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Reciprocal Brokered Deposits, Bank Risk, and Recent Deposit Insurance Policy

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Abstract

This study provides new evidence regarding reciprocal brokered deposits (RBDs), regulatory responses, and bank risk, contributing to prior studies in four ways. First, using updated financial Call Report data and bank failure data through 2012, we re-examine the moral hazard hypothesis that banks using RBDs exhibit higher risk. Second, we uncover a previously overlooked positive association between RBDs and banks' cost of failure. Third, we apply Granger causality tests; and finally, we test whether the FDIC's recent revision of its pricing discourages the use of RBDs and weakens its association with bank risk.

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JEL Classification

G21, G22, G28

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This study provides new evidence regarding reciprocal brokered deposits (RBDs), regulatory responses, and bank risk, contributing to prior studies in four ways. First, using updated financial Call Report data and bank failure data through 2012, we re-examine the moral hazard hypothesis that banks using RBDs exhibit higher risk. Second, we uncover a previously overlooked positive association between RBDs and banks' cost of failure. Third, we apply Granger causality tests; and finally, we test whether the FDIC's recent revision of its pricing discourages the use of RBDs and weakens its association with bank risk.

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1 Introduction and Background

Market incentives to exploit regulatory loopholes have sometimes led to creative products or services. A recent example from the U.S. financial

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sector is "reciprocal deposits" (or "reciprocal brokered deposits", hereafter referred to as RBDs), which entail a virtual exchange of deposit balances among participating banks so that no resulting "account" shows a balance larger than the amount that is fully insured by the Federal Deposit Insurance Corporation (FDIC). Vendors have emerged to offer this service through sophisticated automated networks; see Shaffer (2012) for examples. The product allows banks to circumvent the statutory ceiling on federal deposit insurance coverage (currently $250,000 on most accounts), rendering the FDIC potentially liable for covering all deposits in a participating bank.

Economic theory predicts that participating banks may choose to operate with higher levels of financial risk (moral hazard) or, similarly, that riskier banks may disproportionately utilize RBDs, either by choice or as a consequence of the available supply of deposits. Prior research has confirmed the moral hazard hypothesis for RBDs by reporting empirical evidence that banks using RBDs exhibits (1) higher levels of financial risk in each of more than half a dozen dimensions (Shaffer, 2012); (2) higher probabilities of subsequent failure, even after controlling for specific dimensions of known risk (Shaffer, 2013); and (3) higher levels of overall bank risk as measured by the Z-score (ibid.)

Our paper extends this line of research in four ways: (1) We update and extend the sample period and the set of failed banks to include important recent quarters. (2) We incorporate regulatory data on the cost of failed banks to examine any association between the use of RBDs and the cost of failure, both conditional on failure and unconditional. (3) We apply Granger tests for causality in the observed linkages. (4) We test for evidence of changes in banks' use of RBDs in response to newly implemented regulatory pricing of such deposits.

Our findings partially confirm the predictions of theory and conform to previous empirical findings, while introducing some contrasting details that offer a more nuanced understanding of the data. Banks' use of RBDs is associated with significantly higher levels of risk by several measures – including the expected total (but not relative) cost of failure, a new finding. On the other hand, we find unprecedented evidence that the use of RBDs is associated with significantly lower operating costs, supporting a claim sometimes made by trade groups, as well as with lower proportional costs of failure. Causality tends to run more from financial risk and performance to the use of RBDs than in the other direction, and – contrary to the moral hazard hypothesis – banks with superior profitability and asset quality tend to use RBDs. The FDIC's update of April 2011 to its Final Rule on Base Assessment Rate showed the theoretically predicted effect of reducing banks' incentive to use reciprocal deposits and of weakening the linkage between such use and various measures of banks' risk.

Two other policy developments that emerged during and after the financial crisis lend independent support to the idea that the higher deposit coverage levels provided by RBDs are associated with higher expected costs to the deposit insurer. First, during 2008 (before the start of our sample period), the FDIC instituted a Transaction Account Guarantee (TAG) program that provided unlimited insurance on non-interest bearing bank deposit accounts. The U.S. Congress later affirmed that program in Section 343 of the Dodd-Frank Act, extending the program through the end of 2012. It has been estimated that the TAG program guaranteed \$1.5 trillion in deposits beyond the previous limit (FDIC, 2010). Significantly, the FDIC accompanied the TAG program by an explicit surcharge to banks for the additional coverage.[1] This action demonstrates that the FDIC believed the higher coverage to be associated with additional expected costs of deposit insurance beyond the levels reflected in its existing premium schedule. Given this decision, it appears logically consistent to suppose that a similar surcharge would be appropriate for RBDs, which provide a virtually identical benefit to depositors and presumably similar risk to the deposit insurer.[2]

[1] Initially, participating banks were charged 10 basis points annually for additional deposit amounts insured under the TAG program. In January 2010, this surcharge was increased to 15-25 basis points, depending on each participating bank's risk profile. Banks were allowed to opt in or out of the TAG program until 2010.

[2] Interestingly, the TAG program theoretically should have further reduced the demand for reciprocal deposits - and dampened any empirical association between reciprocal deposits and bank risk - by providing a near-perfect substitute for the subset of deposits in transaction accounts such as commercial checking accounts, which were prohibited by law from receiving interesting payments until the Dodd-Frank Act removed this restriction.

Second, the U.S. Congressional Budget Office issued a report in December 2012 that estimated the expected costs of the TAG program to be higher than the additional fees charged by the FDIC.[3] Based on the shortfall between the surcharge and the expected costs, the report projected a significant net deficit extending beyond the year 2020, even if the TAG program were to expire in 2014. Motivated in part by those estimates, the U.S. Senate denied an extension of the program beyond 2012. The report and the Senate's actions lend further support to the credibility of recent empirical findings for RBDs, and suggest the importance of testing directly for empirical associations between RBDs and costs of bank failure, which we undertake below.

Beyond the question of expected costs and appropriate fees, RBDs may be viewed as controversial more generally, as the sole intent of the product is to exploit a regulatory loophole. One may argue that RBDs provide a more efficient and convenient method of exploiting that loophole than conventional brokered deposits or a "homemade" strategy in which a depositor could divide his money among multiple banks directly. Moreover, RBDs offer an added element of consumer choice, which economic theory would interpret as welfare-enhancing. But Congress, if it agreed with the intent of the product and supported the outcome as a policy issue, could achieve the same outcome by statute, eliminating the need for costly technology, management, and marketing infrastructures to implement the deposit reciprocity. From that perspective, RBDs impose a deadweight welfare loss that could be eliminated by legislation, as illustrated on a more limited basis in the FDIC's temporary TAG program. The fact that Congress has chosen not to ratify unlimited coverage more generally, nor even to approve continuation of the TAG program, suggests that the outcome achieved by RBDs is inconsistent with Congressional intent. Conversely, Congress could also close the loophole if they were sufficiently concerned, suggesting that they are content with the

Because this program was in effect throughout our sample period, we cannot test for that effect, but the theoretical implication is that the empirical results in this paper therefore understate the intrinsic effect of RBDs in the absence of TAG.

[3] See http://www.cbo.gov/sites/default/files/cbofiles/attachments/s3637.pdf (accessed on January 31, 2013).

status quo.

One can identify two further issues surrounding RBDs. Under U.S. law, the pricing of federal deposit insurance is required to be actuarially fair in aggregate over time. This means that, to the extent that RBDs pose any degree of unpriced risk to the FDIC, any banks not using that product will be required in the long run to cross-subsidize other banks using the product. Such cross-subsidization provides a financial incentive for all banks to use RBDs. Banks' response to this incentive would further exacerbate the incremental risk borne by the FDIC. Moreover, one could view this incentive as providing a government-sponsored subsidy to the vendors of RBDs, as it enhances the demand for their product in a way that effectively substitutes for, or complements, any expenditure by the vendors on advertising and marketing activities.

Finally, the reciprocal deposit product is by nature a natural monopoly: Its value to a depositor is monotonically related to the maximum level of coverage provided, which in turn is a monotonic function of the number of participating banks (network economies). Standard economic analysis, along with U.S. antitrust laws, would suggest some concern about potential market power in such a market.

The remainder of this paper is organized as follows. The next section discusses related literature, the research design and hypotheses, and our sample. Section 3 describes the empirical model while Section 4 reports the results. Section 5 adds Granger causality tests as well as tests of a response to the FDIC's revision of its pricing policy during our sample period, while Section 6 concludes.

2 Related Literature, Research Design, and Data

2.1 Literature and Hypothesis

The only published studies of reciprocal deposits as of this writing appear to be Shaffer (2012, 2013). This paper builds on that analysis and, in so doing, draws on the much more extensive empirical literature on bank risk

– primarily, statistical models using observable financial ratios to predict bank failure (the "early warning" literature). Based on that literature, we utilize eight observable financial ratios as indicators of bank risk. The moral hazard hypothesis predicts that the use of RBDs would be associated with higher levels of risk as indicated by each of these measures.

Equity/assets (KA) has been found to be inversely correlated with the risk of subsequent failure or insolvency (e.g., Thomson, 1991; Cole and Gunther, 1995; Wheelock and Wilson, 2000; DeYoung, 2003), and has been shown to be the single best predictor of failure (Estrella, Park, and Peristiani, 2002; Jagtiani, Kolari, Lemieux, and Shin, 2003). The moral hazard hypothesis predicts that KA would tend to be lower for banks that use RBDs than for other banks, all else equal. A mitigating factor is that federal law allows only well-capitalized banks to accept RBDs or other brokered deposits, thus constraining the extent of any empirical linkage between RBDs and KA. Even so, Figure 2 shows (and Table 3 confirms) a notable distinction in the direction predicted by the moral hazard hypothesis.

Net income / assets (ROA) is likewise inversely associated with the risk of failure (Thomson, 1991; Cole and Gunther, 1995; Wheelock and Wilson, 2000; DeYoung, 2003). The moral hazard hypothesis predicts that ROA would be lower for banks that use RBDs, all else equal.

Nonperforming loans / assets (NPL), a measure of credit risk, is associated with a higher risk of failure (Cole and Gunther, 1995; Wheelock and Wilson, 2000; Li, Sanning, and Shaffer, 2011). The moral hazard hypothesis predicts that NPL would be higher for banks that use RBDs, all else equal.

Operating expenses / assets (AC) can be interpreted as a measure of management effectiveness and has been found to be associated with a higher risk of failure (Espahbodi, 1991; Fuller and Kohers, 1994; DeYoung, 2003). The moral hazard hypothesis predicts that AC would be higher for banks that use RBDs, all else equal.

Total loans / assets (LA) is inversely related to liquidity but positively related to portfolio credit risk and probability of failure (Espahbodi, 1991; Thomson, 1991; Wheelock and Wilson, 2000; DeYoung, 2003). Commercial loans / assets (CL) has been found to be associated with a higher risk of failure (Cole and Gunther, 1995; Wheelock and Wilson, 2000).[4] Insider loans / assets (INS) is associated with a higher risk of failure and can be interpreted as a measure of managerial abuse (Thomson, 1991; Cole and Gunther, 1995). [5]The moral hazard hypothesis predicts that each of these three ratios would be higher for banks that use RBDs, all else equal.

While these ratios each relate to a single dimension of financial risk, some studies have used the Z-score as a more comprehensive measure that reflects potentially all sources of risk to a bank (Berger and Bouwman, 2009; Laeven and Levine, 2009; Turk Ariss, 2010; Demirgüç-Kunt and Huizinga, 2010; Beck, De Jonghe, and Schepens, 2013). The Z-score is defined as Z = (average ROA + equity) / standard deviation of ROA and represents the number of standard deviations of profitability needed to drive a bank into insolvency. As such, it is an inverse measure of a bank's risk of failure. The moral hazard hypothesis predicts that the Z-score would be smaller for banks that use RBDs, all else equal.

2.2 Sample and Data

Our analysis utilizes quarterly Call Report data for US commercial banks collected from the Federal Financial Institutions Examinations Council (FFIEC). The sample period is from 2009Q2 (the first quarter of available data on RBDs balances) to 2012Q4. Following Shaffer (2012, 2013), we exclude banks with non-positive total loans or expenses, loans exceeding assets, or equity/assets > 0.4. We also exclude banks that experience an equity growth of more than 100 percent per quarter from the prior December, or Return on Assets that is more than two standard deviations away from the population mean of all banks in the same quarter. For analysis involving the Z-score, we remove banks with $Z > 100$. This data cleaning process leaves about 4000 - 5000 banks in each quarter.

Figure 1 shows the trend of RBD usage among US commercial banks. During our sample period, 17 to 19 percent of US banks report a positive RBD balance, or an average of about 800 banks in each quarter. Following

[4] Some studies have used total loans rather than assets as the denominator of this ratio.
[5] Only 5,643 banks in our sample reported figures for insider loans in September 2009.

a distinct increase after the initial quarter, this ratio exhibited a general decline through the remainder of the sample period. Figure 1 also reports the average ratio of RBDs / assets for banks that use RBDs. This ratio exhibited a modest decline until the beginning of 2011, and remained roughly flat thereafter. Among these banks, the average volume of such usage is about $15 million.

Table 1 summarizes the calculated risk ratios. From 2009 to 2012, US commercial banks experienced increases in total equity / total assets and in net income / total assets, and a commensurate a decrease in the Z-score. Total loans / total assets, non-performing loans / total assets, and insider loans / total assets decreased during this period.

Figure 2 compares each of our risk measures for banks that use RBDs (dashed line) versus banks that do not (solid line). A clear difference is evident between the two lines for at least four of these risk ratios: Banks using RBDs have higher total loan ratios, commercial loan ratios, and insider loan ratios, while exhibiting lower capital ratios on average. According to previous studies, each of these differences is associated with higher risk. During the first half of the sample period, banks that report positive RBD balances exhibit higher operating cost ratios than other banks which, ceteris paribus, would be associated with lower risk.

These comparisons are merely informal and suggestive. The next section provides more formal analysis of possible associations between RBDs and various aspects of bank risk.

3 Empirical Models

3.1 RBDs and Risk Ratios

A first step in formally analyzing bank risk and RBD usage could involve paired t-tests of equal means for each risk ratio for banks that use RBDs versus banks that do not. Instead of undertaking this step, we perform a slightly more informative test, simple regressions comparing each risk ratio separately against the existence or intensity of RBD usage. Statistical significance should be similar for both tests, but the simple regressions have the advantage of providing additional information about the magnitudes of any associations between RBDs and risk. A subsequent section will estimate multiple regressions controlling for other risk factors, as explained below.

In our first step, we estimate the following regression for each of the eight risk ratios defined above:

$$Risk_{i,t} = \beta_0 + \beta_1 RBD_{i,t} + \epsilon_{i,t} \tag{1}$$

$RBD_{i,t}$ is defned as a dummy yes/no usage variable. $Risk_{i,t}$ is one of the risk ratios defined in Section 2 (Table 1). If a bank has positive RBDs balances through a time period, then it will receive a dummy value of 1, 0 otherwise. We also test a similar specification that instead uses the ratio RBD Balance / Total Assets as a regressor:

$$Risk_{i,t} = \beta_0 + \beta_1 BalRBD/Asset_{i,t} + \epsilon_{i,t} \tag{2}$$

In addition, we re-estimate equation 2 for only the subset of banks that use RBDs. There are two reasons for this step. First, estimating RBD/Assets models using all banks will conflate the effects of existence versus intensity of RBD use. If existence matters more than intensity, this will bias the estimated impact of intensity upward. Second, if intensity matters more than existence of RBD use, then our current RBD/Assets estimates will bias the estimated impact of intensity downward.

3.2 RBDs and Failure Risk

We next explore possible associations between RBDs and the overall risk of bank failure, measured directly using data from the FDIC on failed banks. This analysis extends and updates similar analysis in Shaffer (2013). The moral hazard hypothesis would predict that banks using RBDs, or using larger amounts of RBDs, would exhibit a higher frequency of failure, all else equal.

The motivation for this section is that the event of failure is a direct, accurate, and comprehensive measure of bank risk. This approach, however, has two drawbacks: typically only a small percentage of banks fail, creating a small sample of failures to analyze; and failure provides an ex post measure of risk, whereas ideally we would prefer to incorporate additional information by using ex ante measures of risk as in the previous section. Therefore, the results of our failure analysis should be construed as complementing our risk ratio analysis in the previous section.

Table 2 shows number of bank failures and estimated failure cost. For each Call Report period in the sample, we define two failure outcomes. 1) Bank failure occured within one year following the observed financial ratios. That is, the bank fails within 4 quarters after the quarter of financial report. Or 2) Bank failure occured within two years following the observed financial ratios. That is, the bank fails within eight quarters after the quarter of Call Report.

In the first case, we examine Call Report from Q22009 to Q42011, to make sure each quarter of Call Report of each bank in the sample have eight quarters as its failure window. The mean rate of failure is about 1 percent for this failure outcome. In the second case, we use Call report data from Q22009 to Q42010, to make sure each Call Report period to have four quarters as its failure window. The average rate of failure for this outcome is about 2 percent for each quarter. These specifications of the failure window conform to those adopted in previous early warning studies.

For each of the failure outcome defined above, we evaluate the following two logit regressions:

$$\begin{aligned} Logit\ (failure = 1) = {} & \beta_0 + \beta_1 RBD_{i,t} + \beta_2 LA_{i,t} + \beta_3 DA_{i,t} + \beta_4 AC_{i,t} \\ & + \beta_5 NPL_{i,t} + \beta_6 CL_{i,t} + \beta_6 KA_{i,t} + \beta_7 INS_{i,t} + \epsilon_{i,t} \end{aligned} \tag{3}$$

and

$$Logit\ (failure = 1) = \beta_0 + \beta_1 BalRBD/Asset_{i,t} + \beta_2 LA_{i,t} + \beta_3 DA_{i,t} + \beta_4 AC_{i,t} + \beta_5 NPL_{i,t} + \beta_6 CL_{i,t} + \beta_6 KA_{i,t} + \beta_7 INS_{i,t} + \epsilon_{i,t} \quad (4)$$

3.3 RBDs and Cost of Failure

In this section, we extend the analysis of bank failure to explore any associations between RBDs and estimated costs of bank failure to the FDIC. A motivation for this section is the possibility that the use of RBDs may be associated with more costly failures, even if the raw likelihood of failure is not higher; as well as the contrary (and equally informative) possibility that the use of RBDs may not significantly affect the cost of a bank's failure to the FDIC, regardless of any association with the likelihood of failure. That is, this analysis enables us to decompose the expected cost of failure into two components – the likelihood of failure, times the cost of failure conditional on the occurrence of failure.

We evaluate the cost of bank failure in two ways, both unconditional and conditional on the event that the bank has failed. The conditional cost of failure is simply the estimated cost to the deposit insurance fund of each failed bank, a variable provided by the FDIC with some lag after each failure. We test whether the pattern of such costs can be statistically explained by banks' use of RBDs, either alone or controlling for other known risk ratios as described above.

The unconditional expected cost of failure, as noted above, is the product of the predicted probability of failure times the cost of failure conditional on the event of failure. For both types of failure cost, we estimate the following regression to examine the net total association with RBDs:

$$\ln(\$CostofFailure_i) = \beta_0 + \beta_1 RBD_{i,t}(or, BalRBD/Asset_{i,t}) + timefixedeffects_i + \epsilon_{i,t} \quad (5)$$

To evaluate the incremental effect of RBD after controlling for other indicators of risk, we run the following regression:

$$
\begin{aligned}
\ln(\$CostofFailure_i) = \beta_0 + \beta_1 RBD_{i,t}\ (or,\ BalRBD/Asset_{i,t}) \qquad (6)\\
+\beta_2 LA_{i,t} + \beta_3 DA_{i,t} + \beta_4 AC_{i,t} + \beta_5 NPL_{i,t}\\
+\beta_6 CL_{i,t} + \beta_6 KA_{i,t} + \beta_7 INS_{i,t} + time\ fixed\ effects_i + \epsilon_{i,t}
\end{aligned}
$$

The unconditional cost of failure involves a censored sample, because we only observe the FDIC's estimated cost of failure for banks that actually failed, even those banks that did not fail would have imposed a positive cost on the deposit insurance fund if they had failed. Therefore, we provide an alternate set of estimates of the unconditional cost of failure model using a Tobit estimator to deal with this issue. In this case, the standard assumptions of the Tobit estimator are satisfied, because the same factors that cause a bank to fail are also the ones that cause its failure to impose a cost on the FDIC.

4 Basic Results

Table 3 reports estimates of our risk ratios model (equations 1 and 2). For equation 1, the results support the moral hazard hypothesis for seven of the eight risk ratios: banks that use RBDs exhibit significantly lower equity / assets, net income / assets, and Z-scores, but significantly higher nonperforming loan ratios, total loans / assets, commercial loans / assets, and insider loans / assets. These results are consistent with previous findings in Shaffer (2012) for earlier and smaller samples.

Equation 2 shows similar results except for the Z-score, which shows an insignificant coefficient (though its point estimate is still negative); and nonperforming loans / total assets, which exhibits a significantly negative coefficient – that is, banks that use relatively larger amounts of RBDs tend to have better asset quality, all else equal. This finding is repeated in the bottom panel of the table for the subset of banks that report positive RBD balances, and is not consistent with the moral hazard hypothesis. It is consistent with the idea that depositors are more willing to place larger amounts of funds into RBD accounts at safer banks, measured by loan performance, and could suggest both a degree of market discipline operating in the RBD product as well as some mitigation of the components of risk shown in the other columns.

A stronger contrast with prior results is shown for operating expenses / assets. In both equation 1 and equation 2, banks that use RBDs (respectively, that use relatively larger amounts of RBDs) report lower operating cost ratios, which would tend to offset to some degree the higher risk associated with the other ratios. This finding is consistent with claims that RBDs can lower a bank's cost of funds and liquidity management (Lehman (Lehman); McGill and McKean (2010)), and represents a shift from the pattern found in an earlier and smaller sample by Shaffer (2012). It is conceivable that some of this shift might be explained by banks' recovery from the financial crisis of 2007-2009 and adaptation to lessons learned.

The bottom panel of Table 3 reports estimates of equation 2 for the subset of banks that report positive RBD balances. The results are consistent with the middle panel for all but three risk ratios. By contrast, more intensive use of RBDs is associated with significantly higher equity / assets and Z-scores, and with significantly lower commercial loans / assets ratios. These latter findings contrast with patterns reported in Shaffer (2012, 2013) and are not consistent with the moral hazard hypothesis. The reversal of the pattern for the Z-score appears driven in part by the higher equity / assets ratios, as equity is a component in the numerator of the Z-score.

The magnitudes of these effects are summarized in Table 4. Usage of RBDs is associated with substantially different average levels of most risk ratios, and especially with respect to commercial loans / assets (which is more than doubled for banks using RBDs) and insider loans / assets. Regarding intensity of usage of RBDs, a 10 percentage point increase in RBDs / assets is also associated with substantially different values of most risk ratios, again most dramatically seen for commercial loans / assets and insider loans / assets.

Table 5 reports estimates of equations 3 and 4, relating RBDs to bank failures. The results are mixed but show weak support for the moral hazard hypothesis. The RBD dummy is not significant for either failure horizon (one year or two years), but the RBD / assets ratio is marginally significant in two of four specifications, suggesting a higher probability of failure for banks that use relatively higher amounts of RBDs. The point estimate of the coefficient on both RBD variables is always positive, consistent with the moral hazard hypothesis. The magnitude of the point estimate, though not always its t-statistic, is smaller at the two-year forecast horizon than at the one-year forecast horizon, indicating a generally stronger near-term association between RBDs and subsequent failure. The control variables (other risk ratios) are mostly significant with the anticipated signs, consistent with the early warning literature, except for commercial loans / total assets which is never significant.

Table 6 shows that the existence of RBD usage is strongly associated with a higher cost of failure to the deposit insurance fund, conditional on the event of failure. This pattern persists across all four specifications, whether or not we control for other observable risk factors. This important question has not been addressed in prior studies, and the findings are consistent with the predictions of the moral hazard hypothesis. As in Table 5 , the magnitudes of the coefficients on the RBD dummies are larger for the one-year forecast horizon than for the two-year forecast horizon, though the t-statistics show the opposite pattern. However, no significant coefficient is found on the ratio of RBDs / assets. Three of the other risk ratios are always significant with the expected signs, when included: nonperforming loans / total assets, operating expenses / total assets, and commercial loans / total assets. Total loans / assets exhibited a marginally significant positive coefficient, as expected, in the specifications for the two-year forecast horizon.

Table 7 reports estimates for the unconditional cost of failure. Here, the dependent variable is the natural logarithm of the product of the estimated cost of failure (as reported by the FDIC) times the predicted probability of failure from our model in equation 3 or 4. Because we only observe the FDIC's estimated cost of failure for banks that actually failed, the sample size is the same as in Table 6.

The RBD dummy exhibits a significantly positive coefficient when controlling for other risk ratios, indicating a higher unconditional cost of failure for banks that use RBDs even though Table 2 shows that many of those risk ratios themselves tend to vary with RBD usages. However, the RBD dummy is not significant in regressions not controlling for other risk ratios, and the ratio of RBDs / assets is significant (with a negative coefficient) in only one of the four specifications – implying that more intensive use of RBDs is associated with a lower unconditional expected cost of failure over a two-year failure horizon when not controlling for other risk factors. In the lower panel, the risk ratios all exhibit significant coefficients of the anticipated signs except operating expenses / assets, which shows insignificant positive coefficients at the one-year forecast horizon but significantly negative coefficients at the two-year horizon.

Table 8 reports Tobit estimates for the model of unconditional cost of failure. The results here are more mixed. The RBD dummy has a marginally significant positive coefficient in just one of the four specifications (i.e., for a one-year failure horizon, controlling for other risk ratios), while the RBD / assets ratio is likewise significant in only one specification – exhibiting a negative sign for the two-year failure horizon without controlling for other risk ratios.

Because equations 3 and 4 do not rescale the dependent variables based on bank size, it is possible that the results in Tables 6 through 8 may reflect scale-dependent patterns of RBDs and risk. Larger banks generally impose larger costs on the deposit insurance fund when they fail, and it is possible that larger banks may also be more likely to use RBDs. Accordingly, we estimate a variant of equations 3 and 4 in which the dependent variable $ln(\$CostofFailure_i)$ is replaced by the ratio of estimated cost of failure / total assets. These results are reported in Tables 9 through 11 for the conditional and unconditional expected relative costs of failure, respectively.

These results contrast strongly with those in Tables 6 and 7. For the unconditional expected relative cost of failure, RBD has a significantly negative coefficient in every specification, while RBD / assets has a significantly negative coefficient for the one-year failure horizon. That is, for banks that failed during our sample period, the use of RBDs was associated with *proportionately smaller* estimated costs of failure. These results contradict the moral hazard hypothesis and lend support to practitioners' claims that RBDs may help banks mitigate the severity of exogenous adverse shocks. The same pattern appears for unconditional expected relative costs of failure in Tables 10 and 11, where the RBD variables have significantly negative coefficients in every specification apart from one exception in Table 11. Together with the results in Tables 6 and 7, these findings indicate that larger banks are indeed more likely to use RBDs, implying that any moral hazard effects such as noted above may be somewhat more likely to be associated with systemic risk, an important question that we do not directly test.

Overall, the results reported in this section provide multiple aspects of support for the moral hazard hypothesis related to the use of RBDs, consistent with theory and prior studies, but also some new contrasting elements and refinements that offer a more nuanced reading of the data, along with the first tests of expected failure costs and RBDs. The following section presents additional tests: first of causality, and then regarding the impact of an observed change in the FDIC's pricing of deposit insurance.

5 Further analysis

5.1 Granger-Causality Tests

The existence and direction of any causality between RBDs and bank risk is a question of specific interest for regulatory policy, bank management, and other applications. Shaffer (2012) notes that either direction of causality, as well as parallel response by RBDs and risk to other exogenous factors (i.e., no causality between RBDs and risk), would have useful policy implications, but no previous study has explored this question. The type of regulatory policy to be considered determines the implications of the direction of causality. For the purpose of accurately pricing risk, it is sufficient that RBDs be robustly associated with appropriate measures of risk, without regard to questions of causality (ibid.). By contrast, the impact of any policy that would restrict or prohibit the use of RBDs would depend crucially on the existence of a causal link running from RBDs to risk, which has not been previously tested.

Following Berger and DeYoung (1997), we exploit Granger Causality techniques to test whether there is causality relationships between usage of RBD and increased risk ratios. In this test, we assume all of the risk ratios are stationary ($I(0)$), and the error terms are not correlated. Since the data is panel data with about seven thousand observations for each quarter, we include time fixed effects to absorb unobserved cross-section correlation that is constant across banks within each quarter (i.e., to account for changes of macroeconomic conditions or regulatory treatments over time).[6] The Granger-Causality model is specified as follows for each risk ratios and for both RBD dummy and RBD balance to asset ratio:

$$Risk_{i,t} = f_1(Risk_{i,lag}, RBD_{i,lag}, time_t) + \varepsilon_{1i,t} \tag{7}$$

and

$$RBD_{i,t} = f_1(Risk_{i,lag}, RBD_{i,lag} time_t) + \varepsilon_{1i,t} \tag{8}$$

As a reminder, the moral hazard hypothesis predicts that banks using RBDs can profitably choose to operate with higher levels of risk, due to the ability of RBDs to mitigate some degree of market discipline; that is, RBDs may "cause" higher risk. Equation 7 tests this hypothesis. As noted in Shaffer (2012), the reverse direction of causality can also be consistent with moral hazard: the cost advantage of using RBDs would theoretically be larger for riskier banks, so that higher risk may "cause" cost-conscious banks to use RBDs, even if banks do not behave as strict cost minimizers. Equation 8 tests this hypothesis.

We include lags for four periods in each of the independent variables for

[6] Berger and DeYoung (1997) also included a region fixed effect, but our sample includes banks that operates nationwide, so we choose not to include this control.

the above equation, along with time fixed effects.[7] Tables 11 and 12 list the Granger test results for the association of risk ratios and the RBD dummy. Here we estimate equation 8 as a logit regression since its dependent variable is the binary variable RBD defining whether or not the bank reports positive RBD values.

Table 12 indicates that banks using RBDs tend to have higher ratios of total loans / assets and commercial loans / assets; that is, the use of RBDs "Granger causes" higher risk in those two dimensions, consistent with the moral hazard hypothesis. However, such linkages do not show up in other categories of risk, contrary to the moral hazard hypothesis for those categories.

Table 13, by contrast, indicates that all but two categories of risk "Granger cause" banks to use RBDs. Banks with higher risk in terms of total loans / assets, commercial loans / assets, and insider loans / assets are significantly more likely to use RBDs, consistent with a version of the moral hazard hypothesis as noted above. However, more profitable banks and banks with better asset quality (lower relative levels of nonperforming loans) are also significantly more likely to use RBDs, contrary to the moral hazard hypothesis; these two results might suggest a form of market discipline operating through RBDs, whereby depositors are more willing to place large sums of money in banks that are more profitable and have fewer nonperforming loans, even with the extended deposit insurance coverage afforded by the RBD contract. These two patterns would tend to mitigate the overall impact of moral hazard. The other two risk ratios, equity / assets and operating expenses / assets, did not exhibit any significant causal effect on RBDs.

Tables 14 and 15 report estimates of equations 7 and 8, respectively, for associations between risk ratios and the ratio of RBD balances / total assets. The results in Table 14 are qualitatively identical to those in Table 12, providing limited support for the moral hazard hypothesis. The results

[7] As robustness checks, we also estimate equation 7 and 8 with lags of three and five periods of the independent variables. The results are very similar to what is presented here.

in Table 15 are very similar to those in Table 13, except that commercial loans / total assets exhibits no significant association with RBD balances / assets across the four lags.

Overall, our lagged results complement and refine the contemporaneous estimates reported in the previous section. Banks tend to choose to use RBDs if they are more profitable and have higher-quality (lower risk) loans. Banks tend to choose to use RBDs if they are more illiquid (higher LA and higher CL), which fits the theoretical prediction and is consistent with the contemporaneous empirical results. Banks tend to choose to use RBDs if they have more insider loans, which is consistent with the moral hazard theory and with the contemporaneous empirical results. Banks that use RBDs tend to select higher LA and CL. Again, this is consistent with theoretical predictions and the contemporaneous estimates, and says that those are banks that face good lending opportunities and feel able to operate with smaller cushions of investment securities (an inference based on the accounting identity that assets = loans + securities + cash + fixed assets). The smaller securities ratios could reflect some combination of willingness to accept higher liquidity risk and/or confidence that RBDs are more stable funding than other non-core funding.

5.2 Policy Followup and Tests

The FDIC, while categorizing RBDs as a form of brokered deposits, initially exempted them from any risk premium or surcharge. Prompted by a federal legislative mandate to reconsider its definition and pricing of brokered deposits, the FDIC later subjected RBDs to an increased brokered deposit premium adjustment starting in April 2011.[8] This action is consistent with the

[8] The FDIC's Final Rule on Base Assessment Rates was adopted on February 27, 2009 and took effect on April 1, 2009; see http://www.alston.com/financialmarketscrisisblog/blog.aspx?entry=1581 or http://www.fdic.gov/news/board/27Feb09_Final_Rule.pdf . An updated rule was adopted in 2011; see http://www.fdic.gov/news/news/financial/2011/fil11008.pdf (accessed on March 4, 2013): brokered deposits are assessed up to an additional 10 b.p. annually for all small banks not in Risk Category I and all large or highly complex insured depository institutions subject to certain exemptions, starting with an Initial Base Assessment Rate as low as 14 b.p. and potentially adjusted downward by another

idea that RBDs are associated with measurably higher financial risk to the deposit insurance fund, but theoretically should also somewhat dampen demand for RBDs and weaken any empirical relationship between RBDs and bank risk. The evolution of this issue at the policy level further supports the importance of studying possible empirical associations between banks' use of RBDs and their observable risk, and more specifically the importance of testing for shifts in such linkages after the new regulatory pricing. Accordingly, the following section presents formal empirical tests for such effects.

Accordingly, this section presents formal empirical tests for such effects. We pose two hypotheses: first, that the FDIC's pricing change should weaken empirical linkages between RBDs and risk; and second, that the FDIC's pricing change should reduce banks' usage of RBDs. We define a dummy variable "FDIC" to equal one if the time period for each observation in the sample is later than 2011Q1, zero otherwise.

Before conducting formal statistical tests, it is instructive to refer to Figure 2. Of the eight risk ratios shown, it is evident that the gap between RBD banks and non-RBD banks is narrower, or even reversed, after 2011 for half of these ratios: ROA, NPL, AC, and Zscore. For KA, the gap appears slightly narrower but remains appreciable after 2011. Thus, a preliminary scan of the data in visual form appears to lend support to our hypothesis. We turn next to formal regressions for a more precise characterization of these shifts.

To test our first hypothesis, we estimate each of the following two equations:

$$\begin{aligned} Risk_{i,t} = \beta_0 + \beta_1 RBD_{i,t} + \beta_2 FDIC_{i,t} + \beta_3 FDIC_{i,t} * RBD_{i,t} \\ + time\ fixed\ effects_i + \epsilon_{i,t} \end{aligned} \tag{9}$$

5 b.p. for an Unsecured Debt Adjustment. Thus, the use of brokered deposits could potentially more than double the premium rate that some banks pay to the FDIC (e.g., 14 – 5 + 10 = 19 b.p. versus 14 – 5 = 9 b.p.). An e-mail from a senior FDIC staff member to one of the authors (March 4, 2013) clarified that this "brokered deposit adjustment" (including reciprocal deposits) "applies to a bank of any size that is not [CAMELS] 1 or 2 rated or not well capitalized."

$$
\begin{aligned}
Risk_{i,t} = {} & \beta_0 + \beta_1 RBD/Asset_{i,t} + \beta_2 FDIC_{i,t} \\
& + \beta_3 FDIC_{i,t} * RBD/Asset_{i,t} + time\ fixed\ effects_i + \epsilon_{i,t}
\end{aligned} \tag{10}
$$

If the hypothesis is true – that the FDIC's pricing change weakened empirical associations between RBDs and risk – we should observe the coefficient on the interaction term to have the opposite sign as on the RBD term. Table 16 reports the results.

In the top panel, the hypothesis is true for six of our eight risk measures. However, for operating expenses / assets, the interaction term and RBD indeed have opposite signs of coefficients, but with the wrong sign to support the moral hazard hypothesis. For commercial loans / total assets, both the interaction term and RBD have significantly positive coefficients, consistent with the moral hazard hypothesis, but the adverse association is stronger after the FDIC's pricing change. For insider loans / total assets, the relevant coefficients indeed have opposite signs but the coefficient on the interaction term is not statistically significant.

In the lower panel, the hypothesis is supported at the 0.01 level for four risk measures: net income / assets, nonperforming loans / total assets, operating expenses / assets, and the Z-score. Qualitative support for the hypothesis, though not statistically significant, emerges for three others: equity / assets, total loans / assets, and insider loans / assets. Commercial loans / total assets exhibits the same pattern as in the top panel.

Table 17 summarizes the magnitudes of these effects, which are mostly large. For associations between RBD usage and bank risk, the impact of the new pricing is actually larger in magnitude than the underlying association before the pricing change for three of the risk measures (net income / assets, nonperforming loans / total assets, and the Z-score) and roughly equal in magnitude for two others (operating expenses / assets and commercial loans / assets). This same pattern holds for associations between the intensity of RBD usage and bank risk except for commercial loans / assets. Thus, our first hypothesis is supported at high levels of both statistical and economic significance.

We test our second hypothesis by estimating the following equation, using both the dummy and ratio versions of the RBD variable:

$$RBD_{i,t}\ (or,\ BalRBD/Asset_{i,t}) = \alpha_0 + \alpha_1 FDIC_{i,t} + \epsilon_{i,t} \tag{11}$$

The hypothesis implies a negative coefficient on FDIC. For the dummy version of RBD, we estimate a logit regression. Although not reported in a separate table for brevity, we find strong support for the hypothesis, as the robust t-statistics on the FDIC dummy are -4.17 for the RBD dummy and -6.53 for RBD / Assets, both significant at $p < 0.01$.

6 Conclusion

This paper has analyzed the relationship between reciprocal brokered deposits (RBDs) and bank risk in a deeper way, using a larger and more recent sample, than prior studies. We find additional support for the moral hazard hypothesis, but also find contrary evidence in some individual dimensions – especially with regard to operating costs, where our new evidence contradicts the moral hazard hypothesis and supports practitioners' claims that RBDs can reduce a bank's cost of funding and of managing liquidity risk. We present new evidence concerning the important but previously unexplored association between RBDs and expected failure costs, finding mixed results: RBDs are significantly associated with higher total, but lower proportional, failure costs, suggested a previously unsuspected link to systemic risk. Granger causality is found in both directions, though more generally running from risk to RBDs than the other way, and the observed causal linkages contradict the moral hazard hypothesis for profitability and asset quality. The FDIC's revision of its pricing rule in 2011 had the theoretically predicted effect of reducing banks' demand for RBDs as well as weakening the empirical linkage between RBDs and risk.

These findings extend and refine our understanding of banks' use of RBDs, which can have important implications for public policy and systemic risk. Overall, the findings support the FDIC's current policy of explicitly pricing RBDs in its deposit insurance premium schedule, though without suggesting firm conclusions about the appropriate level of such pricing. More generally, because the extended coverage available with RBDs could be implemented at zero cost through legislative action, the lessons learned with RBDs could be informative for policy debates about future expansions of federal deposit insurance coverage.

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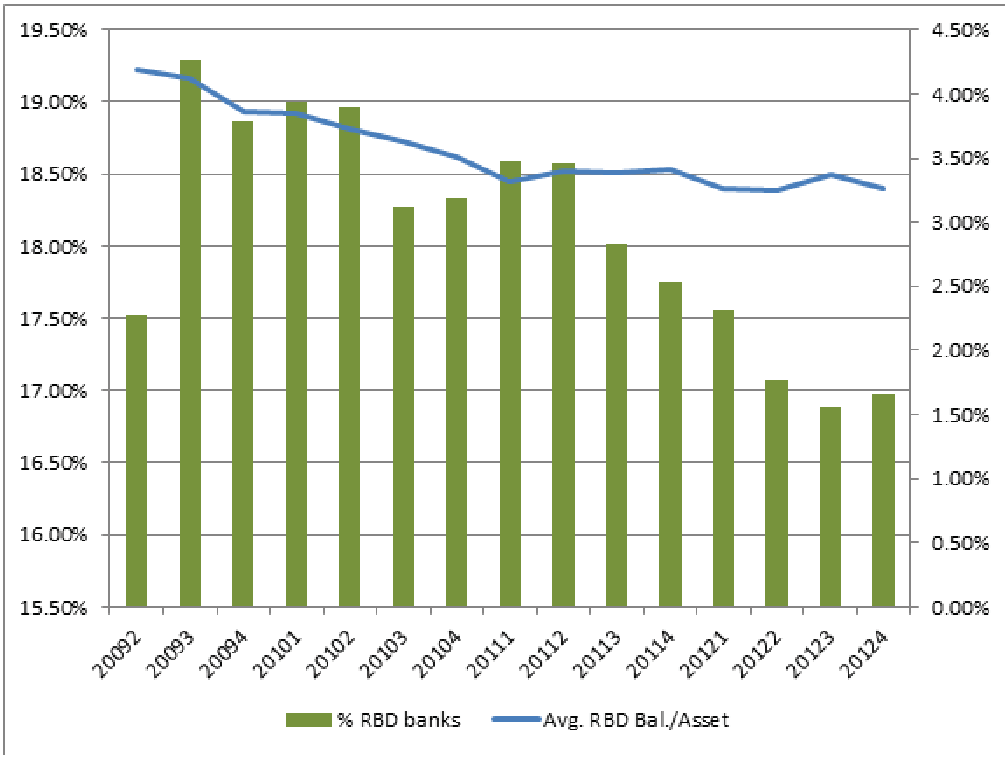
Figure 1: Percent of Banks Using RBD, and Average RBD Balances/Asset Ratio



Note: The Average RBD Balances/Asset ratio is the mean RBD balances for banks that use RBDs only.

Figure 2: Time series of Risk Ratios: RBD Banks versus NonRBD Banks

Table 1: Summary Statistics for Risk Ratios

		2009	2010	2011	2012	All
KA	TotalEquity/TotalAssets	0.1069	0.1068	0.1075	0.1099	0.1079
		(0.0364)	(0.0339)	(0.0316)	(0.0332)	(0.0338)
ROA	NetIncome/TotalAssets	0.0005	0.0012	0.0017	0.0018	0.0014
		(0.0038)	(0.0030)	(0.0023)	(0.0026)	(0.0030)
NPL	NonPerformingLoans/TotalAssets	0.0234	0.0236	0.0208	0.0194	0.0216
		(0.0270)	(0.0273)	(0.0244)	(0.0233)	(0.0255)
AC	OperationExpenses/TotalAssets	0.0015	0.0017	0.0015	0.0014	0.0015
		(0.0016)	(0.0020)	(0.0015)	(0.0014)	(0.0016)
LA	TotalLoans/TotalAssets	0.6629	0.6373	0.6122	0.605	0.6273
		(0.1477)	(0.1476)	(0.1485)	(0.1535)	(0.1512)
CL	CILoans/TotalAssets	0.0199	0.018	0.0198	0.0206	0.0196
		(0.0477)	(0.0448)	(0.0485)	(0.0494)	(0.0477)
INS	InsiderLoans/TotalAssets	0.0152	0.0145	0.0137	0.0125	0.0139
		(0.0175)	(0.0165)	(0.0158)	(0.0148)	(0.0161)
Zscore	(AverageROA + TotalEquity)/Std.(ROA)	191.982	215.713	256.143	306.355	245.556
		(261.7152)	(315.0373)	(340.1374)	(382.9189)	(333.8801)
RBD Bal./Asset	BalanceofRBD/TotalAssets All Banks	0.0075	0.0069	0.0062	0.0056	0.0065
		(0.027)	(0.026)	(0.023)	(0.022)	(0.024)
RBD Bal./Asset	BalanceofRBD/TotalAssets	0.0406	0.0368	0.0338	0.0329	0.0358
	Banks that use RBD	(0.050)	(0.049)	(0.043)	(0.045)	(0.047)

Standard deviations in parentheses

Data are summarized yearly here, but we used quarterly data for all regressions that follow. Figures for ROA and AC are quarterly averages.

Table 2: Failed Bank Sample Statistics by Quarter

Quarter	Number of Failed Banks	Total Failure Cost (1000$)
2009Q1	21	$ 2,395,527
2009Q2	24	$ 9,325,735
2009Q3	50	$ 13,844,626
2009Q4	45	$ 10,602,893
2010Q1	41	$ 5,942,226
2010Q2	42	$ 4,732,479
2010Q3	41	$ 3,057,074
2010Q4	30	$ 2,540,186
2011Q1	26	$ 2,344,709
2011Q2	22	$ 2,641,507
2011Q3	26	$ 2,704,558
2011Q4	18	$ 1,185,727
2012Q1	16	$ 1,313,354
2012Q2	15	$ 597,196
2012Q3	12	$ 482,579
2012Q4	8	$ 353,791
2013Q1	4	N/A
2013Q2	12	N/A
Total	478	$ 64,064,167

The column "Total Failure Cost" shows the total estimated loss for all failed banks during that quarter. The definition of estimated loss can be found here: http://www2.fdic.gov/hsob/help.asp#BF1EC. Date accessed: March 2014. Estimated loss is presented as “N/A” in years for which comprehensive information is not available. the FDIC estimates expected costs with a lag after each failure.

Table 3: RBD Association with Bank Risk Ratios

Dep. Var.	KA	ROA	NPL	AC	LA	CL	INS	Zscore
	All Bank-Quarter Observations, Eq. 1							
RBD Dummy	-0.00615***	-0.000175***	0.00163***	-0.000108***	0.0772***	0.0273***	0.00224***	-2.259***
	[-22.75]	[-5.714]	[6.887]	[-7.501]	[60.86]	[43.42]	[13.22]	[-4.836]
Observations	62,649	62,649	62,649	62,649	62,649	62,649	62,649	22,980
Adj. R-squared	0.005	0.001	0.001	0.001	0.040	0.048	0.003	0.001
	All Bank-Quarter Observations, Eq. 2							
RBDs/Asset Ratio	-0.0443***	-0.00314***	-0.00645*	-0.000957***	0.822***	0.228***	0.0331***	-12.14*
	[-9.784]	[-6.388]	[-1.835]	[-4.775]	[35.11]	[17.13]	[11.38]	[-1.733]
Observations	62,649	62,649	62,649	62,649	62,649	62,649	62,649	22,980
Adj. R-squared	0.001	0.001	0	0.00E+00	0.018	0.013	0.002	0
	Bank-Quarter Observations that have positive RBD balances, Eq. 2							
RBDs/Asset Ratio	0.0180***	-0.00231***	-0.0320***	0.0000512	0.171***	-0.0325**	0.0190***	11.17
	[3.447]	[-3.848]	[-7.338]	[0.207]	[7.851]	[-2.037]	[5.588]	[1.302]
Observations	11,655	11,655	11,655	11,655	11,655	11,655	11,655	4,289
Adjusted R-squared	0.001	0.001	0.004	0	0.005	0	0.003	0

*** P<0.01, ** P<0.05, * P<0.1

Robust t-statistics in brackets

RBD Dummy is defined as equal to 1 if the bank's reported RBD volume is positive. RBD/Asset Ratio is defined as RBD balances / Total Assets. The risk ratios KA, ROA, NPL, AC, LA, CL, INS and Zscore are dependent variables defined in Table 1. Regressions are run separately for the RBD dummy as the sole independent variable, and for the RBD/Asset Ratio as the sole independent variable. There are fewer observations in the Zscore regressions because multiple time periods of data are required to compute each Zscore, as described in the text.

Table 4: Magnitudes of Associations between RBDs and Bank Risk

Risk Measure	KA	ROA	NPL	AC	LA	CL	INS	Zscore
	Percentage change in risk measure associated with usage of RBDs:							
	-6.2%	-8.1%	6.1%	7.4%	12.1%	131.6%	18.9%	4.0%
	Percentage change in risk measure associated with a 10 percentage point increase in RBD Balance/Assets:							
	-4.4%	-15.9%	-4.8%	-7.9%	12.4%	108.3%	28.4%	1.8%

Table 5: RBD Association with Bank Failure

	All Banks								Banks that use RBDs	
	Fail within one year				Fail within two years				Fail within one year	Fail within two years
RBD Dummy	-0.193	0.180			0.100	0.00146				
	[-1.437]	[1.062]			[0.994]	[0.0109]				
RBD/Asset Ratio			-4.118	5.061**			0.179	2.850	11.33	7.577*
			[-1.125]	[1.753]			[0.104]	[1.325]	[1.605]	[1.766]
KA		-84.74***		-85.10***		-62.89***		-63.17***	-127.5***	-56.70***
		[-23.02]		[-23.04]		[-20.11]		[-20.16]	[-4.273]	[-5.406]
ROA		-64.04***		-63.62***		-72.59***		-72.16***	26.40	-82.86*
		[-4.451]		[-4.408]		[-6.501]		[-6.435]	[0.392]	[-1.737]
NPL		19.63***		19.67***		23.82***		23.85***	32.71***	26.13***
		[15.17]		[15.15]		[18.78]		[18.78]	[4.551]	[5.355]
AC		89.37***		91.22***		34.01		35.77	-442.4	-58.51
		[3.262]		[3.300]		[1.413]		[1.490]	[-0.882]	[-0.601]
LA		2.643***		2.618***		3.052***		3.031***	-2.540	-0.752
		[3.303]		[3.263]		[5.179]		[5.135]	[-0.531]	[-0.325]
CL		1.756		1.829		0.398		0.304	-7.723	-2.203
		[1.309]		[1.388]		[0.377]		[0.295]	[-0.955]	[-0.559]
INS		16.77***		16.65***		18.70***		18.52***	21.39	24.41**
		[4.156]		[4.153]		[6.120]		[6.021]	[0.943]	[1.964]
Observations	49,055	49,055	49,055	49,055	31,962	31,962	31,962	31,962	9,060	5,944

Robust t-statistics in brackets
*** p<0.01, ** p<0.05, * p<0.1

The dependent variables are failure within one year or failure within two years. RBD dummy and RBD balance to Asset ratio, and other risk ratios such as KA, ROA, NPL, AC, LA, CL, INS and Zscore are independent variables. Regressions are run separately for RBD dummy as independent variable and RBD/Asset Ratio as independent variable, wih or without other risk ratios for each of the failure outcomes.

Table 6: RBD Association with Conditional Cost of Failure: Ln(Estimated Loss) as Dependent Variable

	RBD Variables Alone			
	Fail within one year		Fail within two years	
RBD Dummy	0.305**		0.244***	
	[2.414]		[2.857]	
RBD/Asset Ratio		-2.221		-1.170
		[-1.254]		[-1.053]
Observations	459	459	794	794
Adj. R-squared	0.024	0.014	0.022	0.013

	RBD Variables Together With Other Risk Ratios			
	Fail within one year		Fail within two years	
RBD Dummy	0.209**		0.173**	
	[2.078]		[2.471]	
RBD/Asset Ratio		-1.516		-0.764
		[-1.078]		[-0.838]
KA	-0.988	-0.764	-0.664	-0.521
	[-0.565]	[-0.433]	[-0.597]	[-0.465]
ROA	-10.88	-10.23	-4.480	-3.900
	[-1.379]	[-1.294]	[-0.765]	[-0.663]
NPL	4.860***	4.844***	4.060***	3.977***
	[7.898]	[7.844]	[8.620]	[8.435]
AC	-46.98***	-48.88***	-59.43***	-61.16***
	[-2.895]	[-2.998]	[-4.480]	[-4.594]
LA	0.213	0.170	0.557*	0.568*
	[0.543]	[0.432]	[1.916]	[1.945]
CL	10.43***	10.58***	10.21***	10.34***
	[12.22]	[12.39]	[16.17]	[16.39]
INS	-2.039	-2.136	-1.450	-1.714
	[-0.904]	[-0.944]	[-0.925]	[-1.090]
Observations	459	459	794	794
Adj. R-squared	0.395	0.391	0.357	0.353

Robust t-statistics in brackets
*** p<0.01, ** p<0.05, * p<0.1

The dependent variables are the conditional cost of failure for failures that happen within one year or two years since the financial report. RBD variables, and other risk ratios such as KA, ROA, NPL, AC, LA, CL, INS and Zscore are independent variables. Regressions are run separately for RBD dummy as independent variable and RBD/Asset Ratio as independent variables, with or without other risk ratios. As a robustness check, all regressions are also run with or without time fixed effects, and with or without a time trend, and the results are similar to those presented here.

Table 7: RBD Association with Unconditional Cost of Failure: OLS Regressions

VARIABLES	RBD Variables Alone			
	Fail within one year		Fail within two years	
RBD	0.306		0.0674	
Dummy	[1.019]		[0.354]	
RBD/Asset		-6.409		-7.977***
Ratio		[-1.534]		[-3.252]
Observations	459	459	794	794
Adj. R-squared	0.024	0.014	0.022	0.013

	RBD Variables Together With Other Risk Ratios			
	Fail within one year		Fail within two years	
RBD	0.357**		0.253***	
Dummy	[2.504]		[2.690]	
RBD/Asset		0.729		-0.495
Ratio		[0.364]		[-0.403]
KA	-59.53***	-59.61***	-42.58***	-42.46***
	[-24.00]	[-23.72]	[-28.48]	[-28.10]
ROA	-58.14***	-57.00***	-57.46***	-56.81***
	[-5.198]	[-5.064]	[-7.293]	[-7.171]
NPL	12.95***	12.87***	13.00***	12.88***
	[14.84]	[14.64]	[20.53]	[20.30]
AC	10.95	9.758	-41.80**	-43.95**
	[0.476]	[0.421]	[-2.344]	[-2.452]
LA	1.709***	1.684***	1.965***	1.979***
	[3.078]	[3.008]	[5.024]	[5.035]
CL	12.81***	13.10***	10.75***	10.95***
	[10.58]	[10.78]	[12.67]	[12.89]
INS	9.981***	9.593***	10.93***	10.59***
	[3.121]	[2.979]	[5.184]	[5.003]
Observations	459	459	794	794
Adj. R-squared	0.789	0.786	0.769	0.767

Robust t-statistics in brackets
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The dependent variables are the conditional cost of failure for failures that happen within one year or two years since the financial report. RBD variables, and other risk ratios such as KA, ROA, NPL, AC, LA, CL, INS and Zscore are independent variables. Regressions are run separately for RBD dummy as independent variable and RBD/Asset Ratio as independent variables, with or without other risk ratios. As a robustness check, all regressions are also run with or without time fixed effects, with or without a time trend, and the results are similar to those presented here.

Table 8: RBD Association with Unconditional Cost of Failure: Tobit Regressions

VARIABLES	RBD Variables Alone			
	Fail within one year		Fail within two years	
RBD	0.172		-0.0975	
Dummy	[0.396]		[-0.399]	
RBD/Asset		-7.451		-8.937***
Ratio		[-1.325]		[-2.967]
Observations	459	459	794	794

	RBD Variables Together With Other Risk Ratios			
	Fail within one year		Fail within two years	
RBD	0.280*		0.162	
Dummy	[1.741]		[1.591]	
RBD/Asset		0.0637		-0.666
Ratio		[0.0331]		[-0.553]
KA	-67.64***	-67.67***	-49.10***	-48.97***
	[-25.81]	[-25.51]	[-30.36]	[-30.03]
ROA	-67.84***	-66.36***	-63.71***	-63.04***
	[-5.308]	[-5.168]	[-7.143]	[-7.035]
NPL	21.57***	21.63***	20.91***	20.91***
	[16.97]	[16.80]	[22.56]	[22.46]
AC	17.67	17.48	-37.52**	-38.91**
	[0.768]	[0.753]	[-2.082]	[-2.152]
LA	3.205***	3.144***	3.558***	3.564***
	[5.313]	[5.173]	[8.308]	[8.303]
CL	16.42***	16.58***	12.86***	12.97***
	[10.59]	[10.62]	[12.64]	[12.74]
INS	13.41***	13.45***	13.74***	13.58***
	[3.933]	[3.908]	[6.192]	[6.097]
Observations	459	459	794	794

Robust t-statistics in brackets
*** p<0.01, ** p<0.05, * p<0.1

The dependent variables are the natural log of conditional cost of failure for failures that happen within one year or two years since the financial report. RBD variables, and other risk ratios such as KA, ROA, NPL, AC, LA, CL, INS and Zscore are independent variables. Regressions are run separately for RBD dummy as independent variable and RBD/Asset Ratio as independent variables, with or without other risk ratios. As a robustness check, all regressions are also run with or without the time fixed effects, with or without a time trend, and the results are similar to those presented here.

Table 9: RBD Association with Conditional Cost of Failure: Estimated Loss to Asset Ratio as Dependent Variable

VARIABLES	RBD Variables Alone			
	Fail within one year		Fail within two years	
RBD	-0.0784***		-0.0647***	
Dummy	[-5.374]		[-5.634]	
RBD/Asset		-0.486**		-0.234
Ratio		[-2.333]		[-1.542]
Observations	459	459	794	794
Adj. R-squared	0.063	0.014	0.031	-0.006

	RBD Variables Together With Other Risk Ratios			
	Fail within one year		Fail within two years	
RBD	-0.0674***		-0.0523***	
Dummy	[-5.050]		[-4.772]	
RBD/Asset		-0.484**		-0.187
Ratio		[-2.545]		[-1.295]
KA	-0.322	-0.261	0.105	0.119
	[-1.387]	[-1.094]	[0.601]	[0.667]
ROA	-0.235	-0.457	-0.0299	-0.0674
	[-0.225]	[-0.428]	[-0.0325]	[-0.0723]
NPL	0.670***	0.690***	0.562***	0.586***
	[8.193]	[8.260]	[7.605]	[7.840]
AC	0.487	0.497	0.614	0.874
	[0.226]	[0.226]	[0.295]	[0.414]
LA	0.0252	0.0251	0.122***	0.120***
	[0.485]	[0.473]	[2.667]	[2.588]
CL	-0.353***	-0.411***	-0.397***	-0.438***
	[-3.107]	[-3.561]	[-4.006]	[-4.387]
INS	0.546*	0.643**	0.575**	0.624**
	[1.822]	[2.101]	[2.338]	[2.504]
Observations	459	459	794	794
Adj. R-squared	0.229	0.196	0.135	0.111

Robust t-statistics in brackets
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The dependent variables are cost of failure to asset ratio for failures that happen within one year or two years since the financial report. RBD variables, and other risk ratios such as KA, ROA, NPL, AC, LA, CL, INS and Zscore are independent variables. Regressions are run separately for RBD dummy as independent variable and RBD/Asset Ratio as independent variables, with or without other risk ratios. As a robustness check, all regressions are also run with or without time fixed effects, with or without a time trend, and the results are similar to those presented here.

Table 10: RBD Association with Unconditional Cost of Failures:Estimated Loss to Asset Ratio as Dependent Variable, OLS Regressions

VARIABLES	RBD Variables Alone			
	Fail within one year		Fail within two years	
RBD	-0.0536***		-0.0537***	
Dummy	[-3.314]		[-4.627]	
RBD/Asset		-0.634***		-0.555***
Ratio		[-2.806]		[-3.669]
Observations	459	459	794	794
Adj. R-squared	0.063	0.056	0.079	0.069

	RBD Variables Together With Other Risk Ratios			
	Fail within one year		Fail within two years	
RBD	-0.0384***		-0.0300***	
Dummy	[-3.905]		[-4.626]	
RBD/Asset		-0.373***		-0.143*
Ratio		[-2.694]		[-1.679]
KA	-2.488***	-2.440***	-2.047***	-2.034***
	[-14.54]	[-14.04]	[-19.87]	[-19.39]
ROA	-1.875**	-2.003**	-2.014***	-2.024***
	[-2.430]	[-2.575]	[-3.709]	[-3.679]
NPL	0.966***	0.979***	1.126***	1.140***
	[16.04]	[16.11]	[25.80]	[25.86]
AC	3.308**	3.253**	1.795	1.921
	[2.083]	[2.029]	[1.460]	[1.544]
LA	0.0857**	0.0843**	0.0799***	0.0788***
	[2.238]	[2.179]	[2.963]	[2.889]
CL	-0.244***	-0.278***	-0.231***	-0.255***
	[-2.915]	[-3.311]	[-3.942]	[-4.318]
INS	0.553**	0.615***	0.709***	0.734***
	[2.507]	[2.762]	[4.881]	[4.998]
Observations	459	459	794	794
Adj. R-squared	0.660	0.654	0.719	0.713

Robust t-statistics in brackets
*** p<0.01, ** p<0.05, * p<0.1

The dependent variables are thehe natural log of estimate loss multiplied by the possibility of failure for failures that happen within one year or two years since the financial report. RBD variables, and other risk ratios such as KA, ROA, NPL, AC, LA, CL, INS and Zscore are independent variables. Regressions are run separately for RBD dummy as independent variable and RBD/Asset Ratio as independent variables, with or without other risk ratios. As a robustness check, all regressions are also run with or without time fixed effects, with or without a time trend, and the results are similar to those presented here.

Table 11: RBD Association with Unconditional Cost of Failures:Estimated Loss to Asset Ratio as Dependent Variable, Tobit Regressions

VARIABLES	RBD Variables Alone			
	Fail within one year		Fail within two years	
RBD	-0.0536***		-0.0537***	
Dummy	[-3.370]		[-4.671]	
RBD/Asset		-0.634***		-0.555***
Ratio		[-2.853]		[-3.704]
Observations	459	459	794	794
	RBD Variables Together With Other Risk Ratios			
	Fail within one year		Fail within two years	
RBD	-0.0384***		-0.0384***	
Dummy	[-4.003]		[-4.003]	
RBD/Asset		0.0637		-0.0300***
Ratio		[0.0331]		[-4.692]
KA	-2.488***	-2.440***	-2.047***	-2.034***
	[-14.90]	[-14.39]	[-20.15]	[-19.67]
ROA	-1.875**	-2.003***	-2.014***	-2.024***
	[-2.491]	[-2.639]	[-3.762]	[-3.731]
NPL	0.966***	0.979***	1.126***	1.140***
	[16.44]	[16.51]	[26.17]	[26.23]
AC	3.308**	3.253**	1.795	1.921
	[2.135]	[2.079]	[1.481]	[1.566]
LA	0.0857**	0.0843**	0.0799***	0.0788***
	[2.294]	[2.233]	[3.005]	[2.930]
CL	-0.244***	-0.278***	-0.231***	-0.255***
	[-2.988]	[-3.393]	[-3.997]	[-4.379]
INS	0.553**	0.615***	0.709***	0.734***
	[2.570]	[2.831]	[4.950]	[5.068]
Observations	459	459	794	794

Robust t-statistics in brackets
*** p<0.01, ** p<0.05, * p<0.1

The dependent variables are the natural log of estimate loss multiplied by the possibility of failure for failures that happen within one year or two years since the financial report. RBD variables, and other risk ratios such as KA, ROA, NPL, AC, LA, CL, INS and Zscore are independent variables. Regressions are run separately for RBD dummy as independent variable and RBD/Asset Ratio as independent variables, with or without other risk ratios. As a robustness check, all regressions are also run with or without time fixed effects, with or without a time trend, and the results are similar to those presented here.

Table 12: Granger Causality Test of RBD Dummy on Risk Ratios

VARIABLES	KA	ROA	NPL	AC	LA	CL	INS
Intercept	0.00459***	0.000706***	0.00157***	0.000246***	-0.001	0.000425***	0.000511***
	[33.04]	[41.56]	[16.97]	[23.72]	[-1.596]	[6.123]	[13.86]
L.RISK	0.901***	0.240***	0.612***	0.488***	0.804***	0.933***	0.786***
	[162.0]	[44.09]	[115.5]	[92.17]	[145.5]	[184.1]	[144.7]
L2.RISK	-0.0141*	0.141***	0.123***	0.145***	0.001	0.0497***	0.0959***
	[-1.917]	[28.70]	[20.12]	[26.72]	[0.0734]	[7.445]	[13.91]
L3.RISK	0.0527***	0.0883***	0.0497***	0.0350***	0.0687***	0.0142**	0.0299***
	[7.634]	[18.53]	[8.321]	[6.772]	[9.811]	[2.231]	[4.391]
L4.RISK	0.0190***	0.223***	0.0925***	0.137***	0.118***	-0.0146***	0.0362***
	[4.018]	[49.63]	[18.60]	[29.72]	[21.43]	[-3.082]	[6.996]
RISK(Total)	0.958	0.691	0.876	0.805	0.991	0.981	0.948
P-Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
L.RBD	-0.000562**	0.000	0.000	0.000	0.001	0.000	0.000
	[-2.186]	[-0.893]	[1.324]	[0.263]	[0.479]	[0.339]	[0.319]
L2.RBD	0.000	0.000	-0.000690*	0.000	0.001	0.000	0.000
	[1.600]	[1.184]	[-1.841]	[-1.374]	[0.920]	[-0.531]	[-0.763]
L3.RBD	0.000	0.000	0.000	8.76e-05**	-0.002	0.001	0.000
	[-0.173]	[0.284]	[0.856]	[2.346]	[-1.142]	[1.254]	[-0.393]
L4.RBD	0.000	0.000	0.000	0.000	0.001	0.000	0.000
	[0.819]	[-0.185]	[0.562]	[-1.323]	[0.736]	[1.239]	[0.787]
RBD(Total)	0.000	0.000	0.000	0.000	**0.001*** **	**0.0008*** **	0.000
P-Value	0.436	0.153	0.225	0.871	**0.014**	**0.000**	0.399

Robust t-statistics in brackets
*** p<0.01, ** p<0.05, * p<0.1
Note: Dependent variables are each of the risk ratios in this model

Table 13: Granger Causality Test of Risk Ratios on RBD Dummy

VARIABLES	KA	ROA	NPL	AC	LA	CL	INS
Intercept	0.009***	-4.860***	-4.636***	-4.728***	-6.106***	-4.842***	-4.914***
	[2.918]	[-52.83]	[-49.42]	[-48.92]	[-23.85]	[-54.19]	[-51.26]
L.RISK	12.850	12.850	5.411	37.480	0.479	3.226	8.680
	[0.546]	[0.546]	[1.068]	[0.764]	[0.368]	[1.192]	[0.961]
L2.RISK	-8.048	-8.048	-3.043	24.090	3.211*	2.475	1.975
	[-0.391]	[-0.391]	[-0.503]	[0.475]	[1.941]	[0.759]	[0.174]
L3.RISK	28.720	28.720	-13.72**	-110.3**	1.229	-5.240	2.463
	[1.428]	[1.428]	[-2.327]	[-2.201]	[0.760]	[-1.406]	[0.219]
L4.RISK	41.87**	41.87**	5.282	27.710	-2.793**	3.364	-2.026
	[2.242]	[2.242]	[1.100]	[0.611]	[-2.178]	[1.022]	[-0.248]
RISK(Total)	-0.6352817	**75.381*** **	**-6.073*** **	-21.072653	**2.126*** **	**3.825*** **	**11.093*** **
P-Value	0.695	**0.000**	**0.008**	0.480	**0.000**	**0.000**	**0.000**
L.RBD	5.159***	5.159***	0.728***	5.134***	5.088***	5.115***	5.133***
	[46.08]	[46.08]	[138.5]	[45.89]	[45.07]	[45.44]	[46.00]
L2.RBD	1.442***	1.442***	0.130***	1.445***	1.447***	1.430***	1.441***
	[9.171]	[9.171]	[20.67]	[9.248]	[9.233]	[9.098]	[9.166]
L3.RBD	0.694***	0.694***	0.0451***	0.713***	0.712***	0.708***	0.705***
	[3.780]	[3.780]	[7.482]	[3.900]	[3.911]	[3.866]	[3.828]
L4.RBD	0.868***	0.868***	0.0422***	0.874***	0.859***	0.848***	0.858***
	[5.450]	[5.450]	[8.882]	[5.490]	[5.420]	[5.334]	[5.368]
RBD(Total)	8.187	8.163	8.177	8.166	8.105	8.101	8.137
P-Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Robust t-statistics in brackets
*** p<0.01, ** p<0.05, * p<0.1
Note: Dependent variables are each of the risk ratios in this model

Table 14: Granger Causality Test of RBD Balance to Asset Ratio on Risk Ratios

VARIABLES	KA	ROA	NPL	AC	LA	CL	INS
Intercept	0.00461***	0.000712***	0.00159***	0.000245***	-0.001	0.000470***	0.000510***
	[33.65]	[43.87]	[17.60]	[24.57]	[-1.614]	[7.086]	[14.33]
L.RISK	0.901***	0.240***	0.612***	0.488***	0.804***	0.932***	0.787***
	[161.9]	[44.10]	[115.5]	[92.15]	[145.5]	[184.0]	[144.8]
L2.RISK	-0.0139*	0.141***	0.123***	0.145***	0.000	0.0499***	0.0959***
	[-1.892]	[28.71]	[20.11]	[26.71]	[0.0669]	[7.475]	[13.92]
L3.RISK	0.0524***	0.0884***	0.0499***	0.0351***	0.0685***	0.0144**	0.0299***
	[7.583]	[18.53]	[8.356]	[6.785]	[9.791]	[2.264]	[4.391]
L4.RISK	0.0190***	0.222***	0.0926***	0.137***	0.118***	-0.0138***	0.0361***
	[4.010]	[49.60]	[18.62]	[29.71]	[21.49]	[-2.912]	[6.969]
RISK(Total)	0.958	0.692	0.877	0.805	0.991	0.983	0.948
P-Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
L.RBD	0.000	0.002	0.012	0.001	0.028	0.027	-0.005
	[0.0315]	[1.828]	[2.442]	[1.371]	[1.411]	[4.607]	[-1.742]
L2.RBD	0.002	-0.001	-0.009	-0.00128**	-0.002	-0.0279***	0.005
	[0.451]	[-0.665]	[-1.561]	[-2.028]	[-0.0656]	[-3.857]	[1.522]
L3.RBD	-0.005	-0.001	0.001	0.001	-0.038	0.009	-0.001
	[-1.086]	[-0.906]	[0.144]	[1.507]	[-1.634]	[1.354]	[-0.244]
L4.RBD	0.003	0.000	0.000	0.000	0.0381**	0.007	-0.001
	[0.808]	[0.440]	[-0.109]	[-0.0957]	[2.183]	[1.334]	[-0.636]
RBD(Total)	0.000	0.000	0.003	0.000	**0.026*** **	**0.0146*** **	-0.002
P-Value	0.896	0.448	0.260	0.366	**0.001**	**0.000**	0.105

Robust t-statistics in brackets

*** p<0.01, ** p<0.05, * p<0.1

Note: Dependent variables are each of the risk ratios in this model

Table 15: Granger Causality Test of RBD Balance to Asset Ratio on Risk Ratios

VARIABLES	KA	ROA	NPL	AC	LA	CL	INS
Intercept	0.000331*	0.000131**	0.000339***	0.000253***	-0.000342*	0.000246***	0.000
	[1.849]	[2.034]	[5.062]	[3.687]	[-1.697]	[4.824]	[1.364]
L.RISK	-0.007	-0.019	-0.001	0.022	0.000	0.002	0.004
	[-0.960]	[-0.720]	[-0.256]	[0.404]	[-0.101]	[0.410]	[0.425]
L2.RISK	-0.003	0.007	-0.004	-0.022	0.000	0.000	0.006
	[-0.344]	[0.301]	[-0.582]	[-0.382]	[0.139]	[0.0799]	[0.459]
L3.RISK	0.0280***	0.032	-0.006	0.009	0.00350*	-0.001	0.009
	[3.106]	[1.379]	[-0.904]	[0.171]	[1.912]	[-0.165]	[0.670]
L4.RISK	-0.0185***	0.0529**	0.006	-0.014	-0.00263*	-0.002	-0.008
	[-2.995]	[2.428]	[1.122]	[-0.303]	[-1.823]	[-0.362]	[-0.821]
RISK(Total)	-0.0007493	**0.073*** **	**-0.005** **	-0.00488	**0.0009*** **	-0.00015	**0.011*** **
P-Value	0.637	**0.002**	**0.037**	0.872	**0.002**	0.880	**0.000**
L.RBD	0.774***	0.774***	0.774***	0.774***	0.774***	0.774***	0.774***
	[148.1]	[148.2]	[148.1]	[148.2]	[148.1]	[148.2]	[148.1]
L2.RBD	0.0851***	0.0853***	0.0853***	0.0852***	0.0853***	0.0852***	0.0854***
	[12.95]	[12.98]	[12.98]	[12.96]	[12.98]	[12.96]	[13.00]
L3.RBD	-0.0278***	-0.0281***	-0.0282***	-0.0282***	-0.0283***	-0.0282***	-0.0283***
	[-4.604]	[-4.656]	[-4.673]	[-4.669]	[-4.687]	[-4.672]	[-4.689]
L4.RBD	0.107***	0.108***	0.107***	0.107***	0.107***	0.107***	0.107***
	[23.46]	[23.63]	[23.58]	[23.55]	[23.45]	[23.54]	[23.53]
RBD(Total)	0.939	0.939	0.939	0.939	0.937***	0.938***	0.938
P-Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Robust t-statistics in brackets
*** p<0.01, ** p<0.05, * p<0.1
Note: Dependent variables are each of the risk ratios in this model

Table 16: RBD Association with FDIC's Final Rule on Base Assessment Rate

VARIABLES	KA	ROA	NPL	AC	LA	CL	INS	Zscore
RBD	-0.00755***	-0.000403***	0.00269***	-0.000177***	0.0744***	0.0261***	0.00252***	-3.166***
Dummy	[-20.95]	[-9.555]	[8.193]	[-9.501]	[48.60]	[34.69]	[11.62]	[-5.917]
FDIC	0.00246***	0.000597***	-0.00295***	-0.000203***	-0.0342***	0.00116***	-0.00177***	3.358***
Dummy	[8.216]	[24.51]	[-13.59]	[-14.72]	[-25.98]	[3.200]	[-13.19]	[7.977]
RBD*FDIC	0.00208***	0.000679***	-0.00396***	0.000174***	-0.00477*	0.00249**	-0.000493	4.940***
	[3.978]	[12.21]	[-8.772]	[6.151]	[-1.912]	[2.028]	[-1.541]	[4.893]
Observations	68,989	68,989	68,989	68,989	68,989	68,989	68,989	24,672
R-squared	0.008	0.016	0.006	0.004	0.048	0.048	0.006	0.007
RBD/Asset	-0.0493***	-0.00496***	0.00335	-0.00167***	0.725***	0.205***	0.0371***	-21.83***
Ratio	[-8.202]	[-7.570]	[0.679]	[-6.542]	[26.18]	[13.27]	[9.964]	[-2.840]
FDIC	0.00282***	0.000674***	-0.00343***	-0.000181***	-0.0353***	0.00121***	-0.00180***	3.784***
Dummy	[10.39]	[29.63]	[-17.11]	[-14.19]	[-28.86]	[3.245]	[-14.30]	[9.564]
RBD/Asset*FDIC	0.00519	0.00688***	-0.0408***	0.00134***	0.0256	0.0531*	-0.00735	82.36***
	[0.614]	[7.735]	[-5.982]	[3.539]	[0.479]	[1.922]	[-1.287]	[5.166]
Observations	68,989	68,989	68,989	68,989	68,989	68,989	68,989	24,672
R-squared	0.003	0.015	0.005	0.003	0.028	0.013	0.006	0.006

Robust t-statistics in brackets
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The dependent variables are the risk ratios including KA, ROA, NPL, AC, LA, CL, INS and Zscore.

Table 17: Magnitudes of Effects of FDIC's Revised Pricing on Risk Links with RBDs

DepVar	KA	ROA	NPL	AC	LA	CL	INS	Zscore
RBD Dummy	27.5%	168.5%	147.2%	98.3%	6.4%	(+95.4%)	19.6%	156.0%
RBD to Assets	10.5%	138.7%	1217.9%	80.2%	(+3.5%)	(+25.9%)	19.8%	377.3%

Negative Ratio of Interactive Coefficient to Raw RBD Coefficient, Except Positive Ratio where Noted.