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March 7, 2016

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Mr. Robert E. Feldman, Executive Secretary
Attention: Comments
Federal Deposit Insurance Corporation
550 17th Street, N.W.
Washington, D.C. 20429

Re: RIN 3064-AE37

Ladies and Gentlemen:

I am writing on behalf of Promontory Interfinancial Network, LLC ("*Promontory*")[1] to comment on the Notice of Proposed Rulemaking on Assessments issued by the Federal Deposit Insurance Corporation (the "*FDIC*") on February 4, 2016.[2] In the 2016 NPR, the FDIC requests comment on a proposed rule that would amend 12 C.F.R. Part 327 to modify the deposit insurance assessment system for established small banks (the "*Proposed Rule*"). The Proposed Rule would set assessment rates for small banks using a financial ratios method based largely on a new statistical model that estimates the probability of failure over three years. Promontory incorporates the attached Schedule 1, Data Analysis, into this letter by reference.

INTRODUCTION AND SUMMARY

Under the Notice of Proposed Rulemaking on Assessments issued on July 13, 2015,[3] the FDIC proposed (1) applying to Risk Category I small banks (small banks that are well-capitalized with CAMELS ratings of 1 or 2) a ratio of core deposits to total assets in which reciprocal deposits would be treated as non-core and (2) replacing the adjusted brokered deposit ratio for Risk Category I banks (the "*Adjusted Brokered Deposit Ratio*") with both a new core deposit ratio and a separate one-year asset growth rate factor (adjusted for mergers and acquisitions).

In the 2016 NPR, acknowledging comments from Promontory, national and state trade organizations, and several hundred small banks, the FDIC has withdrawn the core deposit ratio and replaced it with a brokered deposit ratio. In the new brokered deposit ratio, consistent with

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[1] Founded in 2002, Promontory provides services to the banking and brokerage industries. Promontory's deposit allocation services include CDARS®, the Certificate of Deposit Account Registry Service®, for time deposits, ICS®, the Insured Cash Sweep® service, for non-time deposits, and IND®, the Insured Network Deposits® service, for automated sweeping of funds to non-time deposit accounts.

[2] FDIC, *Notice of Proposed Rulemaking on Assessments*, 81 Fed. Reg. 6,108 (February 4, 2016) ("*2016 NPR*").

[3] FDIC, *Notice of Proposed Rulemaking on Assessments*, 80 Fed. Reg. 40,838 (July 13, 2015) ("*2015 NPR*").

current regulations, reciprocal deposits are excluded from the numerator for Risk Category I small banks. The salutary effect is that such banks are not penalized for reciprocal brokered deposits.

For non-reciprocal brokered deposits, however, the 2016 NPR departs from the current assessment methodology by using a statistical model that treats the brokered deposit ratio and the asset growth rate factor as separate independent variables. Whereas the current Adjusted Brokered Deposit Ratio is non-zero only in the presence of both brokered deposits in excess of 10% of domestic deposits and asset growth in excess of an average of 40% over four years, the 2016 NPR penalizes Risk Category I small banks for <u>either</u> brokered deposits exceeding 10% of total assets <u>or</u> asset growth in excess of 10% over one year.

Promontory applauds the FDIC for having withdrawn the proposed core deposit ratio that appeared in the 2015 NPR and for having excluded reciprocal deposits from brokered deposits in the 2016 NPR for purposes of calculating the brokered deposit ratio of Risk Category I small banks. The FDIC has excluded reciprocal deposits from brokered deposits in assessment calculations for Risk Category I small banks since 2009,[4] and the continuation of this approach recognizes that the FDIC has been right all along in doing so.

Promontory respectfully submits, however, that the FDIC has also been right all along in treating the brokered deposit ratio and the asset growth rate factor for Risk Category I small banks as a combined single variable, referred to in Schedule 1 as an interaction term, so that such banks are not penalized for exceeding one of the dual thresholds in this independent variable if they do not exceed the other. By recognizing that the brokered deposit ratio and the asset growth rate factor are properly combined, the FDIC under current regulations targets banks that might actually be using brokered deposits to fund excessively rapid asset growth without penalizing banks that use such deposits in the constructive ways that the FDIC has also recognized are possible. For the FDIC now to reverse course on this point would be to replace a reasoned and successful approach with one that disregards the principal process by which brokered deposits have been said by the FDIC itself to carry potential risks.

DISCUSSION

1. <u>The FDIC Is Right to Exclude Reciprocal Deposits from the Numerator in the Brokered Deposit Ratio</u>.

As recommended by Promontory and hundreds of other commenters, the 2016 NPR excludes reciprocal deposits from the numerator of the brokered deposit ratio as applied to Risk Category I small banks. This change from the 2015 NPR represents sound, data-driven policymaking by the FDIC and is clearly correct, for the reasons stated in Promontory's comments on the 2015 NPR.

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[4] *See* FDIC, *Notice of Final Rule on Assessments*, 74 Fed. Reg. 9,525, 9,532 (March 4, 2009) ("*2009 Notice of Final Rule*").

2. The FDIC Should Retain Its Current Policy of Treating the Brokered Deposit Ratio and the Asset Growth Rate as a Combined Single Variable.

The adjusted brokered deposit ratio that applies to a Risk Category I small bank under current regulations is zero if non-reciprocal brokered deposits do not exceed 10% of domestic deposits or if the four-year cumulative gross asset growth rate (adjusted for mergers and acquisitions) does not exceed 40% (10% per annum). As a result, the Adjusted Brokered Deposits Ratio not only avoids penalizing a Risk Category I small bank for reciprocal brokered deposits, but also avoids penalizing such a bank for non-reciprocal brokered deposits if the bank has low levels of such deposits or the bank has low levels of annual growth.

Under the 2016 NPR, in contrast, a Risk Category I small bank would face a higher assessment for brokered deposits above the 10% threshold even if they were not being used to fund rapid growth. In addition, such a bank would face a higher assessment for an annual growth rate above 10% even if the growth were not being funded by brokered deposits. This bifurcation of the single combined variable into two separate variables is not supported either by what the FDIC itself has observed about the nature of brokered deposit risk or by the FDIC's statistical model.

The Current FDIC Assessment System Correctly Focuses on Small Banks That Use Brokered Deposits to Fund Excessively Rapid Asset Growth.

The FDIC has recognized that brokered deposits offer important potential benefits if they are not used to fund excessively rapid asset growth. The FDIC has stated: "Brokered deposits can be a valuable funding source when banks manage them well and use them to grow prudently."[5] Brokered deposits represent free markets at work. Among other things, brokered deposits increase deposit options for consumers, facilitate industry innovation, and provide banks – especially community banks – with access to funding that they could not otherwise obtain. Money is fungible, and brokered deposits are deposits, neither inherently good nor inherently evil.

Nevertheless, brokered deposits (as well as some other types of deposits, such as deposits gathered through rate boards) can give rise to risk, if they are misused in funding asset growth. The FDIC has recently observed:

> Brokered deposits can be a suitable funding source when properly managed as part of an overall, prudent funding strategy. However, some banks have used brokered deposits to fund unsound or rapid expansion of loan and investment portfolios, which has contributed to weakened financial and liquidity positions over successive economic cycles.[6]

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[5] FDIC, *Study on Core Deposits and Brokered Deposits*, https://www.fdic.gov/regulations/reform/coredeposit-study.pdf, at 34 (July 8, 2011) ("*FDIC Brokered Deposit Study*").

[6] FDIC, *Frequently Asked Questions Regarding Identifying, Accepting, and Reporting Brokered Deposits* ("*FDIC FAQ*"), https://www.fdic.gov/news/news/financial/2015/fil15051b.pdf, at A3 (citing FDIC Brokered Deposit Study).

In other words, brokered deposits are potentially risky when they fund "[r]apid growth," which "is associated with higher bank failure rates . . . ."[7]

Consistent with the FDIC's findings, the challenge for thoughtful regulation is to target for assessment increases those brokered deposits that actually present elevated risk, without unfairly and counterproductively penalizing banks for brokered deposits that are being put to good and prudent use. In establishing a risk-based assessment system, the FDIC until now has sought to do just that. As stated in the FDIC Brokered Deposit Study:

> [I]n October 2008, the FDIC issued a notice of proposed rulemaking proposing to increase assessment rates for well-managed, well-capitalized banks that used brokered deposits to grow quickly and noted that "A number of costly institution failures, including some recent failures, have experienced rapid asset growth before failure and have funded this growth through brokered deposits."[8]

In keeping with this focus, the FDIC explicitly designed the Adjusted Brokered Deposits Ratio to serve as a measurement not of brokered deposits *per se*, but of "the extent to which brokered deposits are funding rapid asset growth."[9] Under current regulations, if a bank's brokered deposits are low (not more than 10% of its domestic deposits), or if its asset growth is low (not

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[7] Mindy West, Chief, Policy Program Development, and Chris Newbury, Associate Director, Division of Insurance and Research, *FDIC Presentation: Brokered and High Cost Deposits*, slide 40, https://www.fdic.gov/regulations/resources/minority/events/interagency2009/Presentations/Brokered.pdf (undated). 1. *Accord Remarks by Martin J. Gruenberg, Chairman, FDIC, to the 2013 ICBA National Convention, Las Vegas, Nevada*, https://www.fdic.gov/news/news/speeches/archives/2013/spmar1313.pdf, at 4 (March 13, 2013) (referring to "rapid growth" and "high-risk activities funded by volatile deposits").

Similarly, in material loss reviews, the FDIC has focused on rapid asset growth funded by brokered deposits (rather than condemning brokered deposits *per se*). For example:

> Broadway's access to brokered deposits helped fuel the bank's rapid asset growth and, therefore, was integral to the bank's ability to obtain and sustain its excessive CRE and ADC concentrations

FDIC, *OIG Material Loss Review of Broadway Bank, Chicago, Illinois*, Report No. MLR-11-004, https://www.fdicig.gov/reports11%5C11-004.pdf, at 13 (November 2010).

The same pattern has been observed in other failures. "With respect to the causes of institutions' failures, we found overly aggressive growth strategies fueled by volatile and costly wholesale funding (e.g. brokered deposits, FHLB loans, etc.) . . . ." Department of the Treasury Office of Inspector General, *Semiannual Report to Congress: October 1, 2009 - March 31, 2010*, https://www.treasury.gov/about/organizational-structure/ig/Documents/March%202010%20SAR%20Final%20%20(04-30-10).pdf at 10 (April 1, 2010).

[8] FDIC Brokered Deposit Study at 1 (quoting FDIC, *Notice of Proposed Rulemaking*, 73 Fed. Reg. 61,560, 61,565 (Oct. 16, 2008)). Other problems that are sometimes attributed to brokered deposits, such as excessively high rates, are closely related to, and ultimately part of, the potential misuse of such deposits to fund excessively rapid growth. For example, a bank that offers high rates to obtain brokered deposits typically does so because it wants the deposits to fund growth. If growth is not on the agenda, the incentive for such a bank to offer the high rates is absent.

[9] 2009 Notice of Final Rule, 74 Fed. Reg. at 9,530.

more than 40% over four years), then brokered deposits manifestly are not funding rapid asset growth, and a Risk Category I small bank's assessment rate is not increased.

There Is No Good Reason to Bifurcate the Brokered Deposit/Asset Growth Variable.

In the 2015 NPR, the FDIC acknowledged that "the current deposit insurance assessment system" – which includes the Adjusted Brokered Deposits Ratio for Risk Category I small banks, with its combined brokered deposit and asset growth variable – "effectively reflects the risk posed by small banks."[10] Given the process by which brokered deposits are hypothesized to lead to elevated risk through excessive growth, this finding is no surprise. In this respect, the FDIC's current Adjusted Brokered Deposits Ratio is well-tailored to achieve its objective.

The 2016 NPR states that the FDIC seeks "to more accurately reflect risk."[11] In the case of the combined brokered deposits-asset growth variable, however, the FDIC's stated rationale for replacing the Adjusted Brokered Deposits Ratio with separate brokered deposit and growth variables does not mention predictive accuracy. Nor does it provide any evidence that the change would increase such accuracy. Rather, the 2016 NPR merely states: "Few Risk Category I banks have both high levels of non-reciprocal brokered deposits and high asset growth, so the adjusted brokered deposit ratio affects relatively few banks."[12] Likewise, the 2015 NPR stated:

> The adjusted brokered deposit ratio increases a Risk Category I small bank's assessment rate only if the bank has both large amounts of brokered deposits and high asset growth. Few banks have both, so the ratio affects few banks."[13]

In other words, according to the 2015 NPR and the 2016 NPR, the combined variable with its conjunctive dual thresholds is faulty not because it fails to predict, but merely because it currently affects fewer banks than separate variables would.

The problem with this rationale is that there is nothing inherently better about imposing what amounts to a penalty on more banks. A regulation should not be made broader merely to make it broader. That few small banks in Risk Category I have both high brokered deposits and high growth means that, since 2009, few such banks have been using brokered deposits to fund imprudent growth. This is hardly a reason to subject more Risk Category I small banks to increased assessments.

The only plausible rationale for splitting the combined variable into two separate variables would arise if doing so improved the performance of the model. But the FDIC has provided no evidence that splitting the combined variable improves performance. On the contrary, as discussed

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[10] 2015 NPR, 80 Fed. Reg. at 40,842.

[11] 2016 NPR, 81 Fed. Reg. at 6,108.

[12] *Id.* at 6,112 n.26.

[13] 2015 NPR, 80 Fed Reg. at 40,843.

in the next section, splitting the combined variable appears to have the <u>opposite</u> effect. There is, accordingly, no reason for the FDIC to abandon the combined variable that has worked well in the Adjusted Brokered Deposits Ratio of existing FDIC regulations.

A Model with the Combined Variable Performs Better.

The absence of any evidence that the change from a combined variable to separate variables improves predictive accuracy should suffice, in itself, to maintain the current approach, especially given that the current approach reflects the FDIC's understanding of how brokered deposits and rapid growth interact to create elevated risk. Here, however, there is compelling evidence that the proposed splitting of the combined variable would make the FDIC model perform <u>less</u> well.

As set forth in the attached Schedule 1, Data Analysis, Promontory has obtained from the FDIC, through a Freedom of Information Act ("*FOIA*") request, all the Call Report data on which the new statistical model described in the 2016 NPR (the "*NPR Model*") relies. Using the results of the FOIA request together with other publicly-available data on failures and mergers and acquisitions (the "*FDIC Dataset*"), Promontory has created a close approximation of the NPR Model ("*Model 1*") and has compared the performance of Model 1 with the performance of a model that is identical to Model 1 except for the use of a combined single variable, with dual thresholds, in place of the separate brokered deposit and asset growth variables in the NPR Model and Model 1 ("*Model 2*").

Comparison of the performance of Model 1 and Model 2 leads to the following conclusions, which are further described in Schedule 1:

- For the full 1985-2014 period, Model 2 performs <u>at least as well</u> as Model 1. The independent variables in Model 2 have the same coefficient signs (positive or negative) as in Model 1, each independent variable in Model 2 is statistically significant at 0.000, and Model 2's effectiveness as measured by each regression's log likelihood ratio is statistically significant at 0.000. The accuracy rates for Model 2 are equivalent to those for Model 1 at 98.7% for each regression.

- For the two most relevant sub-periods, 1994-2014 and 2005-2014, Model 2 performs <u>better</u> than Model 1, which fails to maintain the expected coefficient signs and statistical significance across all independent variables.

  - In one of the three regressions for 1994-2014 (the full period after the savings and loan failure period) as well as one of the three regressions for 2005-2014 (the period that includes the recent financial crisis), the coefficient sign for the separate asset growth rate variable in Model 1 changes from positive to negative.

  - This result implies, counterintuitively and contrary to the FDIC's substantive analysis of failure processes, that a <u>higher</u> one-year asset growth predicts a <u>lower</u> probability of failure. Given this anomaly in Model 1, it is not surprising that the asset growth rate variable loses its statistically significant predictive power in these same regressions.

CONCLUSION

The FDIC has consistently acknowledged that brokered deposits have potential value, but increase risk if they are used to fund excessively rapid asset growth. Inherent in this understanding of how brokered deposits may contribute to failure is an understanding that the effect depends on an interaction between brokered deposits and asset growth. Consistent with this understanding, the Current Model treats brokered deposits and asset growth as a single combined variable with dual thresholds. In other words, the Current Model properly targets the misuse of brokered deposits for imprudent growth, but avoids penalizing properly-used brokered deposits or growth achieved through core deposits.[14]

The FDIC has also emphasized that the changes it proposes to implement through the 2016 NPR are based not on a belief that the Current Model has been ineffective, but on an effort to improve the model's performance. In proposing to replace the combined single variable for brokered deposits and asset growth reflected in the current Adjusted Brokered Deposits Ratio with two separate variables, however, the FDIC appears not to have considered retaining the combined single variable approach, which would be necessary to see whether this particular change actually is an improvement. Promontory's data analysis indicates that, had the FDIC done so, it would have found that the interactive effect of brokered deposits and asset growth is best measured by an interactive term with dual thresholds, as under the Current Model. A single combined variable approach not only predicts with high accuracy over the full 1985-2014 period, but also avoids the anomalies in the FDIC-like Model 1 for the 1994-2014 and 2005-2014 periods.

With no reason to believe that splitting the variable will improve model performance, and good reason to believe that it will impair performance, the only remaining argument for splitting the two variables is that, as the 2016 NPR suggests, doing so will affect more small banks. The prospect of penalizing a larger number of small banks is not, however, a valid basis on which to alter an approach to assessment that the FDIC agrees has been effective. Accordingly, Promontory respectfully submits that the FDIC should follow in its new model the combined single variable approach for brokered deposits and asset growth, with dual thresholds, as it appears in the Adjusted Brokered Deposits Ratio for Risk Category I small banks.

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[14] The FDIC has also taken care to make both of the dual thresholds in the combined variable high enough to avoid penalizing activity that does not present elevated risk. For example, the FDIC increased the asset growth threshold to 40% in the 2009 Final Rule from 20% in the notice of proposed rulemaking after finding that a 20% four-year growth rate would not represent excessive growth. *See* 2009 Notice of Final Rule, 74 Fed. Reg. at 9,532.

Thank you for consideration of our comments. Should you wish to discuss them further, please contact the undersigned at (703) 292-3333 (mjacobsen@promnetwork.com).

Sincerely,

Mark P. Jacobsen
President and Chief Executive Officer

Attachments: Schedule 1 and Appendices

SCHEDULE 1: DATA ANALYSIS

1. Models and Variables

In the Notice of Proposed Rulemaking on Assessments issued by the Federal Deposit Insurance Corporation (the "*FDIC*") on February 4, 2016,[1] the FDIC relies on a new statistical model designed to predict the probability of bank failure over a three-year period (the "*NPR Model*"). The NPR Model, as described in the 2016 NPR, relies on Call Report data and CAMELS ratings from 1985 through 2011 and failures through the end of 2014.[2]

The statistical model currently used by the FDIC for small bank assessments (the "*Current Model*") combines a Risk Category I small bank's brokered deposit ratio and asset growth rate into a single independent variable that assumes a non-zero value if both the brokered deposit ratio and the asset growth rate exceed specified thresholds (an "*Interaction Term*"). The NPR Model, in contrast, separates the Interaction Term into two independent variables, a brokered deposit ratio that assumes a non-zero value if brokered deposits are greater than 10% of total assets and an asset growth rate factor that assumes a non-zero value if the annual asset growth rate, adjusted for mergers and acquisitions of failed banks, is greater than 10% (the "*Separated Variables*").

Promontory has obtained from the FDIC, through a Freedom of Information Act ("*FOIA*") request, all the Call Report data on which the NPR Model relies. Using the results of the FOIA request together with other publicly-available data on failures and mergers and acquisitions (the "*FDIC Dataset*"), Promontory has created a close approximation of the NPR Model ("*Model 1*").[3] Model 1 differs from the NPR Model only in that it omits CAMELS ratings, because the FDIC treats even historical CAMELS ratings as confidential and they are, therefore, unavailable to Promontory.[4] Despite this constraint, Model 1 produces results that are highly consistent with the results of the NPR Model as

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[1] FDIC, *Notice of Proposed Rulemaking on Assessments*, 81 Fed. Reg. 6108 (February 4, 2016) ("*2016 NPR*").

[2] The NPR Model also relies on data from 1984 in computing a one-year asset growth rate for 1985.

[3] Promontory has also used publicly-available bank failure data and information on mergers and acquisitions of failed banks.

[4] In comparing models, tracking the FDIC's approach, Promontory has run three probit regressions on the calculated and winsorized financial ratios as independent variables (excluding the unavailable CAMELS ratings) for the period from 1985 through 2014. Probit Regression 1 includes bank records for the years ending 1985, 1988, 1991, etc., Probit Regression 2 includes bank records for the years ending 1986, 1989, 1992, etc., and Probit Regression 3 includes bank records for the years ending 1987, 1990, 1993, etc.

reported in the 2016 NPR, presumably because the CAMELS ratings are correlated with the other independent variables in the NPR Model.[5]

Promontory has also created a second model ("*Model 2*"), which is identical to Model 1 (and therefore also similar to the NPR Model), with the sole exception that, in Model 2, the Separated Variables are replaced by an Interaction Term that, in an approach similar to that of the Current Model, assumes a non-zero value only if both the brokered deposit ratio and the one-year asset growth rate exceed the 10% thresholds specified in the NPR.

Promontory has compared the performance of Model 2 with that of Model 1 to determine whether the proposed new Separated Variables approach (as in the 2016 NPR) produces results that are sufficiently better than those of the current Interaction Term approach (as in the Current Model) to justify replacing the current approach.[6] As set forth below, Promontory's analysis shows that the Interaction Term approach performs better than the Separated Variables approach in predicting bank failure.

2. Consistency of Model 1 with NPR Model

The following comparisons confirm that Model 1 closely approximates the NPR Model:

Coefficient Comparisons: Comparing the results of applying Promontory's Model 1 with the results of applying the NPR Model, and beginning with observing the coefficients' signs, one finds that Model 1 predicts that each independent variable has the same directional effect (*i.e.*, positive or negative effect) on probability of failure that the NPR Model predicts. The magnitude of these effects does vary across Model 1 and the NPR Model, but such variation is to be expected given the absence from Model 1 of an independent variable for CAMELS ratings.

Statistical Significance: Each independent variable in Model 1 is statistically significant in every regression. The p-values for each independent variable are found to be 0.000, with the exception of one-year asset growth having a p-value of 0.001 (which remains extremely statistically significant) in Model 1, Regression 2.

Model Effectiveness: The Model 1 regressions are all effective in their ability to predict probability of failure. The log-likelihood ratio ("*LLR*") p-values are statistically significant at 0.000 within each regression.

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[5] Indeed, in seeking to approximate the NPR Model, Promontory has found that the omission of CAMELS ratings has no adverse effect on the statistical significance of the remaining independent variables in predicting bank failure.

[6] There is no indication in the 2016 NPR that the FDIC performed such a comparison in developing the NPR Model.

Accuracy Rate: The accuracy rates[7] for Model 1 are 98.7% for Regression 1, 98.7% for Regression 2, and 98.8% for Regression 3.

3. Comparative Findings

Having determined that Model 1 closely approximates the NPR Model, Promontory has compared the performance of Model 2 (which uses the Interaction Term) with that of Model 1 (which uses the Separated Variables), for the full 1985-2014 period and for relevant sub-periods.

Overall Comparison

Coefficient Comparisons: Comparing the results of applying Model 2 with the results of applying Model 1, and beginning with observing the coefficients' signs, Promontory observes that Model 2 predicts that each independent variable has the same directional effect (*i.e.*, positive or negative effect) on probability of failure that Model 1 predicts. The magnitude of these effects varies somewhat, sometimes negligibly, as is to be expected from different models.

Statistical Significance: As in Model 1, each independent variable in Model 2 is statistically significant in every regression. The p-values for each independent variable are found to be 0.000.

Model Effectiveness: As in Model 1, the Model 2 regressions are all effective in their ability to predict probability of failure. The LLR p-values are statistically significant at 0.000 within each regression.

Accuracy Rate: The accuracy rates for Model 2 are equivalent to those for Model 1. The accuracy rates for Model 2 are 98.7% for each of the three regressions.

Relevant Sub-Periods

Promontory has further found that, for more recent and therefore arguably more relevant sub-periods of the 1985-2014 period, Model 2's performance is superior to that of Model 1. For the more recent periods, Model 2 is better able to maintain the expected coefficient signs and statistical significance across all independent variables.

In the course of reconstructing the FDIC Dataset using data produced by the FDIC in response to Promontory's FOIA request, Promontory observed that three distinct periods of bank failures emerge within the time horizon that the FDIC studied (*i.e.*, 1985 – 2014). These three periods are presented in Figure 1 below.

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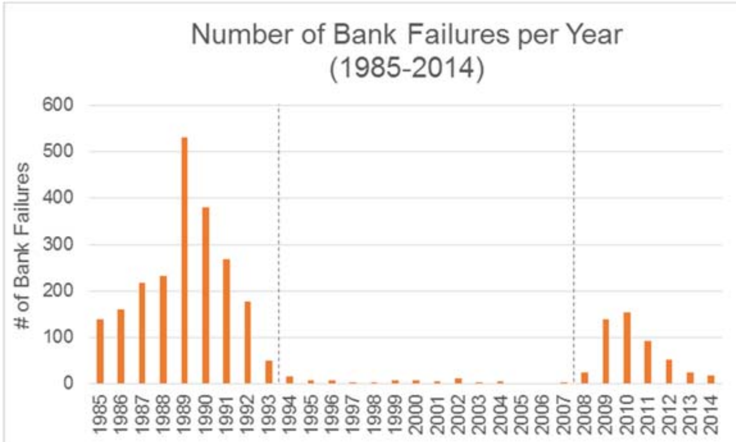
7 The accuracy rate as given here is the number of times the model correctly predicts failure (or non-failure) divided by the number of observations.

Figure 1



Source: FDIC

From 1985 through 2014, 2,733 banks, 99.5% of which were small banks, failed. The period from 1985 through 1993 contains 2,156 of these failures, or approximately 79% of the total failures studied. The period from 1994 through 2007 contains 73 failures (3% of all failures). Finally, the period from 2008 through 2014 contains 504 failures (18% of all failures). It is apparent that the distribution of bank failures across the time horizon is weighted at the beginning of the time period and, to a lesser extent, at the end. In addition, the regulatory and economic environments have substantially evolved and changed from 1985 through 2014.

Accordingly, one relevant sub-period consists of the last ten years of the 1985-2014 period, from 2005 through 2014. This period coincides with a period of increased failures during the financial crisis, beginning in 2008, and also includes the preceding three-year window consistent with the FDIC's approach to modeling failure. A second relevant sub-period consists of the 21 years from 1994 through 2014, which immediately follows the elevated failure levels of 1985-1993 resulting from the savings and loan failures.

When Model 1 and Model 2 are applied to the FDIC Dataset for 2005-2014 (the period most comparable to current circumstances, including the recent financial crisis) and 1994-2014 (the full post-savings and loan crisis period), serious anomalies appear in Model 1, but not in Model 2. These anomalies indicate that Model 2, with the Interaction Term, performs better than the FDIC-like Model 1 in predicting bank failure.

In Regression 3 for the 2005-2014 time period, and in regression 2 for the 1994-2011 time period, the coefficient sign for the separate asset growth rate variable in Model 1 changes from positive to negative. This result implies, counterintuitively and contrary to the FDIC's substantive analysis of failure processes, that a higher one-year asset growth predicts a lower probability of failure. Given this anomaly in Model 1, it is not surprising that the asset growth rate variable loses its statistically significant predictive power in these same regressions.

Even after considering all three regressions for Model 1 from each of these time periods, and taking the average of their coefficients as the FDIC does in its statistical model, one finds that the average coefficient for asset growth rate as a separate independent variable falls to 0.0036 in the 1994-2011 time period and 0.0037 in the 2005-2011 time period. These average values are far below the 0.0156 average value for the NPR Model over the full 1985-2014 period.

In contrast to the anomalous Model 1, Model 2, which includes the Interaction Term, maintains the expected coefficient signs for all independent variables throughout each of the regressions in all of the selected time periods. In addition, the Interaction Term (*i.e.*, the combined brokered deposit ratio and asset growth rate variable) maintains statistical significance across all regressions for each selected time period.

Conclusion

For the full 1985-2014 time period, Model 2 performs at least as well as the FDIC-like Model 1. For the more recent and relevant time periods of 1994-2014 and 2005-2014, Model 2 – in avoiding anomalous coefficient signs and maintaining statistical significance throughout – performs better than Model 1. For these reasons, an assessments model that retains the Interaction Term approach of the Current Model, with its conjunctive dual thresholds, is superior to the Separated Variables approach of the NPR Model.

APPENDIX A: DATA FIELDS USED TO DERIVE INDEPENDENT AND DEPENDENT VARIABLES IN THE PROMONTORY ANALYSIS

Model Input Name	Description	FDIC RIS Database
ASSET	Total assets	FTS
BRO	Brokered deposits	FTS
IBEFTAX	Income before income taxes and extraordinary items, other adjustments	FTS
LNAG	Agricultural loans	FTS
LNCI	Commercial & industrial loans	FTS
LNCONOTH	Other loans to individuals for household, family and other personal expenditures (consumer loans) includes single payment, installment, and all student loans	FTS
LNDEPAC	Total loans to depository institutions and acceptances to other banks	FTS
LNFG	Loans to foreign governments and official institutions (including foreign central banks)	FTS
LNRE	Loans secured by real estate	FTS
LNREAG	Loans secured by farmland (including farm residential and other improvements) held in domestic offices	FTS
LNRECONS	Construction and land development loans secured by real estate held in domestic offices	FTS
LNREDOM	Loans secured by real estate held in domestic offices	FTS
LNREMULT	Multifamily (5 or more) residential properties secured by real estate held in domestic offices	FTS
LNRENRES	Nonfarm nonresidential properties secured by RE held in domestic offices	FTS
LNRERES	Total loans secured by 1-4 family residential properties held in domestic offices	FTS
LS	Lease financing receivables	FTS
NAGTY	Nonaccrual loans and lease which are guaranteed by the U.S. government	FTS
NALNLS	Total nonaccrual loans and leases financing receivables	FTS
ORE	Other real estate owned	FTS
P9GTY	Loans and leases which are guaranteed by the U.S. government past due 90 days or more and still accruing interest	FTS
P9LNLS	Total loans and lease financing receivables past due 90 or more days and still accruing interest	FTS
C_CERT	Acquired institutions certificate number	MERG
NEWCERT	The acquiring institutions certificate number	MERG
CERT	A unique number for institution identification and for the issuance of insurance certificates	MERG
EFFDATE	Represents the calendar date of a change or processed transaction	MERG
FAILED	A flag used to indicate whether an institution has failed. Failures include assisted mergers and payoffs	MERG
L_ASSET	The consolidated assets of an institution at time of closing	MERG
UPDDATE	The date of the last update to this institutions merger history record	MERG
RBC1AAJ	Tier 1 risk-based capital by adjusted average assets is based on the risk-based capital definition for Prompt Corrective Action	RAT
BKCLASS	Represents the institutions class as of the report date	STRU
CALLYM	Represents the calendar date for which the financial data was collected	STRU
ESTYMD	The calendar date an institution was established or opened	STRU

APPENDIX B: GLOSSARY OF INDEPENDENT VARIABLES USED IN PROMONTORY'S MODELS

1. Model 1

Independent Variable	Description
PINLRWIN*	Tier 1 leverage ratio (%)
PINNIBFTWIN	Net Income before Taxes/Total Assets (%). Net income is for the most recent twelve months.
PINNPLWIN	Nonperforming Loans and Leases/Gross Assets (%)
PINOREOWIN	Other Real Estate Owned/Gross Assets (%)
PINBROWIN	Brokered Deposits Ratio (%). The ratio is the difference between brokered deposits and 10 percent of total assets to total assets. If the ratio is less than zero, the value is set to zero.
PINOYGWIN	One-year Asset Growth factor (%). Percentage growth in assets (merger adjusted) over the previous year in excess of 10 percent. If the factor is negative, the value is set to zero.
PINLMIWIN	Loan Mix Index

* "WIN" indicates the variable is winsorised.

2. Model 2

Independent Variable	Description
PINLRWIN*	Tier 1 leverage ratio (%)
PINNIBFTWIN	Net Income before Taxes/Total Assets (%). Net income is for the most recent twelve months.
PINNPLWIN	Nonperforming Loans and Leases/Gross Assets (%)
PINOREOWIN	Other Real Estate Owned/Gross Assets (%)
PINBROWIN**	Brokered Deposits Ratio (%). If the ratio is less than zero, the value is set to zero.
PINLMIWIN	Loan Mix Index

* "WIN" indicates the variable is winsorised.
**If one-year asset growth factor is zero, the brokered deposits ratio is set to zero.

APPENDIX C: COMPARISON OF COEFFICIENTS

1. 1985-2014

Coefficient Comparison: Regression 1 (Last Data Point = 2009)			
Independent Variable	**FDIC Statistical Model**	**Promontory Model 1**	**Promontory Model 2**
Intercept	-5.1717	-2.2351	-2.2212
Tier 1 Leverage Ratio	-0.3195	-0.0820	-0.0822
Net Income Before Taxes/Assets	-0.1347	-0.1165	-0.1195
Loan Mix Index	0.0184	0.0057	0.0060
Brokered Deposit Ratio	0.0470	0.0188	0.0371
Nonperforming Assets/Assets	0.2604	0.1354	0.1334
Other Real Estate Owned/Assets	0.1357	0.1203	0.1157
One-year Asset Growth	0.0217	0.0073	NA
Weighted Avg. CAMELS Rating	0.4604	NA	NA

Coefficient Comparison: Regression 2 (Last Data Point = 2010)			
Independent Variable	**FDIC Statistical Model**	**Promontory Model 1**	**Promontory Model 2**
Intercept	-4.9279	-2.5157	-2.5202
Tier 1 Leverage Ratio	-0.3381	-0.0618	-0.0610
Net Income Before Taxes/Assets	-0.1635	-0.1355	-0.1382
Loan Mix Index	0.0240	0.0080	0.0082
Brokered Deposit Ratio	0.0840	0.0322	0.0415
Nonperforming Assets/Assets	0.2268	0.1239	0.1239
Other Real Estate Owned/Assets	0.1495	0.1073	0.1047
One-year Asset Growth	0.0081	0.0035	NA
Weighted Avg. CAMELS Rating	0.2786	NA	NA

Coefficient Comparison: Regression 3 (Last Data Point = 2011)			
Independent Variable	**FDIC Statistical Model**	**Promontory Model 1**	**Promontory Model 2**
Intercept	-5.4491	-1.7462	-2.0251
Tier 1 Leverage Ratio	-0.3073	-0.1902	-0.0948
Net Income Before Taxes/Assets	-0.2518	-0.1456	-0.1730
Loan Mix Index	0.0195	0.0074	0.0051
Brokered Deposit Ratio	0.0707	0.0345	0.0330
Nonperforming Assets/Assets	0.2318	0.1295	0.1207
Other Real Estate Owned/Assets	0.1215	0.0848	0.0860
One-year Asset Growth	0.0170	0.0080	NA
Weighted Avg. CAMELS Rating	0.4207	NA	NA

Coefficient Comparison: Average of Three Regressions			
Independent Variable	**FDIC Statistical Model**	**Promontory Model 1**	**Promontory Model 2**
Intercept	-5.1829	-2.1657	-2.2555
Tier 1 Leverage Ratio	-0.3216	-0.1113	-0.0793
Net Income Before Taxes/Assets	-0.1833	-0.1325	-0.1436
Loan Mix Index	0.0206	0.0070	0.0064
Brokered Deposit Ratio	0.0672	0.0285	0.0372
Nonperforming Assets/Assets	0.2397	0.1296	0.1260
Other Real Estate Owned/Assets	0.1356	0.1041	0.1021
One-year Asset Growth	0.0156	0.0063	NA
Weighted Avg. CAMELS Rating	0.3866	NA	NA

2. 1994-2014

Coefficient Comparison: Regression 1 (Last Data Point = 2009)			
Independent Variable	FDIC Statistical Model	Promontory Model 1	Promontory Model 2
Intercept	NA	-2.8887	-2.8738
Tier 1 Leverage Ratio	NA	-0.0620	-0.0611
Net Income Before Taxes/Assets	NA	-0.1159	-0.1266
Loan Mix Index	NA	0.0091	0.0095
Brokered Deposit Ratio	NA	0.0253	0.0371
Nonperforming Assets/Assets	NA	0.1299	0.1294
Other Real Estate Owned/Assets	NA	0.0886	0.0779
One-year Asset Growth	NA	0.0077	NA
Weighted Avg. CAMELS Rating	NA	NA	NA

Coefficient Comparison: Regression 2 (Last Data Point = 2010)			
Independent Variable	FDIC Statistical Model	Promontory Model 1	Promontory Model 2
Intercept	NA	-3.1915	-3.1992
Tier 1 Leverage Ratio	NA	-0.0404	-0.0397
Net Income Before Taxes/Assets	NA	-0.1513	-0.1556
Loan Mix Index	NA	0.0120	0.0121
Brokered Deposit Ratio	NA	0.0361	0.0379
Nonperforming Assets/Assets	NA	0.1147	0.1223
Other Real Estate Owned/Assets	NA	0.0587	0.0563
One-year Asset Growth	NA	-0.0032	NA
Weighted Avg. CAMELS Rating	NA	NA	NA

Coefficient Comparison: Regression 3 (Last Data Point = 2011)			
Independent Variable	FDIC Statistical Model	Promontory Model 1	Promontory Model 2
Intercept	NA	-2.6505	-2.6912
Tier 1 Leverage Ratio	NA	-0.0784	-0.0747
Net Income Before Taxes/Assets	NA	-0.1969	-0.2103
Loan Mix Index	NA	0.0078	0.0085
Brokered Deposit Ratio	NA	0.0283	0.0325
Nonperforming Assets/Assets	NA	0.1533	0.1524
Other Real Estate Owned/Assets	NA	0.0235	0.0158
One-year Asset Growth	NA	0.0062	NA
Weighted Avg. CAMELS Rating	NA	NA	NA

Coefficient Comparison: Average of Three Regressions			
Independent Variable	FDIC Statistical Model	Promontory Model 1	Promontory Model 2
Intercept	NA	-2.9102	-2.9214
Tier 1 Leverage Ratio	NA	-0.0603	-0.0585
Net Income Before Taxes/Assets	NA	-0.1547	-0.1642
Loan Mix Index	NA	0.0096	0.0100
Brokered Deposit Ratio	NA	0.0299	0.0358
Nonperforming Assets/Assets	NA	0.1326	0.1347
Other Real Estate Owned/Assets	NA	0.0569	0.0500
One-year Asset Growth	NA	0.0036	NA
Weighted Avg. CAMELS Rating	NA	NA	NA

3. 2005-2014

Coefficient Comparison: Regression 1 (Last Data Point = 2009)			
Independent Variable	FDIC Statistical Model	Promontory Model 1	Promontory Model 2
Intercept	NA	-2.5212	-2.5415
Tier 1 Leverage Ratio	NA	-0.0627	-0.0600
Net Income Before Taxes/Assets	NA	-0.1689	-0.1726
Loan Mix Index	NA	0.0067	0.0069
Brokered Deposit Ratio	NA	0.0223	0.0262
Nonperforming Assets/Assets	NA	0.1844	0.1788
Other Real Estate Owned/Assets	NA	0.1027	0.0983
One-year Asset Growth	NA	0.0046	NA
Weighted Avg. CAMELS Rating	NA	NA	NA

Coefficient Comparison: Regression 2 (Last Data Point = 2010)			
Independent Variable	FDIC Statistical Model	Promontory Model 1	Promontory Model 2
Intercept	NA	-1.6867	-1.7085
Tier 1 Leverage Ratio	NA	-0.1976	-0.1943
Net Income Before Taxes/Assets	NA	-0.0701	-0.0741
Loan Mix Index	NA	0.0108	0.0112
Brokered Deposit Ratio	NA	0.0228	0.0287
Nonperforming Assets/Assets	NA	0.0984	0.0929
Other Real Estate Owned/Assets	NA	0.0740	0.0695
One-year Asset Growth	NA	0.0087	NA
Weighted Avg. CAMELS Rating	NA	NA	NA

Coefficient Comparison: Regression 3 (Last Data Point = 2011)			
Independent Variable	FDIC Statistical Model	Promontory Model 1	Promontory Model 2
Intercept	NA	-2.7367	-2.7283
Tier 1 Leverage Ratio	NA	-0.0626	-0.0636
Net Income Before Taxes/Assets	NA	-0.1189	-0.1164
Loan Mix Index	NA	0.0127	0.0126
Brokered Deposit Ratio	NA	0.0333	0.0316
Nonperforming Assets/Assets	NA	0.0866	0.0880
Other Real Estate Owned/Assets	NA	0.0483	0.0492
One-year Asset Growth	NA	-0.0022	NA
Weighted Avg. CAMELS Rating	NA	NA	NA

Coefficient Comparison: Average of Three Regressions			
Independent Variable	FDIC Statistical Model	Promontory Model 1	Promontory Model 2
Intercept	NA	-2.3149	-2.3261
Tier 1 Leverage Ratio	NA	-0.1076	-0.1060
Net Income Before Taxes/Assets	NA	-0.1193	-0.1210
Loan Mix Index	NA	0.0101	0.0102
Brokered Deposit Ratio	NA	0.0261	0.0288
Nonperforming Assets/Assets	NA	0.1231	0.1199
Other Real Estate Owned/Assets	NA	0.0750	0.0723
One-year Asset Growth	NA	0.0037	NA
Weighted Avg. CAMELS Rating	NA	NA	NA

APPENDIX D: FULL REGRESSION RESULTS FOR THE TIME PERIODS 1985-2014, 1994-2014, AND 2005-2014

1. <u>1985-2014</u>

Model 1, Regression 1 (Regression with 2009 as the last data point for independent variables)

Probit Regression Results

Dep. Variable:	FAILURE	**No. Observations:**	93370
Model:	Probit	**Df Residuals:**	93362
Method:	MLE	**Df Model:**	7
Date:	Wed, 02 Mar 2016	**Pseudo R-squ.:**	0.4217
Time:	16:46:49	**Log-Likelihood:**	-4226.1
converged:	True	**LL-Null:**	-7307.2
		LLR p-value:	0.000

	coef	**std err**	**z**	**P>|z|**	**[95.0% Conf. Int.]**
PINLRWIN	-0.0820	0.006	-14.412	0.000	-0.093 -0.071
PINNIBFTWIN	-0.1165	0.008	-14.026	0.000	-0.133 -0.100
PINNPLWIN	0.1354	0.007	19.663	0.000	0.122 0.149
PINOREOWIN	0.1203	0.009	13.293	0.000	0.103 0.138
PINBROWIN	0.0188	0.004	4.430	0.000	0.011 0.027
PINOYGWIN	0.0073	0.001	6.625	0.000	0.005 0.009
PINLMIWIN	0.0057	0.000	14.495	0.000	0.005 0.006
const	-2.2351	0.056	-40.267	0.000	-2.344 -2.126

```
reg1_model.pred_table()
```

```
array([[ 91827.,    134.],
       [  1083.,    326.]])
```

Model 1, Regression 2 (Regression with 2010 as the last data point for independent variables)

Probit Regression Results

Dep. Variable:	FAILURE	**No. Observations:**	88581
Model:	Probit	**Df Residuals:**	88573
Method:	MLE	**Df Model:**	7
Date:	Wed, 02 Mar 2016	**Pseudo R-squ.:**	0.4048
Time:	16:46:50	**Log-Likelihood:**	-3911.1
converged:	True	**LL-Null:**	-6571.4
		LLR p-value:	0.000

	coef	**std err**	**z**	**P>|z|**	**[95.0% Conf. Int.]**
PINLRWIN	-0.0618	0.006	-10.881	0.000	-0.073 -0.051
PINNIBFTWIN	-0.1355	0.009	-14.554	0.000	-0.154 -0.117
PINNPLWIN	0.1239	0.007	16.731	0.000	0.109 0.138
PINOREOWIN	0.1073	0.009	11.788	0.000	0.089 0.125
PINBROWIN	0.0322	0.004	7.491	0.000	0.024 0.041
PINOYGWIN	0.0035	0.001	2.770	0.006	0.001 0.006
PINLMIWIN	0.0080	0.000	21.339	0.000	0.007 0.009
const	-2.5157	0.056	-44.812	0.000	-2.626 -2.406

```
reg2_model.pred_table()
```

```
array([[ 87204.,     126.],
       [  1025.,     226.]])
```

Model 1, Regression 3 (Regression with 2011 as the last data point for independent variables)

Probit Regression Results

Dep. Variable:	FAILURE	**No. Observations:**	90251
Model:	Probit	**Df Residuals:**	90243
Method:	MLE	**Df Model:**	7
Date:	Wed, 02 Mar 2016	**Pseudo R-squ.:**	0.5026
Time:	16:46:50	**Log-Likelihood:**	-3431.7
converged:	True	**LL-Null:**	-6899.9
		LLR p-value:	0.000

	coef	**std err**	**z**	**P>|z|**	**[95.0% Conf. Int.]**
PINLRWIN	-0.1902	0.007	-26.923	0.000	-0.204 -0.176
PINNIBFTWIN	-0.1456	0.010	-15.302	0.000	-0.164 -0.127
PINNPLWIN	0.1295	0.008	16.425	0.000	0.114 0.145
PINOREOWIN	0.0848	0.009	9.102	0.000	0.067 0.103
PINBROWIN	0.0345	0.004	9.665	0.000	0.028 0.042
PINOYGWIN	0.0080	0.001	6.483	0.000	0.006 0.010
PINLMIWIN	0.0074	0.000	15.923	0.000	0.007 0.008
const	-1.7462	0.060	-29.286	0.000	-1.863 -1.629

```
reg3_model.pred_table()
```

```
array([[ 88731.,    197.],
       [   915.,    408.]])
```

Model 2, Regression 1

Probit Regression Results

Dep. Variable:	FAILURE	**No. Observations:**	93370
Model:	Probit	**Df Residuals:**	93363
Method:	MLE	**Df Model:**	6
Date:	Wed, 02 Mar 2016	**Pseudo R-squ.:**	0.4199
Time:	16:50:42	**Log-Likelihood:**	-4238.9
converged:	True	**LL-Null:**	-7307.2
		LLR p-value:	0.000

	coef	**std err**	**z**	**P>|z|**	**[95.0% Conf. Int.]**
PINLRWIN	-0.0822	0.006	-14.409	0.000	-0.093 -0.071
PINNIBFTWIN	-0.1195	0.008	-14.410	0.000	-0.136 -0.103
PINNPLWIN	0.1334	0.007	19.481	0.000	0.120 0.147
PINOREOWIN	0.1157	0.009	12.812	0.000	0.098 0.133
PINBROWIN	0.0371	0.006	6.594	0.000	0.026 0.048
PINLMIWIN	0.0060	0.000	15.361	0.000	0.005 0.007
const	-2.2212	0.055	-40.069	0.000	-2.330 -2.113

```
reg1_model.pred_table()
```

```
array([[ 91832.,     129.],
       [  1077.,     332.]])
```

Model 2, Regression 2

Probit Regression Results

Dep. Variable:	FAILURE	**No. Observations:**	88581
Model:	Probit	**Df Residuals:**	88574
Method:	MLE	**Df Model:**	6
Date:	Wed, 02 Mar 2016	**Pseudo R-squ.:**	0.4036
Time:	16:50:42	**Log-Likelihood:**	-3918.9
converged:	True	**LL-Null:**	-6571.4
		LLR p-value:	0.000

	coef	**std err**	**z**	**P>|z|**	**[95.0% Conf. Int.]**
PINLRWIN	-0.0610	0.006	-10.738	0.000	-0.072 -0.050
PINNIBFTWIN	-0.1382	0.009	-14.820	0.000	-0.156 -0.120
PINNPLWIN	0.1239	0.007	16.829	0.000	0.109 0.138
PINOREOWIN	0.1047	0.009	11.534	0.000	0.087 0.123
PINBROWIN	0.0415	0.006	7.503	0.000	0.031 0.052
PINLMIWIN	0.0082	0.000	22.268	0.000	0.008 0.009
const	-2.5202	0.056	-45.157	0.000	-2.630 -2.411

```
reg2_model.pred_table()
```

```
array([[ 87196.,    134.],
       [  1021.,    230.]])
```

Model 2, Regression 3

Probit Regression Results

Dep. Variable:	FAILURE	**No. Observations:**	90251
Model:	Probit	**Df Residuals:**	90244
Method:	MLE	**Df Model:**	6
Date:	Wed, 02 Mar 2016	**Pseudo R-squ.:**	0.4760
Time:	16:50:42	**Log-Likelihood:**	-3615.4
converged:	True	**LL-Null:**	-6899.9
		LLR p-value:	0.000

	coef	std err	z	P>|z|	[95.0% Conf. Int.]
PINLRWIN	-0.0948	0.006	-16.941	0.000	-0.106 -0.084
PINNIBFTWIN	-0.1730	0.009	-20.007	0.000	-0.190 -0.156
PINNPLWIN	0.1207	0.007	16.693	0.000	0.107 0.135
PINOREOWIN	0.0860	0.009	9.928	0.000	0.069 0.103
PINBROWIN	0.0330	0.004	7.650	0.000	0.025 0.041
PINLMIWIN	0.0051	0.000	12.599	0.000	0.004 0.006
const	-2.0251	0.053	-38.022	0.000	-2.129 -1.921

```
reg3_model.pred_table()
```

```
array([[ 88768.,     160.],
       [   976.,     347.]])
```

2. <u>1994-2014</u>

Model 1, Regression 1

Probit Regression Results

Dep. Variable:	FAILURE	**No. Observations:**	54567
Model:	Probit	**Df Residuals:**	54559
Method:	MLE	**Df Model:**	7
Date:	Thu, 03 Mar 2016	**Pseudo R-squ.:**	0.4467
Time:	13:48:54	**Log-Likelihood:**	-1418.7
converged:	True	**LL-Null:**	-2564.0
		LLR p-value:	0.000

	coef	**std err**	**z**	**P>|z|**	**[95.0% Conf. Int.]**
PINLRWIN	-0.0620	0.010	-5.994	0.000	-0.082 -0.042
PINNIBFTWIN	-0.1159	0.014	-8.031	0.000	-0.144 -0.088
PINNPLWIN	0.1299	0.012	10.631	0.000	0.106 0.154
PINOREOWIN	0.0886	0.022	4.081	0.000	0.046 0.131
PINBROWIN	0.0253	0.004	5.817	0.000	0.017 0.034
PINOYGWIN	0.0077	0.001	5.178	0.000	0.005 0.011
PINLMIWIN	0.0091	0.001	15.757	0.000	0.008 0.010
const	-2.8887	0.105	-27.439	0.000	-3.095 -2.682

```
reg1_model.pred_table()
```

```
array([[  5.40810000e+04,   4.50000000e+01],
       [  3.25000000e+02,   1.16000000e+02]])
```

Model 1, Regression 2

Probit Regression Results

Dep. Variable:	FAILURE	**No. Observations:**	50635
Model:	Probit	**Df Residuals:**	50627
Method:	MLE	**Df Model:**	7
Date:	Thu, 03 Mar 2016	**Pseudo R-squ.:**	0.4032
Time:	13:48:58	**Log-Likelihood:**	-1519.0
converged:	True	**LL-Null:**	-2545.1
		LLR p-value:	0.000

	coef	**std err**	**z**	**P>|z|**	**[95.0% Conf. Int.]**
PINLRWIN	-0.0404	0.009	-4.387	0.000	-0.058 -0.022
PINNIBFTWIN	-0.1513	0.018	-8.635	0.000	-0.186 -0.117
PINNPLWIN	0.1147	0.013	8.984	0.000	0.090 0.140
PINOREOWIN	0.0587	0.019	3.171	0.002	0.022 0.095
PINBROWIN	0.0361	0.005	7.995	0.000	0.027 0.045
PINOYGWIN	-0.0032	0.002	-1.418	0.156	-0.008 0.001
PINLMIWIN	0.0120	0.001	22.847	0.000	0.011 0.013
const	-3.1915	0.098	-32.465	0.000	-3.384 -2.999

```
reg2_model.pred_table()
```

```
array([[  5.01480000e+04,   4.30000000e+01],
       [  3.72000000e+02,   7.20000000e+01]])
```

Model 1, Regression 3

Probit Regression Results

Dep. Variable:	FAILURE	**No. Observations:**	51027
Model:	Probit	**Df Residuals:**	51019
Method:	MLE	**Df Model:**	7
Date:	Thu, 03 Mar 2016	**Pseudo R-squ.:**	0.5212
Time:	13:49:01	**Log-Likelihood:**	-1285.4
converged:	True	**LL-Null:**	-2684.9
		LLR p-value:	0.000

	coef	**std err**	**z**	**P>|z|**	**[95.0% Conf. Int.]**
PINLRWIN	-0.0784	0.011	-7.421	0.000	-0.099 -0.058
PINNIBFTWIN	-0.1969	0.014	-14.491	0.000	-0.223 -0.170
PINNPLWIN	0.1533	0.012	13.140	0.000	0.130 0.176
PINOREOWIN	0.0235	0.017	1.408	0.159	-0.009 0.056
PINBROWIN	0.0283	0.004	7.644	0.000	0.021 0.036
PINOYGWIN	0.0062	0.001	4.203	0.000	0.003 0.009
PINLMIWIN	0.0078	0.001	12.716	0.000	0.007 0.009
const	-2.6505	0.108	-24.578	0.000	-2.862 -2.439

```
reg3_model.pred_table()
```

```
array([[ 50492.,     62.],
       [   340.,    133.]])
```

Model 2, Regression 1

Probit Regression Results

Dep. Variable:	FAILURE	**No. Observations:**	54567
Model:	Probit	**Df Residuals:**	54560
Method:	MLE	**Df Model:**	6
Date:	Thu, 03 Mar 2016	**Pseudo R-squ.:**	0.4419
Time:	13:59:40	**Log-Likelihood:**	-1430.9
converged:	True	**LL-Null:**	-2564.0
		LLR p-value:	0.000

	coef	**std err**	**z**	**P>|z|**	**[95.0% Conf. Int.]**
PINLRWIN	-0.0611	0.011	-5.818	0.000	-0.082 -0.041
PINNIBFTWIN	-0.1266	0.014	-8.779	0.000	-0.155 -0.098
PINNPLWIN	0.1294	0.012	10.712	0.000	0.106 0.153
PINOREOWIN	0.0779	0.022	3.611	0.000	0.036 0.120
PINBROWIN	0.0371	0.006	6.337	0.000	0.026 0.049
PINLMIWIN	0.0095	0.001	16.505	0.000	0.008 0.011
const	-2.8738	0.107	-26.841	0.000	-3.084 -2.664

```
reg1_model.pred_table()
```

```
array([[  5.40780000e+04,   4.80000000e+01],
       [  3.27000000e+02,   1.14000000e+02]])
```

Model 2, Regression 2

Probit Regression Results

Dep. Variable:	FAILURE	**No. Observations:**	50635
Model:	Probit	**Df Residuals:**	50628
Method:	MLE	**Df Model:**	6
Date:	Thu, 03 Mar 2016	**Pseudo R-squ.:**	0.3990
Time:	13:59:42	**Log-Likelihood:**	-1529.5
converged:	True	**LL-Null:**	-2545.1
		LLR p-value:	0.000

	coef	**std err**	**z**	**P>|z|**	**[95.0% Conf. Int.]**
PINLRWIN	-0.0397	0.009	-4.410	0.000	-0.057 -0.022
PINNIBFTWIN	-0.1556	0.017	-8.955	0.000	-0.190 -0.122
PINNPLWIN	0.1223	0.013	9.701	0.000	0.098 0.147
PINOREOWIN	0.0563	0.019	3.039	0.002	0.020 0.093
PINBROWIN	0.0379	0.006	6.490	0.000	0.026 0.049
PINLMIWIN	0.0121	0.001	23.360	0.000	0.011 0.013
const	-3.1992	0.097	-32.981	0.000	-3.389 -3.009

```
reg2_model.pred_table()
```

```
array([[  5.01440000e+04,   4.70000000e+01],
       [  3.69000000e+02,   7.50000000e+01]])
```

Model 2, Regression 3

Probit Regression Results

Dep. Variable:	FAILURE	**No. Observations:**	51027
Model:	Probit	**Df Residuals:**	51020
Method:	MLE	**Df Model:**	6
Date:	Thu, 03 Mar 2016	**Pseudo R-squ.:**	0.5143
Time:	13:59:45	**Log-Likelihood:**	-1303.9
converged:	True	**LL-Null:**	-2684.9
		LLR p-value:	0.000

	coef	**std err**	**z**	**P>|z|**	**[95.0% Conf. Int.]**
PINLRWIN	-0.0747	0.011	-7.105	0.000	-0.095 -0.054
PINNIBFTWIN	-0.2103	0.013	-15.689	0.000	-0.237 -0.184
PINNPLWIN	0.1524	0.011	13.274	0.000	0.130 0.175
PINOREOWIN	0.0158	0.017	0.946	0.344	-0.017 0.048
PINBROWIN	0.0325	0.005	7.125	0.000	0.024 0.041
PINLMIWIN	0.0085	0.001	14.291	0.000	0.007 0.010
const	-2.6912	0.108	-24.933	0.000	-2.903 -2.480

```
reg3_model.pred_table()
```

```
array([[ 50493.,      61.],
       [   338.,     135.]])
```

3. <u>2005-2014</u>

Model 1, Regression 1

Probit Regression Results

Dep. Variable:	FAILURE	**No. Observations:**	15531
Model:	Probit	**Df Residuals:**	15523
Method:	MLE	**Df Model:**	7
Date:	Wed, 02 Mar 2016	**Pseudo R-squ.:**	0.5211
Time:	14:58:31	**Log-Likelihood:**	-792.44
converged:	True	**LL-Null:**	-1654.6
		LLR p-value:	0.000

	coef	**std err**	**z**	**P>|z|**	**[95.0% Conf. Int.]**
PINLRWIN	-0.0627	0.013	-4.647	0.000	-0.089 -0.036
PINNIBFTWIN	-0.1689	0.016	-10.479	0.000	-0.201 -0.137
PINNPLWIN	0.1844	0.016	11.536	0.000	0.153 0.216
PINOREOWIN	0.1027	0.034	3.020	0.003	0.036 0.169
PINBROWIN	0.0223	0.005	4.447	0.000	0.012 0.032
PINOYGWIN	0.0046	0.002	2.273	0.023	0.001 0.009
PINLMIWIN	0.0067	0.001	9.125	0.000	0.005 0.008
const	-2.5212	0.146	-17.299	0.000	-2.807 -2.236

```
reg1_model.pred_table()
```

```
array([[ 15134.,      52.],
       [   233.,     112.]])
```

Model 1, Regression 2

Probit Regression Results

Dep. Variable:	FAILURE	**No. Observations:**	15146
Model:	Probit	**Df Residuals:**	15138
Method:	MLE	**Df Model:**	7
Date:	Wed, 02 Mar 2016	**Pseudo R-squ.:**	0.4437
Time:	14:58:47	**Log-Likelihood:**	-1008.1
converged:	True	**LL-Null:**	-1812.1
		LLR p-value:	0.000

	coef	**std err**	**z**	**P>|z|**	**[95.0% Conf. Int.]**
PINLRWIN	-0.1976	0.017	-11.602	0.000	-0.231 -0.164
PINNIBFTWIN	-0.0701	0.018	-3.925	0.000	-0.105 -0.035
PINNPLWIN	0.0984	0.014	7.157	0.000	0.071 0.125
PINOREOWIN	0.0740	0.024	3.043	0.002	0.026 0.122
PINBROWIN	0.0228	0.007	3.466	0.001	0.010 0.036
PINOYGWIN	0.0087	0.002	3.607	0.000	0.004 0.013
PINLMIWIN	0.0108	0.001	15.229	0.000	0.009 0.012
const	-1.6867	0.158	-10.652	0.000	-1.997 -1.376

```
reg2_model.pred_table()
```

```
array([[ 14720.,      36.],
       [   256.,     134.]])
```

Model 1, Regression 3

Probit Regression Results

Dep. Variable:	FAILURE	**No. Observations:**	12748
Model:	Probit	**Df Residuals:**	12740
Method:	MLE	**Df Model:**	7
Date:	Wed, 02 Mar 2016	**Pseudo R-squ.:**	0.3670
Time:	14:58:58	**Log-Likelihood:**	-1123.5
converged:	True	**LL-Null:**	-1774.9
		LLR p-value:	4.085e-277

	coef	**std err**	**z**	**P>|z|**	**[95.0% Conf. Int.]**
PINLRWIN	-0.0626	0.011	-5.461	0.000	-0.085 -0.040
PINNIBFTWIN	-0.1189	0.020	-5.820	0.000	-0.159 -0.079
PINNPLWIN	0.0866	0.013	6.422	0.000	0.060 0.113
PINOREOWIN	0.0483	0.019	2.542	0.011	0.011 0.086
PINBROWIN	0.0333	0.007	4.921	0.000	0.020 0.047
PINOYGWIN	-0.0022	0.003	-0.727	0.467	-0.008 0.004
PINLMIWIN	0.0127	0.001	20.290	0.000	0.011 0.014
const	-2.7367	0.129	-21.256	0.000	-2.989 -2.484

```
reg3_model.pred_table()
```

```
array([[ 12305.,      44.],
       [   327.,      72.]])
```

Model 2, Regression 1

Probit Regression Results

Dep. Variable:	FAILURE	**No. Observations:**	15531
Model:	Probit	**Df Residuals:**	15524
Method:	MLE	**Df Model:**	6
Date:	Wed, 02 Mar 2016	**Pseudo R-squ.:**	0.5190
Time:	15:03:40	**Log-Likelihood:**	-795.88
converged:	True	**LL-Null:**	-1654.6
		LLR p-value:	0.000

	coef	std err	z	P>|z|	[95.0% Conf. Int.]
PINLRWIN	-0.0600	0.013	-4.487	0.000	-0.086 -0.034
PINNIBFTWIN	-0.1726	0.016	-10.749	0.000	-0.204 -0.141
PINNPLWIN	0.1788	0.016	11.335	0.000	0.148 0.210
PINOREOWIN	0.0983	0.034	2.895	0.004	0.032 0.165
PINBROWIN	0.0262	0.005	5.604	0.000	0.017 0.035
PINLMIWIN	0.0069	0.001	9.539	0.000	0.005 0.008
const	-2.5415	0.146	-17.405	0.000	-2.828 -2.255

```
reg1_model.pred_table()
```

```
array([[ 15135.,      51.],
       [   234.,     111.]])
```

Model 2, Regression 2

Probit Regression Results

Dep. Variable:	FAILURE	**No. Observations:**	15146
Model:	Probit	**Df Residuals:**	15139
Method:	MLE	**Df Model:**	6
Date:	Wed, 02 Mar 2016	**Pseudo R-squ.:**	0.4406
Time:	15:03:45	**Log-Likelihood:**	-1013.6
converged:	True	**LL-Null:**	-1812.1
		LLR p-value:	0.000

	coef	**std err**	**z**	**P>|z|**	**[95.0% Conf. Int.]**
PINLRWIN	-0.1943	0.017	-11.426	0.000	-0.228 -0.161
PINNIBFTWIN	-0.0741	0.018	-4.166	0.000	-0.109 -0.039
PINNPLWIN	0.0929	0.014	6.823	0.000	0.066 0.120
PINOREOWIN	0.0695	0.024	2.870	0.004	0.022 0.117
PINBROWIN	0.0287	0.006	4.549	0.000	0.016 0.041
PINLMIWIN	0.0112	0.001	15.916	0.000	0.010 0.013
const	-1.7085	0.159	-10.754	0.000	-2.020 -1.397

```
reg2_model.pred_table()
```

```
array([[ 14720.,      36.],
       [   259.,     131.]])
```

Model 2, Regression 3

Probit Regression Results

Dep. Variable:	FAILURE	No. Observations:	12748
Model:	Probit	Df Residuals:	12741
Method:	MLE	Df Model:	6
Date:	Wed, 02 Mar 2016	Pseudo R-squ.:	0.3669
Time:	15:03:50	Log-Likelihood:	-1123.7
converged:	True	LL-Null:	-1774.9
		LLR p-value:	3.155e-278

	coef	std err	z	P>|z|	[95.0% Conf. Int.]
PINLRWIN	-0.0636	0.011	-5.623	0.000	-0.086 -0.041
PINNIBFTWIN	-0.1164	0.020	-5.789	0.000	-0.156 -0.077
PINNPLWIN	0.0880	0.013	6.587	0.000	0.062 0.114
PINOREOWIN	0.0492	0.019	2.588	0.010	0.012 0.086
PINBROWIN	0.0316	0.006	4.966	0.000	0.019 0.044
PINLMIWIN	0.0126	0.001	20.526	0.000	0.011 0.014
const	-2.7283	0.127	-21.404	0.000	-2.978 -2.478

```
reg3_model.pred_table()
```

```
array([[ 12305.,      44.],
       [   327.,      72.]])
```