



# Comparing Capital Requirements in Different Regulatory Frameworks

September 2019





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# Preface

The Board of Governors of the Federal Reserve System is responsible for protecting the safety and soundness of depository institutions affiliated with holding companies. This responsibility requires regulating the capital of holding companies of groups that conduct both depository and insurance operations.<sup>1</sup> Unfortunately, the insurance and banking sectors do not share any common capital assessment methodology. Existing capital assessment methodologies are tailored to either banking or insurance and unsuitable for application to the other sector.<sup>2</sup>

The Board proposes relying on these existing sectoral capital assessment methodologies to assess capital for most holding companies that own both insured depository institutions and insurers. In this proposed approach, capital requirements would be aggregated across sectors to calculate a group-wide capital requirement. Just as adding money denominated in different currencies requires exchange rates, meaningfully aggregating capital resources and requirements calculated under different regulatory frameworks requires some translation mechanism between them. This paper refers to the process of translating capital measures between regulatory frameworks as “scaling.”

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<sup>1</sup> 12 USC 5371.

<sup>2</sup> Insurance methodologies are also generally country specific.



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# Executive Summary

This white paper examines scaling. Scaling has not previously been the subject of academic research, and industry practitioners don't agree on the best methodology.

This paper introduces a scaling method based on historical probability of default (PD) and explains why the Board's proposal uses this approach. This method uses historical default rates as a shared economic language to enable translation. Concretely, scalars pair solvency ratios that have identical estimated historical insolvency rates. An analysis of U.S. data produces the simple scaling formulas below.

NAIC Authorized Control Level Risk-Based Capital =  $.0106 * \text{Risk-Weighted Assets}$

NAIC Total Adjusted Capital =  $\text{Bank Tier 1 Capital} + \text{Bank Tier 2 Capital} - .063 * \text{Risk-Weighted Assets}$

This paper also compares the PD method and alternatives, including those suggested by commenters in response to the Board's advance notice of proposed rulemaking (ANPR).<sup>3</sup> While other implementable methods make broad assumptions regarding equivalence, the historical PD method only assumes that companies have equivalent financial strength when defaulting.<sup>4</sup> The major disadvantage of the PD approach is that it needs extensive data. Plentiful data exists on U.S. markets but not many international markets. Because of this and because the Board's current population of supervised insurance groups has immaterial international insurance operations, scalars for other jurisdictions were not developed.

## Key Concepts

- Scaling can be simplified into the calculation of two parameters: (1) a required capital scalar and (2) an available capital scalar.
- There are at least three considerations of importance in assessing the scaling methods: (1) reasonableness of the assumptions, (2) ease of implementation, and (3) stability of the parameterization.
- Our analysis identifies a trade-off between the reasonableness of a methodology's assumptions and the easiness of its implementation. Easily producing stable results generally requires bold assumptions about the comparability of regulatory frameworks.
- The Board's recommended scaling approach (PD method) relies on an analysis of historical default rates in the different regulatory frameworks.

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<sup>3</sup> Capital Requirements for Supervised Institutions Significantly Engaged in Insurance Activities, 81 Fed. Reg. 38,631 (June 14, 2016), <https://www.gpo.gov/fdsys/pkg/FR-2016-06-14/pdf/2016-14004.pdf>.

<sup>4</sup> See the "Historical Probability of Default" section for details of this method. An empirical check on the assumption regarding companies defaulting at similar levels of financial strength can be found in the "Reasonableness of Assumptions" section.



# Introduction

In its ANPR of June 2016, the Board proposed a building block approach (BBA) for regulating the capital of banking organizations with substantial insurance operations.<sup>5</sup> For these institutions, the building block approach would first calculate the capital resources and requirements of its subsidiary institutions in different sectors. After making adjustments that provide consistency on key items and ensure risks are not excluded or double counted, the building blocks would be scaled to a standard basis and then aggregated to calculate enterprise-level available capital and required capital.

Building blocks originate in regulatory frameworks, referred to as “regimes,” with different metrics and scales. They need to be standardized before they can be stacked together. This paper refers to the process of translating capital measures from different regimes into a common standard as “scaling.” Based on the firms that would be subject to the proposed rule currently, only two regimes would be material: the regime applicable to U.S. banks and the regime applicable to U.S. insurers, which is the National Association of Insurance Commissioner (NAIC) Risk-Based Capital (RBC) requirements.<sup>6</sup> These regimes use starkly different rules, accounting standards, and risk measures. While both the banking and insurance risk-based capital standards use risk factors or weights to derive their capital requirements, they differ in the risks captured, the risk factors used, and the base measurement that is multiplied by these factors. In banking, the regulatory risk measure applies risk weights to assets and off-balance-sheet activities. This produces risk-weighted assets (RWA). In insurance, the reported risk metric—“Authorized Control Level Risk-Based Capital Requirement (ACL RBC)” —uses a different methodology. Among other differences, this methodology emphasizes risks on liabilities and gives credit for diversification between assets and liabilities.

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<sup>5</sup> This approach is expanded upon in the Board’s proposed rule.

<sup>6</sup> Where material, unregulated financial activity would also be assessed under one of those regimes and aggregated.



# Scaling Framework and Assessment Criteria

Scaling translates available capital (AC) and required capital (RC) between two different regimes. This paper refers to the original regime as the applicable regime and the output regime—under which comparisons are ultimately made—as the common regime. The Board’s proposal uses NAIC RBC as the common regime.

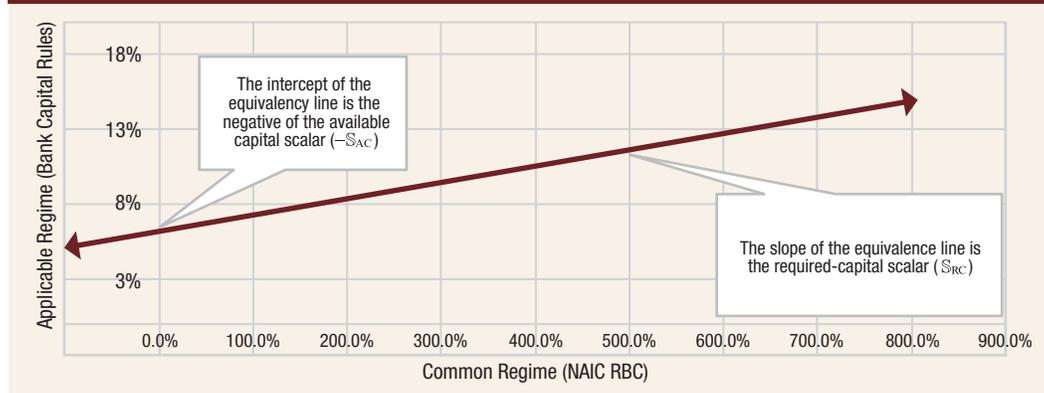
The scaling formulas below provide a generalized scaling framework with two parameters and enough flexibility to represent our proposal and all scaling methods suggested by commenters. One parameter, referred to as the required capital or  $S_{RC}$  applies to RC in the applicable regime and captures the average difference in the “stringency” of the regimes’ RC calculations and the units used to express the RC. We assume that differences in stringency between regimes’ risk measurements can be modeled by a single multiplicative factor. The second parameter, referred to as the available capital scalar or  $S_{AC}$  adjusts for the relative conservatism of the AC. This parameter represents the additional amount of conservatism in the calculation of AC in the applicable regime relative to the common regime. Unlike the multiplicative scaling of required capital, we assume available capital is an additive adjustment that varies based on a company’s risk. This allows the issuance of additional capital instruments, such as common stock, to increase available capital equally in both regimes, while still allowing for the regimes to value risky assets and liabilities with differing degrees of conservatism.

$$RC_{\text{common}} = S_{RC} * RC_{\text{applicable}}$$

$$AC_{\text{common}} = AC_{\text{applicable}} + S_{AC} * RC_{\text{applicable}}$$

These scaling parameters also have graphical interpretations that illustrate their meaning. An equivalency line between the solvency ratios of regimes (AC divided by RC) has a slope of  $S_{RC}$  and intercept of  $-S_{AC}$  when plotted with the common regime as the x-axis. [Figure 1](#) depicts this relationship, and appendix 1 shows a full derivation of this graphical illustration.

**Figure 1. Illustration of hypothetical equivalence line**



In this two-parameter framework, a scaling methodology represents a way of calculating  $S_{RC}$  and  $S_{AC}$ . Possible scaling methodologies range from making very simple assumptions about

equivalence to using complex methods involving data to estimate these relationships. There are at least three considerations of importance in assessing the scaling methods. We identify these as the reasonableness of the assumptions, ease of implementation, and stability of the parameterization.

The first of these is the reasonableness of the assumptions. Methodologies that make crude assumptions likely won't produce accurate translations. Accurate translations between regimes enable a more meaningful aggregation of metrics, thus allowing the Board to better assess the safety and soundness of institutions and ultimately to better mitigate unsafe or unsound conditions.

Another important consideration is the method's ease of implementation. The most theoretically sound methodology would lack practical value if it cannot be parameterized.

A final consideration is the stability of their parameterization—the extent to which changes in assumptions or data affect the value of the scalars. Scaling should be robust across time unless the underlying regimes change. This stability provides predictability to firms and facilitates planning.

# Historical Probability of Default

A sensible economic benchmark for solvency ratios is the insolvency or default rates associated with them, and the Historical PD method uses these rates as a Rosetta stone for translating ratios between regimes. For example, under this method a bank solvency ratio that has historically resulted in a 5 percent PD translates to the insurance solvency ratio with an estimated 5 percent PD.<sup>7</sup>

Mechanically, this calculation uses (logistic) regressions to estimate the relationship between the solvency ratios and default probability.<sup>8</sup> Setting the logit of PD in both regimes equal to each other gives an equation that relates the solvency ratios in the two regimes as shown below.

$$a_{applicable} + b_{applicable} * \frac{AC_{applicable}}{RC_{applicable}} = \frac{PD}{1 - PD} = a_{common} + b_{common} * \frac{AC_{common}}{RC_{common}}$$

In these formulas, “b” represents the slope of the estimated relationship between a regime’s solvency ratio and (logistic) default probability and “a” represents the intercept. Simplifying this equation produces the equations below, as demonstrated in [appendix 2](#).

$$S_{RC} = \frac{b_{common}}{b_{applicable}}$$

$$S_{AC} = \frac{a_{applicable} - a_{common}}{b_{applicable}}$$

This section will illustrate the approach and describe how it was used to derive the proposed scalars for U.S. banking and U.S. insurance. The approach will then be discussed in terms of the three identified considerations for scaling methods. This analysis reveals that the method generally can provide an accurate and stable translation of regimes for which robust data are available, which is why the Board has proposed to rely on the method for setting the scalar between the U.S. banking regime and the U.S. insurance regime.

## Application to U.S. Banking and Insurance

To apply this approach, we obtained financial data on depository institutions and insurers. Insurance financial data came from statutory financial statements. Bank data came from year-end Call Reports.<sup>9</sup> The Call Report, which is filed by the operating depository institutions, provides the best match for the insurance data, which are only for the operating insurance companies as of year-end. The usage of operating company data also comports with the

<sup>7</sup> The PD needs to be monotonic on the financial strength ratios for this approach to produce a single mapping.

<sup>8</sup> The logistic transformation is used because the regression involves probabilities. If ordinary least squares were used instead, estimated probabilities of default could be lower than 0 percent or higher than 100 percent for some solvency ratios.

<sup>9</sup> Call report data were downloaded from the publicly available Federal Financial Institutions Examination Council database and supplemented with internal data. See “Bulk Data Download,” Federal Financial Institutions Examination Council, <https://cdr.ffiec.gov/public/PWS/DownloadBulkData.aspx>.

Board’s proposed grouping scheme, which would be at a level below the holding company. For the solvency ratios, we used ACL RBC for insurers because it can easily be calculated from reported information and serves as the basis for state regulatory interventions in the NAIC’s Risk-Based Capital for Insurer’s Model Act.<sup>10</sup> Many different solvency ratios are calculated for banks. We used the total capitalization ratio. This broad regulatory capital ratio is the closest match in banking for ACL RBC for insurance in terms of which instruments are included.<sup>11</sup>

Several filters were applied to the data. Only data after 1998 and before 2015 were used based on data availability, state adoption of insurance risk-based capital laws, and the three-year default horizon discussed below.<sup>12</sup> Very small entities—those with less than \$5 million in assets—were excluded from both sectors. These firms had total asset size only sufficient to pay a handful of claims or large loan losses; their default data appeared unreliable and could not generally be corroborated by news articles or other sources. Organizations with very high and low capital ratios were also excluded (insurance ratios < -200% or >1500% ACL RBC; banks with total capitalization <3% or >20% RWA). Additionally, carriers not subject to capital regulation and those that fundamentally differ from other insurers were excluded. These included captive insurers (for example, an insurer owned by a manufacturer that insures only that manufacturer); government-sponsored enterprises (for example, workers compensation state funds); and monoline group health or medical malpractice insurers. P&C fronting companies were also removed. Summary statistics showing the magnitude of these exclusions can be seen in [appendix 3](#).

We also obtained default data for the banking and insurance sectors. A three-year time horizon for defaults was used in both regimes to balance the competing considerations of wanting to observe a reasonable number of defaults beyond the most weakly capitalized companies and maximizing the number of data points that could be used in the regression.<sup>13</sup> Because of the Board’s supervisory mission, “default” was defined as ceasing to function as a going concern due to financial distress. This definition did not always align with the point of regulatory intervention or commonly available data. Consequently, existing regulatory default data sets were supplemented to best align with the default definition.<sup>14</sup>

Insurance default data were obtained from the NAIC’s Global Insurance Receivership Information Database (GRID).<sup>15</sup> Because some insurers cease to function as going concerns without being reported in this data set, which is voluntary and impacted by confidentiality, a

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<sup>10</sup> The BBA would not be impacted by using different multiples of these amounts because the required capital scalar is multiplicative. For instance, Company Action Level (CAL) RBC is two times ACL RBC. If this were used in the scaling regressions, all insurance solvency ratios would be cut in half. This would produce corresponding changes to the scaling equations and required capital ratios, but the overall capital requirement would remain constant when expressed in terms of dollars. Similarly, the rule would not be impacted by using some fraction of risk-weighted assets (for example, 8 percent) for banks.

<sup>11</sup> The proposed rule uses limits and other adjustments to further align the definition of regulatory capital between the two regimes and ensure sufficient quality of capital.

<sup>12</sup> For state adoption dates, see “Risk Based Capital (RBC) for Insurers Model Act,” National Association of Insurance Commissioners, <http://www.naic.org/store/free/MDL-312.pdf>, 15–20.

<sup>13</sup> The impact of this assumption was analyzed and is discussed in the context of the stability of the method’s parameterization in the “[Stability of Parameterization](#)” section.

<sup>14</sup> An empirical check on the reasonableness of these assumptions and alignment can be found in the “[Reasonableness of Assumptions](#)” section.

<sup>15</sup> The NAIC’s GRID database can be accessed at <https://i-site.naic.org/grid/gridPA.jsp>.

supplemental analysis was also performed.<sup>16</sup> An insurer was also considered to be in default if it fell below the minimum capital requirement and (1) had its license suspended in any state, (2) was acquired, or (3) discontinued underwriting new businesses. Extensive checks were performed on random companies as well as all outliers (those with high RBC ratios that default and low RBC ratios that do not default). This resulted in the development of criteria above and the identification of some additional defaults based on news articles and other data sources.<sup>17</sup>

For banking organizations, default data were extracted from the FDIC list of failures.<sup>18</sup> For this analysis, banking organizations were also considered to be in default if they were significantly undercapitalized (total capitalization below 6 percent of RWA) and did not recover, which might occur in a voluntary liquidation. Additionally, banking organizations with total capitalization ratios under 6 percent of RWA for multiple years were manually checked for indications that operations ceased. The different default rates by industry are shown in [table 1](#) and [figure 2](#).

To estimate the probabilities of default from these data, we used a logistic regression, which is commonly used with binary data, to estimate the parameters  $a$  and  $b$  in the equation below. The regression used cluster-robust standard errors with clustering by company. Additional details about these regressions can be found in [table 2](#) with a discussion of their goodness of fit and robustness following in the sections below.

$$\text{logit}(PD_i) = a + b * \left(\frac{AC}{RC}\right)_i + \varepsilon_i$$

The parameters on the P&C and life insurance regressions were analyzed separately because the regimes are distinct; however, the regression results were very close to each other with no

**Table 1. Default rates by industry**

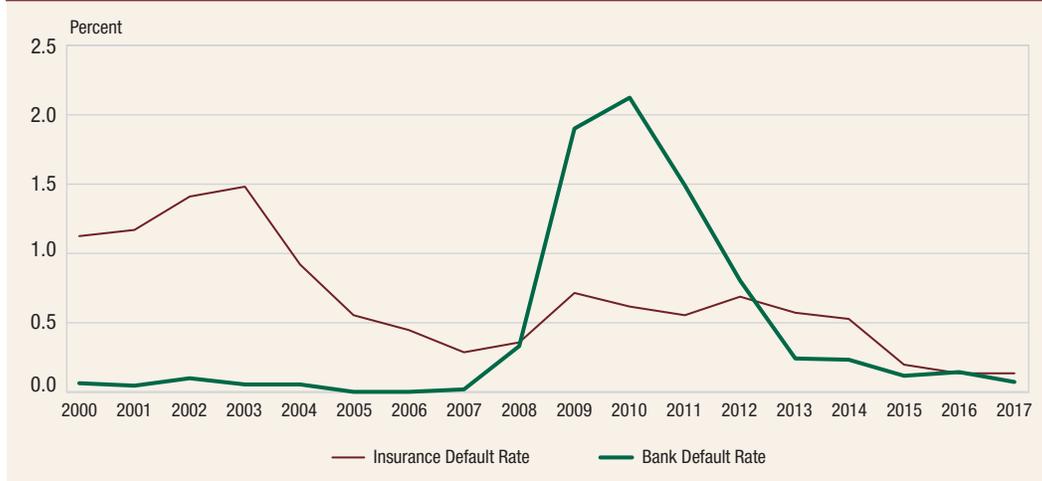
Year	Insurance defaults	Bank defaults
2000	23	4
2001	23	3
2002	27	6
2003	28	3
2004	17	3
2005	10	0
2006	8	0
2007	5	1
2008	6	19
2009	12	112
2010	10	122
2011	9	80
2012	11	40
2013	9	12
2014	8	11
2015	3	5
2016	2	6
2017	2	3

<sup>16</sup> The NAIC describes GRID as “a voluntary database provided by the state insurance departments to report information on insurer receiverships for consumers, claimants, and guaranty funds” at <https://eapps.naic.org/cis/>. See also NAIC, GRID FAQs, available at <https://i-site.naic.org/help/html/GRID%20FAQs.html> (“In some states a court ordered conservation may be confidential.”)

<sup>17</sup> A handful of companies were identified as no longer being going concerns based on qualitative sources such as news articles, rating agency publications, or in notes to the financial statements that could not easily be applied to all companies. Additionally, several companies were removed who appear to have ceased functioning as going concerns at a time prior to the sample based on the volume of premiums written. Two companies were dropped from the data set for having aberrant data.

<sup>18</sup> See <https://www.fdic.gov/bank/individual/failed/banklist.csv>.

**Figure 2. Default rates by industry**



significant statistical difference.<sup>19</sup> The results of the combined insurance and banking regressions are displayed in [table 2](#).

**Table 2. Insurance and banking regressions**

Parameter	Banking	P&C Insurance	Life Insurance	Combined Insurance
Slope (b)	-66.392	-0.714	-0.662	-0.704
Robust standard error	(1.854)	(0.052)	(0.102)	(0.046)
Intercept (a)	3.723	-0.402	-0.602	-0.432
Robust standard error	(0.201)	(0.178)	(0.440)	(0.164)
Observations	92,215	21,031	6,862	27,893
Pseudo R <sup>2</sup>	24.9%	23.3%	20.3%	23.3%

Using the formulas from the start of this section that relate logistic regression output to scaling parameters,  $\mathbb{S}_{RC}=1.06\%$  and  $\mathbb{S}_{AC}=-6.3\%$ .

These results appear reasonable and suggest that the banking capital requirement is approximately equivalent to the insurance capital requirement but that the regimes differ in their structure. The insurance regime’s conservative accounting rules lead to a conservative calculation of available capital. These rules set life insurance reserves at above the best-estimate level, don’t allow P&C carriers to defer acquisition expenses on policies, and don’t give any credit for certain types of assets. Because of this conservative calculation of available capital, the required capital calculation is relatively lower with ACLR RBC translating to only about 1 percent of RWA.

<sup>19</sup> Because the two slope values are very close (-.662 and -.714), the p value of a test of differences is close to 50 percent). The constant terms show larger differences (-.402 vs. -.602) and could indicate that P&C companies have slightly less balance sheet conservatism compared with life insurers; however, the difference is not statistically significant either (p ~ .44).

## Reasonableness of Assumptions

Because regulators design solvency ratios to identify companies in danger of failing, default rates are a natural benchmark for assessing them economically. Comparing solvency ratios based on this benchmark is more reasonable than the alternatives, but it does have limitations.

One important limitation is that definitions of default across sectors may be difficult to compare. To some extent, defaults are influenced by regulatory actions, which are entwined with the underlying regime itself. Although adjustments can be made (as we do with our default definition in the U.S. markets), there is likely still some endogeneity. However, defaults still provide a more objective assessment of the regime than the alternatives discussed in “[Review of Other Scaling Methods](#)” under which these differences would be assumed not to exist. For instance, one primary alternative would be to scale by assuming the equivalency of regulatory intervention points. Another would assume that the accounting is comparable.

As a test of the comparability of the default definitions, we estimated each sector’s loss given default. If the default definitions in both sectors were equivalent economically, then the cost of these defaults should also be close. Based on data from the FDIC, the average bank insolvency in the period studied was approximately 10.7 percent of assets with a median of 22.4 percent. The median is significantly higher than the mean because of the very large Washington Mutual failure. Excluding Washington Mutual, the mean insolvency cost was 18.7 percent. We estimated the cost of insurance insolvencies by comparing the cost to insurance guarantee fund assessments during the sample period with the assets of insurers that defaulted using our definition. This produced an estimate of insolvency costs of 16.9 percent of net-admitted assets. This is between the median and mean of the bank distribution and close to the bank mean when Washington Mutual is excluded. This supports our assumption that institutions identified as defaulting can be considered to have comparable financial strength.

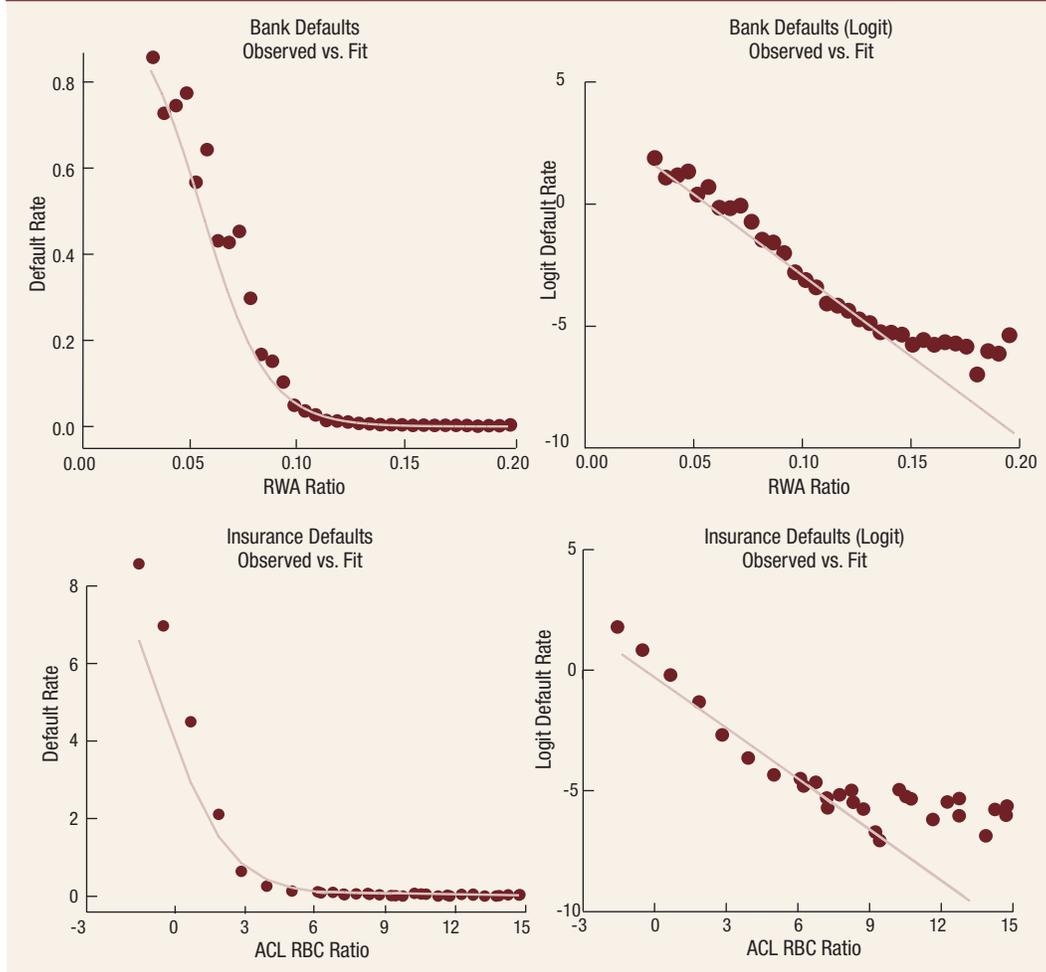
Historical insolvency rates also do not reflect regime changes and can be influenced by government support. In the application to U.S. banking and insurance, no adjustment was made for these factors, which are difficult to quantify and would likely offset each other to some extent over the period studied. Banking organizations have been more affected by past government support, which might imply the regressions underestimate PD, but there has recently been a significant tightening of the regime after the 2008 financial crisis, which would have an opposite effect.<sup>20</sup> Additionally, support from the major government programs during the financial crisis depended on the firm being able to survive without it. On the insurance side, government support during the crisis was much less extensive, but there has also not been a similar recent strengthening of the regime.<sup>21</sup> To the extent the regimes were to have material, directional changes, this assumption would be less reasonable and likely need to be revisited in a future study.

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<sup>20</sup> Since the crisis, a number of reforms have been made to the banking capital requirements in the United States, including a reduction in the importance of internal models and additional regulation of liquidity. These reforms would make banks less likely to default at a given total capitalization ratio.

<sup>21</sup> The major changes to insurance regulation following the crisis have been the introduction of an Own Risk and Solvency Assessment along with some enterprise-wide monitoring. These would make insurers safer at a given capital ratio. The recently passed principle-based reserving requirements, which generally lowered reserves on many insurance products, would have the opposite effect.

**Figure 3. Goodness of fit graphs of historical PD regressions**



An additional limitation is the assumption of linearity in the relationship between solvency ratios and default probabilities after the logistic transformation. Figure 3 shows the goodness of fit of the PD estimation for U.S. banking and insurance. The red dots represent actual observed default rates. The light red line represents the output from the regressions discussed above. The figures on the left are the same as those on the right after the logistic transformation.

The regressions produce a reasonably good fit to the available data, but the linear fit breaks down for very highly capitalized companies in both sectors. Consistent with other research, beyond a certain point, capital does not appear to have a large impact on the probability of a company defaulting. We considered a piece-wise fit to address this issue, but decided against it for three reasons. First, this issue has little practical impact because it only affects very strongly capitalized companies. Differentiating between these companies is not the focus of the capital rule. Second, a piece-wise function would drastically increase the complexity of the process. Simple scaling formulas can be derived if a single logistic regression is used for

each.<sup>22</sup> Translating piece-wise regressions into workable scaling formulas would require simplifications that could outweigh any otherwise improved accuracy. Third, the required number of parameters needed to fit a piece-wise model would more than double and introduce additional uncertainty about the parameters.

## Ease of Implementation

The biggest disadvantage of this approach is data availability. The approach requires a large number of default events to calibrate the impact of the solvency ratio accurately. Although these data are available on the currently needed regimes, they may not be available in other regimes for which scalars could be needed in the future.

## Stability of Parameterization

The parameter estimates appear stable and robust. As one basic measure of stability and robustness, we estimated the standard error of the scaling estimates by simulating from normal distributions with the mean of the underlying regression parameters and standard deviation of their standard error. This measure indicated a 95 percent confidence interval of between .010 and .013 for  $S_{RC}$  and between -.054 and -.071 for  $S_{AC}$ . This confidence interval is a fairly tight range given the spread of other methods.

We also tested the robustness of the methodology on out-of-sample data. To do this, we split the sample at the year 2010. Data from prior to 2010 were used to parameterize the model while data from 2010 and subsequent years were used to assess the goodness of fit. [Figure 4](#) displays the results of this test. The model performs fairly well on this test. The goodness of fit on the out-of-sample data appears comparable to those within the entire data set.

We also tested the parameterization for sensitivity to key assumptions, which would not be captured by the estimated standard errors. A description of these tests and the resulting scalars are displayed in [table 3](#). We also attempted to test the impact of the exclusion of some data, including companies with very high or very low solvency ratios, but we found that the regression showed little relationship between the capital ratios and default probabilities in both regimes when outlier entities that have ratios that are orders of magnitude apart from typical companies are included.

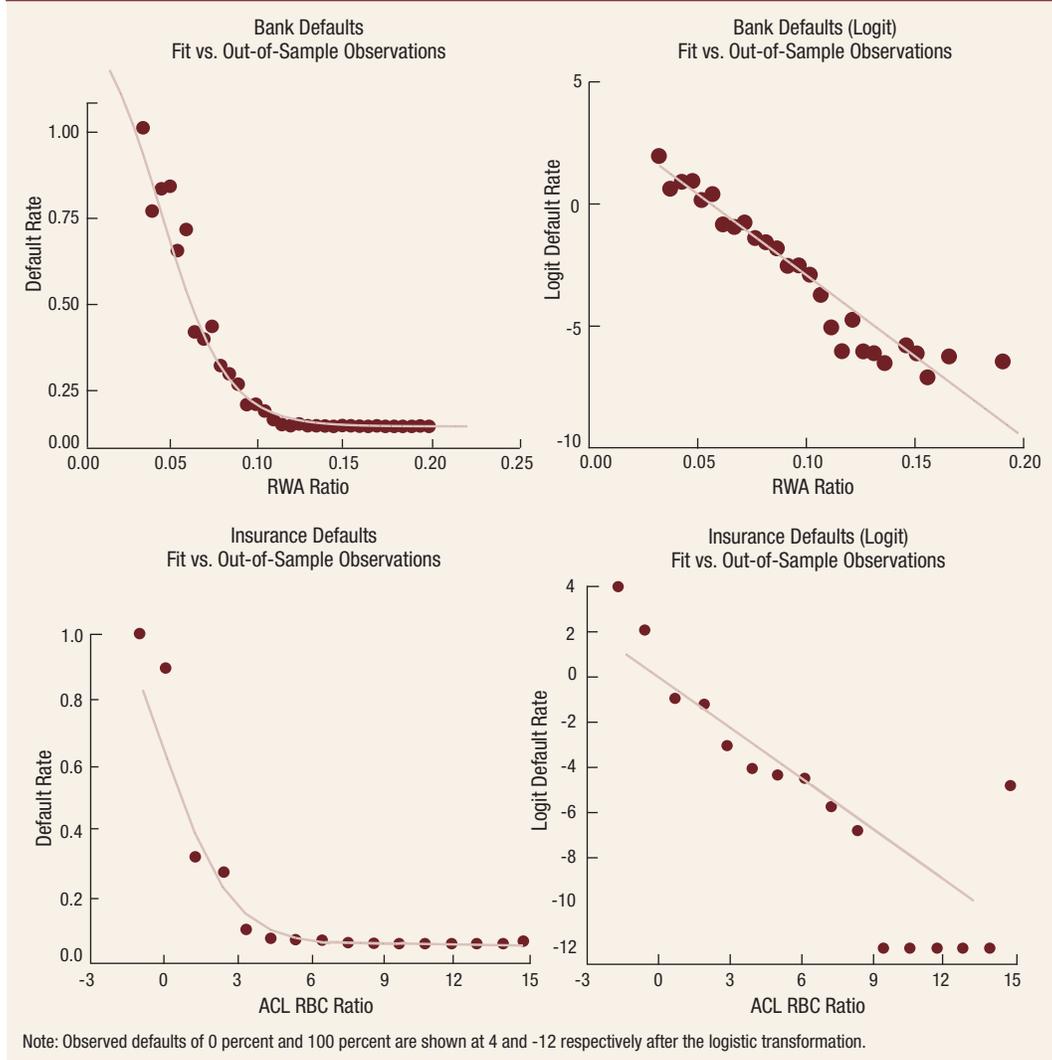
## Summary and Conclusion

The use of historical default probabilities can produce a reasonable scalar for U.S. banking and insurance. The primary disadvantage is the data required, which may not be available for other jurisdictions. Because this method has a relatively robust parameterization, the parameters would not need to be updated on a set schedule and could be instead be revisited if new data or conditions suggest a change is warranted.

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<sup>22</sup> See [appendix 2](#) for the derivation of the simple formulas if no piece-wise regression is used.

**Figure 4. Goodness of fit of methodology with out-of-sample data**



**Table 3. Results of robustness tests of historical PD method**

Name	Description	$S_{AC}$	$S_{RM}$
Baseline	Assumptions used in the proposal	-6.26%	1.06%
Excluding firms under \$100 million	Firms with a largest size of less than \$100 million in assets are excluded	-6.51%	1.17%
Wider solvency ratio bounds	Insurance bounds are to allow ratios between -300% to 2000% of ACL RBC to be used in the regression. Banking bounds are similarly moved to 2% and 30% of RWA.	-6.06%	1.10%
Largest half of companies	The smallest 50% of companies as measured by their peak total asset size are excluded from both the banking and insurance samples.	-5.72%	2.21%
1-year default definition	A one-year default horizon is used in place of the baseline three-year window.	-6.15%	0.96%
No Crisis	The financial crisis (2009–10) is excluded from the sample by using a one-year default horizon and excluding observations from year-end 2008 and year-end 2009.	-5.60%	0.91%



# Review of Other Scaling Methods

Other methods exist for calibrating the scaling parameters. This section gives a description of these methods and compares them to the historical PD method based on the desired characteristics described before. The methods are arranged roughly in order of their ease of parameterization. At one end of the spectrum, not scaling is very simple, but it is not likely to produce an accurate translation. At the other end of the spectrum, scaling based on market-derived probabilities of default and scaling based on a granular analysis of each regime’s methodologies have theoretical advantages but cannot be parameterized even for U.S. banking and U.S. insurance. Between these extremes, some methods can be parameterized but generally have less reasonable assumptions than the historical PD method.

## Not Scaling

One scaling method would be to assume that no scaling is required, as might be tempting for solvency ratios of the same order of magnitude. This method would be equivalent to assuming that  $S_{AC}$  were equal to zero and  $S_{RC}$  were equal to one.

Although this approach would be very stable and not require parameterization, the assumption generally appears unreasonable because of the many differences between regimes. A typical ACL RBC ratio would be hundreds of percent. The average bank operates with an RWA ratio near 16 percent. Furthermore, although the numerators in these ratios might be deemed as comparable under certain circumstances, the denominators are conceptually very different. The denominator in insurance is required capital; the denominator in banking is risk-weighted assets.

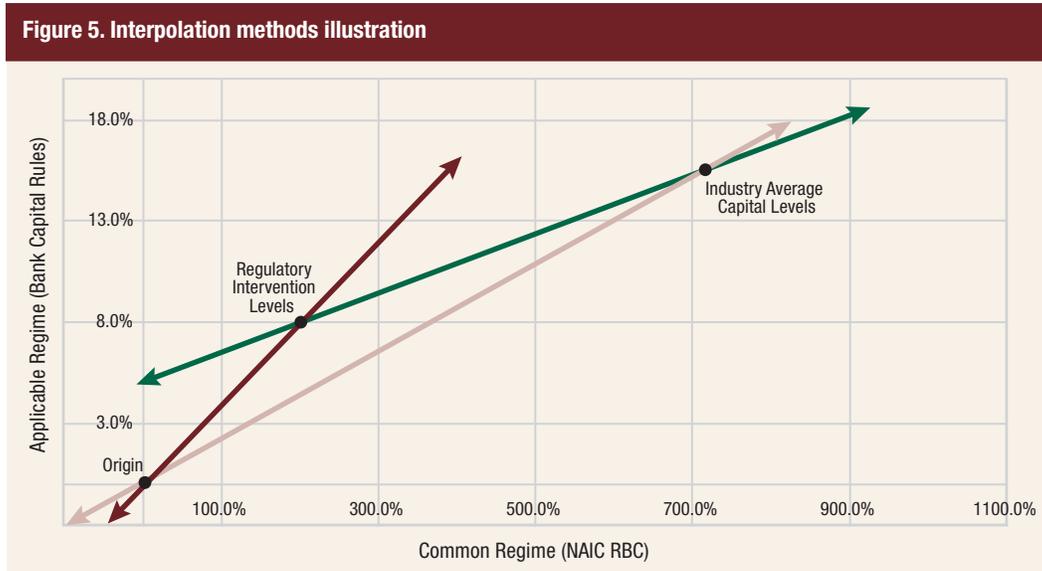
## Scaling by Interpolating Between Assumed Equivalent Points

This category of methods would take two assumed equivalent solvency ratios and use interpolation between these to produce an assumed equivalence line and the implied scaling parameters. The methods in this category would vary primarily in terms of how they derive the assumed equivalency points (see table 4).

Assumed equivalence	Reasonableness of assumptions	Ease of parameterization	Stability of parameterization
Available capital calculations	Regimes are known to differ materially in how they compute key aspects of available capital including insurance reserves	Parameterized by assumption	Very stable by assumption
Regulatory intervention levels	Regulatory objectives vary, which could justify intervening at different levels	Very easy	Very stable because regulatory intervention points do not frequently change
Industry average capital levels	Corporate structure considerations in each of these industries are very different, and the average financial strength is unlikely to be comparable.	Easy	Least stable – the industry’s capital ratio frequently changes and the ratio of U.S. industry averages has varied by almost 50% between 2002 and 2007.

It is possible to mix and match from these assumptions to produce a scaling methodology as illustrated in figure 5. In this figure, each of the three assumptions is plotted as an assumed equivalence point. For example, an 8 percent level of bank capital and 200 percent of ACL RBC translate to comparable regulatory interventions so (200 percent, 8 percent) is shown as

the regulatory intervention equivalence point. An assumption that scaling is not required on available capital translates to equivalence at (0 percent, 0 percent) because a company with no available capital in one regime would also have no available capital after scaling. Three different lines are illustrated which show the three different ways these assumptions could be combined to produce scaling methodology.



Most commenters on the ANPR suggested one of these methods, but commenters were split as to which assumptions were better. A plurality of commenters suggested not assuming equivalence in available capital calculations because, as the Board noted in the ANPR, regimes do differ significantly in how they calculate available capital. However, one disadvantage of this method is that the average capital levels in a regime may not always be available, so it might not be possible to parameterize it for all regimes.

It is also possible to add different adjustments to these methods. For instance, rather than directly using the regulatory intervention points, one could first adjust these to make them more comparable. To the extent that one knew that the regulatory intervention point was set at a given level (for example, 99.9 percent over 1 year vs. 99.5 percent over one year) then it would be possible to adjust the intervention point in one regime to move it to a targeted confidence level that aligns with another regime. However, given that these targeted calibration levels are more aspiration than likely to ultimately be supported by empirical data, this adjustment does not significantly improve the reasonableness of the underlying assumptions.

Some other adjustments could marginally improve the analysis. For instance, although it is plausible that industries in similarly developed economies could be similar, assuming equivalence across starkly different economies is less reasonable. In particular, the level of general country risk within a jurisdiction is likely to affect both insurance companies and insurance regulators, and some adjustment for this could improve the method.

Although these adjustments do marginally improve the methods, methods in this category would still not be making as reasonable of assumptions as the historical PD method. We do not consider it appropriate to use any method in this category in setting the scalar between

the Board's bank capital rule and NAIC RBC. This category of methods could, however, have utility where simple assumptions are needed to support calibration.

## Scaling Based on Accounting Analysis

A different data-based method that was considered would use accounting data in place of default data. Under this method, the distribution of companies' income and surplus changes would be analyzed similarly to how the Board calibrated the surcharge on systemically important banks.<sup>23</sup> If companies routinely lost multiples of the regulatory capital requirement, the regulatory capital requirement likely is not stringent.

Turning this intuition into a scaling methodology requires an additional assumption about equivalent ratios.<sup>24</sup> Numbers can be scaled to preserve the probability of having this ratio (or worse) after a given time horizon. For example, if we define insolvency as having assets equal to liabilities and assume this definition is comparable in both regimes, then we can scale capital ratios based on the probability of a loss larger than the capital ratio being observed. A derivation of scaling formulas from these assumptions is contained in [appendix 4](#).

Although this method appears more reasonable than the simple interpolation methods, the assumptions are not as sound as for the historical PD method. Although there is some endogeneity with defaults, there is much more with accounting data. Regimes differ greatly in how they calculate net income and surplus changes such that benchmarking against a distribution of these values may not bring the desired comparability. The additional assumption required on equivalence is also problematic as it would essentially require incorporating one of the problematic assumptions discussed in the previous section on interpolation.

In terms of the ease of parameterization, the method ranks somewhere between the historical PD method and the simple methods based on interpolation. Income data are plentiful relative to both historical default data and market-derived default data. This ubiquity of the data could allow for calibration of additional regimes and allow changes in regimes to be picked up before default experience emerges.

To parameterize this method for U.S. banking and insurance, we started with the distribution of bank losses discussed in the calibration of the systemic risk charge for banks (see [figure 6](#)).

To apply this method to insurance, historical data on statutory net income relative to a company's authorized control level were extracted from SNL. Data were collected on the 95 insurance groups with the relevant available data in SNL and over \$10 billion in assets as of 2006.<sup>25</sup> Quarterly data points were used over the period of time for which they were available (2002 to 2016). A regression was then run on the estimated percentiles and log of the net income values to smooth the distribution and allow extrapolation. [Figure 7](#) shows the distribution of ACL RBC returns resulting from this analysis.

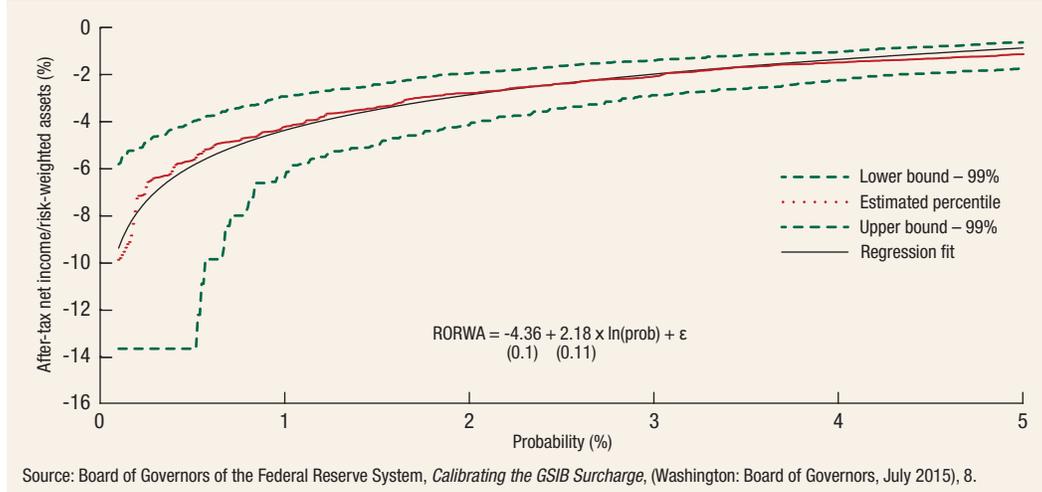
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<sup>23</sup> Board of Governors of the Federal Reserve System, *Calibrating the GSIB Surcharge*, (Washington: Board of Governors, July 20, 2015), <https://www.federalreserve.gov/aboutthefed/boardmeetings/gsib-methodology-paper-20150720.pdf>.

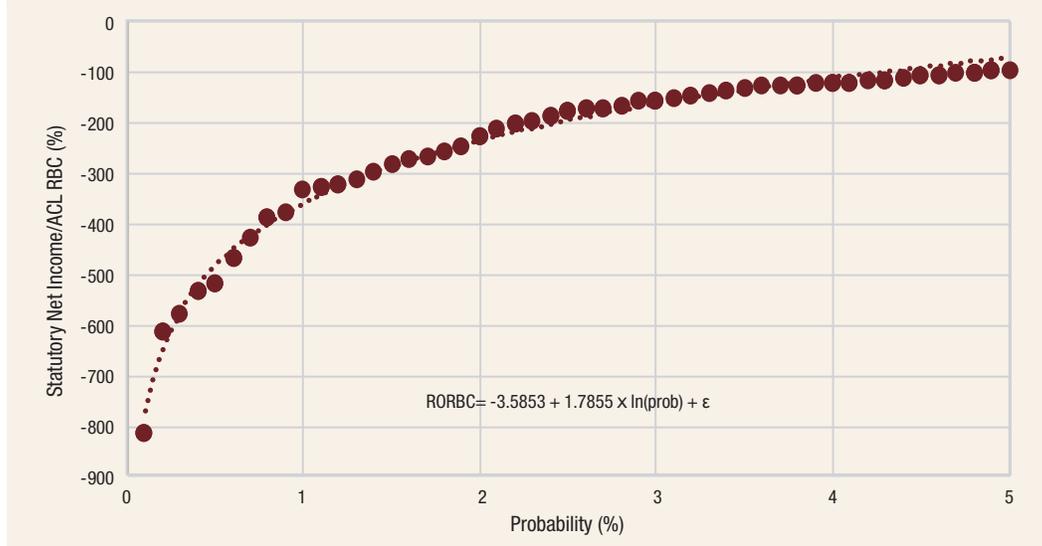
<sup>24</sup> This parameter and assumption were not necessary in calibrating the surcharge on systemically important banks because that only depended on the change in default probability as capital changes, rather than the absolute magnitude of the default probability.

<sup>25</sup> Ninety-five groups met the size criteria, but three of these groups did not have RBC or income data and produced errors when attempting to pull the data. Two of these companies were financial guarantors.

**Figure 6. Returns on risk-weighted assets (RORWA) (bottom five percentiles, 50 largest BHCs in each quarter, 2Q87 through 4Q14)**



**Figure 7. Return on ACL RBC (bottom five percentiles)**



Unlike with historical PD, an analysis of the top 50 life and P&C groups based on year-end 2006 assets under this method strongly suggested a different calibration. Historically, P&C carriers are significantly less likely than life carriers to experience large losses relative to their risk-based capital requirements. In 2008, nearly half the largest life insurance groups experienced losses that were above their authorized control level regulatory capital requirement. P&C insurers were much less likely to experience comparable losses. [Table 5](#) shows the scalars produced when the NAIC RBC life regime is used as the base.

## Scaling Based on a Sample of Companies in Both Regimes

Another scaling method would be to analyze a group of companies in both regimes. From a sample of companies in both regimes, it would be possible to run a regression to parameterize an equivalency line that represents the expected value in the common regime based on their information in the applicable regime.

Although analyzing a single group of companies under both regimes would provide a solid foundation for assuming equivalence theoretically, there are problems with this method under the stated criteria.

One issue is that calculating a given company's ratio under both regimes would likely not be appropriate because it would involve applying the regime outside of its intended domain. Applying the bank capital rules to insurers or the insurance capital rules to banks for calculating the scalar will not necessarily give comparable results. Although a result for a bank could be calculated under the insurance capital rules, this result may not really be comparable to insurers scoring similarly because their risk profiles differ. Indeed, the lack of a suitable regime for companies in both sectors is the primary reason the Board is proposing the BBA rather than applying one of the existing sectoral methodologies to the consolidated group.

Another disadvantage of this method is the difficulty of implementation. Companies typically do not calculate their results under multiple regimes. The limited available data, including the data from the Board's prior QIS, do not statistically represent the situations where a scalar is needed. Barriers to obtaining a representative sample of companies make this method very difficult to parameterize.<sup>26</sup>

Because of these problems, we do not recommend using this methodology as a basis for scaling under the proposal.

## Scaling Based on Market-Derived PDs

The intuition of this method is similar to the historical probability of default method, but it would use market data to calibrate the relationship between solvency ratios and expected defaults. Market data can be used to calculate implied default probabilities with some additional assumptions. Credit default swap (CDS) prices or bond spreads depend heavily on default probabilities, and a Merton model can translate equity prices and volatilities into default probabilities.

Using market-derived default probabilities in place of historical data would have theoretical advantages over the recommended method. Because market signals are forward looking, this method could better capture changes in regimes. It might also be better able to address issues with past government support if the market no longer perceives institutions as likely to be rescued.

**Table 5. Scalars based on accounting analysis results**

Regime	$S_{AC}$	$S_{RC}$
P&C NAIC RBC	12.82%	20.50%
Bank capital	0.70%	1.60%

<sup>26</sup> The limitations of this method may not apply in the international insurance context where the development of an appropriate international capital standard for insurance companies might make it possible to benchmark various insurance regimes.

Although theoretically appealing, the data limitations prevent this method from being used. Bonds are heterogeneous and not frequently traded; equity prices are difficult to translate into default probabilities. Even in the largest markets where CDS data exists, only a handful of companies have CDS information, and these companies are not necessarily representative of the broader market. For U.S. insurance, an additional issue is that regulatory ratios are not available at the holding company level and market data are unavailable at the operating company level.<sup>27</sup>

We attempted to parameterize the scalar for the U.S. market using CDS data from Bloomberg and simple assumptions on recovery rates, but were unable to produce sensible results. Although the historical data show a strong relationship between capital levels and default probabilities, the strong relationship did not hold in our CDS analysis.

Several data restrictions might explain this issue. Only a small number of issuers have observable credit default spreads. Additionally, these are generally at the holding company level, which necessitated making assumptions for insurers as no group solvency ratio exists. Additionally, only relatively well-capitalized banking organizations appear to have CDSs traded currently, potentially creating a section bias. The historical PD data demonstrates that beyond a certain point, capital does not strongly affect default probability.

Other potential explanations of this result exist. Changes in risk aversion and liquidity premiums across the panel period could also explain the results. Time-fixed effects were included in some specifications of the regressions, but they did not improve the outcome of this method. Endogeneity between banks' held capital and their stress testing results may also contribute to the lack of sensible results.

Because of the lack of sensible results, we do not recommend using this method to set the scalars.

## Scaling Based on Regime Methodology Analysis

Another method would be to try to derive the appropriate scalars from a bottom-up analysis of the regimes, including the factors applied to specific risks and the components of available capital. Unfortunately, the differences between the regimes can be inventoried, but such an inventory cannot theoretically or practically be turned into a scaling methodology. In each regime, the risks captured are tailored to those present in the sector. The insurance methodology has complex rules around the calculation of natural catastrophe losses, and the bank regime has complex rules that apply for institutions that have significant market-making operations. Deriving an appropriate scaling methodology from the bottom up based on these differences would require quantifying each of them and then weighting to these differences to calculate an average. This calculation would be infeasible between banking and insurance regimes given the number of differences. Additionally, there are theoretical problems with trying to derive a weighting methodology from the differences that appropriately reflects the risk profiles of both banks and insurers.

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<sup>27</sup> Although in some cases a sum of the capital of subsidiaries may be a reasonable proxy for the capital of the group, this approach would not be true for many entities including those with large foreign operations or using affiliated reinsurance transactions (captives). Only a handful of companies have reasonable proxies available for both NAIC RBC and the market-implied default rate of the company.

## Conclusion

This white paper describes our attempt to identify and evaluate different scaling methodologies. We find the PD approach based on historical data could be used to translate information between regimes in a way that preserves the economic meaning of solvency ratios. This method, however, requires data that are not currently available for some regimes outside of the United States. The election of the scaling approach is therefore a choice between using a single simple approach to scaling in all economies or differentiating the scaling approach by country and using the historical PD domestically. We recommend the latter. Although this approach will involve more work and some uncertainty for companies operating in countries with limited data, it should allow for scaling that is more accurate and aid comparability.

Scalars for non-U.S. regimes are not specified in the proposed rule given the Board's supervisory population. These may be set through individual rulemakings as needed. For the scalar between Regulation Q and NAIC RBC, the Board's proposal relies on the historical probability of default method.

We believe that the historical PD method derived in this paper will produce the most faithful translation of financial information between the U.S. banking and insurance regimes. Historical insolvency rates are currently the most credible economic benchmark to assess regimes against, and the long track record and excellent data on both the insurance and the bank U.S. regimes make this analysis feasible.



# Appendix 1: Graphical Interpretation of Scaling Parameters Derivation

We assume that there is some linear transformation between solvency ratios in different regimes, which we decompose into AC and RC to facilitate aggregation.

$$\alpha + \beta * \frac{AC_{\text{common}}}{RC_{\text{common}}} = \frac{AC_{\text{applicable}}}{RC_{\text{applicable}}}$$

Solving for the ratio in the common regime and then rewriting:

$$\frac{AC_{\text{common}}}{RC_{\text{common}}} = \left( \frac{AC_{\text{applicable}}}{RC_{\text{applicable}}} - \alpha \right) * \frac{1}{\beta}$$

$$\frac{AC_{\text{common}}}{RC_{\text{common}}} = \frac{AC_{\text{applicable}} - \alpha * RC_{\text{applicable}}}{\beta * RC_{\text{applicable}}}$$

If the denominators and numerators are equal then:

$$RC_{\text{common}} = \beta * RC_{\text{applicable}}$$

$$AC_{\text{common}} = AC_{\text{applicable}} - \alpha * RC_{\text{applicable}}$$

Using the equations for  $S_{RC}$  and  $S_{AC}$  :

$$S_{RC} = \beta$$

$$S_{AC} = -\alpha$$



## Appendix 2: Derivation of the Historical Probability of Default Formulas

Using a logistic regression, the probability of a company defaulting can be expressed as

$$p(d) = \frac{1}{e^{a+b \cdot \frac{AC}{RC}}}$$

where  $a$  and  $b$  are fit with the regression,  $AC$  is available capital and  $RC$  is required capital.

Setting the two default probabilities equal to each other to preserve this relationship when scaling produces:

$$\frac{1}{e^{a_{applicable} + b_{applicable} \cdot \frac{AC_{applicable}}{RC_{applicable}}}} = p(d) = \frac{1}{e^{a_{common} + b_{common} \cdot \frac{AC_{common}}{RC_{common}}}}$$

These equations can then be simplified to allow calculation of the scaled solvency ratio.

$$a_{applicable} + b_{applicable} \cdot \frac{AC_{applicable}}{RC_{applicable}} = a_{common} + b_{common} \cdot \frac{AC_{common}}{RC_{common}}$$

$$b_{applicable} \cdot \frac{AC_{applicable}}{RC_{applicable}} = a_{common} - a_{applicable} + b_{common} \cdot \frac{AC_{common}}{RC_{common}}$$

$$\frac{AC_{applicable}}{RC_{applicable}} = \frac{a_{common} - a_{applicable}}{b_{applicable}} + \frac{b_{common}}{b_{applicable}} \cdot \frac{AC_{common}}{RC_{common}}$$

Using the graphical-interpretation formulas in appendix 1, the scalars are:

$$S_{AC} = -\frac{a_{common} - a_{applicable}}{b_{applicable}} = \frac{a_{applicable} - a_{common}}{b_{applicable}}$$

$$S_{RC} = \frac{b_{common}}{b_{applicable}}$$



## Appendix 3: Data Summary Statistics

Table A.1 and table A.2 show summary statistics on banks and insurers. A.1 shows the statistics when all firms are excluded. A.2 shows the filtered data used for the regressions.

Table A.1. Summary statistics on insurers and banks, all firms							
Variable	mean	sd	p5	p25	p50	p75	p95
Total assets	410,000	2,100,000	20,000	56,000	120,000	270,000	1,200,000
Risk-weighted assets	290,000	1,700,000	11,000	35,000	79,000	180,000	820,000
RWA ratio	22%	133%	10%	12%	15%	20%	37%
Bank observations				122,147			
Net-admitted assets	1,800,000	11,000,000	2,800	14,000	56,000	300,000	4,900,000
ACL RBC ratio	69365%	6700000%	276%	575%	971%	2491%	37816%
Insurance observations				54,663			

Table A.2. Summary statistics on insurers and banks, baseline assumptions							
Variable	mean	sd	p5	p25	p50	p75	p95
Total assets	460,000	2,300,000	26,000	69,000	140,000	310,000	1,400,000
Risk-weighted assets	340,000	1,900,000	18,000	47,000	99,000	220,000	1,000,000
RWA ratio	14%	3%	10%	12%	14%	16%	19%
Bank observations				92,215			
Net-admitted assets	3,000,000	16,000,000	7,300	35,000	150,000	710,000	11,000,000
ACL RBC ratio	728%	324%	262%	477%	690%	952%	1332%
Insurance observations				27,893			



# Appendix 4: Derivation of Accounting Analysis Scaling Formulas

Using a logarithmic regression between a company's income relative to their required capital yields the following formulas:

$$\frac{Income}{RC} = a + b * \ln(probability)$$

$$Prob(Income < r) = e^{\frac{r-a}{b}}$$

Setting the probabilities of loss (negative income) greater than the solvency ratio equals yields:

$$e^{\frac{-r_{common} - a_{common}}{b_{common}}} = e^{\frac{-r_{applicable} - a_{applicable}}{b_{applicable}}}$$

Solving for the solvency ratio in the applicable regime:

$$\frac{-r_{applicable} - a_{applicable}}{b_{applicable}} = \frac{-r_{common} - a_{common}}{b_{common}}$$

$$\frac{r_{applicable} + a_{applicable}}{b_{applicable}} = \frac{r_{common} + a_{common}}{b_{common}}$$

$$r_{applicable} + a_{applicable} = \frac{r_{common} + a_{common}}{b_{common}} * b_{applicable}$$

$$r_{applicable} = \frac{r_{common} + a_{common}}{b_{common}} * b_{applicable} - a_{applicable}$$

$$r_{applicable} = \frac{b_{applicable}}{b_{common}} * r_{common} + \left( a_{common} * \frac{b_{applicable}}{b_{common}} - a_{applicable} \right)$$

Using the formulas related to the graphical interpretation of the scaling formula, these formulas become

$$\mathbb{S}_{AC} = \left( a_{applicable} - a_{common} * \frac{b_{applicable}}{b_{common}} \right)$$

$$\mathbb{S}_{RC} = \frac{b_{applicable}}{b_{common}}$$

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