patterns in the short-term and long-term may change:
    - Plan sponsors who elected ARP to lower minimum required contribution (MRC), may only pay the new, lower MRC.
    - Additional interest rate relief under the Infrastructure Investment and Jobs Act may change contribution patterns for an extended period.
  - Plans in distress are the most likely to elect immediate relief and represent the greatest risk to the PBGC.

Plan Status, Benefit Design, and Features to be Valued

Our Understanding

&

Observations

- We understand that PIMS currently does not use the following data inputs, which may underestimate the stochastic liabilities; however, calibration factors are used to scale up to the starting liabilities:
  - Estimated male/female split in the SE plan universe. PIMS currently uses a 100% male data set.
  - Marriage percentage to reflect beneficiaries.
  - For participants currently over age 65, there are no late retirement adjustments.
  - Supplementary and ancillary benefits are not valued (may not be guaranteed benefits).

Plan Status, Benefit Design, and Features to be Valued

Recommendations

- Consider requesting electronic cashflows in future Schedule SB filings, as discussed earlier, to improve the precision of projected liabilities.
  - Would this change be considered a burden on plan sponsors complying with the Paperwork Reduction Act?
  - Could enhanced precision of forecast be used to justify additional paperwork burden?

Plan Sponsor's Financial Information Used as Input to Determine Future Bankruptcies

Our Understanding

&

Observations

- PIMS bankruptcy probability estimates are weighted heavily on the following historical CompuStat data:
  - Leverage, cashflow, firm size/employment, pension plans' funding ratio, and if the plan is in the financial/utility industry
- We understand that the PBGC uses empirical estimates of the volatility of bond ratings to estimate bankruptcy probabilities over time.
- Historic bankruptcy probabilities affiliated with bond ratings are used to assign bankruptcy estimates in the stochastic model as described in the PIMS System Description.
- To ensure that bankruptcy estimates are reasonably related to existing default estimates, PBGC compared the predicted bankruptcy probabilities against Standard and Poor's subordinated debt ratings for those firms that have reported ratings from 1980-1996.

Plan Sponsor's Financial Information Used as Input to Determine Future Bankruptcies

Recommendations	• Consider using the following to refine bankruptcy probabilities: — Additional CompuStat data, such as profitability, liquidity, solvency and activity ratios used in the Altman Z score — Hedge ratios of the sample plans found in the asset allocation and duration of the fixed income security sections of the Schedule R • Hedge Ratio may have small impact on sponsor bankruptcy, but may affect likelihood of plan insolvency (and degree of PBGC responsibility) in event of bankruptcy — PBGC 4010 filing firm financial information for plans with large unfunded liabilities or PBGC Form 10 – Early Warning System or Missed Quarterly Contributions — Risk Transfer Transactions (Lump sum windows, annuity purchases, etc.) reported in the PBGC filings

Plan Sponsor's Financial Information Used as Input to Determine Future Bankruptcies

Recommendations (continued)

- We partnered with Conning and Company to review the bankruptcy modeling aspect of PIMS.
- The findings of that analysis (included as Appendix B) confirm that the PBGC approach, including use of Logit distribution, is reasonable.
- Conning recommends considering additional macroeconomic variables to be added to the Logit regression model, such as GDP growth.
- Consider rerunning regression analysis (perhaps every 5 years) to assess whether weights currently assigned to different variables remain the most appropriate predictors of future bankruptcy probabilities.

Economic and Regulatory Inputs

Our Understanding & Observations	

Our Understanding

&

Observations

- PIMS currently uses a fixed asset allocation data set for all sample plans in the projection:
  - 48% stock market returns
  - 22% long-term 30 Year Treasury bond returns
  - 30% long-term 30 Year Treasury bond yields
- This is from an older study that may no longer represent the asset allocation of the entire SE universe.
- PIMS currently does not use the asset allocation in the Schedule R to project assets of the entire SE universe or any LDI strategies because of current system limitations.
- We understand the inflation assumption currently used in PIMS is based on the Social Security Intermediate Assumption (currently 2.4% in 2020 Trustees Report).

Economic and Regulatory Inputs

Recommendations	
Recommendations	• Consider using the latest asset allocation of the entire SE universe from the Form 5500 Schedule R as a guide to update the current PIMs asset allocation, if needed, or to adjust the asset allocation annually during the projection process. — May improve the ability of PIMS to estimate the future asset performance of the SE universe. • Consider incorporating lump sum and annuity payout assumptions for the sample plans and SE universe found in the Schedule SB attachments, Part V (Statement of Actuarial Assumptions and Methods). — Cash outs driven by the low interest environment have a negative impact on a plan’s funded ratio (though less impact on funded status in dollars) if the funding ratio is below 100%.

PBGC Asset, Liability, and Premium Information

Our Understanding

&

Observations

- Frozen/ongoing (FY20: 62.6% / 37.4%) plan breakdown of the SE universe is currently used in estimating PBGC premiums in PIMS.
- PBGC liabilities currently use projected PBGC interest rates based on 30 Year Treasury rate plus 42 bps spread (historical spread over the past three years) in latest projection, and PBGC assets are currently projected to 12/31.

PBGC Asset, Liability, and Premium Information

Recommendations

- Consider reflecting a “Risk Transfer Activity” assumption in PIMS because it reduces PBGC premiums over the projection period while leaving the plan’s larger liabilities with the plan sponsor.
- Consider using the 30-year Treasury rates plus the “appropriate spread” that results from the stochastic models instead of trying to constrain the results using historical spreads over the past three or four years to determine a forward looking PBGC interest rate.

Zone Status Availability for ME Plans

Our Understanding

&

Observations

- Plan Zone Status is taken from the most recently available Form 5500 Filing Schedule MB.
- This will often not be the most recently available Zone Status information, and as a result, information is taken from the annual zone certification submissions to supplement the deficiency.
  - Only plans issued as Critical and Declining are updated from currently available certification status information filed with the DOL.

Zone Status Availability for ME Plans

Recommendations

- Consider reflecting Zone Status information from latest available annual zone status certification to avoid using outdated information resulting from a lag in Schedule MB reporting.
  - IRS annually receives zone status certifications for each multiemployer plan certified by the plan's actuary.
    - Request IRS tracking information for these submissions in a readable format to gain access to more current information for all plans in the ME system.
    - If possible, request for the PBGC to be included as a required recipient for the annual zone certification submission email provided to epcu@irs.gov.
  - Consider adding current plan year zone status to the list of items submitted for "plan information" with the annual PBGC premium filing to gain more current information.

Zone Status Availability for ME Plans

Recommendations (continued)

- Consider reviewing projections for plans that are generally available via Funding Improvement Plan and Rehabilitation Plan annual monitoring to have more data points for modeling reasonability review rather than a snapshot Zone Status, which can be compiled in connection with Zone Status research.
  - — Information may be obtained from the IRS or research in the Form 5500 Filings or fund websites.
- If projections reviewed per the recommendation above, also consider adding a request for Green plans to submit projections annually to have more data points for modeling reasonability review and a more comprehensive look at projected multiemployer system health.
  - — Even if a plan is not Endangered or Critical, the actuary still prepares annual projections to certify Green
    - Information is available as part of the annual actuarial valuation work.

Standard Data Input Assessment of ME PIMS

Our Understanding & Observations	
	• Data inputs and demographic assumptions from Form 5500 filings and supplemental information from the Central States Plan are used to generate cash flows for each plan in the ME Universe. • Demographic assumptions include restriction that no employee is older than 65. • Mortality assumptions reflect RP-2014 base table with static projection to 2032 using the MP-2019 improvement scale. • Active counts are collected from the Schedule MB information, with subsequent years rolling forward with stochastic population growth/(decline) under the population sub-model – population decline has a mean of -1.3% and a standard deviation of 8%. • It is assumed that assets are invested under a single allocation.

Standard Data Input Assessment of ME PIMS

Recommendations	• Consider requesting cash flows, which are now generally available from annual actuarial valuation processing and can be provided annually. • Leading actuarial valuation software is designed to generate cash flows, which will minimize any additional burden on plan sponsors. • This will help: — Validate the cashflows generated by PIMS — Adjust the cashflows of the guaranteed benefits in PIMS — Confirm whether the interest rate sensitivities are reasonable (convexity and duration) — Adjust any future benefits payment patterns in PIMS, as needed — Reduce number of calibration steps — By offering transparency of financial implications of holding a Plan, and assisting all stakeholders in the understanding of managing pension risks

Standard Data Input Assessment of ME PIMS

Recommendations (continued)

- Consider reviewing assumptions and/or data by industry to streamline inputs and processing.
- Data currently available to the PBGC for Central States does carry considerable weight due to size, however, that plan does not capture the full view of the ME universe.
  - Reviewing the chart on the following slide demonstrates that while Central States is a large fund, it is still a small percentage of the entire ME universe.
    - The chart summarizes information for the ME funds that have the 10 highest Current Liability amounts as reported in the data for the 2020 Projection Report.
    - These funds vary by industry, participants, and zone status (most of which are Green).

Standard Data Input Assessment of ME PIMS

Plan	Zone Status	Current Liability (000's)	% of ME Universe	Total Participant Count	% of ME Universe	Industry
WESTERN CONFERENCE OF TEAMSTERS PENSION PLAN	Green	58,688,471	6.03%	384,948	5.79%	Transportation & Warehousing
CENTRAL STATES, SOUTHEAST & SOUTHWEST AREAS PENSION PLAN	Critical and Declining	17,632,202	4.78%	72,098	3.66%	Transportation & Warehousing
CENTRAL PENSION FUND OF THE IUOE & PARTICIPATING EMPLOYERS	Green	74,083,306	2.95%	609,637	1.92%	Construction
NATIONAL ELECTRICAL BENEFIT FUND	Green	36,267,147	2.81%	202,017	5.28%	Construction
1199SEIU HEALTH CARE EMPLOYEES PENSION FUND	Green	34,440,301	2.14%	555,962	2.51%	Other Industry
IAM NATIONAL PENSION FUND	Green	25,322,193	2.06%	280,019	2.66%	Manufacturing
BOILERMAKER-BLACKSMITH NATIONAL PENSION TRUST	Endangered	26,211,969	1.65%	264,517	0.69%	Construction
NEW ENGLAND TEAMSTERS & TRUCKING INDUSTRY PENSION	Critical and Declining	20,275,441	1.44%	72,703	0.69%	Transportation & Warehousing
PLUMBERS AND PIPEFITTERS NATIONAL PENSION FUND	Endangered	15,333,674	1.25%	149,498	1.42%	Construction
SHEET METAL WORKERS' NATIONAL PENSION FUND	Endangered	14,839,784	1.21%	139,772	1.33%	Construction

Standard Data Input Assessment of ME PIMS

Recommendations (continued)

- Consider Special Financial Assistance (SFA) Data
  - — Focus on Central States data has been mainly due to availability.
  - — Consider utilizing all the data delivered to the PBGC with the SFA application to adjust the ME PIMS projection model.
    - Data for approximately 250 plans in the ME system will soon become available to PBGC.
    - Census files, cash flows, projections, extensive documentation, etc.
  - — Utilize the application information to refine current methodologies and/or review modeling for reasonability.
  - — Utilize actual data to generate cash flows, if feasible.
  - — Also review data of denied applications for plans ultimately deemed ineligible for SFA but may be in jeopardy.
    - Consider more direct focus in modeling on those plans that narrowly miss eligibility for SFA.

Standard Data Input Assessment of ME PIMS

Recommendations (continued)

- Consider Special Financial Assistance (SFA) Adjustments and behavior trends.
  - — ME PIMS has already considered adjustments for plans electing to receive SFA.
    - Listing of eligible plans for SFA has been predetermined by PBGC
    - Adjustments for SFA amounts
    - Behavior modeling including adjustments to contributions and investment returns
  - — May consider creating a probability of SFA elections based on comments and feedback on the interim rules published July 2021.
    - Commenters indicate possible hesitation for plans that received MPRA benefit suspensions to elect SFA relief because of potential conflicts in fiduciary responsibility for the plan's active and retiree populations.
    - We believe it is not certain that plans that applied for MPRA relief will elect SFA and recommend allowing for this possible behavior.

Standard Data Input Assessment of ME PIMS

Recommendations (continued)

- Consider extending retirement age beyond age 65 for actives. Current retirement trends find workers regularly remaining in active service beyond age 65 to receive continued pay and benefits.
  - Social Security Normal Retirement Age for a majority of the active workforce is between 66 and 67 years old and the Minimum Required Distribution Age was recently increased to 72 years old.
  - If commencement beyond 65 is implemented for deferred vesteds (DVs) as well, actuarial increases can be combined with a forfeiture assumption.
    - Determine average percentage of DV population over 65 from plans managed by the PBGC or request a DV scatter or age distribution be included in the Schedule MB submission.
  - In our experience, extended retirement assumptions for actives and DVs have had a material impact on results.

Standard Data Input Assessment of ME PIMS

Recommendations (continued)

- Consider reviewing mortality assumptions reflecting Pri-2012 and projected improvement scale on a generational basis.
  - Review industries and consider potential blue collar, partial or full weighted, adjustments.
- Consider short-term and/or long-term adjustments to the population growth/(decline) assumption.
  - Review plan workforce increases/(decreases) from Form 5500 data to identify industry workforce patterns. Consider adjusting underlying stochastic assumptions to reflect industry specific workforce patterns.
  - Review of the recently completed AACG report substantiates our suggestion that the population growth expectation should be reviewed based on other factors since experience is not uniform.
    - Study includes additional data points and a more expansive assumption base, including industry trends captured through plan maturity and zone certification status as well as economic trends.

Standard Data Input Assessment of ME PIMS

Recommendations (continued)

- Consider short-term and/or long-term adjustments to the contribution assumptions.
  - Review contribution inputs from Form 5500 data.
  - For 2020 base year data, many employer contributions were lower than usual due to COVID-19 workforce and hours reductions.
  - This trend may continue for a short period of time or may have been a one-time decrease depending on the industry.
  - Consider setting an average contribution for the baseline of the projection rather than including snapshot data.
  - Also consider reflecting industry workforce growth or decline in contribution projections.
- Consider using the asset allocation information from the Schedule R of the Form 5500 data to project the assets accordingly.

Standard Data Input Assessment of ME PIMS

How to Identify Participating Employers

- We are not aware of any method of obtaining information for ***all*** participating employers outside of direct request to the plans.
- Consider updating PBGC multiemployer plan reporting requirements to obtain more information about participating employers.
- Consider reviewing the current Schedule R reporting of employers contributing more than 5% of total contributions to the fund to identify the largest participating employers of each plan.
  - Incorporating this as a standard process may be beneficial and provide further information to the PBGC even if recently proposed changes to the Schedule R to include the top 10 highest contributing employers regardless of whether they contributed 5% of total contributions are not accepted.

Calibration Review

Calibration of Sample Plans/Firms to the SE Universe

See Methodology Deployed to Select Representative Plans as the Input Data for SE PIMS Section on Page 20.

Calibration of Plan Benefits

Our Understanding

&

Observations

- For plans that are still accruing pension benefits and have multiple divisions, we understand that one accrual rate is chosen (due to PIMS current system limitations) to represent several accrual rates in a sample plan.
  - — The chosen accrual rate is selected by making a general assumption per user discretion or using the accrual rate used by the greatest number of active employees.
    - In some situations, this method might not produce the closest accrual rate reflected in the normal cost

Calibration of Plan Benefits

Recommendations

- Consider using a sample plan’s accrual rate that is closest to the accrual rate reflected in the normal cost rate (normal cost ÷ total payroll) for ongoing plans with multiple divisions accruing under different benefit formulas under a single sample plan – results in an unbiased selection process.

Calibration of Plan Benefits

Recommendations (continued)

- Consider using Schedule SB liabilities projected over 10 years as a reasonability check:
  - Use a single interest rate scenario.
  - Compare the Schedule SB projected liabilities to the PIMS liabilities and normal costs to make sure the numbers are reasonably aligned and are within a tolerance level acceptable to the PBGC.
- Consider incorporating the possibility of a plan freeze for ongoing plans in future projections to reflect how the SE universe might change over time by:
  - Reviewing plans with lower funded ratios through the PBGC 4010 filing
  - Reviewing companies having financial difficulties through the PBGC Form 10 filing
  - Reviewing volume of remaining funding balances in the plan through the Schedule SB filing

Calibration of Plan Benefits

Recommendations (continued)

- Consider potential long-term idea, if changes to SE PIMS are contemplated that reflect impact of hedging on PBGC's exposure:
  - Consider collecting (at least for frozen plans) data on asset allocations to reflect interest rate risk exposure and how plan sponsors are willing to take on lower expected returns so plans can eventually transfer risks by:
    - Looking at the plan's funded status based on the accounting liabilities, which will need to be estimated.
    - Reviewing frozen plans that have glide paths which increases asset exposure to fixed income securities as accounting funded ratios increase.
  - This change could be considered in the context of adjusting variable premiums to reflect exposure to interest rate risk, which would presumably require legislation.
  - Interest rate hedging may have modest impact on sponsor bankruptcy, if contribution obligations are driving insolvency. May have real impact on degree of PBGC obligation.

Calibration of Starting Position Plans

Out of scope. The review focus is limited to ongoing Single-employer and multiemployer pension plans as inputs to SE-PIMS and ME-PIMS models.

Calibration of Cashflows for ME Plans

Our Understanding

&

Observations

- Calibrations are run in two separate stages:
  - First Stage includes use of a macro to find the optimal age, service and accrual adjustments to best match Current Liability and benefit payment information from the Schedule MB.
  - Second Stage uses Actuarial Services and Technology Department mortality to project these determined demographics into future years, allowing the calculation of the benefit payment streams.
- The active calibration includes specific demographic statistics and assumptions for approximately 350 plans.
- The inactive calibration uses Central States as a basis for both age and service calibration (within a range of +/- 5 years) and to create an accrual pattern calibration – baseline, steepened, flattened.
- Calibrations are based on full plan benefits, not guaranteed benefits.
- Active retirement age assumption calibration uses a maximum of 65.

Calibration of Cashflows for ME Plans

Recommendations

- Consider a potential move to an industry specific starting point for inactive calibration since ME plans are generally comprised of employers within the same industry.
  - If other plan data is unavailable, cash flow data for plans by industry may be a better resource to help refine the process. See recommendations on next slide regarding cash flow collection.
- Consider periodically reviewing the guaranteed benefit streams of plans recently taken over by the PBGC to gauge accuracy of cash flow calibrations.
- Consider extending retirement age beyond age 65 for active cash flow calibrations as previously mentioned since trends find workers regularly remaining in active service beyond age 65.

Calibration of Cashflows for ME Plans

Recommendations (continued)

- Consider annually reviewing the 10-year cash flow projection included as an attachment to the Schedule MB Filing in order to review calibrated cash flows for reasonability.
  - Cash flows are not reported by status but can be used in aggregate as a reasonability measure for ME PIMS.
  - Requires manual data entry but potentially request a future Schedule MB update to include projected cash flows as part of the electronic form submission rather than attachments to ease data collection efforts. This update could potentially include cash flows by status.

Appendix

Appendix A

Standard Data of SE Plan

Observations

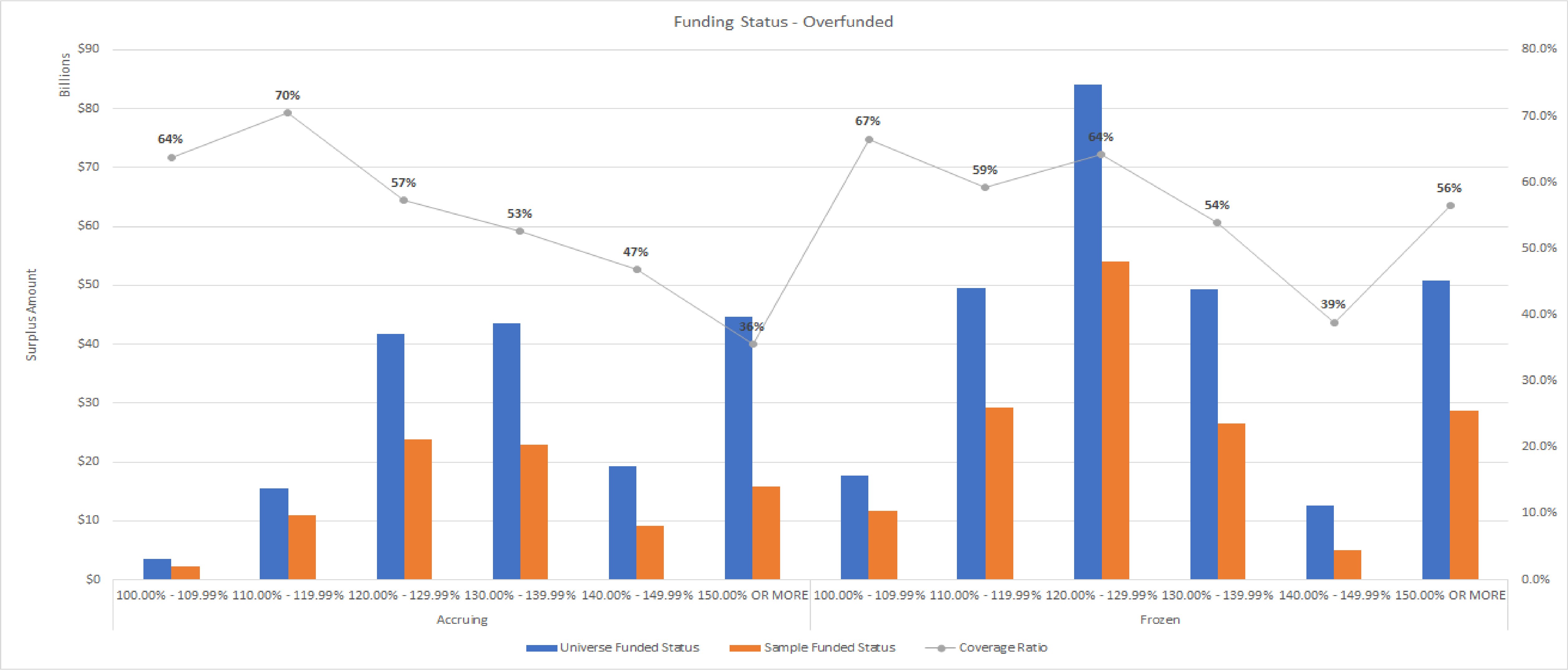
SE Data Structure Inputs	Not Used	Produced by PRAD	Sourced from 3rd Party	Prescribed	PIMS ID Metadata	Internal System Calc	Sourced from Filings	Sourced from Filing Attachment	Assumed	Estimated	Used Prior Year	Unknown	Total
Economy	186	21	35	3	2	2							249
Firm	72	31	71		12	7							193
IRS	66	8		32	13	8							127
PBGC	97	24	20	10	4	1	1						157
Plan Common	84	9			7	1	26						127
Plan Detail	43	16			4	4	43	11	4	3	6	0	134

Standard Data of SE Plan

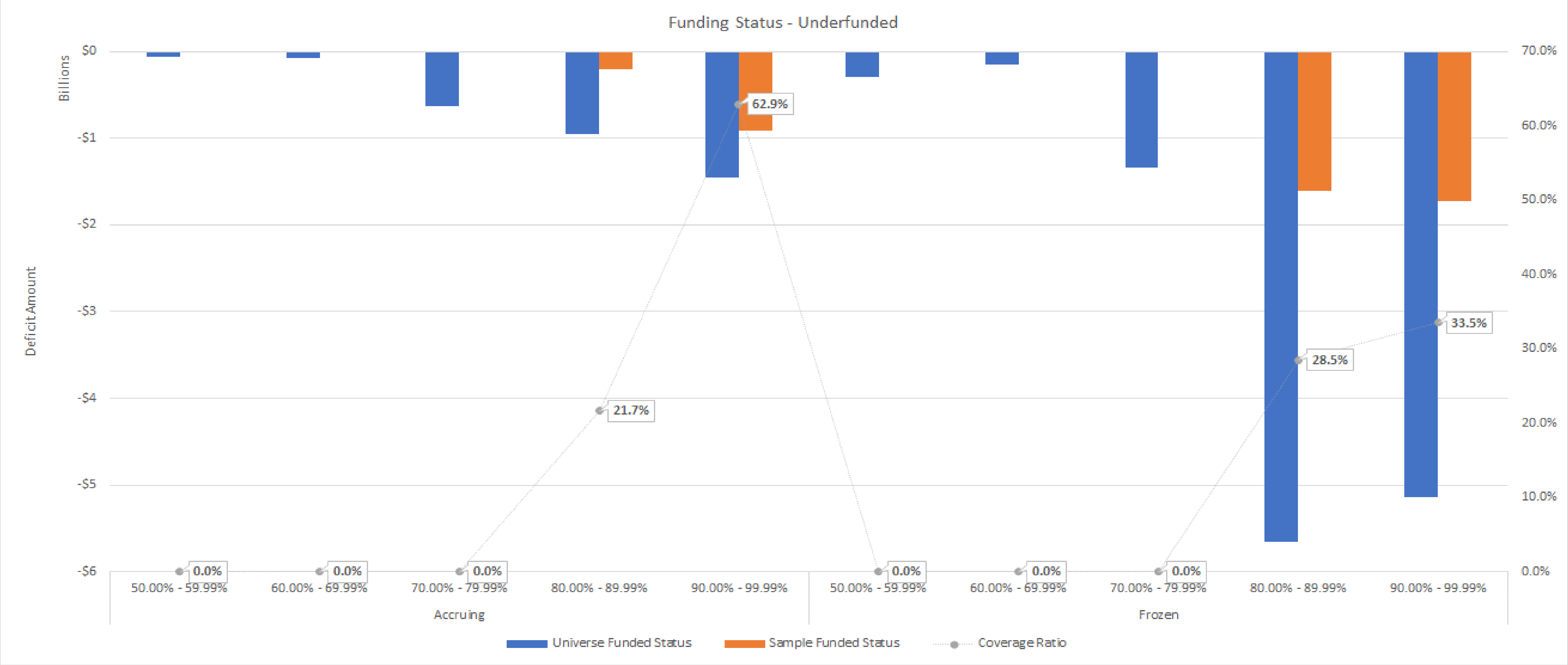
Observations (continued)

SE Data Structure Inputs	Not Used	Produced by PRAD	Sourced from 3rd Party	Prescribed	PIMS ID Metadata	Internal System Calc	Sourced from Filings	Sourced from Filing Attachment	Assumed	Estimated	Used Prior Year	Unknown	Total
Plan Census Data	12		2		2	3		3		9			31
Plan Benefit Formulas	30		5		12			150		8			205
Plan Experience Decrements	31	6	2	1				4	2	8		5	59
Plan Benefit	11	1			6	4		5		9			36
Total	**632**	**116**	**135**	**46**	**62**	**30**	**70**	**173**	**6**	**37**	**6**	**5**	**1,318**
As Percent	**48%**	**9%**	**10%**	**3%**	**5%**	**2%**	**5%**	**13%**	**1%**	**3%**	**1%**	**0%**	**100%**

Funded Status – Overfunded Coverage

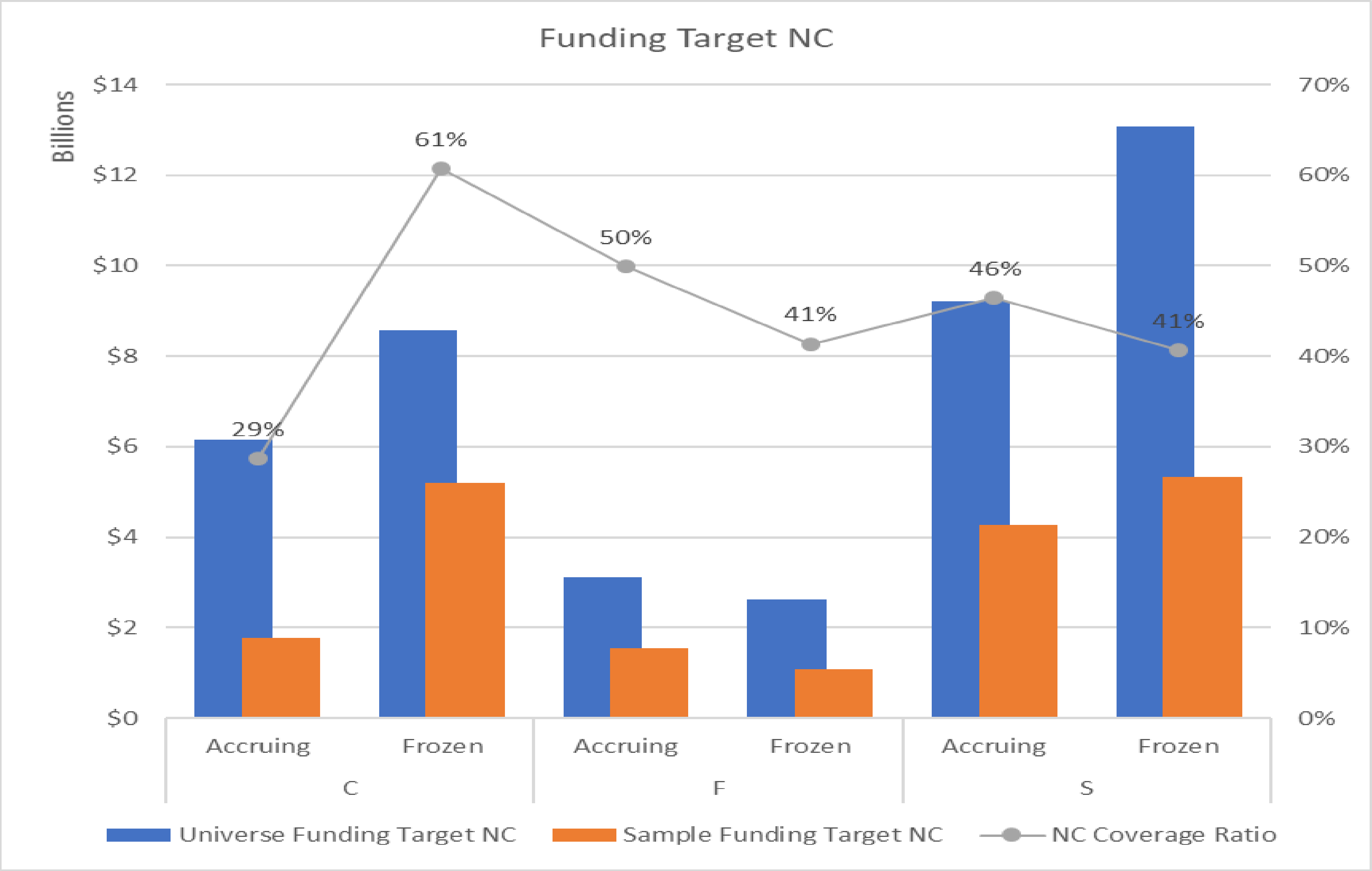


Funded Status – Underfunded Coverage



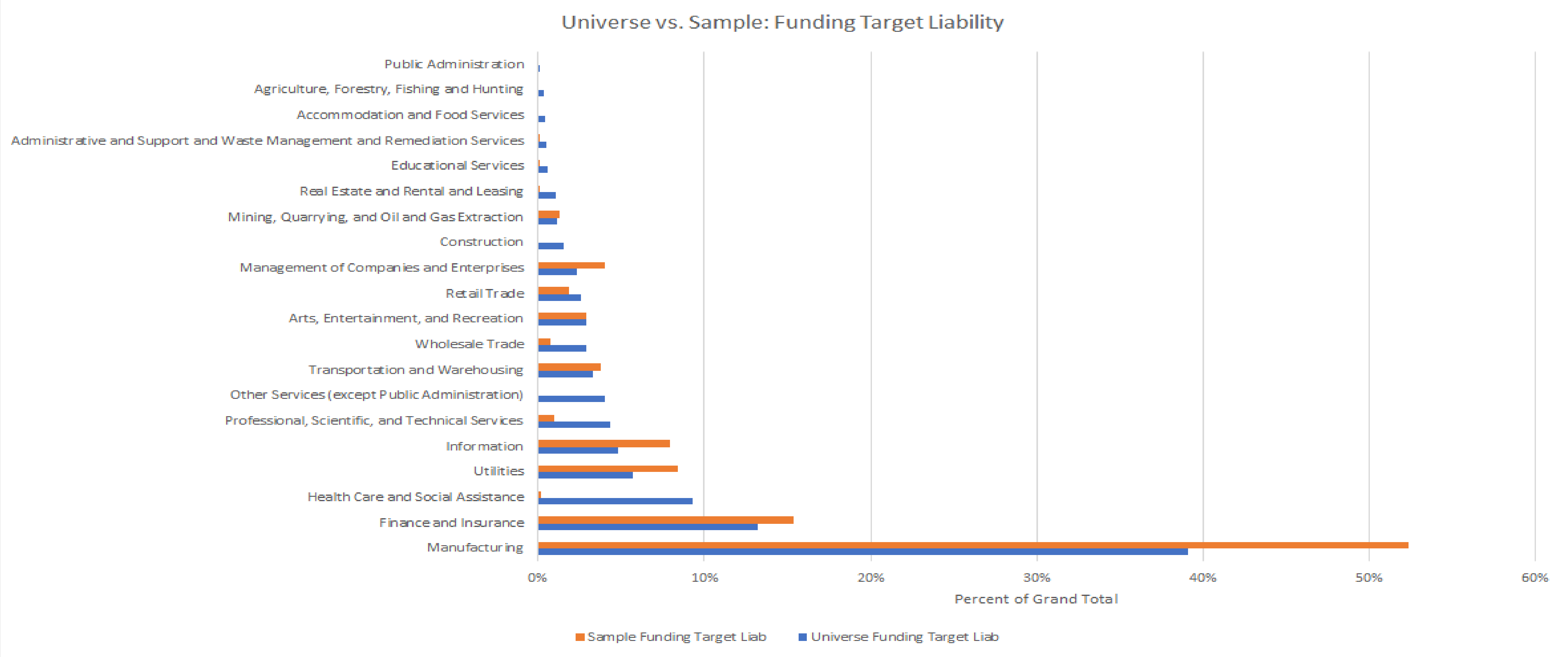
BUCK

Funding Target Normal Cost – Coverage

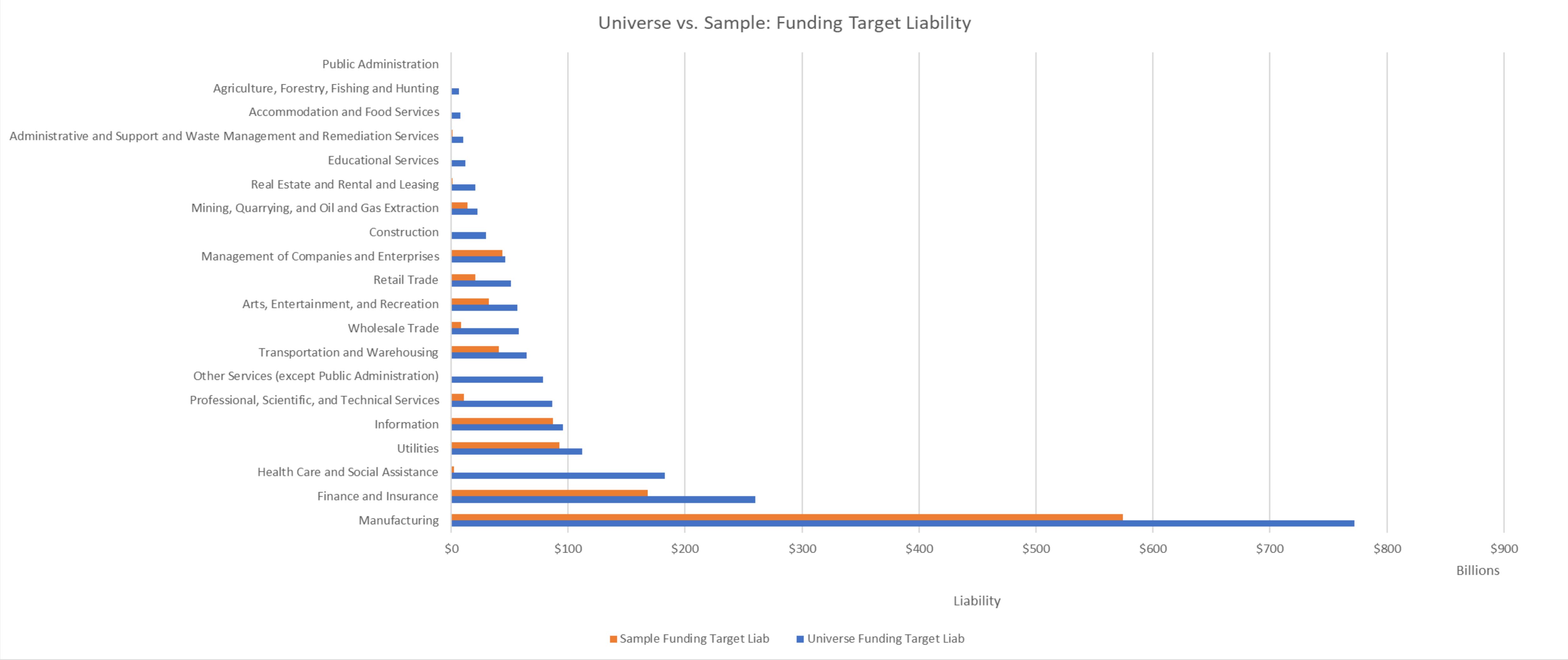


BUCK

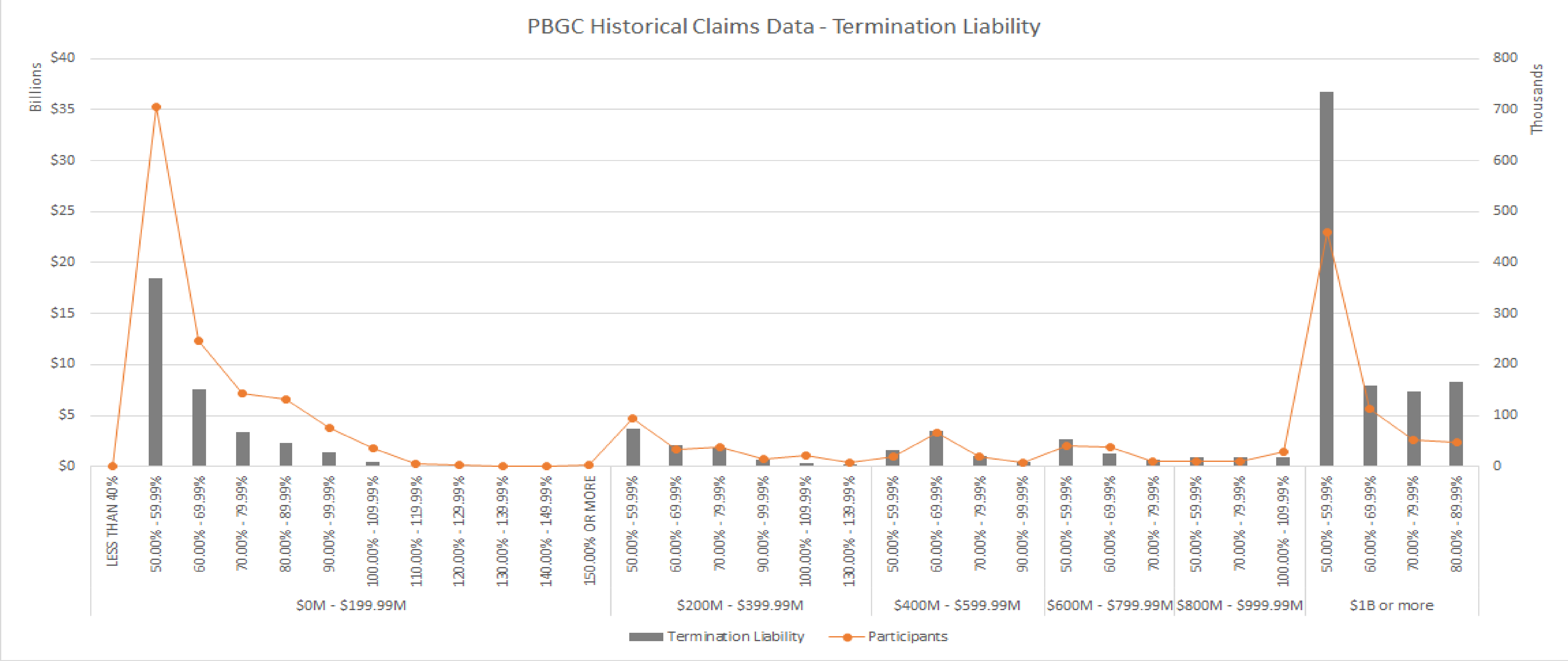
Industry – Distribution



Industry – Coverage



Historical Claims



Appendix B

Modeling Methodology Review

Conducted by Conning, Inc. on behalf of Buck Consulting

MHZ/6004047.2

Table of Contents

1 Executive Summary

- Review conducted by quantitative finance experts from Conning, Inc.'s Risk Solutions group.
- Conning, Inc.'s Risk Solutions group conducted a research review of two pension sponsor bankruptcy models. The models considered were one based on the Altman Z-score and one based on logistic regression.
- The Altman Z-score model is considered by the authors to be a viable and appropriate model but lists some of its limitations.
- The authors note that the number of drivers of default in the Alman Z-score might not be sufficient to capture the complexity of corporate defaults.
- The logistic model is considered by the authors to be superior to the Alman Z-score due to the higher number of driving factors, the scope to extend the model and the use of statistical estimation techniques to estimate the model robustly.
- Because all models have limitations the authors suggest that users of moth modeling approaches consider continual monitoring of the model inputs, the use of scenario analysis and stress testing of the model and model extensions which might mitigate some of the limitations.
- The authors conducted a thorough review of the academic literature and summarize their findings in this report. A full set of references is also given.

2 Introduction and Scope

This report details the results of a review undertaken by Conning, Inc.'s Risk Solutions group on behalf of Buck Consulting. The defined scope of the project is to review aspects of the current process implemented by the PBGC as well as changes to the process that Buck Consulting might recommend. Conning, Inc.'s Risk Solutions group is particularly expert in areas of quantitative finance, financial modeling, statistical analysis, econometrics, and stochastic modeling.

The following area of the PBGC's processes and methodologies have been identified for review, where Conning's expertise may be of relevance.

- **Sponsor Bankruptcy Modeling:** As part of the PBGC's forecasting model, it has the method of predicting plan sponsor bankruptcy that uses *some* elements of the "Altman Z-Score", that have been tailored to match the data available to the PBGC. Buck Consulting is interested in Conning's view concerning the bankruptcy model as well as other approaches to credit risk modeling. Buck Consulting would like to hear Conning's views on how the PBGC is doing its modeling, and whether there are elements of what Conning would do for credit risk which might be applicable or recommended.

We now consider this area in some detail and comment on our findings.

3 Sponsor Bankruptcy Modeling

The scope of this section is to review two approaches to sponsor bankruptcy modeling that have been proposed. These are the Altman Z-Score and the Logit model. Specifically, this section will be concerned with:

- Reviewing, understanding, and summarizing the two model approaches.
- Highlighting the strengths and limitations of the model approaches.
- Detailing alternative approaches from the academic literature elements of which could be considered in the future.
- Suggesting other possible extensions for future consideration.
- Commenting on the appropriateness of the two modeling approaches to the task at hand.

3.1 Summary of Approach to Bankruptcy Modeling

To date, the PBGC has been using a model based on the Altman Z-score for modeling bankruptcy. Briefly one can calculate the Altman Z-score as follows:

Altman Z-Score = 1.2A + 1.4B + 3.3C + 0.6D + 1.0E

Where:

- A = working capital / total assets
- B = retained earnings / total assets
- C = earnings before interest and tax / total assets
- D = market value of equity / total liabilities
- E = sales / total assets

A score below 1.8 means a company is likely headed for bankruptcy, while companies with scores above 3 are not likely to go bankrupt.

Proposed as an alternative is a Logit or Logistic regression model where the probability of default of a firm i at time t has the form;

$$P(B_{it}) = \frac{e^{X_{it}\beta}}{1+e^{X_{it}\beta}} \qquad \text{[1]}$$

where B_{it} is a binary variable equal to one if the firm enters bankruptcy in year t, X_{it} is the vector of variables affecting the probability of bankruptcy for firm i in year t, β is a vector of parameters to be estimated, and $X_{it}.\beta$ is the inner product of these two vectors.

The vector of variables consists of financial and economic variables relevant to default such as leverage, cash flow, size and change in employment levels.

The parameters β are estimated from 30,000 firm year observations from 1980 to 1997, of firms that recorded a bankruptcy as well as those that didn't. Either the firms bankrupted (1) or not (0). Logistic regression is used to determine the model parameters.

3.2 Strengths and Limitations of Proposed Approaches

Following a review of the information provided to Conning and further research, the following section lists some of the strengths and limitations of the two approaches.

Altman Z-Score:

Strengths:

- Simple to implement and understand
- Gives a good short-term view of credit/default risk and how it is changing
- Default probability increased prior to 2007 as credit markets generally deteriorated

Limitations:

- No stochastic component meaning that there is no assessment of potential unexpected losses from default probability fluctuations in the future
- Entirely linear relationship between the covariates and the bankruptcy probability. These are known to be non-linear [1]
- Number of covariates in the model may be insufficient to capture the complexity of corporate bankruptcy
- May have overestimated actual default during the 2008 crisis
- No link to models of external market factors like a sudden credit shock or sharp fall in equity prices
- No modeling of correlation between the different sponsors (i.e. if one sponsor is bankrupt does the probability that another is bankrupt increase?)
- Coefficients scaling the covariates seem to be largely empirically derived and may not be statistically speaking the best values for the model
- Models based on company balance sheet data may be prone to error in rare cases where such data have been fraudulently falsified

Logit Model:

Strengths:

- Larger number of variables are incorporated when compared to the Altman Z-score
- Estimation is relatively straight forward from empirical data using logistical regression
- May be more rigorous than the Altmann Z-score with the coefficients being estimated from regression rather than empirically/qualitatively
- Large body of research on the approach and extensions to it

Limitations:

- Data window from 1980 to 1997 may miss some important drivers of bankruptcy in the recent data

- Entirely linear relationship between the covariates and the bankruptcy probability. These are known to be non-linear [1]
- Estimation of the model is tilted to larger firms. Dynamics of smaller firms may be different
- No stochastic component meaning that there is no assessment of potential unexpected losses from default probability fluctuations in the future
- No link to models of external market factors like a sudden credit shock or sharp fall in equity prices
- No modeling of correlation between the different sponsors (i.e. if one sponsor is bankrupt does the probability that another is bankrupt increase?)
- Models based on company balance sheet data may be prone to error in rare cases where such data have been fraudulently falsified

3.3 Comments on the Appropriateness of Methodologies

Conning find that both the Altman Z-Score and Logit model proposed are appropriate to the task of assessing the probability of bankruptcy for pension fund liabilities covered by the PBGC. Both models have some limitations, however, this is true of all models. A review of the academic literature (using the JSTOR database) suggests the Logit (logistic) model could be considered the standard model from the academic literature and has a wide and long-standing body of research behind it. We would consider then the logistic model methodology to be a superior choice over the Altman Z-Score.

It is important however to understand what the limitations listed mean in terms of how the output from any model is interpreted and what other mitigation procedures might be prudent. For both models, the following should be considered:

1. **How often the model is run.** Given that the input data is at "time 0" each time the model is run and given that we know that credit quality can deteriorate quickly leading up to default it is important to consider how often the model is run. Annually is potentially not frequently enough.
2. **Monitoring inputs.** It might be important to monitor all or a subset of covariates for sudden large changes at a higher frequency than normal model run times. Changes above a certain threshold or a large number of changes across many sponsors could be flagged to an analyst for further review or trigger an extraordinary run of the model.
3. **Scenario analysis and stress testing**. Given that neither model uses historical data or has a link to any stochastic models of market risk factors scenario analysis and stress testing of the model should be considered to understand the spread of likely values for the probability of bankruptcy in stressed markets. At least the covariates should each be individually and jointly stressed to understand what might happen under changing market conditions.
4. **Model Extensions.** The academic literature has many interesting extensions which could be considered. Some of these are explored in subsequent sections. In particular, the inclusion of market and macroeconomic factors, a consideration of correlation

between sponsors and with financial market factors and the inclusion of stochastic projections might be considered.

3.4 Extensions and Other Credit Risk Modeling Approaches

Conning has undertaken a review of the academic literature centered on corporate bankruptcy modeling. This section is intended to give a brief review of some of the most promising and relevant models, as well as those which contain suggested improvements to the logit model class. This section also acts as a short primer on credit risk modeling approaches commonly adopted in financial modeling. This might serve to inform future work or aspects of these modeling approaches which might be incorporated into the PBGC's approach.

It is not intended that this section serves as a full specification of model implementation but rather a guide to the ideas that prevail in the literature.

3.4.1 Extended Logit Model Using Splines

In [1] the author explores ways of extending the specification of the logistical model using splines of the covariate financial ratios. The logistic model proposed in this paper also includes macro-economic variables as well as firm specific variables which might serve as another useful extension to be explored. The primary advantage of the splines approach is that nonlinearity in the dependency of the probability of bankruptcy with respect to the input covariates can be modeled. The predictive power of the model was also shown to improve by 70-90%. Independently and using a different mode of analysis improvements in predictive power from modeling non-linearity were shown in [3].

In [1] an extension is proposed in which the normal specification of the logistic model is given as;

$$\theta_{i,t} = \ln\left(\frac{p_{i,t}}{1-p_{i,t}}\right) = \alpha + \beta' x_{i,t-1} + \gamma' z_{t-1},$$

Where $P_{i,t}$ is the probability of bankruptcy, α is an intercept, $x_{i,t-1}$ is a vector of firm specific covariates with coefficients β and z_{t-1} is a vector of macroeconomic variables with coefficients γ.

This could be extended to include polynomial terms to introduce non-linearity, but this has been shown to produce unreasonable global fits and poor behavior near the boundaries [4]. Instead, the author suggests the use of a spline model extension. The author explores the extension of the model with a set of additional basis functions to model the non-linearity. The set of basis functions chosen is the truncated power basis of order S:

$$\{1, x_{i,t-1}, x_{i,t-1}^2, \ldots, x_{i,t-1}^S, (x_{i,t-1} - k_1)_+^S, \ldots, (x_{i,t-1} - k_M)_+^S\},$$

Where $k_1,\ldots,k_m$ are the M dividing points of the local polynomials referred to as knots (how many and which knots are used is model set up choice), and;

$$(x_{i,t-1} - k)_+^S = \begin{cases} 0, & \text{if } x \leq k \\ (x_{i,t-1} - k)^S, & \text{if } x > k \end{cases}$$

The probability of bankruptcy equation is then modified as follows:

$$\begin{aligned} \theta_{i,t} &= \ln\left(\frac{p_{i,t}}{1 - p_{i,t}}\right) \\ &= \alpha + \sum_{s=1}^{S} \beta_s x_{i,t-1}^s + \sum_{m=1}^{M} \eta_m (x_{i,t-1} - k_m)_+^S + \gamma' z_{t-1}. \end{aligned}$$

In the case of this paper the order of the basis function S is chosen to equal 2. The parameters η_m are a vector of coefficients that must be estimated.

In the paper, the final spline function chosen was a natural spline with a different form from the one above. The general motivation for the extension and the form of the probability function is however the same.

One limitation of the approach is that it is perhaps harder to understand and implement than the standard logistic model.

3.4.2 Hazard Models

In [5] it is argued that hazard models are more appropriate than single period models for forecasting bankruptcy. The authors describe a simple technique for estimating a discrete-time hazard model of bankruptcy. They find that about half of the accounting ratios that have been used in previous models are not statistically significant. Moreover, market size, past stock returns, and idiosyncratic returns variability are found to be all strongly related to bankruptcy.

This class of model may therefore be a good alternative to consider for the purposes of the PBGC’s modeling. Indeed in the [5], the author explores the similarities between “static models” (such as the logit or Altman Z-score), which use point in time balance sheet data as covariates) and hazard models which can be estimated using time series data. This takes account of variability in the covariates and an increase in explanatory power.

3.4.3 Neural Networks

A full review of the performance of neural networks to the problem of sponsor bankruptcy is beyond the scope of this document. However, we consider the problem at hand to be a good candidate for such techniques. This is because the problem is characterized by many inputs (e.g. covariates and macroeconomic variables) with a single output (default probability or binary status 1=defaulted 0=surviving). Neural networks are also known to capture non-linear and other complex relationships between input and output data that traditional regression techniques do not.

There are many research papers that look at this type of modeling for predicting bankruptcy. Some of these, including [6], directly compare the performance of neural networks with logistic models of the type explored above. There was a performance enhancement over the logistic model in terms of classification accuracy, type I error (identifying a default when there was none) and type II error (identifying no default when one occurred).

Another reference on this subject that may be useful is [7].

3.4.4 Structural Credit Models

The structural credit models as pioneered by Merton [2] are based on the well-known Black and Scholes theory of option pricing. The basic idea behind Merton's development of a pricing theory for corporate bonds is the interpretation of corporate liabilities as options on the value of the firm issuing those bonds.

Extending this simple idea Merton postulated that firstly, the default of a firm is determined by its value, and secondly the event of default occurs if the value of the firms assets V falls below the outstanding debt B. Valuation of equity is carried out by applying the solution for the valuation of a European call option developed by Black and Scholes. Considering the connection of equity and liabilities on a firms balance sheet the value of a debt issue can be obtained, and by furthermore using continuous compounding and incorporating the yield to maturity y(t, T), a representation for the appropriate credit spread can be derived;

$$y(t,T) - r = \frac{1}{T-t} ln\left(\frac{1}{d}\Phi(h_1) + \Phi(h_2)\right)$$

where;

$$d = \frac{Be^{-r(T-t)}}{V}$$

$$h_1 = -\frac{\frac{1}{2}\sigma^2(T-t) - ln(d)}{\sigma\sqrt{T-t}}$$

$$h_1 = -\frac{\frac{1}{2}\sigma^2(T-t) + ln(d)}{\sigma\sqrt{T-t}}$$

and;

- y(t, T) is the yield to maturity of the defaultable liability (e.g. a corporate bond)
- r is the risk free rate
- T − t is the time to maturity
- B is the outstanding debt of the issuing firm
- V is the value of the firms assets

- $\Phi(h)$ represents the cumulative distribution function of the standard normal distribution evaluated at h

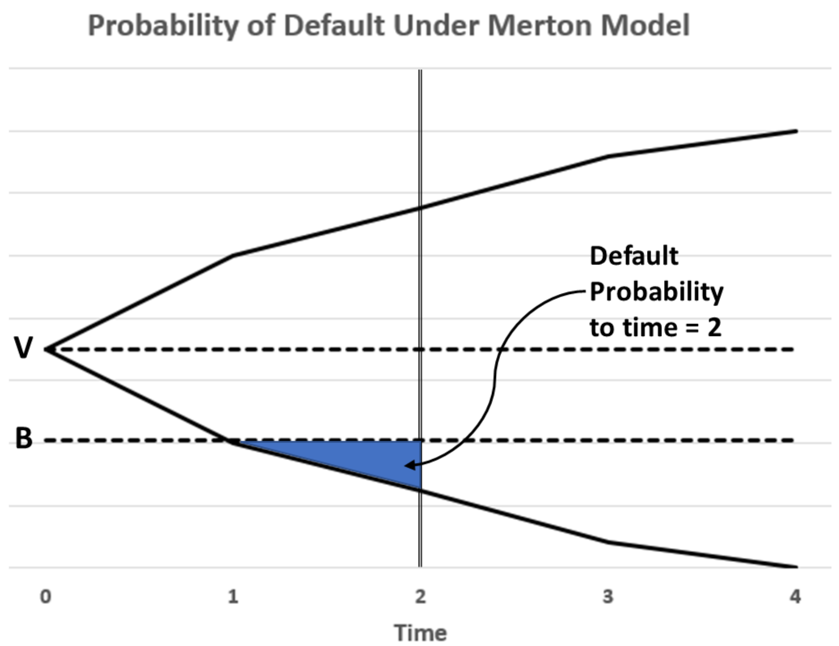
This then gives an expression for the spread of the defaultable liability, or the additional yield that is required to compensate an investor for the probability of default. The Merton model is relatively simple but performs well in some situations with regards to how the results of the model compare with empirical observation. Various extensions have also been proposed, including the addition of a random jump process which may trigger defaults.

Implicit within this idea is that the distribution of V is normally distributed. This could be used as the basis of an alternative method for assessing default probability on the basis of the volatility (and perhaps expected growth) of the firm's assets V. Under the structural models we can define the concept of a distance to default DD;

$$DD^{+} = \frac{V - B}{\sigma_V}$$

Where;

σ_V is the standard deviation of the firm's assets. This means that when the value of the firm's assets drops below the outstanding debt the firm is in default. The probability of default up to time t is the area under the curve for $V \leq B$. This can be visualized in the plot below:



Incorporating this or similar might be a way of bringing in an element that differentiates each firm by risk (in terms of volatility of its assets). (Prepared by Conning, Inc. Source © 2021 Conning, Inc.)

3.4.5 Reduced Form Credit Models

Another dominant class of credit model for corporate bonds are the reduced form models. It is perhaps more difficult to see how these types of models could be applied to the problem of sponsor bankruptcy.

A very rough but key distinction between the structural and the reduced form models is the information that is available to the modeler. In the structural models, we assume to have very detailed information about the firm, and its financial position. Instead in the reduced form models, we assume to have much less information, such as financial time series data for asset returns or credit spreads. Reduced form models are generally applied as security pricing models rather than default prediction models. In the case of the PBGC, we have detailed information from the firms' balance sheets, but we are not really interested in pricing a security, and so the reduced models are probably not the best choice for this application. However, structural and reduced form models are not completely antithetical, see for instance [8].

However, we include a brief description of this class of model here for completeness.

Reduced form models attempt to model the default of a bond as an unpredictable event. They do not rely on the value of the firm as the driver of defaults but use external processes. In a reduced form model external credit ratings are one of the main factors distinguishing the issuers with respect to credit quality.

One of the earliest reduced form models was proposed by Jerome Fons in 1994 [9]. In this approach, the only source of information included in the model is historical default probabilities, rating information and an estimate for the recovery rate. The recovery rate, µ, is defined as the percentage of the exposure which investors receive in the case of default.

In the reduced form model of Fons, a cumulative probability of default is specified, C_R, for each rating category R and a time horizon of t years which reflects the probability, that a bond defaults up to year t after holding the rating R. The marginal default probability, M_R, in year t after holding credit rating R is defined to be the difference in cumulative probabilities between year t and t-1. Finally, a forward probability of default, FR, is now defined as the probability of defaulting in year t after holding the rating, R, given that default has not occurred up to time t-1 and can therefore be expressed as a conditional probability of default (conditional on the bond surviving to time t-1). We also define a cumulative survival rate, $S_R(t)$ representing the probability that a bond survives to time t having held the rating R;

$$S_R(t) = 1 - C_R(t)$$

The reduced form model of Fons uses these concepts to build a model for corporate bond pricing and credit spreads. The original version of the Fons model is constructed for zero coupon bonds, (i.e., bonds not paying a periodic coupon). The price of a zero coupon bond with spread, s, to the risk free rate r, maturing in T years and assuming continuous compounding, is given by the simple pricing formula;

$$P(0,T) = Be^{(r+s)T}$$

Whereas before B represents the final liability or payoff of the bond (= 1 for a zero coupon bond). From the principles of risk neutral valuation, the price can be expressed as the expected value of the payoffs received from the asset. As the only payoff of a zero coupon bond takes place at maturity, for every point of time t < T only the case of default with the recovered fraction of the face value B has to be incorporated. Together with the notation for the different default and survival probabilities as introduced above, the credit spread, s, can now be obtained as;

$$s = -\frac{1}{T} ln \left(\sum_{t=1}^{T} S_R(t-1) F_R(t) \mu e^{-r(t-T)} + S_R(T) \right)$$

Fons assumed a constant recovery of market value, μ, and calibrated the remaining parameters of the model to default and survival probabilities derived from Moody's data. The model was successful in explaining some of the observed features of the average term structure of the spreads on defaultable bonds, however generally underestimated the market spreads. This underestimation suggests that additional factors other than default and survival rates were required to fully describe the corporate bond market. Nevertheless, the model laid the foundations of the theoretical underpinnings of more advanced reduced form models, such as that of Jarrow, Lando, Turnbull as well the model used within Conning's GEMS® Economic Scenario Generator.

3.5 References

[1] Taking the Twists into Account: Predicting Firm Bankruptcy Risk with Splines of Financial Ratios, Paolo Giordani, Tor Jacobson, Erik von Schedvin and Mattias Villani, **The Journal of Financial and Quantitative Analysis**, AUGUST 2014, Vol. 49, No. 4 (AUGUST 2014), pp. 1071-1099

[2] Merton, R. "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates." **Journal of Finance**, 29 (1974), 449-470.

[3] Bharath, S., and T. Shumway. "Forecasting Default with the Merton Distance to Default Model." **Review of Financial Studies**, 21 (2008), 1339-1369.

[4] Hastie, T.; R. Tibshirani; and J. Friedman. **The Elements of Statistical Learning**, 2nd ed., Springer Series in Statistics. New York: Springer (2009).

[5] Forecasting Bankruptcy More Accurately: A Simple Hazard Model, Tyler Shumway, **The Journal of Business**, January 2001, Vol. 74, No. 1 (January 2001), pp. 101124

[6] Neural Networks in Bankruptcy Prediction - A Comparative Study on the Basis of the First Hungarian Bankruptcy Model, M. VIRÁG and T. KRISTÓF, **Acta Oeconomica**, 2005, Vol. 55, No. 4 (2005), pp. 403-426

[7] Artificial neural networks in bankruptcy prediction: General framework and cross-validation analysis, G. Zhang, M. Hu, Daniel C. Indro, Published 1999, **Computer Science, Eur. J. Oper. Res.**

[8] Structural Versus Reduced Form Models: A New Information Based Perspective, Robert A. Jarrow, and Philip Protter, 2004, **Journal of Investment Management**, Vol. 2, No. 2, (2004), pp. 1–10

[9] Fons, Jerome S., **Using Default Rates to Model the Term Structure of Credit Risk**, Financial Analysts Journal, Vol. 50, No. 5, (September/October 1994), pp. 25-33

About Conning

Conning (www.conning.com) is a leading investment management firm with a long history of serving the insurance industry. Conning supports institutional investors, including pension plans, with investment solutions and asset management offerings, risk modeling software, and industry research. Founded in 1912, Conning has investment centers in Asia, Europe and North America.

Legal Disclaimer

References & Actuarial Certification

References

Bankruptcy Files

- bankruptcy calibration.msg
- firm_weighting spreadsheet for FY 19 SE PIMS.msg
- firm_weighting_fy19_v1_recheck.xlsx
- FY19 SEPIMS bankruptcy calibration process.docx
- SE_Firm_Data_Prep_(prelimFY20).xlsb

Calibration Files

- ActCalib_Datalog.csv
- ActCalib_Output_1.22.2021.csv
- Calib FY20.06 Active CalibrationVBA_o age shift.xlsb
- Calib FY20.06 Active IPxLV_w_Grids_AGe65.xlsb
- Firm_weighting_fy19_v1 recheck
- Fy_20_flat_prem_dual_scale_factors
- FY20.08 InactiveCalibration VBA no age shift.xlsb
- InactCalib_DataLog.csv
- InactCalib_Output_1.22.2021.csv
- PIMS TechNote Calibration Process v3
- SE Bundle 2018 FY

Contract & Proposal Files

- 06_RFQ+-+16PBGC20Q0104+PIMS+Peer+Review_SF+1449_rev+09+24+2020.pdf
- Buck Form 30 (s).pdf
- Buck's Volume 1 Technical Proposal 16 PBGC 20Q0104.docx
- Buck's Volume II Past Performance 16 PBGC 20Q0104.docx
- Buck's Volume III Price Quote PBGC 16 PBGC 20Q0104.docx
- Contagion Final Report.pdf
- fy-2018 projections report.pdf
- LeapFILE Email on 04222021 with First Zip Files. Pdf

Documentation Files

- Interest Rate in SE PIMS for Funding and VRP
- PIMS Data Manual FY 21.docx
- PIMS Inputs and Assumptions (2020.04.14).docx
- PIMS Inputs and Assumptions Meeting Summary_VF.docx
- PIMS Overview 2011.pdf
- PIMS tech Note - Program Flows v5.xls
- PIMS User Guide.pdf
- SE Data Structure_Chart_SE_FY15 (Econ Highlighted).xlsx
- SE System Descriptons_updated.docx
- SE_ME_data_structure.xlsx
- xf_understanding_the data.pdf

References

Process Log Files

- Log_2020-06-21_002_SE_yearly reset.html
- Log_2020-06-23_006_SE_Import 500 Data.html
- Log_2020-06-24_004_SE_Populate PIMS tables.html
- Populate PIMS - Error and Warning Research Summary.xlsb

SE PIMS Data Files

- (Old) FY17 tvested retireds 100yr projection template.xlsm
- active.hire.xxxx.xlsx
- Fields to Populate
- PIMS Data Manual FY21.docx
- PIMS Technote - Program Flow v5.xls
- salary.xxxxx.xlsx
- SE Data Structure 08262021
- SE Data Structure 09092021
- SE Data Structure 08202021
- SE Data Structure Chart SE FY15 (Econ Highlighted).xls
- SE Plan Data
- firm_2021_04_09_05_34_40.xlsx

Non-Seriatim Files

- PIMS Starting Point - Non-Seriatim Cash Flow.msg
- RunRpt4310836.dat
- Starting_Position_Sept_30_2019_June_16_2020.xlsx
- Starting_Position_Sept_30_2019_mwb_AB2.xlsb_the data.pdf

Additional SE PIMS Data Files

- SE Plans Bundle 2018PY_rev
- SE Data_Structure 10082021
- Buck SE claims data 11.4.2021

SE PIMS Decrement Table Files

- active.hire.xxxxx.xlsx
- benreduc.xxxx.xlsm
- disable.xxxxx.xlsm
- FY2020 SE Weekly Progress Report Master.xlsb
- retiree.xxxxx.xlsm
- salary.xxxxx.xlsm
- separate.xxxxx.xlsm
- tvesteds_2021_04_09_05_40_17.xlsx

References

ME PIMS Files

- 09302020_100GF_Individual Cashflow_IPV5510_IPVFB_Report.xlsx
- 09302020_100GF_Individual Cashflow_IPV5510_IPVFB_Report.xlsx.dup
- Data Dictionary 20190708.xlsx
- FY20 ASD Data.xlsm
- FY20 ASD Data.xlsm.dup
- FY20 ME Data FY20.12_setPart1.xlsb
- FY20 ME Data_FY20.12.xlsb
- FY20 ME Data_FY20.12.xlsb.dup
- FY20 PR Data.xlsx
- FY20 PR Data.xlsx
- FY20 PR Data.xlsx.dup
- ME data process.xlsx
- ME data process.xlsx.dup
- ME FY20.12 Model documentation
- ME PIMS Overview Document.doc
- Multiemployer Spreadsheet Model Description 20299520.docx
- SE_ME Data Structure.xlsx
- Study performed by Advanced Analytical Consulting Group
- Boyce Memo

SE PIMS Data Tables Files

- SE_ME Data Structure.xlsx
- acctbal_2021_04_09_03_36_49.xlsx
- actives_2021_04_09_05_30_41.xlsx
- benreduc_2021_04_09_05_31_55.xlsx
- Bfcashbal_2021_04_09_05_32_33.xlsx
- bfcbcombo_2021_04_09_05_32_47.xlsx
- bffcombo_2021_04_09_05_33_13.xlsx
- bfflat_2021_04_09_05_33_01.xlsx
- bfsalary_2021_04_09_05_33_13.xlsx
- cash balance formula.xlsx
- default benreduc rates.xlsx
- default disable rates.xlsx
- default separate rates.xlsx
- disable_2021_04_09_05_33_42.xlsx
- FY20 account balances master.xlsb
- hire_2021_04_09_05_35_08.xlsx
- partic_2021_04_09_05_36_20.xlsx
- plan_2021_04_09_05_36_16.xlsx
- plan_amort_2021_04_09_05_36_29.xlsx
- plnref_2021_04_09_03_30_13.xlsx
- retire_2021_04_09_05_36_46.xlsx
- salaries_2021_04_09_05_37_28.xlsx
- separate_2021_04_09_05_38_12.xlsx
- sponsor_2021_04_09_05_36_01.xlsx

Actuarial Certification

This report was prepared using generally accepted actuarial principles and techniques in accordance with all applicable Actuarial Standards of Practice (ASOPs), particularly ASOP No. 23.

Data Used for the Analysis:

Buck performed the SE and ME data input analysis and assessment using approximately 100 files, including data and modeling manuals supplied by the PBGC. The files and manuals were reviewed for reasonableness but were not audited. The accuracy of our analysis and assessment is dependent on the accuracy of the data provided.

This report was prepared under the supervision of Stuart Schulman who is a Fellow of the Society of Actuaries, an Enrolled Actuary and a Member of the American Academy of Actuaries and David Harwood Jr. who is an Enrolled Actuary and a Member of the American Academy of Actuaries. Both have met the Qualification Standards of the American Academy of Actuaries to render the actuarial opinions contained herein and are available to answer any questions.