OCTOBER 24, 2016

SUBTASK 4.3 REPORT

EVALUATION OF MODELING OF SPONSOR FAILURE RISK AND PBGC PLAN ADMINISTRATION

One of Three Twelve-Month Reports

IN-DEPTH TECHNICAL REVIEW OF THE PENSION BENEFIT GUARANTY CORPORATION'S MULTIEMPLOYER AND SINGLE-EMPLOYER PENSION MODELS

Prepared for:

Social Security Administration
6401 Security Blvd.
Baltimore, MD 21235
Contract SS00-15-30598

Prepared by:

FTI Consulting, Inc.
3 Times Square
New York, NY 10036

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Introduction

In July 2015, the Social Security Administration (SSA) engaged the FTI Consulting team (FTI) to conduct an 18-month, in-depth technical review of the Pension Benefit Guaranty Corporation's (PBGC) single-employer (SE) and multiemployer (ME) Pension Insurance Modeling System (PIMS). Task 4 of the Statement of Work (SOW) consists of 10 subtasks required for this in depth review - nine specific areas of review and a final report.[1] Three of the subtask reports are due at the end of each of the six-, 12- and 18-month periods. This report for Subtask 4.3, along with those for Subtasks 4.2 and 4.7, is due at the end of the 12-month period (with approved extension). As a part of our review of PIMS, this report documents our evaluation of the simulation and plan sponsor viability within PIMS.

Due to the long period between the formulation of the project and the eventual award of work and start of the analysis, and given the ongoing evolution of the PIMS model, certain questions originally expected to be addressed under this subtask in the SOW for this project have been eliminated. These include items where the PIMS team is in the process of studying the area (e.g., mass withdrawal from multiemployer plans) and model and/or parameter changes are in process or likely.

We address the following key questions raised in Subtask 4.3:

- Is the modeling of bankruptcies appropriate?
- Is the interrelationship between underfunding and potential bankruptcy appropriate?
- Is there adequate representation of any tendency to contagion of failure within industries or across the economy?
- For plans simulated to undergo the transition to PBGC administration, is the modeling of the transition and the PBGC administration of the plans adequate – e.g., the size and distribution of recovered assets, the conversion of plan benefits into guaranteed benefits, the payment of the benefits, and the asset allocation of the PBGC fund?
- Should the ME program consider other broad factors with respect to future plan sponsor vulnerability? What are the most important factors? What data sources would be available should PBGC try to incorporate these factors into its model?

[1] Social Security Administration, Evaluation of the Pension Benefit Guaranty Corporation's Pension Models, Description/Specification/Work Statement, page 14.

Authors and Contributors

Authors

Alok Khare, Ph.D., CFA, CAIA
FTI Consulting, Inc.

Glenn Meyers, Ph.D.
FTI Consulting, Inc.

Liaw Huang, Ph.D., FSA, MAAA, EA, FCA
The Terry Group

Contributors

Stephen Prowse, Ph.D., CFA
FTI Consulting, Inc.

Hal Tepfer, FSA, EA, MAAA
CBiz Savitz

John Moore, FSA, MAAA, FCA, EA
The Terry Group

Joseph Nichols, ASA, EA, MAAA, MSPA
FTI Consulting, Inc.

Findings

Appropriateness of PIMS Bankruptcy Modeling

1) PBGC's approach to modeling bankruptcy using a dynamic logit model is consistent with the current state of the art in bankruptcy modeling. We recommend that PBGC continue this approach to model bankruptcy instead of exploring other approaches available in the literature.

2) PBGC should update the results reported in Table 6-6 of the 2010 PIMS Guide so that reported coefficients are for the equation used to model the probability of bankruptcy, as is done in Table 6-4. (PBGC has confirmed that the present coefficients relate to the equation used to model the probability of a firm not going bankrupt.) In the updated version, PBGC should also report the t-statistics of the coefficients in Table 6-6.

3) PBGC should attempt to incorporate the time-varying nature of coefficients in its bankruptcy modeling.

4) The sample of firms used to estimate the bankruptcy equation should be enlarged and updated.

5) More market-based variables should be incorporated in the model. See appendix for a list of accounting and market-based variables used in some recent studies.

6) Use of degree of industry unionization or the trend in same as an explanatory variable might well improve the model's long-term performance.

7) PBGC should also consider use of a GARCH (1,1) process to forecast firm-level predictor variables, instead of the AR(1) process currently used.

8) PBGC currently uses in-sample goodness of fit measures to evaluate competing model specifications. We recommend carving out a hold-out sample, to evaluate competing specifications on an out-of-sample basis.

Plan Underfunding and Bankruptcy

9) PBGC's inclusion of a pension plan's funding ratio in its bankruptcy model is appropriate. Relatedly, we recommend a test of the explanatory power of that ratio as alternatively calculated based on accounting and market values.

10) We further recommend that PBGC assess the benefits of measuring a firm's pension funding relative to its enterprise value, and/or modifying the debt-to-equity ratio used in the bankruptcy equation to include pension underfunding as long-term debt.

Adequacy of PIMS Representation of Contagion

11) To reflect economy wide contagion in the bankruptcy modeling, we recommend that PBGC consider:

    - Incorporating macroeconomic variables and measures of firm interconnectedness in its bankruptcy modeling.

    - Using a Cox proportional hazard model with a time-varying baseline hazard function dependent on macroeconomic variables and measures of firm interconnectedness. See Appendix for a list of relevant macroeconomic variables.

    - Simulating bankruptcies of all firms in a given industry in tandem (i.e., determining their bankruptcy risk based on shared industry shocks) instead of simulating bankruptcies for various firms independently as is the present practice. In respect to SE plans, this approach could also address the phenomenon of intra-industry contagion.

Simulation of Transition to PBGC Coverage

12) Many SE plans taken over by the PBGC have assets sufficient to cover retiree liabilities, and as a result, ongoing benefits paid are not capped at the maximum PBGC guarantee level. PBGC should study the impact of not capping retirees' benefits, to determine if this produces a material difference in PIMS's forecasts.

13) PIMS models an investment policy that hedges the interest rate risk of trusteed liabilities. However, PBGC's 2014 Annual Report does not make clear whether the agency has an interest rate hedging policy for the trust fund. Therefore, PBGC should review PIMS's modeling of the trust fund's investment returns to determine if it is consistent with current policy, as PBGC's risk profile would be impacted by whether it employs an interest rate risk hedging policy.

Appropriateness of PIMS Bankruptcy Modeling

Here, we review PBGC's modeling of sponsor failure risk for SE plans relative to the best practices available in the relevant literature.[2]

Current Practice

PIMS assumes that the probability of bankruptcy of a firm is described by a logistic function – commonly known as a logit model for bankruptcy.[3] In the logit model that PBGC uses, the probability of a firm's bankruptcy is a function of several firm level variables. According to PIMS 2010 Guide, the bankruptcy model presently uses the following variables (all in logarithmic form) to estimate the probability of a firm's bankruptcy:[4]

- Firm's leverage based on equity-to-debt ratio, lagged one and two years;[5]
- Ratio of (a) cash flow[6] less all pension contributions to (b) total asset value,[7] lagged one and two years;
- Firm size, as measured by number of employees, and firm size growth, lagged one year;
- Funding ratio,[8] lagged one year;
- Interaction of firm size and firm leverage, both lagged one year; and
- Indicator variables for firms in the finance and utility industries.

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[2] Our review is based on the model as described in Pension Insurance Modeling System, *PIMS System Description for PIMS SOA "Core" (vFY09.1), Version 1.0* Revised 9/22/2010 [henceforth "PIMS 2010 Guide"]. Confirmed by PBGC staff as still applicable at the time of this writing.

[3] PIMS 2010 Guide, page 6-4. Technically, bankruptcy probability is described by equation (6-1) of PIMS 2010 Guide – reproduced below. In the equation (6-1), "B_{it} is a binary variable equal to one if the i^{th} firm enters of 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}*β is the inner product of these two vectors."

$$(6\text{-}1) \quad P(B_{it}) = \frac{e^{X_{it}\beta}}{1+e^{X_{it}\beta}},$$

[4] More exactly, the variables are: $\ln(ED_{t-1})$; $\ln(ED_{t-2})$; $(CF_{t-1}-Cont_{t-1})/A_{t-1}$; and $(CF_{t-2}-Cont_{t-2})/A_{t-2.}$; $\ln(N_{t-1})$; $\ln(ED_{t-1})\ln(N_{t-1})$; $\Delta\ln(N_{t-1})$; ln (funding ratio_{t-1}); F; and UT.

[5] PBGC currently uses, "...the book value of debt as a proxy for the market value of debt." [PIMS 2010 Guide, page 6-5].

[6] PBGC measures cash flow as, "Income before Extraordinary Items plus Depreciation plus Deferred Taxes." [PIMS 2010 Guide, page 6-6].

[7] PBGC, "…approximate[s] the market value of assets divided by the sum of book value of debt plus the market value of equity." [PIMS 2010 Guide, page 6-5].

[8] PBGC calculates the funding ratio as, "…pension assets divided by pension liabilities" [PIMS 2010 Guide, page 6-7], also noting that, "Many firms sponsor more than one pension plan. The various plans sponsored by a firm often significantly differ in their funding levels (e.g., a plan covering salaried workers may be well funded while a plan covering only hourly workers is underfunded). While the [bankruptcy] model might be made richer by taking into consideration variations in funding levels across the plans sponsored by firms, data limitations restrict the model to funding measurements that aggregate over all the sponsored plans." [2010 Guide, page 6-7, fn. 10].

Current Model Estimates

The model is currently estimated using data for, "…firms that sponsored defined benefit plans over the sample period 1980 to 1997" and had a minimum employment of 500 in their earliest observation.[9] The data come from the Compustat database. Because the model's estimation, "… require[s] two years of lagged data… observations without two preceding years of data [in Compustat] are excluded."[10] As such, the model is quite old and should be re-estimated.[11]

Significantly, certain of the model's coefficients as most recently estimated (in September 2009 – see PIMS 2010 Guide, Table 6-6) bear reversed signs (e.g., negative to positive) as compared to those reported earlier (2010 Guide, Table 6-4), and are also inconsistent with relevant economic and financial theory. For example, the estimated coefficient for the equity-to-debt ratio is positive, which means that, *ceteris paribus*, the bankruptcy probability for a firm with less debt is higher than the bankruptcy probability for an otherwise identical firm with more. Similarly, as a firm gets closer to bankruptcy, it is likely to lay off workers and its size is expected to fall. Thus, *ceteris paribus*, a firm's bankruptcy probability should decrease as its size increases, whereas the sign of the coefficient relating that probability to firm size [ln(firm size)] in PBGC's current model, as reported in Table 6-6,[12] is positive.

We discussed this issue in a June 28, 2016 call with PBGC staff. We were told that the apparent inconsistency is due to the fact that the results reported in Table 6-6 are likely for a model that predicts probability of a firm *not* going bankrupt, *i.e.*, 1 – probability of bankruptcy. In subsequent comments, PBGC staff confirmed that this is indeed the case and agreed that the results reported in Table 6-6 need to be updated.[13]

Further, PBGC reports t-statistics of the coefficients in Table 6-4 but does not do so in Table 6-6. Therefore, we cannot determine whether the coefficient estimates that were statistically significant in Table 6-4 continue to remain so in Table 6-6.[14]

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[9] PIMS 2010 Guide, page 6-8, also noting that, "…[w]e found in early testing of the bankruptcy model that relationships between firm size, firm financial ratios, and bankruptcy rates differ significantly for small firms. While a well specified nonlinear model might capture these differences, our interest with PIMS is focused on larger firms for which the bulk of pension underfunding is concentrated. Rather than attempt such a model, we instead restricted the database to those firms that have a minimum employment of 500 in their earliest observation."

[10] PIMS 2010 Guide, page 6-8, also noting that, "…[t]o ensure unbiased coefficients, we estimated the bankruptcy model using weights to reflect sample selection size. The weights are the ratios of population-to-sample counts for bankrupt and non-bankrupt firms." Further, "The weights were partitioned across three firm-size categories (500-1000, 1,001-10,000, more than 10,000 employees)." [PIMS 2010 Guide, page 6-8, fn. 15].

[11] In our June 28, 2016 call, PBGC staff told us that they are updating the model and transitioning to a new database, but are having technical difficulties in matching firm data between that database and Compustat.

[12] Based on similar reasoning, one expects coefficients for the variables $(CF_{t-1}\text{-}Cont_{t-1})/A_{t-1}$; $(CF_{t-2}\text{-}Cont_{t-2})/A_{t-2}$.; $\ln(ED_{t-1})\ln(N_{t-1})$; $\Delta\ln(N_{t-1})$; and ln (funding ratio_{t-1}) to be negative, not positive as reported in Table 6-6.

[13] More specifically, we were told that, depending on the technical setting in SAS program used to estimate the bankruptcy model, the coefficients generated might relate to either the probability of a firm's bankruptcy OR the probability of its not going bankrupt. Thus, based on this explanation, it seems that the coefficients in Table 6.4 might apply to the former and those in Table 6.6 to the latter.

[14] As Table 6-4 shows, not all coefficients in PBGC's bankruptcy equation are statistically significant at 95% confidence level. [PIMS 2010 Guide, 6-10].

Therefore, we recommend that PBGC update the results reported in Table 6-6 of the 2010 PIMS Guide so that reported coefficients are for the equation used to model the probability of bankruptcy, as is done in Table 6-4. In the updated version, PBGC should also report the t-statistics of the coefficients in Table 6-6.

Relatedly, PBGC staff explained that PIMS documentation has been updated in a piecemeal manner, which may have encouraged inconsistent reporting of methods and/or results. Based on the foregoing, we recommend that the PIMS manual be updated, in part to assure full internal consistency.

Bankruptcy Simulation

For stochastic simulation, due to "…plan and plan sponsor data limitations and computational constraints, PIMS uses a sample of PBGC-insured plans."[15]

Further, "A PIMS simulation consists of a user-specified number of scenarios," with each scenario consisting of "…one time path of up to 20 years."[16] "Typically, pension plan data are available with at least a two-year lag. As a consequence, it is necessary to deterministically advance these data to the PIMS starting date. PIMS is run stochastically for future periods."[17] Figure 7-3 in the PIMS 2010 Guide describes how the simulation works. Essentially, in any scenario, PIMS starts by generating economy-wide stock returns and interest rates. Then, for each year, it generates the values of the firm-specific variables required to predict bankruptcy probability[18] and determines whether, hypothetically, the selected firm will go bankrupt. Specifically, in any year of simulation, PIMS calculates two numbers:[19]

- A random number between 0 and 1; and
- A bankruptcy probability based on the logit model.

If the bankruptcy probability for a firm is less than the random number drawn for that firm, "…the firm does not go bankrupt, otherwise a bankruptcy is simulated."[20]

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[15] "While the sample currently available for PIMS simulations represents only about 4 percent of PBGC-insured plans with greater than 100 participants, these represent almost half of all insured plans' liabilities and underfunding. The weighting scheme effectively creates "partner firms" for each plan sponsor in the PIMS sample. Partner firms have scaled copies of the same pension plans sponsored by the sample firm." [PIMS 2010 Guide, page.2-20].

[16] PIMS 2010 Guide, page 7-6.

[17] PIMS 2010 Guide, page 2-20, also noting at fn. 10: "The pension plan data are advanced using PIMS in a deterministic mode since the stock return, interest rate, and changes in inflation rate are known from published sources. Thus, the plan's liabilities, contributions, benefits and so on, can be simulated forward to coincide with the PIMS starting date. Also, firm level data is known with a one year lag. PIMS advances this data stochastically through one year to bring it up to PIMS year zero."

[18] PIMS Guide 2010, Section 2.3.2 describes econometric equations and the process of making random draws to generate Firm level variables.

[19] PIMS 2010 Guide, page 2-12.

[20] PIMS 2010 Guide, page 2-12.

Implications of Recent Research

The modeling of bankruptcy entails choices regarding:

1. Analytical approach;
2. Choice of predictor variables; and
3. Choice of estimation period and treatment of missing data.

Based on our experience and review of academic literature, we document current best practices to determine whether any changes in PBGC's current approach are called for.

The techniques used to model bankruptcy can be broadly classified into two categories: (a) statistical and (b) "intelligent."[21] In this review, we focus on statistical techniques because PIMS currently uses one, and the cost of switching to an entirely different process is apt to be prohibitive. Further, our review suggests that statistical techniques have been much more fully evaluated, both under a variety of economic conditions and for diverse industries.

Statistical techniques fall into the following categories:

A. Multivariate Discriminant Analysis ("MDA") developed by Altman (1968):[22] The technique involves determining a linear combination of pre-identified predictor variables (*e.g.*, financial ratios) that can best discriminate between bankrupt and non-bankrupt firms.[23]

B. Static Logit/Probit Models: These explicitly model a firm's bankruptcy probability as a function[24] of pre-identified predictor variables.[25] For estimation

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[21] Kumar, P., & V. Ravi, 2007, "Bankruptcy Prediction in Banks and Firms via Statistical and Intelligent techniques–A Review," *European Journal of Operational Research*, July 2007, pages 1-28 provides, "…a comprehensive review of the work done, during the 1968–2005, in the application of statistical and intelligent techniques to solve the bankruptcy prediction problem faced by banks and firms." The paper categorizes techniques as: "(i) statistical techniques, (ii) neural networks, (iii) case-based reasoning, (iv) decision trees, (iv) operational research, (v) evolutionary approaches, (vi) rough set based techniques, (vii) other techniques subsuming fuzzy logic, support vector machine and isotonic separation and (viii) soft computing subsuming seamless hybridization of all the above-mentioned techniques."

[22] Altman, E. I., "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy," *The Journal of Finance*, September 1968, pages 589-609; also see Deakin, E. B., "A Discriminant Analysis of Predictors of Business Failure," *Journal of Accounting Research,* Spring, 1972, pages 167-179; and Grice, J. S., and R.W. Ingram, "Tests of the Generalizability of Altman's Bankruptcy Prediction Model," *Journal of Business Research*, August 2001, pages 53-61.

[23] MDA is general technique that involves determining linear combinations of pre-determined independent variables that can discriminate between two classes. See, *e.g.*, Hair, J. F., W.C. Black, B.J. Babin, R.E. Anderson and R.L. Tatham, *Multivariate Data Analysis*, *6th Edition* (Upper Saddle River, NJ: Pearson Prentice Hall, 2006).

[24] From a conceptual perspective, the only difference between logit and probit models is the functional form used to relate predictor variables to the probability of bankruptcy. Logit models use the logistic function whereas probit models use the normal distribution function for modeling.

[25] Martin, D., "Early Warning of Bank Failure: A Logit Regression Approach," *Journal of Banking & Finance*, November 1977, pages 249-276; Ohlson, J. A., "Financial Ratios and the Probabilistic Prediction of Bankruptcy," *Journal of Accounting Research*, Spring, 1980, pages 109–131; and Mensah, Y. M., "An Examination of the

purposes, these models assume that a firm's probability of bankruptcy remains constant over time and do not utilize multiple observations for the same firm.[26]

C. Distance-to-Default ("DD") Models: As Campbell *et al.* (2008) note, DD is, "…a measure of the difference between the asset value of the firm and the face value of its debt, scaled by the standard deviation of the firm's asset value."[27] These models[28] are based on the seminal work done by Merton (1974),[29] which implies that there is "a deterministic relationship between DD and the probability of default" for a firm.[30] Another market-based measure is "the default intensity obtained from the calibration of reduced-form models."[31] However, academic research has not focused a lot on default intensity because they are difficult to calibrate.[32] DD is a much more common empirical measure[33] and is widely used in finance.[34]

Stationarity of Multivariate Bankruptcy Prediction Models: A Methodological Study," *Journal of Accounting Research,* Spring, 1984, pages 380-395.

[26] Brown, Jeffrey R., Douglas J. Elliott, Tracy Gordon, and Ross Hammond, "A Review of the Pension Benefit Guaranty Corporation Pension Insurance Modeling System," *The Wharton School, Pension Research Council Working Paper*, September 2013 [henceforth Brown et al. (2013)], pages 1-63, noting at page 26, "In the 1980s, logit models of bankruptcy were **static** in the sense that each firm was assigned a predicted probability of bankruptcy, and this was assumed to be constant over time (or, if multiple observations of a firm were available, they were treated as separate firms)."

[27] Campbell, J. Y., J. Hilscher, and J. Szilagyi, "In Search of Distress Risk," *The Journal of Finance,* December 2008, [henceforth Campbell et al. (2008)], page 2914.

[28] See, *e.g.*, Hillegeist, S. A., E.K. Keating, D.P. Cram, and K.G. Lundstedt, "Assessing the Probability of Bankruptcy, *Review of Accounting Studies*, March 2004 [henceforth Hillegeist et al. (2004)]; Trujillo-Ponce, A., R. Samaniego-Medina, and C. Cardone-Riportella,"Examining What Best Explains Corporate Credit Risk: Accounting-Based Versus Market-Based Models," *Journal of Business Economics and Management,* May 2012, pages 253–276.

[29] Merton, R. C., "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates," *The Journal of Finance,* November 1973, pages 449-470. The paper provided the insight that a firm's equity can be viewed as a call option on the firm's assets with a strike price equal to the face value of that firm's debt and therefore a firm will default when its asset value falls below the strike price. In other words, gap between a firm's asset value and its debt's face value (suitably scaled) is an indicator of a firm's likelihood of default.

[30] Campbell et al. (2008), page 2914.

[31] Das, S. R., P. Hanouna, P. and A. Sarin, "Accounting-Based Versus Market-Based Cross-Sectional Models of CDS Spreads," *Journal of Banking & Finance,* April 2009 [henceforth Das et al. (2009)], pages 719-730.

[32] Das et al. (2009), page 5, noting "Arora et al. (2005) find, reduced-form models are difficult to calibrate because of the differing quality of bond pricing information on the reference entities."

[33] Moody's KMV has developed a method for the empirical estimation of DD. For a description of the approach, see, e.g., Crosbie, Peter J., and Jeffrey R. Bohn, "Modeling Default Risk," (KMV, LLC, San Francisco CA, 2003); also see Bharath, S. T., and T. Shumway, "Forecasting Default with the Merton Distance to Default Model," *Review of Financial Studies,* May 2006 [henceforth, Bharath and Shumway (2008)], pages 1339-1369.

[34] Das et al. (2009), page 5, noting that "…the distance to default remains the mostly widely used market-based credit risk metric"; also see Brown et al. (2013), page 26, noting that, "…[e]mpirical DD measures have been widely used in finance."

D. <u>Hazard Models</u>: Unlike static logit models, the hazard models take into account time to default ("duration analysis"). As Bauer and Agarwal (2014) note, "[i]n recent years hazard models, using both market and accounting information, have become state of the art in predicting firm bankruptcies."[35] Shumway (2001) developed a "hazard model that uses all available information to determine each firm's bankruptcy risk at each point in time" and showed that: [36]

> By ignoring the fact that firms change through time, static models [used in earlier literature] produce bankruptcy probabilities that are biased and inconsistent estimates of the probabilities that they approximate. Test statistics that are based on static models give incorrect inferences.

Hazard models improve upon <u>static</u> logit and probit models in the sense that the estimation procedure takes into account time to default by incorporating information for a firm both at the time of default and prior to the default. In other words, while static models use only one observation per firm, the hazard models use multiple observation per firm and thereby incorporate a firm's time-to-default into the firm's probability of default estimation.[37] Brown et al. (2013) refer to these models as dynamic logit models[38] and note that, "…dynamic logit models place structure on the errors to recognize the information contained in a series of observations of the same firm."[39]

Wu, Gaunt and Gray (2010) compare five models - MDA,[40] static logit model,[41] static probit model,[42] Shumway's dynamic logit model[43] and a model based on DD[44] – finding the dynamic logit model to perform best.[45]

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[35] Bauer, J., and V. Agarwal, "Are Hazard Models Superior to Traditional Bankruptcy Prediction Approaches? A Comprehensive Test," *Journal of Banking & Finance,* March 2014 [henceforth, Bauer and Agarwal (2014)], pages 432-442; also see Duffie, D., L. Saita, and K. Wang, "Multi-Period Corporate Default Prediction with Stochastic Covariates," *Journal of Financial Economics,* March 2007 [henceforth, Duffie et al. (2007)] noting that, "The latest generation of modeling is dominated by duration analysis." (Page 639).

[36] Shumway, T., "Forecasting Bankruptcy More Accurately: A Simple Hazard Model," *The Journal of Business*, January 2001, pages 101-124.

[37] Also see, e.g., Chava, S., and R.A. Jarrow, "Bankruptcy Prediction with Industry Effects," *Review of Finance*, August 2004, pages 537-569; Vassalou, M., and Y. Xing, 2004, "Default Risk in Equity Returns," *The Journal of Finance*, April 2004, pages 831-868; Hillegeist et al. (2004); and Bharath and Shumway (2008). Campbell et al. (2008) also follow the methodology advanced in Shumway (2001).

[38] Other terms used to describe these models are panel logit model, pooled logit model, or Cox proportional hazard model.

[39] Brown et al. (2013), page 25.

[40] Altman (1968).

[41] Ohlson 1980.

Bauer and Agarwal (2014) evaluate Shumway-based hazard models, "…against the traditional accounting-based approach or the contingent claims approach… [u]sing a complete database of UK Main listed firms between 1979 and 2009," finding that, "…hazard models are superior to the alternatives."[46]

As mentioned earlier, PIMS uses a logit model for computing probability of default. According to Brown et al. (2013), PIMS's logit model is dynamic,[47] a "…choice [that] placed the model somewhat ahead of its time by academic standards in the early 1990s."[48] Shumway (2001) notes, "…estimating hazard models with a logit program is so simple and intuitive that it has been done by academics and regulators without a hazard model justification … The Pension Benefit Guaranty Corporation forecasts bankruptcies by estimating a logit model by firm year."[49]

As such, PBGC's dynamic logit model appears to be hazard-based, still considered, "…state of the art in predicting firm bankruptcies."[50]

Model Specification

Nevertheless, there remain some serious issues that PBGC needs to address in its bankruptcy modeling. As Brown et al. (2013) succinctly note:[51]

> [T]here is a range of data concerns. For example, the process for updating parameter estimates based on new data has been inconsistent and inadequate. Conversations with PBGC staff confirm that the model has not been re-estimated in many years and thus, in all likelihood, the model parameters likely differ from today's best available estimates.

Predictor Variables: Market or Accounting?

Brown further observes that, "The parameters used in PBGC's bankruptcy model appear to be based on the empirical models that were common in the early 1990s when the PIMS model was developed. These include proxies for liquidity, leverage, firm size, and industry controls."[52] As noted earlier, the variables

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[42] Zmijewski, M.E., 1984, Methodological Issues Related to the Estimation of Financial Distress Prediction Models, *Journal of Accounting Research* 22, *Studies on Current Econometric Issues in Accounting Research*, page 59-82 henceforth Zmijewski (1984).

[43] Shumway (2001).

[44] Hillegeist et al. (2004).

[45] Y. Wu, C. Gaunt, C., and S. Gray, 2010, "A Comparison of Alternative Bankruptcy Prediction Models," *Journal of Contemporary Accounting & Economics*, June 2010, pages 34-45; henceforth Wu, Gaunt and Gray (2010).

[46] Bauer and Agarwal, 2014, Abstract.

[47] Confirmed by PBGC staff.

[48] Brown et al. (2013), page 25, noting that, "PBGC uses what might be called a 'dynamic' logit model to estimate bankruptcy probabilities."

[49] Shumway (2001), page 111 and fn 2.

[50] Bauer and Agarwal (2014), Abstract.

[51] Brown et al. (2013), page 23.

[52] Brown et al. (2013), page 26.

in PIMS bankruptcy model are mainly accounting variables,[53] whereas, "Mensah (1984) finds that the distribution of accounting ratios changes over time, and hence recommends that such models be redeveloped periodically."[54] Further, Agarwal & Taffler (2008) note:[55]

> (i) accounting statements present past performance of a firm and may or may not be informative in predicting the future, (ii) conservatism and historical cost accounting mean that the true asset values may be very different from the recorded book values, (iii) accounting numbers are subject to manipulation by management, and in addition, (iv) Hillegeist et al. (2004) argue that since the accounting statements are prepared on a going-concern basis, they are, by design, of limited utility in predicting bankruptcy.

Chava and Jarrow (2004) argue that, "…accounting variables add little predictive power when market variables are already included in the bankruptcy model."[56] However, our review of recent academic literature suggests that current practice entails a combination of accounting and marketing data.[57] Christidis and Gregory (2010) note, "…that 'dynamic logit' models that incorporate market variables of the form developed by Chava and Jarrow (2004) and Campbell et al (2008) add considerable power to pure accounting based models."[58]

A related question is whether PBGC should consider including DD in its bankruptcy model. An important consideration here is the cost, complexity and time-consuming nature of estimating DD. While DD is widely used in finance, Campbell et al. (2008) find that in the presence of the market-based variables used in their model, DD "…adds relatively little explanatory power."[59] More recently, Bauer and Agarwal (2014) also find that a dynamic logit model performs better than a contingent claim (*i.e.*, DD) based approach. Therefore, we conclude that PBGC need not directly include DD in its model, but rather include additional market-based variables, insofar as feasible, especially those considered in Chava and Jarrow (2008) and Campbell et al. (2008). Table 1 of Brown et al. (2013) provides a listing of the predictor variables used in some leading studies, including those used by Chava and Jarrow (2008) and Campbell et al. (2008). The appendix to this report reproduces that listing for ready reference.

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[53] The only market-based measure that PIMS uses is the year-end value of market equity, as enters into the computation of leverage.

[54] Agarwal, V., and R. Taffler, "Comparing the Performance of Market-Based and Accounting-Based Bankruptcy Prediction Models," *Journal of Banking & Finance,* August 2008 [henceforth, Agarwal & Taffler (2008)].

[55] Agarwal & Taffler (2008), page 3.

[56] Chava and Jarrow (2004), Abstract.

[57] See, e.g., Campbell et al. (2008) – the paper uses ratios that combine accounting and market data; Brown et al. (2013) noting "Beaver et al. (2005) use both accounting and market variables, and show that although accounting variables remain significant in models that also include market variables, the market variables have been increasing in explanatory power relative to accounting variables over time."

[58] Christidis, A. C. Y., and A. Gregory, "Some New Models for Financial Distress Prediction in the UK," *Xfi - Centre for Finance and Investment,* Discussion Paper No. 10, September 2010. Available at SSRN: http://ssrn.com/abstract=1687166 or http://dx.doi.org/10.2139/ssrn.1687166.

[59] Campbell et al. (2008), page 2901.

Further, for simulation, PIMS uses an AR(1) process to generate values of firm-specific predictor variables.[60] Given the strong evidence of heteroscedasticity documented by PBGC,[61] we recommend that PBGC consider using GARCH (1,1) model to forecast such values.

Unionization as a Predictive Variable

Beyond the customary accounting and market-based variables, and consistent with findings in both our Subtasks 4.1 and 4.2 reports, "Grice and Dugan (2001) note that unions ... affect a firm's likelihood of filing for bankruptcy, yet these factors are rarely included in bankruptcy models (including PBGC's)."[62] There are at least two potential ways in which PBGC could incorporate the impact of unionization in its bankruptcy modeling – i) inclusion of a variable measuring the level of, or trend in, industry unionization, or ii) use of an indicator variable for industries with a high degree of unionization, as identified in our Subtask 4.1 report.

Time-Varying Coefficients

Studies have found that the relationship between predictor variables and probability of bankruptcy for a firm varies both with macro-economic conditions and the industry at issue.[63] As Brown et al. note, "A relatively simple way to circumvent this problem is to divide the sample based on factors believed to drive time variation in the coefficients."[64] For example, one could divide the sample by business cycle regimes – contraction and expansion – and, within each regime, by industry (e.g., finance, utility, manufacturing, etc.; high- or low union representation;[65] or other potentially salient features).[66]

Such an approach should be feasible, as PIMS already, "…contains a feature to permit the use of up to 10 distinct bankruptcy equations based on the size of the firm, although this feature was not utilized in

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[60] PIMS 2010 Guide, Chapter 2.3.2.

[61] PIMS 2010 Guide, page 21-15, noting, "Tests for heteroscedasticity in the firm variable equations reveal that the variability (variance) of each equation's error term is significantly related to a vector of firm variables."

[62] Brown et al. (2013), page 31.

[63] Anyane-Ntow, K., "Accounting Information and Its Relationship to the Corporate Financial Distress Process," *Journal of Applied Business Research,* 1991, pages 29-35, finding in part that the "…critical factors associated with financial distress of manufacturing firms differ from those associated with service organizations… and along the different phases of the financial distress continuum [*i.e.*, macroeconomic conditions]." Also see Mensah, Y. M., "An Examination of the Stationarity of Multivariate Bankruptcy Prediction Models: A Methodological Study," *Journal of Accounting Research*, Spring, 1984, pages 380-395.

[64] Brown et al. (2013), page 32.

[65] Brown et al. (2013), page 32, further noting that, "…there are reasons to think that PBGC might want to allow industry effects to operate differently in different economic environments. For example, industries with a high concentration of defined benefit plans may also be industries with high operating leverage (for example, wages fixed by long-term union contracts) and high financial leverage (due to being old-economy, large tangible-asset firms) that may do extremely poorly in downturns, whereas other industries may behave quite differently."

[66] PIMS currently accounts for variation among finance, utility and other industries through use of an indicator variable. While this is a useful approach, it only captures average differences in bankruptcy probabilities among three industries, and does not allow other coefficients in the bankruptcy model to vary across industries. If PBGC decides to segregate sample observations by business cycle regime and/or industry, there would be no need to include these indicator variables.

the September 30, 2009 PBGC close."[67] Further, it is an approach consistent with the regime-based modeling recommended in our Subtask 4.1 report for forecasting stock returns and interest rates. Depending upon the simulated regime and the industry of the firm being analyzed, PIMS would select an appropriate equation to predict probability of bankruptcy. We will further discuss this issue in the context of contagion modeling.

Model Evaluation

According to PIMS 2010 Guide, PBGC evaluated its estimated bankruptcy model by comparing average predicted rates of default for all firms with a given bond rating to actually observed default rates for those firms over the model's estimation period of 1980 to 1997.[68] In other words PIMS essentially uses in-sample validation. However, Agarwal & Taffler (2008), for example, note that, "…such models are likely to be sample specific."[69]

As PBGC uses its bankruptcy model to make out-of-sample forecasts, we recommend it consider developing a new bankruptcy model by evaluating the current model's performance on an out-of-sample basis.[70] This can be easily implemented by expanding the database currently used for bankruptcy modeling and dividing the new database into two parts – an estimation sample and a hold-out sample.[71]

There are several ways to evaluate competing model specifications. Two common measures of in-sample goodness of fit are: (a) percent correctly predicted; and (b) the McFadden Pseudo r-Squared statistic.[72] Shumway (2001) provides a variant of the percent-correctly-predicted measure for assessing out-of-sample model performance.[73] To evaluate an out-of-sample forecast, Chava and Jarrow (2004) use two methods – one follows Shumway (2001), and the other is based on area under Receiver

[67] PIMS 2010 Guide, page 6-13.

[68] PIMS 2010 Guide, Table 6-5. Also see page 6-11: "A basic approach for evaluating an estimated bankruptcy model is to compare the average probability of bankruptcy predicted by the bankruptcy model in the five basic debt rating categories, A (strong investment grade), BBB (investment grade), BB (adequate), B (vulnerable), and below B (extremely vulnerable and default) with the Compustat-reported default rates for companies in those rating categories."

[69] See Agarwal & Taffler (2008), noting, "Accounting-ratio based models are typically built by searching through a large number of accounting ratios with the ratio weightings estimated on a sample of failed and non-failed firms. Since the ratios and their weightings are derived from sample analysis, such models are likely to be sample specific."

[70] As previously noted, in the June 28, 2016 call with PBGC referenced earlier, we were told that they are re-estimating the bankruptcy model and transitioning to a new database. We recommend that this suggestion be considered in that process.

[71] Brown et al. (2013), page 31 noting "A commonly used – and relatively simple to implement – approach [to estimate bankruptcy equation] would be to divide up realized time periods into an earlier and a later "holdout" period. The bankruptcy model can be estimated on the earlier data, and then these coefficients applied to a simulation that represents the same length of time as the later period. One can then compare the simulated results to the actual realizations from the later holdout period. Indeed, given how long it has been since the bankruptcy model has been updated, PBGC could apply this validation methodology to the period that follows the estimation sample currently used."

[72] Woolridge, J.M., *Econometric Analysis of Cross Section and Panel Data* (MIT Press, October 2001), page 465.

[73] Shumway (2001), Table 3.

Operating Characteristics ("ROC").[74] Two other statistics widely used to assess out-of-sample predictive accuracy are Gini rank correlation coefficients and Kolmogorov–Smirnov statistics.[75]

Plan Underfunding and Bankruptcy

A defined benefit plan is said to be underfunded when the present value of its liabilities exceeds the value of its assets. As PBGC notes, "…pension underfunding is amortized over some time period and must be serviced by periodic cash contributions. Thus, other things equal, firms with pension underfunding face a larger burden compared to firms with fully funded plans."[76] The academic literature also has found that during financial difficulties, there is an increase in pension underfunding. For example, Duan et al. (2015) found that, "…the degree of underfunding increases significantly as firms near default."[77]

Thus, PBGC's approach of incorporating a pension plan's funding in bankruptcy modeling is appropriate. PBGC presently incorporates, "…the log of the pension funding ratio (pension assets divided by pension liabilities) as an independent variable" in its model.[78] A related question is whether to use market values or book values in measuring funding ratio. In our opinion, this is a question best resolved empirically.

Further there are alternative ways to measure plan funding. For example, according to Cardinale, the size of the pension funding relative to its enterprise value is a significant predictor of credit spreads. Furthermore, there is an asymmetric impact between overfunding and underfunding, as the market does not seem to reward excess assets as it punishes excess liabilities.[79] Moody's now recognizes pension underfunding as long-term debt.[80] Following this approach, the debt-to-equity ratio can be adjusted to account for the impact of pension underfunding.[81]

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[74] Chava and Jarrow (2004), Table 1. The area under ROC curve is commonly known as the AUC statistic. An AUC score of 1 means that the bankruptcy model can perfectly discriminate between firms likely and unlikely to go bankrupt, whereas an AUC score of zero means that the model has no such capability.

[75] See, e.g., Tinoco, M. H., and N. Wilson, "Financial Distress and Bankruptcy Prediction Among Listed Companies Using Accounting, Market and Macroeconomic Variables," *International Review of Financial Analysis,* December 2013, pages 394-419; and Anderson, R., "The Credit Scoring Toolkit: Theory and Practice for Retail Credit Risk Management and Decision Automation," *Oxford University Press*, August 2007.

[76] PIMS 2010 Guide, page 6-7.

[77] Duan, Y., Hotchkiss, E.S. and Y. Jiao, "Corporate Pensions and Financial Distress," AFA 2015 Boston Meetings, January 2015. Available at SSRN: http://ssrn.com/abstract=2550311 or http://dx.doi.org/10.2139/ssrn.2550311.

[78] PIMS 2010 Guide, page 6-7; also see fn. 10, noting, "Many firms sponsor more than one pension plan. The various plans sponsored by a firm often significantly differ in their funding levels (e.g., a plan covering salaried workers may be well funded while a plan covering only hourly workers is underfunded). While the model might be made richer by taking into consideration variations in funding levels across the plans sponsored by firms, data limitations restrict the model to funding measurements that aggregate over all the sponsored plans."

[79] Cardinale, M., "Corporate Pension Funding and Credit Spreads", 2007.

[80] Moody's Analytical Approach Presentation, 2013.

[81] Long et al showed that plan size and funded status seem to impact stock prices the most. [Long, C., et al, "Pensions in Practice: How corporate pension plans impact stock prices", 2010].

We recommend that PBGC also consider a) measuring pension funding for a firm relative to that firm's enterprise value and/or b) modifying the debt-to-equity ratio used in the bankruptcy equation to include pension underfunding as a long-term debt.

Adequacy of PIMS Representation of Contagion

Intra-Industry Contagion

Background

Often compounding the effects of economy-wide (macro) contagion, and ultimately manifesting in both ME- and SE-plan insolvencies, the spread of financial distress specific to a given industry ("intra-industry contagion") has been widely studied,[82] and can often be attributed to the uneven impact of globalization and technological change across industries, coupled with interdependencies among the firms within a given industry.[83] However, in some cases, such as construction and related-product markets, an industry-specific "hypersensitivity" to macro contagion can also kick in, due to a greater inherent cyclicality in demand for the products and/or services at issue. Furthermore, at the plan level, like financial obligations and supply chain relationships among firms in the same or allied industries, ME plans can serve as a vehicle for the transmission of financial distress among such firms, further undermining plan viability.[84]

As noted earlier and partially illustrated in Exhibits D and E on the following pages, intra-industry contagion is manifest in the concentration of PBGC liabilities, both SE- and ME-plan-related, in a relatively limited number of industries,[85] a situation neither new nor surprising given the underlying economic trends. While the number of industries with only one or two trusteed SE plans is quite large (see Exhibit D) – superficially suggesting a relative absence of intra-industry contagion – in fact, many of those same industries are also home to problematic ME plans indicative of financial distress among

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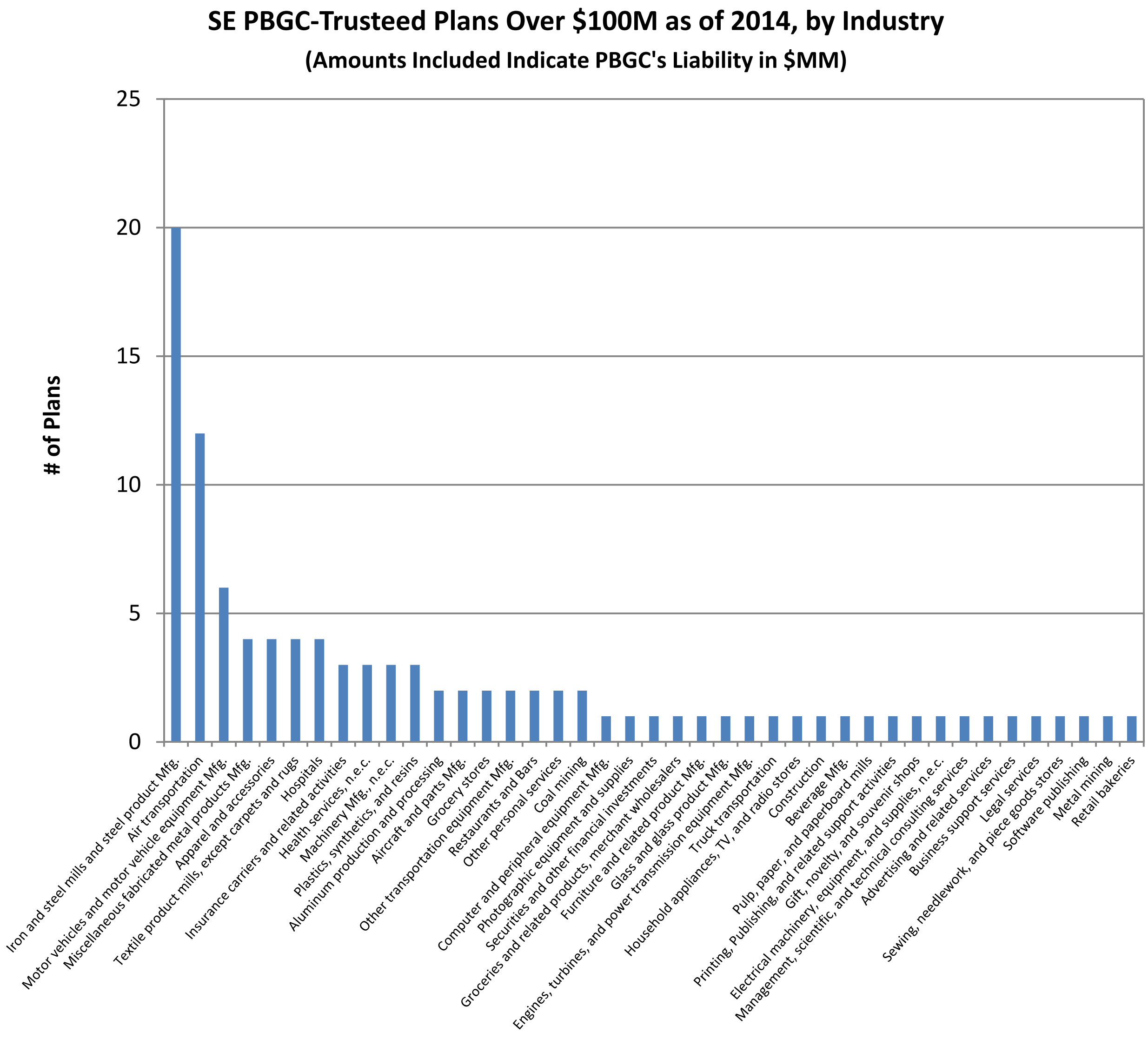
[82] See, for example, Akhigbe, Madura and Martin, op. cit., concluding, in part, that the negative intra-industry effects of a bond downgrade for a given firm are greater when coupled with a significant share price decline, and/or the downgraded firm is dominant in the industry, and/or it is more closely related to its rivals, and/or the downgrade is due to a deterioration in the firm's financial prospects (page 1). Also relevant for our purposes is Larry Lang and Rene Stulz, "Contagion and Competitive Intra-Industry Effects of Bankruptcy Announcements," *Journal of Financial Economics*, August 1992, finding a two-sided impact of such announcements: for industries that are highly levered and/or stock returns for the bankrupt firm and its rivals are highly correlated (often the case), a significant negative effect on rivals' valuation is observed; conversely, for highly concentrated industries with low leverage, a significant positive impact is observed, "…suggesting that in such industries competitors benefit from the difficulties of the bankrupt firm." (Page 1) In the longer run, however, the latter effect may be overshadowed by, for example, increased global competition, first manifested in the financial health of the bankrupt firm. Also see Koopman, Lucas, and Schwaab, op. cit., for a more recent overview of much of the relevant literature.

[83] Both financial and supply-chain-related.

[84] See, for example, U.S. Government Accountability Office (GAO), "Private Pensions: Timely Action Needed to Address Impending Multiemployer Plan Insolvencies," March 2013, pages 21-22. Indeed, as the GAO points out, such contagion can spread to plans in other industries, as well ('…because the contribution base of multiemployer plans can overlap, financial stress in one plan has the potential to spill over to other plans.").

[85] Out of the 259 examined in our Subtask 4.1 report. More generally, see pages 27-35 of that report.

Exhibit D



Sources: File titled "FOD20130930.xls" provided by the PBGC and unionstats.com, Union Membership, Coverage, Density, and Employment by Industry, by year (1983-2014). Although the data was extracted from U.S. Census Bureau's Current Population Survey ("CPS"), its industry categories have been changed three times since 1983; two minor changes in 1992 and 2009, and a significant change in 2003. FTI created a consistent categorization system adjusting for those disparities. Unionstats.com provided a conversion file to unify pre-1992 and post-1992 classifications. For the post-2002 industry conversions, FTI matched the industries using the industry name, industry hierarchy, and historical employment figures.

many sponsoring firms – i.e., trucking, grocery stores, printing & publishing, coal mining, furniture manufacturing, and glass and glass-product manufacturing (see Exhibit E).

Adequacy of PIMS Representation of the Phenomenon

As in the case of economy-wide contagion, in assessing the adequacy of PIMS's representation of intra-industry contagion, it is important to bear in mind that "adequacy" in this in this instance can only be judged relative to a realistically achievable standard, given the state of the applicable science and budget constraints.

In respect to PIMS's representation of intra-industry contagion, "adequacy," at least theoretically, can be judged in terms of either of two kinds of performance:

(a) Ability to anticipate an occurrence of contagion, that could entail any number of firms and related plans, and be staged over a period that could range anywhere from just a few years to several decades; or

(b) At the onset of any given occurrence, ability to anticipate the rate at which the "infirmity" will spread, the number of plans ultimately affected, and the magnitude of the effect.

In respect to both forms of performance, a distinction should be drawn between contagion requiring decades to make itself fully felt (as in the domestic auto and steel industries) – call this "chronic" contagion – and contagion requiring just a few years to make itself fully felt (as in the financial and construction sectors, post-2007) – call this "acute" contagion.

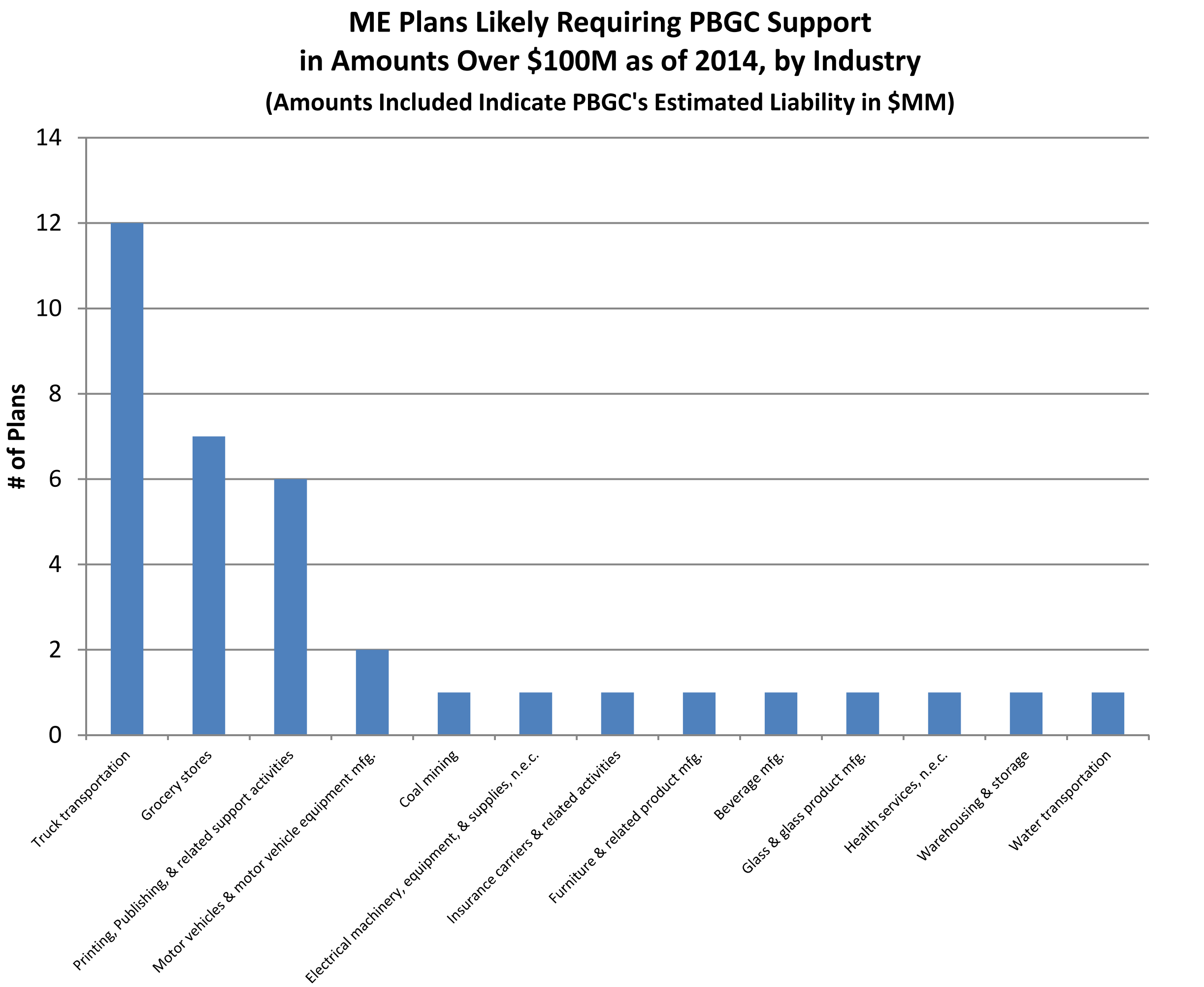
Chronic Contagion

As to "chronic" contagion, as suggested in both our Subtasks 4.1 and 4.2 reports, we believe that, should budgets accommodate, there is room for improvement in the PBGC's ability to anticipate such occurrences, or at any rate identify them once they are underway. Further, in respect to acute "flare-ups" of contagion during periods of macroeconomic distress (really, transitory accelerations in the long-term, chronic process), by focusing relatively early-on on those dominoes still standing but most at risk to fall (whether plan sponsors, plans or both), it may be possible to better gauge future impacts on a year-to-year basis.

Exhibit F depicts the transition from one MWG[86]-assigned risk category to another of all 12 ME plans in the trucking industry which, as of 2015, represented a PBGC liability of over $100 million. Where a plan was not considered even a "remote" insolvency risk, it is represented by an empty slot, filled in only in the year in which it is first classified either as that, or a risk greater and/or more immediate. As shown, over a period of only five years (2010-2014), and despite none having previously been considered anything more than a remote risk (and six not even that), all twelve of these plans came to be classified as "probables," and associated estimated PBGC liabilities consequently added to the agency's balance sheet.

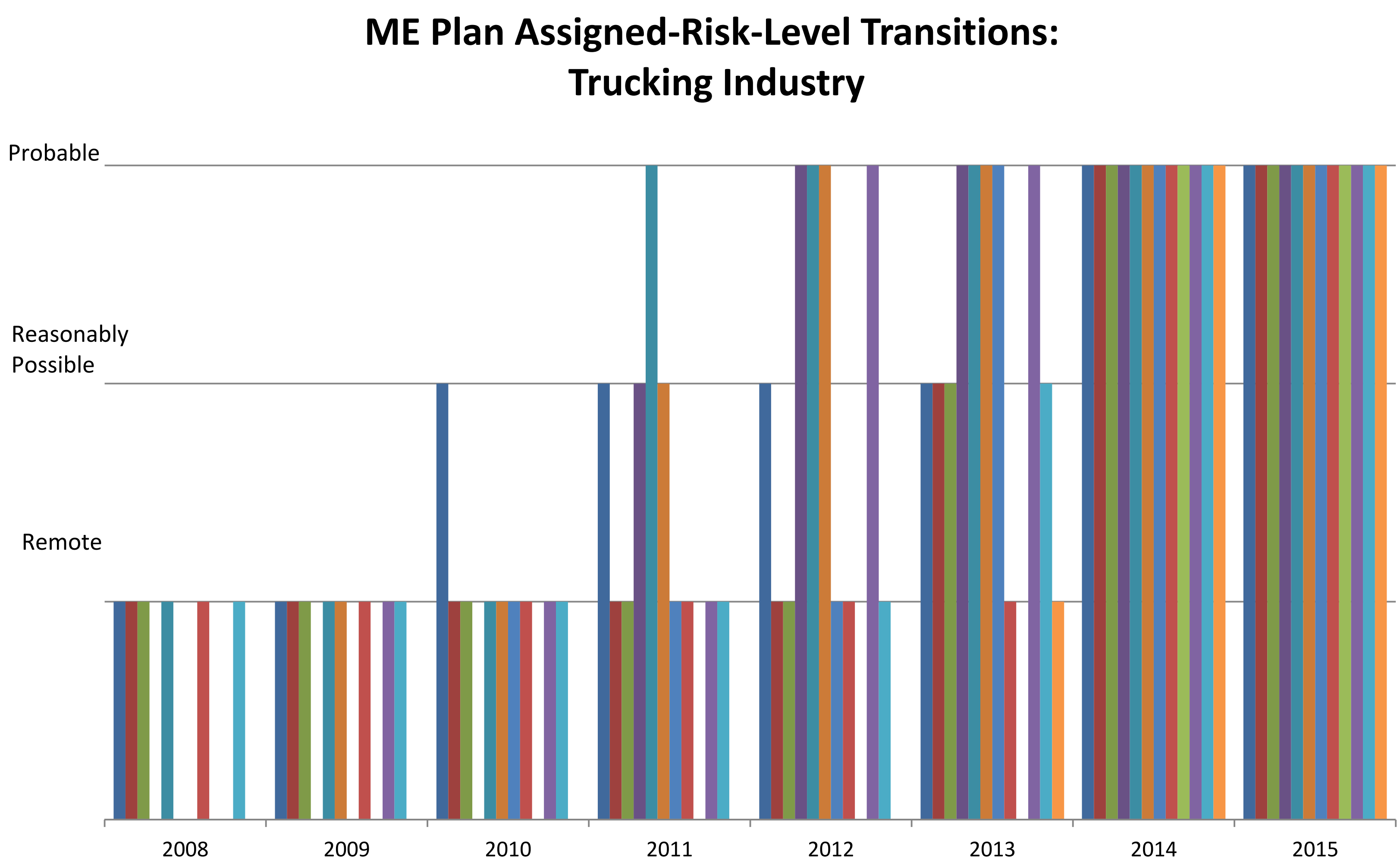
[86] PBGC Multiemployer Working Group.

Exhibit E



Sources: File titled "ME PROBSwReserves 9 30 14.xls" provided by the PBGC which included plans that the PBGC believed were probable to become liabilities in the future and unionstats.com, Union Membership, Coverage, Density, and Employment by Industry, by year (1983-2014). Although the data was extracted from U.S. Census Bureau's Current Population Survey ("CPS"), its industry categories have been changed three times since 1983; two minor changes in 1992 and 2009, and a significant change in 2003. FTI created a consistent categorization system adjusting for those disparities. Unionstats.com provided a conversion file to unify pre-1992 and post-1992 classifications. For the post-2002 industry conversions, FTI matched the industries using the industry name, industry hierarchy, and historical employment figures.

Exhibit F



Note: Excludes plans representing PBGC liabilities of less than $100 million as of 2015.
Source: "PROBS 09302014 with liab greater than 100M.xlsx" and "ASD Probs and RPs.xlsx" provided by the PBGC.

In the broadest of terms, this relatively abrupt proliferation of problems[87] can be attributed to the particular vulnerability of these plans, and their sponsors, to the decline in asset values and downturn in aggregate demand following the 2008 financial crisis,[88] due to industry-specific factors of a type elsewhere discussed, and reflected, *inter alia*, in especially rapid declines in the number of active workers covered by bargaining agreements. Between 1990 and 2015, the number of such workers in the grocery industry declined by 37%; in the trucking industry, by 62%; and in the printing and publishing industry, 78%. In contrast, the number of covered workers in all other industries combined declined by only 10%.[89]

The significance of any of the foregoing factors, however, must also be considered in light of PBGC staff's understanding that, over this same period, the classification methodology used by the MWG had become more accurate – implying that, under the new methodology, some of the plans not classified as risky until the later years would have been so classified more promptly.[90] Additionally, lagged recognition of a probable liability may also result from a failure to reflect events occurring just beyond the ten-year cut-off point applied in defining "probables."

Similar, if not even more striking, patterns in the migration of ME plans from one risk category to another are depicted in Exhibits G and H, for the printing and publishing and grocery industries, respectively. Factors behind the particular vulnerability of plans in both are discussed, albeit in summary terms, in our Subtask 4.1 report.

Finally, in considering the foregoing, one must bear in mind that the MWG's plan designations determine the plans constituting PBGC's booked liabilities and affect PIMS's forecasts only insofar as they are used to determine the initial-year values upon which PIMS's forecasts are based. For example (and at the risk of oversimplifying), were the MWG to designate a larger number of plans as "probable" (i.e., booked) liabilities in the initial year, PIMS's "tree" of alternative liability values would reflect that change in the form of consistently greater dollar amounts; but in all other aspects the tree would remain unchanged.

Potential means of better reflecting both chronic and acute contagion in PIMS's bankruptcy modeling include:

1. Incorporating macroeconomic variables and measures of firm interconnectedness in its bankruptcy modeling.

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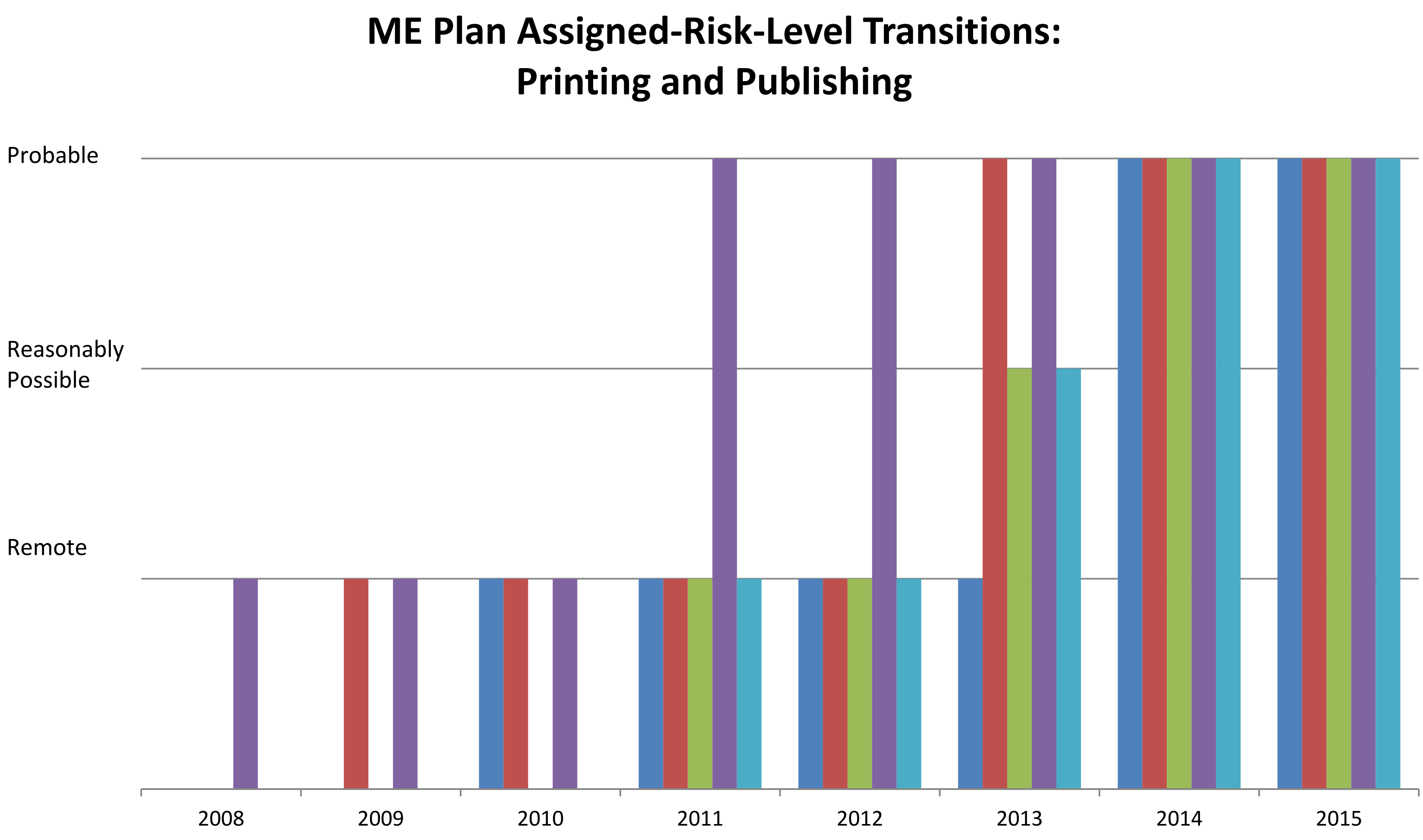
[87] Whether stemming from projected insolvencies in the near- or relatively long term.

[88] Because assigned risk categories are based largely on Form 5500 data reflective of plan status two years prior, and also owing of the accumulative nature of financial distress under such conditions, some considerable lag between the onset of these macro problems and their full impact on plan financial health is to be expected.

[89] Unionstats.com and FTI calculations.

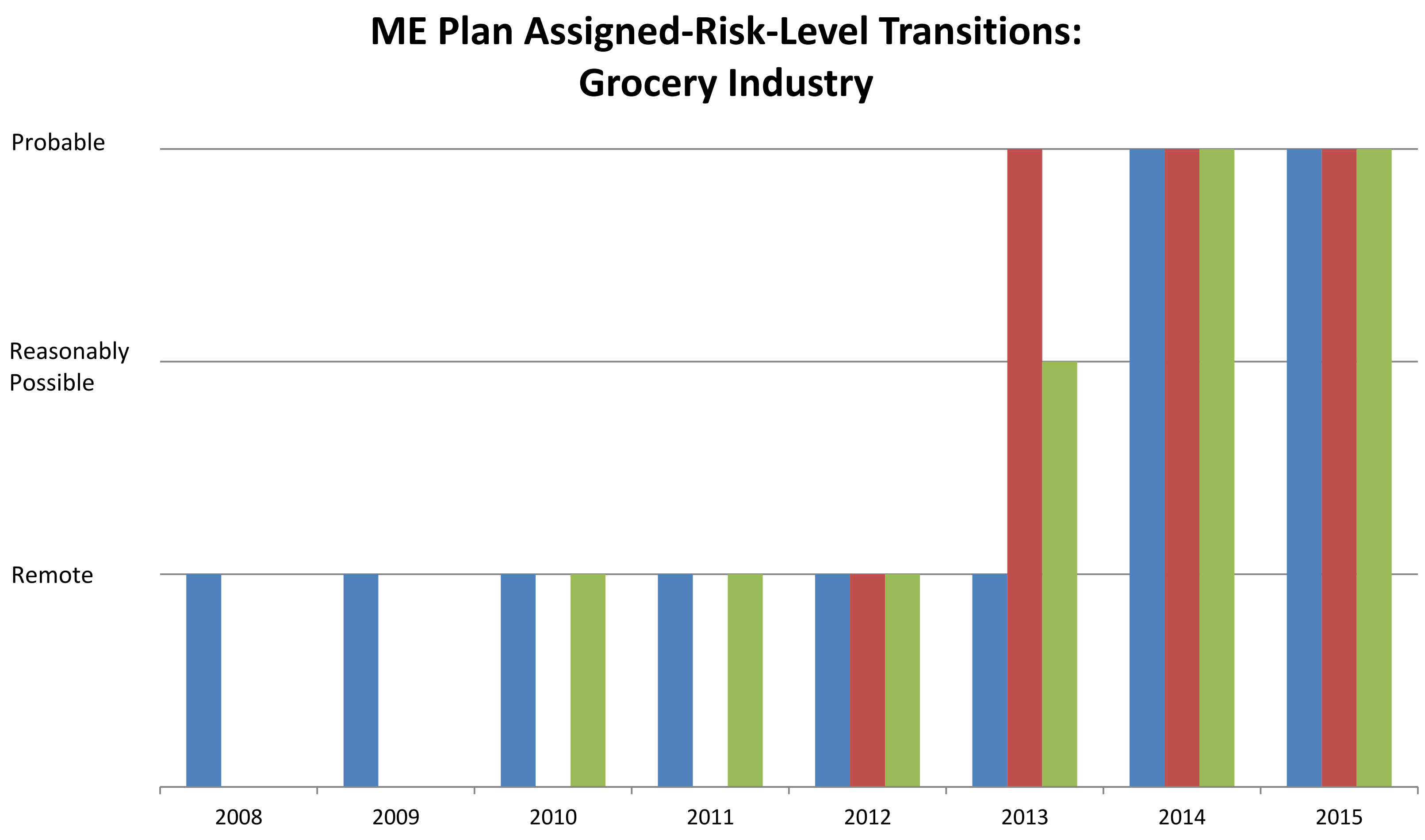
[90] On the other hand, in response to an FTI information request, PBGC staff previously indicated that, in respect to the calculation of PBGC liabilities, the procedures used by the MWG in 2015 did not differ from previous procedures. (See responses to our MWG-related information requests as passed on by Ms. Tucker on June 14, 2016.) Presumably, these two at least facially differing views can be reconciled.

Exhibit G



Note: Excludes terminated plans and plans representing PBGC liabilities of less than $100 million as of 2015.
Source: "PROBS 09302014 with liab greater than 100M.xlsx" and "ASD Probs and RPs.xlsx" provided by the PBGC.

Exhibit H



Note: Excludes terminated plans and plans representing PBGC liabilities of less than $100 million as of 2015.
Source: "PROBS 09302014 with liab greater than 100M.xlsx" and "ASD Probs and RPs.xlsx" provided by the PBGC.

2. Using a Cox proportional hazard bankruptcy model with a time- varying baseline hazard function dependent on macroeconomic variables and measures of firm interconnectedness. See Appendix for a list of relevant macroeconomic variables.
3. Simulating bankruptcies of all firms in a given industry in tandem (i.e., determining their bankruptcy risk based on shared industry shocks) instead of simulating bankruptcies for various firms independently as is the present practice.
4. Relatedly, employing a stratified plan sampling technique incorporating some minimum number of plans in industries exhibiting the greatest declines in union membership.

Acute Contagion

Apart from the insights that might be gleaned through study of long-term, industry- or union-specific influences on plan solvency, "acute" contagion presents the analyst with a less tractable forecasting problem. Certainly, at the level of firm valuation, the markets have proven themselves unable to anticipate such occurrences, much less their ultimate toll (as evidenced by, among other things, the unpredictability of stock prices, as addressed in our Subtask 4.1 report). But, having noted that, it is also important to recognize that, at the plan level, significant problems are apt to set in only sometime after plan sponsor valuations take their first hit (valuations being forward-looking as to cash flows, while plan contributions are basically current). That lag might enable one to forecast "acute" plan distress due to intra-industry contagion[91] farther in advance than (for example) sponsor stock values. However, such an approach would require more timely evaluation of plan financials than the Form 5500 database now permits. Were such an undertaking feasible by other means – if only for a subset of the largest ME plans – it might nonetheless be worthwhile.[92]

Economy-Wide Contagion

Background

The clustering of defaults on an economy-wide basis is a well-known phenomenon. On the next page, we reproduce Giesecke et al. (2011), figure 1, which, "…plots the annual value-weighted percentage default rates for bonds issued by U.S. domestic nonfinancial firms for the 1866–2008 period."[93] As those authors note, the historical experience is characterized by long periods with relatively few defaults followed by episodes of significant clustering of defaults. The academic literature offers several explanations for this clustering:[94]

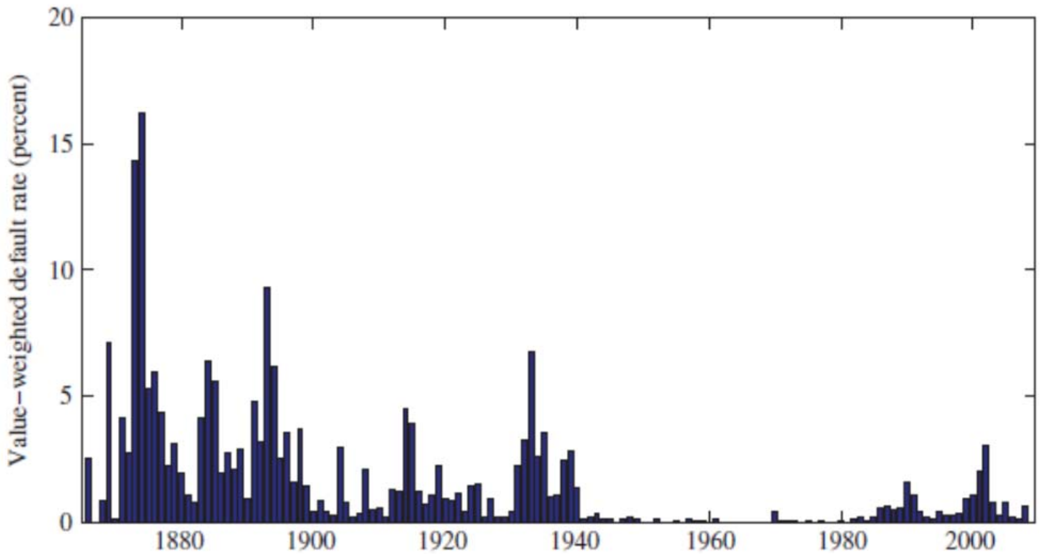
[91] Or, for that matter, any number of other factors.

[92] More specifically, adverse trends in some of the measures of plan financial health included in the Multiemployer Working Group's "Plan Data and Analysis" forms (PDAs) could be correlated with NAICS industry codes.

[93] Giesecke, Kay, Longstaff, F.A., Stephen Schaefer and Ilya Strebulaev, "Corporate Bond Default Risk: A 150-Year Perspective," *Journal of Financial Economics*, January 2011 [henceforth Giesecke et al. (2011)], page 237.

[94] See Das, Sanjiv R., Darrell Duffie, Nikunj Kapadia, and Leandro Saita, "Common Failings: How Corporate Defaults are Correlated," *Journal of Finance*, February 2007 [henceforth, Das et al. (2007)]; and Duffie, Darrell, Andreas Eckner, Guillaume Horel, and Leandro Saita, "Frailty Correlated Default," *Journal of Finance,* October 2009, pages 2053-2123, noting, "We find strong evidence for the presence of common latent factors, even when controlling for

Fig. 1. Historical default rates



> First, firms may be exposed to common or correlated risk factors whose co-movements cause correlated changes in conditional default probabilities.
>
> Second, the event of default by one firm may be "contagious," in that one such event may directly induce other corporate failures, as with the collapse of Penn Central Railway in 1970.
>
> Third, learning from default may generate default correlation. For example, to the extent that the defaults of Enron and World-Com revealed accounting irregularities that could be present in other firms, they may have had a direct impact on the conditional default probabilities of other firms.

PIMS, however, incorporates correlated defaults in only a quite limited way,[95] its predictor variables being primarily firm-specific.[96] Further, in PIMS simulations, the bankruptcies for each partner firm are generated randomly and independently.

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observable factors that provide the most accurate available model of firm-by-firm default probabilities." (Page 289.)

[95] In our June 28, 2016 call, PBGC noted that the random variable used to generate industry shocks could potentially lead to correlated defaults.

[96] Brown et al. (2013), page 23, noting that the PBGC bankruptcy model, "…does not allow for macroeconomic factors to lead directly to correlated defaults among firms. The bankruptcy model relies primarily – although not exclusively - on firm-specific accounting measures, and thus does not model the potentially important linkages with overall economic activity that market-based measures may be more apt to capture."

Thus, as Brown observes, to anticipate economy-wide contagion in its model,[97] PBGC would have to: (a) incorporate the interconnectedness of firms, and (b) simulate various firms' bankruptcies in tandem instead of sequentially.[98]

Reflecting Interconnectedness

The academic literature suggests several ways in which PBGC might reflect economy-wide contagion in its bankruptcy modeling. For example, both Duffie et al. (2007)[99] and Campbell et al. (2008)[100] directly incorporate macroeconomic variables in a dynamic logit model. Using a three-regime model, Giesecke et al. (2011), "… find that stock returns, stock return volatility, and changes in GDP are strong predictors of default rates."[101] Koopman et al. (2012) find that, "…[a]pproximately one third of systematic variation [in firm default rates] is captured by macroeconomic/financial factors."[102] A list of the macroeconomic variables they evaluated is reproduced in the appendix.

For PBGC modeling, the Campbell et al. (2008) paper is of particular relevance because it:

- Provides a framework for incorporating macroeconomic variables in a dynamic logit model of the kind PBGC currently uses;
- Offers a model that "…captures a large share of the time-variation in bankruptcies;" and
- Offers a test for the hypothesis as to whether, "…time effects can be omitted from [such a] model."[103]

Another relevant paper is Wu, Gaunt and Gray (2010), proposing a model, "…comprising key variables from each of … five models[104] and add[s] a new variable that proxies for the degree of diversification

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[97] As PBGC staff noted in their comments, there is an economy-wide component of the shocks correlated with stock returns and interest rate movements. In our opinion, however, this does not fully capture the effects of economy-wide contagion.

[98] See Brown et al. (2013), page 12, noting, "Capturing this dynamic [contagion] would involve two changes: first, moving from a model in which individual firms are passed through the model in sequence to one in which they go through in parallel; second, developing an empirically-grounded way to assess connections between firms."

[99] Duffie et al. (2007), finding that, "For US Industrial firms, based on over 390,000 firm-months of data spanning 1980 to 2004, the term structure of conditional future default probabilities depends on a firm's distance to default (a volatility-adjusted measure of leverage), on the firm's trailing stock return, on trailing S&P 500 returns, and on US interest rates."

[100] Campbell et al. (2008) use the following variables in their model: "…the monthly log excess return on each firm's equity relative to the S&P 500 index (EXRET), the standard deviation of each firm's daily stock return over the past 3 months (SIGMA), and the relative size of each firm measured as the log ratio of its market capitalization to that of the S&P 500 index (RSIZE)."

[101] Giesecke et al. (2011), Abstract.

[102] Koopman, Siem Jan and Lucas, Andre and Schwaab, Bernd, "Dynamic Factor Models with Macro, Frailty and Industry Effects for US Default Counts: The Credit Crisis of 2008," ECB Working Paper No. 1459, August 2012. Available at SSRN: http://ssrn.com/abstract=2128480.

[103] Campbell et al. (2008), page 2916.

[104] These models are developed in (i) Altman (1968), (ii) Ohlson 1980, (iii) Zmijewski 1984, (iv) Shumway 2001, and (v) Hillegeist et al. 2004.

within the firm… shown to be negatively associated with the risk of bankruptcy."[105] PBGC might consider a similar approach, especially given the significance of intra-industry contagion, as discussed below.

In this connection, we would note that, following 2008 financial crisis, there has been substantial research in measuring linkages among firms to assess systemic risk which PBGC could draw upon to introduce an explicit measure of economy-wide contagion in its model. For example, Blei and Ergashev (2014) develop a new "…measure of systemic risk, ACRISK, where AC stands for asset commonality."[106] The ACRISK measure is based on two statistics: (a) a Herfindahl Hirschman Index (HHI) measuring the concentration of a firm's asset portfolio; and (b) "DI," measuring "…the distance between the diversification pattern of an individual firm's portfolio and that of the aggregate portfolio."[107]

Another approach to modeling economy-wide contagion is the use of a Cox proportional hazard model. This can be thought of as a two-part model, entailing: (a) a common component describing how bankruptcy risk evolves through time ("baseline hazard"); and (b) another component basing bankruptcy risk on firm-specific factors. Baseline hazard can be a function of macroeconomic variables. (See Nam et al. (2008), as cited below.) And as Brown et al. (2013) note: [108]

> For example, Hillegeist, et al. (2004) use the number of bankruptcies within the past year (relative to the number of firms in the sample) as the baseline hazard, and show that this increases the predictive power of the model. Nam et al. (2008) use change in interest rates and exchange rate volatility to model the baseline hazard and find that these are important for modeling bankruptcy in Korean data. These papers suggest a way that PBGC may be able to capture macroeconomic trends and/or bankruptcy contagion effects – by using macroeconomic variables to establish the baseline hazard rate. ***This is potentially important for modeling "waves" of bankruptcy.***

PIMS Simulation and Contagion Modeling

As noted earlier, in a PIMS simulation, the bankruptcies for each partner firm are generated randomly and independently. PIMS can be easily modified to consider bankruptcies of firms in tandem. For example, it could make a random draw from the same distribution it uses to generate industry-specific shocks, then using that given shock to predict bankruptcy for all the firms in a given industry that are found to be particularly vulnerable (given their firm-level characteristics), instead of making a separate random draw for each firm.

We recognize that evaluation of all such proposals will require PBGC to invest time and other resources, but given that bankruptcy modeling is at the core of SE-PIMS, it may well be worth such investment.[109]

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[105] Wu and Grant (2010), Abstract.

[106] Giesecke et al. (2011), Abstract.

[107] Blei and Ergashev (2014), page 9.

[108] Brown et al. (2013), page 25, emphasis added.

[109] Brown et al. (2013), page 15, noting, "Given the importance and the complexity of the bankruptcy modeling process, and the substantial developments in the field since this model was created, PBGC may find it particularly valuable to invest additional resources in evaluation and validation."

Further, given the need to regularly update the bankruptcy model, we recommend that PBGC set aside annual budget for this and either assign dedicated internal staff for this exercise or use outsourced assistance, if deemed necessary.[110]

Simulation of Transition to PBGC Coverage

When a single-employer plan is simulated to undergo PBGC administration, PIMS models the trustee process as follows:

1. A plan is only simulated to be trusteed once it is less than 80% funded on a termination basis.
2. The projected gross claim is reduced by 5% to account for recovery.
3. Plan termination liabilities are calculated using a simplified approach where accrued vested benefits up to the time of termination are limited by PBGC guarantees. PIMS does not model the PBGC priority categories, nor does it model the benefit cutback for benefit improvement adopted in the five years preceding termination.[111]
4. Assets and liabilities are transferred to PBGC trusteed fund. Active participants are converted to retirees or term-vested. Benefits for actives, retirees and term-vesteds are capped by PBGC's maximum guarantees.[112]
5. Assets transferred to PBGC are reduced by one year of minimum required contribution as "due and unpaid employer contribution."

The PIMS modeling of plan transfers is reasonable. However, there are two areas where PBGC should further explore enhancements. First, some of the threshold parameters used in PIMS modeling are based primarily on PBGC's past experience - for example, the 80% funded threshold and the 5% recovery assumption. We recommend the PBGC monitor these factors for newly trusteed plans to make sure that these assumptions continue to be reasonable. Second, in a distressed termination, plan assets are likely to fully cover retirees' benefits (Priority Category 3). When allocating based on priority categories, and based on the assumptions that assets are sufficient to cover all retirees' benefits, then retiree benefits are fully preserved. PBGC should study the impact of not capping retirees' benefit to PBGC guarantees to determine if there is a material difference in PIMS forecast.

Once PIMS projects that a plan is trusteed, certain assumptions are made for the operation of PBGC's trust fund and revolving fund, including the following:

[110] Brown et al. (2013), page 15, noting, "The ability to implement some of these model enhancements would require that PBGC has sufficiently modern and powerful computational hardware at their disposal (whether in‐house or outsourced on an as‐needed basis), and that PIMS code is optimized for maximum computational efficiency."

[111] PBGC has commented that priority category modeling is limited by not having salary distribution data within each age/service groupings for active employees. We agree. Our recommendation with respect to priority categories is on retirees' benefits, in case the plan assets are sufficient to cover all of retirees' benefits.

[112] See PIMS System Description, section 3.5, 3.6, 4.2 and 4.6. The capping of benefits can be found in the module ASSUMP.CPP.

- The asset returns and benefit payments from the trust fund and revolving fund are modeled separately. The trust fund and revolving fund pay a proportional share of benefits based on the ratio of trust fund assets to the present value of benefits. PBGC premiums go into the revolving fund. Expenses are paid from the trust fund.

- A maximum of 30% of PBGC's single-employer program's assets are invested in equity. Only the trust fund has equity investments. The fixed-income portion of the trust fund is invested to immunize PBGC's liability. The remainder of fixed-income assets, if any, are invested in 30-year Treasury bonds. Revolving funds are invested in 30-year Treasury bonds. If the PBGC's single-employer program is 130% funded, then both the fixed income portion of the trust fund and the revolving fund are assumed to invest in 15-year Treasury bonds.[113]

The PIMS modeling of PBGC's trust fund and revolving fund is adequate. For PBGC's trust fund, PIMS models an investment policy to hedge the interest rate risk of trusteed liabilities. However, PBGC's 2014 annual report did not disclose an interest rate risk hedging policy.[114] We recommend PBGC review PIMS modeling of the trust fund's investment returns so that it is consistent with its current investment policy as PBGC's risk profile may be impacted by whether or not it actively hedges its interest rate risks.

The administration of multiemployer plans does not transfer to PBGC in the event of insolvency, which would be a concept similar to that of mass withdrawal. PIMS does not model individual employer withdrawals and the Form 5500 data does not split out employer contributions and liability withdrawal payments. Additionally withdrawal liability payments are subject to negotiation between plan trustees and sponsoring employers. Thus, it is difficult to assess the parameters used in modeling the pattern of withdrawal liability payments. Nevertheless, we find the method of using a collectability rate and a rate of decay for withdrawal payments to be reasonable.

With respect to the modeling of mass withdrawal probability, we find the withdrawal probability formula complex and difficult to validate. Due to the change in scope of the SOW, additional effort was not allocated to further examine mass withdrawal issues. Nevertheless, the factors used in the formula capture the most important variables. We recommend replacing the mass withdrawal formula with a simpler formula that uses fewer factors, and calibrates the formula to the overall mass withdrawal liability. One possibility is to use the two stress metrics developed by the Society of Actuaries in the report "Multiemployer Plan Stress Metrics" as the factors impacting mass withdrawal probability.[115] We expect these two metrics would capture most of the dynamics the current formula is intended to model.

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[113] On the modeling of PBGC's trust assets, see PIMS System Description section 4.4, the module PBGC.CPP, and the post-PIMS processing spreadsheet.

[114] 2014 PBGC Annual Report, pages 32 – 38.

[115] The two metrics are unfunded liability amortized over 15 years divided by the number of active participants, and the unfunded liability amortized over 15 years divided by the Normal Cost including expense plus unfunded liability amortized over 15 years. See Society of Actuaries, "Multiemployer Plan Stress Metrics", page 10.

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Spreadsheet Files

"ASD Probs and RPs.xlsx"

"FOD20130930.xls”

"ME PROBSwReserves 9 30 14.xls”

“PROBS 09302014 with liab greater than 100M.xlsx"

Website URL’s

http://www.census.gov/programs-surveys/cps.html

http://www.unionstats.com.

Appendix

Table 1: Parameter estimates from major logit bankruptcy studies and PIMS

Results from Campbell et al. (2008) are reproduced from Table 3, Logit Regression of Bankruptcy/Failure Indicator on Predictor Variables, Bankruptcy Model 2. The first set of results from Shumway (2001) are reproduced from Table 2, Forecasting Bankruptcy with Altman's Variables, Panel B: Hazard Model Estimates. The second set of results from Shumway (2001) are reproduced from Table 6, Forecasting Bankruptcy with Market-Driven Variables, Panel B: Market and Accounting Variables. Results from Chava and Jarrow (2004) are reproduced from Table 5, Panel A: Estimation using 1962-99 data for NYSE-AMEX-NASDAQ companies including financials (column 2, Public firm model). Results from Ohlson (1980) are reproduced from Table 4: Prediction results, Model 1. Finally, results from PIMS 1 are reproduced from Table 6-4 and PIMS 2 are reproduced from Table 6-6. Bold numbers indicate significance at the 5% level or below, except for PIMS 2 which did not provide t-statistics or p-values. Cash flow variables from PIMS 2 are assumed to be net of pension contributions, as in PIMS 1, although this was not specified. Dates for PIMS 1 and 2 are best estimates based on descriptive evidence.

Variable definition	Name of variable	Campbell et al. 1963-1998	Shumway 1 1962-1992	Shumway 2 1962-1992	Chava & Jarrow 1962-1999	Ohlson 1970-1976	PIMS 1 1980-1997	PIMS 2 1980-2009
Intercept	Intercept or Constant	**-7.65**	**-3.226**	**-13.303**	**-14.886**	-1.32	**-4.725**	4.662
Profitability variables								
Net income/Book value of total assets	NITA			-1.982	**-1.9236**	-2.37		
Net income/Market value of total assets (with lags, geometrically weighted)	NIMTAAVG	**-32.52**						
EBIT/Total Assets	EBIT/TA		**-8.946**					
Sales/Total assets	S/TA		0.158					
First difference in net income/Sum of abs. value of net incomes in numerator	CHIN					-0.521		
Liquidity Variables								
Stock of cash and short term investments/market value of total assets	CASHMTA	**-4.89**						
Working capital/Book value of total assets	WC/TA		-0.732			-1.43		
Current liabilities/Current assets	CLCA					0.757		
Funding provided by operations/Total Liabilities	FUTL					**-1.83**		
One if net income was negative for last 2 years	INTWO					**0.285**		
Cash flow net of pension contributions/Total assets (1 lag)**	$(CF_{t-1} - Cont_{t-1})/A_{t-1}$						**-3.7866**	3.8125
Cash flow net of pension contributions/Total assets (2 lags)**	$(CF_{t-2} - Cont_{t-2})/A_{t-2}$						**-1.4679**	2.0676
Leverage Variables								
Total liabilities/Book value of total assets	TLTA			**3.593**	**4.0338**	**6.03**		
Total liabilities/Market value of total assets	TLMTA	**4.32**						
Retained earnings/Book value of total assets	RE/TA		-0.818					
One if total liabilities exceeds total assets	OENEG					**-1.72**		
Market equity/Book value of total liabilities	ME/TL		**-1.712**					
Log Market equity/Book value of total debt (1 lag)	$ln(ED_{t-1})$						**-0.8336**	0.9197
Log Market equity/Book value of total debt (2 lags)	$ln(ED_{t-2})$						0.781	-0.2406
Log Pension funding ratio	$ln(FundingRatio_{t-1})$						-0.0902	0.1302
Size variables								
Log of firm's market equity/Total valuation of S&P 500	RSIZE	**0.246**						
Log of firm's market equity/Total valuation of NYSE and AMEX	Relative Size or RSIZ			**-0.467**	**-0.3475**			
Size	SIZE					**-0.407**		
Log Employment (1 lag)	$ln(Nt-1)$						**-0.2925**	0.2503
Log Change in Employment (1 lag)	$\Delta ln(N_{t-1})$						**-0.7154**	0.6676

Table 1, continued: Parameter estimates from major logit bankruptcy studies and PIMS

Variable definition	Name of variable	Campbell et al. 1963-1998	Shumway 1 1962-1992	Shumway 2 1962-1992	Chava & Jarrow 1962-1999	Ohlson 1970-1976	PIMS 1 1980-1997	PIMS 2 1980-2009
Market variables								
Log of gross excess return/Value-weighted S&P 500 total return (with lags, geometrically weighted)	EXRETAVG	**-9.51**						
Gross excess return/Value weighted NYSE and AMEX return	EXRET (2)			**-1.809**	**-2.662**			
Square root of the sum of squared stock returns over 3-month period (annualized)	SIGMA	**0.92**			**0.8312**			
Idiosyncratic standard deviation of stock returns	SIGMA2			5.791				
Market to book ratio	MB	**0.099**						
Log price per share	PRICE	**-0.882**						
Other firm variables								
Log age	Ln(age)		0.015					
Missing pension funding ratio	Missing FR_{t-1} dummy						-0.0275	
Manufacturing and minerals	Ind2				-0.4597			
Transportation, communications, and utilities	Ind3 or UT				-0.0178		**-1.642**	1.6721
Financials and insurance	Ind4 or F				-1.226		**-3.0279**	2.7136
Manufacturing and minerals (interaction with NITA)	NITA*IND2				0.3414			
Transportation, communications, and utilities (interaction with NITA)	NITA*IND3				**-2.5921**			
Financials and insurance (interaction with NITA)	NITA*IND4				**-3.4877**			
Manufacturing and minerals (interaction with TLTA)	TLTA*IND2				0.3547			
Transportation, communications, and utilities (interaction with TLTA)	TLTA*IND3				-0.3423			
Financials and insurance (interaction with TLTA)	TLTA*IND4				-0.2175			
Interaction of ED and N	$ln(ED_{t-1})ln(N_{t-1})$						-0.0485	0.0373

Table 1: Macroeconomic Time Series Data

The table gives a full listing of included macroeconomic time series data x_t and binary indicators b_t. All time series are obtained from the St. Louis Fed online database, http://research.stlouisfed.org/fred2/.

Category	Summary of time series in category	Shortname	Total no
(a) Macro indicators, and business cycle conditions	Industrial production index	indpro	5
	Disposable personal income	dspi	
	ISM Manufacturing index	napm	
	Uni Michigan consumer sentiment	umich	
	New housing permits	permit	
(b) Labour market conditions	Civilian unemployment rate	unrate	4
	Median duration of unemployment	uempmed	
	Average weekly hours index	AWHI	
	Total non-farm payrolls	payems	
(c) Monetary policy and financing conditions	Government bond term structure spread	gs10	6
	Federal funds rate	fedfunds	
	Moody's seasoned Baa corporate bond yield	baa	
	Mortgage rates, 30 year	mortg	
	10 year treasury rate, constant maturity	tssprd	
	Credit spread corporates over treasuries	credtsprd	
(d) Bank lending	Total Consumer Credit Outstanding	totalsl	2
	Total Real Estate Loans, all banks	realln	
(e) Cost of resources	PPI Fuels and related Energy	ppieng	3
	PPI Finished Goods	ppifgs	
	Trade-weighted U.S. dollar exchange rate	twexbmth	
(f) Stock market returns	S&P 500 yearly returns	s_p500	2
	S&P 500 return volatility	vola	
			22