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Using Loan Rates to Measure and Regulate Bank Risk: Findings and an Immodest Proposal

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Abstract

There is strong evidence that the interest rates charged by banks on the flow of newly extended Commercial & Industrial (C&I) loans predict future loan performance and CAMEL rating downgrades by bank supervisors. While internal risk ratings have little explanatory power for future loan performance, they do help predict future CAMEL downgrades. These findings suggest that supervisors might consider using interest rates in the off-site surveillance of banks. At the same time, we propose that reformers consider basing capital requirements and deposit insurance premia on loan interest rates instead of (or in addition to) internal risk ratings and models.

Key words: Deposit insurance reform, credit risk pricing, risk-based capital regulation.

1. Introduction

Everyone seems to like the idea of risk-based regulation of banks, but no one seems sure how to do it. Take the Basle Committee's efforts to tie capital requirements to bank loan risk. First the Committee proposed tying capital to ratings of banks' loans by some external rating agency. That external ratings approach was criticized, so the Committee suggested setting capital based on banks' own, internally generated ratings instead. But, of course, once capital gets tied to these internal ratings, banks will be tempted to exaggerate, i.e., overrate loans to minimize their required capital. The FDIC's efforts to charge risk-based insurance premia will have similar problems should they choose to rely on internal ratings—banks will overrate their loans if their deposit insurance premia depend on it.

The goal of this paper is not to criticize efforts toward risk-based regulation, but to propose a simple idea that may help those efforts: rate-based regulation. We suggest that supervisors use the interest rates banks charge on their loans as an alternative (or supplement) to the banks' own risk ratings. The basic idea could hardly be simpler: if banks charge riskier borrowers higher loan rates, as theory suggests they will, then differences across banks or time in loan rates should tell supervisors something about the relative riskiness of banks' loan portfolios.[1] In the Appendix, we sketch a simple model that illustrates how the internal ratings-based approach to regulation is incompatible with bank incentives to maximize the put option from deposit insurance while an interest-rate based approach has the ability to implement first-best risk-choice.

Interest rates may have several advantages over ratings for regulatory purposes. For one, they are easier to verify than some of the complicated models banks use to generate internal ratings. Interest rates are also ''infinitely granular,'' thus solving the bucket problem that has vexed reformers or bankers. Lastly (and most speculatively), loan prices may reflect aggregate or market information about risk that is not incorporated in ratings by individual banks, much the same way the price of a stock reflects more information than that of any individual stock analyst.

There are practical problems with our idea that we ignore at this point. Relationship pricing, for example, would complicate matters, as would the non-price terms of lending banks use to control risk. Banks with market power might get away with charging higher spreads than are justified by pure risk considerations. Finally, we understand that a relationship between risk and return at the loan level might not exist at the portfolio level since the imperfect correlation across borrowers in performance reduces portfolio risk.[2]

Before bothering with those practical problems, however, we first need to show that loan rates really do provide useful information about future loan performance. To that end, we matched data on commercial loan rates from the *Survey of Terms of Bank Lending* (*STBL*) with data on loan performance from banks' *Call Reports of Income and Condition* (*CRIC*). Our data cover roughly 300 banks—virtually all the largest banks and a sample of small and medium sized banks—over 1984–2001. These data are not ideal. Information on loan performance is available only at the bank level, not the loan level. Plus, the data on loan rates is measured on a flow basis, whereas the performance is measured relative to banks' current stock of loans. These are the best data currently available, however (as far as we know). Even with these less than ideal data, we find that loan rates are still highly significant in predicting loan performance one-to-four quarters later. Given the loan rates, the internal ratings banks have been reporting since 1997 are of little to no value in predicting loan performance. Banks with higher loan spreads are also more likely to have their CAMEL rating downgraded by regulators, suggesting that interest rates would be

1 A referee points out that our notion of rate-based regulation is somewhat akin to Kane's (1986) suggestion of ''ex-post settlement,'' wherein banks would be forced to share upside returns with deposit insurers. Turning regulators into *de facto* shareholders might change their incentives, however, a potential problem that our rate-based regulation would not seem to share. Another key difference is that our rate-based regulation would price *ex ante* risks.

2 While individual loans can be risky and priced accordingly, the portfolio can be much less risky when borrower performance is imperfectly correlated. As long as banks hold a higher loan loss allowance against the greater expected credit risk, there is not necessarily a greater threat of bank failure. We have two lines of defense against this point. First, data constrains our analysis to be done at the portfolio level, so this is a question of how to implement interest-rate based regulation and not a criticism of our contribution. Second, we find evidence that portfolio spreads help predict CAMEL downgrades, which suggests that higher portfolio spreads are associated empirically with a greater probability of bank distress.

useful for off-site supervision of banks. Loan spreads do provide valuable information about loan risk, we conclude, so researchers, bank supervisors and regulators should think about how to collect better data on loan rates and how to deploy that information efficiently.

2. Literature on risk and loan pricing

Data constraints have kept the literature on bank loan pricing surprisingly small. Bank loans are an essentially private contract so banks and borrowers do not make it a custom to publicize loan terms or performance (i.e., defaults). The handful of studies most relevant to ours use data either from the *STBL* or from the Loan Pricing Corp (LPC), a private vendor that collects and publishes terms on syndicated loans to large, corporate borrowers. Strahan (1993) uses LPC data to estimate the link between spreads on syndicated loans and a variety of proxies for firm risk.[3] Most variables are significant in explaining spreads, and in a given year, roughly two-thirds of the variation in all-in-spreads (including fees) on loans drawn under commitments is explained by variation in the risk spreads. In their study of defaults on syndicated bank loans, Altman and Suggitt (2000) find similar default patterns in the syndicated market as in the corporate bond market, except that loan defaults are relatively accelerated over the first two years of the loan's life. Berger and Udell (1989) use STBL data to study collateral usage by banks. Collateralized loans tend to have higher spreads, they find, and worse performance. Hannan (1991) finds that bank loan rates are indeed affected by local market power, even after controlling for loan risk.

These other findings generally support our basic premise—that loan risk should be reflected in loan spreads. They also tell us to consider market power and other non-price terms of lending (e.g., collateral). None of them investigate precisely the question we take up below, that is, whether loan spreads help predict *ex post* loan performance, and if so, whether spreads predict better than the loan ratings banks report.

3. Do loan spreads predict loan performance?

Our first set of results uses confidential bank-level data from the *STBL* and the *CRIC*. The micro-data from the *STBL* are generated from a quarterly survey of approximately 300 banks. The frequency distribution since 1984 is described in table 1.[4] The survey covers all commercial and industrial loans and commitments of at least $1000 made to U.S. addresses during the first full business week for each of February, May, August, and November. Since we do not have performance measures at the loan level, it is necessary to

3 Strahan's (1993) risk proxies are size, earnings, leverage, capitalized lease obligations, market-to-book value, security, interest coverage, whether the firms' have bond ratings, whether the rating is investment grade, tangible assets, sales, and liquidity.

4 In principle, the microdata is available since 1976, but the inability to measures of loan performance in Call Reports before 1984 forces us to discard the earlier data.

Table 1. **Frequency distribution of STBL-reporting banks**
The sample includes all banks that report making loans during the survey week in February, May, August, and November of the *Survey of Terms of Business Lending*.

	Quarter				
Year	1	2	3	4	Total
1984	317	316	311	310	1,254
1985	304	300	308	299	1,211
1986	297	292	306	310	1,205
1987	309	308	318	307	1,242
1988	310	311	303	303	1,227
1989	298	317	311	309	1,235
1990	305	310	312	310	1,237
1991	324	325	319	314	1,282
1992	316	314	315	311	1,256
1993	304	289	295	281	1,169
1994	282	286	285	280	1,133
1995	275	286	281	280	1,122
1996	288	275	260	257	1,080
1997	254	271	252	260	1,037
1998	255	252	251	252	1,010
1999	261	261	249	239	1,010
2000	222	227	224	217	890
2001	236	231	227	232	926
Total	5,157	5,171	5,127	5,071	20,526

aggregate all of the loans made during the survey week in order to create a portfolio of new bank loans. For each loan, we construct a spread over a maturity-matched instrument, using the CD rate for maturities of less than one year and constant-maturity Treasury security rate for maturities of one year or greater. Weighting by the product of size and maturity for each loan, we construct a portfolio average for each of the spread, loan maturity, a dummy variable for the loan being secured, a dummy variable for a small loan (face value less than $250,000) and, when appropriate, the internal risk rating.

The mean portfolio interest rate over the time period is 9.35% with a standard deviation of 2.14%. Figure 1 illustrates the mean portfolio rate across banks over time, and it appears that changes in these portfolio rates closely track changes in the federal funds rate over time. Figure 2 illustrates three cross-sections of the distribution of portfolio interest rates. Over time, the distribution has become more concentrated around the mean, presumably due to increased competition. The behavior of average non-price loan terms is displayed in figure 3. About half of the average C&I loan portfolio is comprised of small loans and about 70% is secured. In the late 1980s, the average maturity of the portfolio of loans made during the survey week was only about 10 months, but this figure has increased dramatically over the 1990s. Finally, note that well-documented deterioration in C&I loan quality starting in late 1998 that has continued to date.

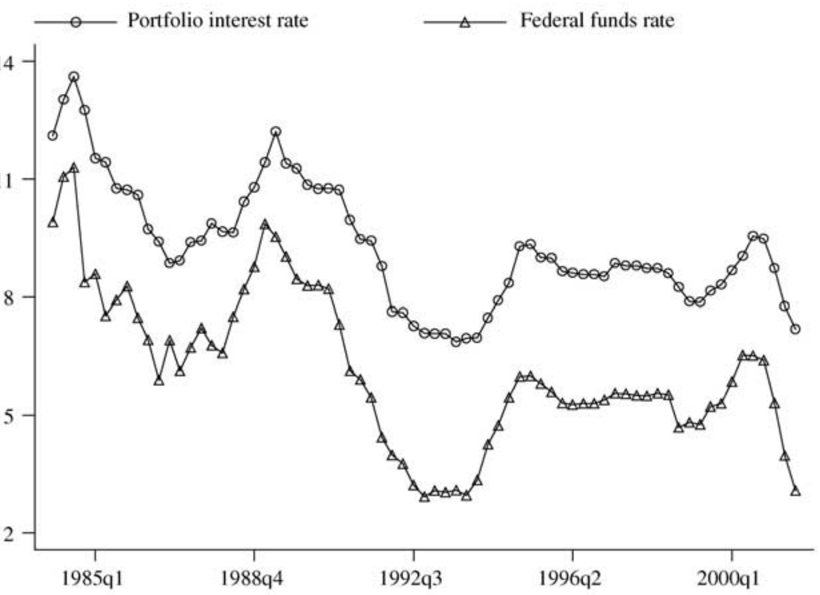

***Figure 1*.** **New C&I loan portfolio interest rates.**

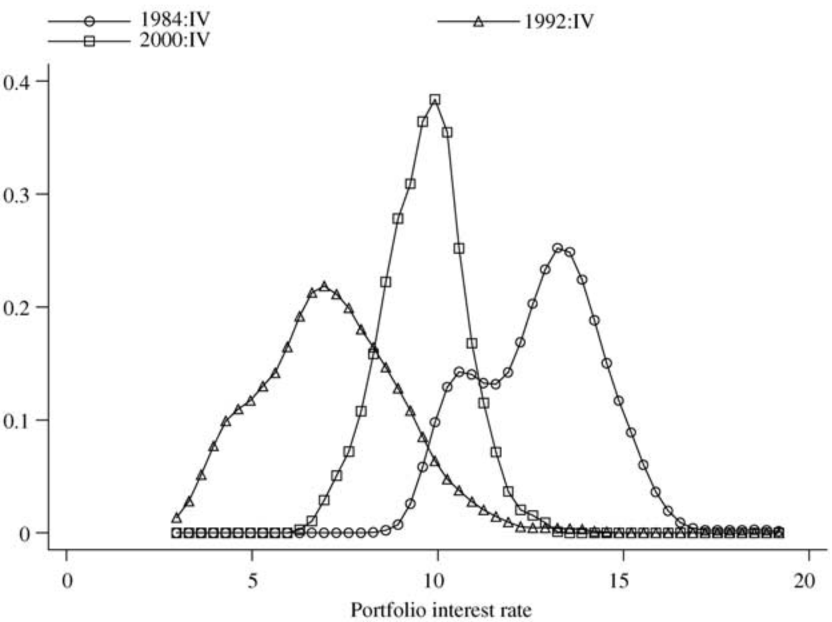

***Figure 2*.** **Cross-sectional densities of portfolio interest rates.**

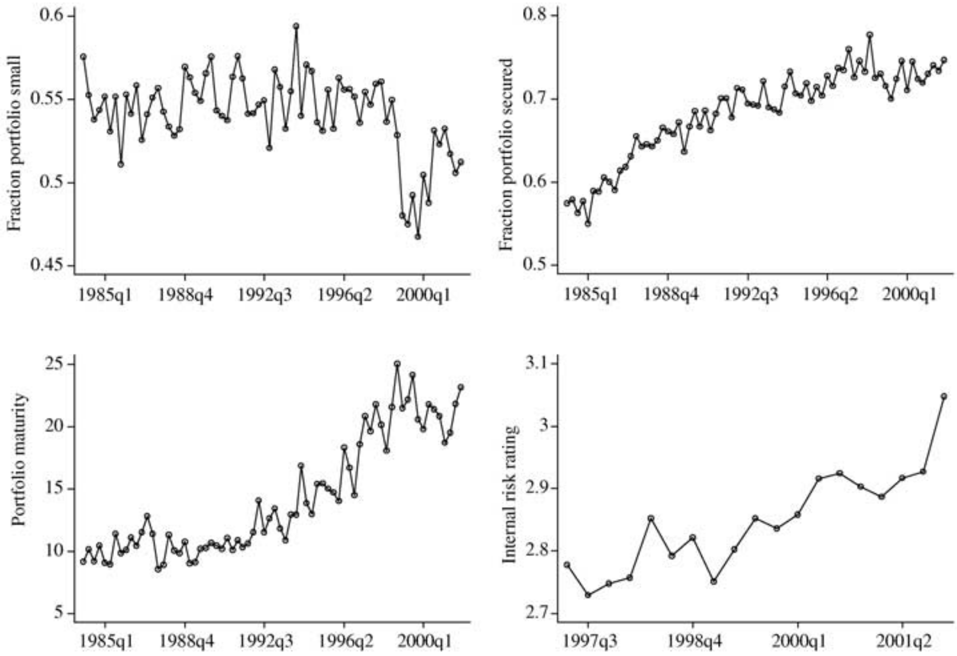

Figure 3. **Non-price terms of new C&I loans.**

3.1. Call reports

The main constraint when using the Call Reports is that information about non-performing commercial and industrial (C&I) loans from Schedule RC-N and C&I loan charge-offs and recoveries from Schedule RI is only available back to 1984. Time series for non-performing loans have been corrected for differences in reporting forms across banks and over time in order to construct consistent time series. Similar corrections are made to create a time series for bank securities holdings. We emphasize that the provision data covers all loans, as a finer data series is not collected. Data for each of loan provisions and charge-offs from Schedule RI has been transformed from its year-to-date reporting form to create a meaningful quarterly time series. We thus limit our analysis to the population of insured commercial banks chartered in the United States 1984:I–2001:IV.

3.2. Empirical issues

While bank loan portfolios with higher interest rates should be more risky, several real world factors could confound the link between rates and risk. Our use of a full set of time dummies means the portfolio interest ‘‘rate’’ in our regressions is actually the spread over the average spread on all C&I loans in a given period. If loan performance depends on the overall level of spreads, however, our use of time dummies would sweep out that aggregate effect. To guard against that, we also report results without time dummies.

Another potential problem is the presence of market power by banks in lending. While Strahan (2002) finds no evidence that loan prices are correlated with either state or local area Herfindahl–Hirshman indices, a large literature presumes that banks produce private information about borrowers that give them (the banks) some degree of market power. In order to deal with fixed differences across banks that affect the mapping from risk to return, we employ bank fixed effects in several of the specifications below. In these regressions, the question is no longer whether or not banks with higher interest rates appear to have a more risky loan portfolio, but rather whether or not banks that are increasing their portfolio interest rates appear to be increasing the risk of their loan portfolio. This bank fixed effect should not only control for fixed differences in market power across banks, but also help control for other unobserved factors that would affect the position of the efficient frontier across banks. A third possible problem is ‘‘loan seasoning’’—the lag between loan origination and delinquency—could also complicate the link between loan rates and risk. We confront that problem by including lagged values of loan spreads (up to four quarters) in our regressions.[5]

3.3. Results

Table 2 reports the results from a regression of each loan performance variable—non-performing C&I loans/total C&I loans, C&I loans charge-offs/total C&I loans, and loan provisions/total loans—on four lags of the C&I portfolio spread and four lags of C&I loan growth to control for loan demand. Standard errors have been corrected for heteroskedasticity and are clustered at the bank level in specifications that do not use bank fixed effects. Panel A reports results without time effects while Panel B reports results with time effects. Given that we use the portfolio spread, it is not clear that time effects are necessary.

Coefficients from the first four rows of the first column in Panel A of table 2 indicate that the current loan portfolio spread is very significant in predicting future loan performance. When comparing across banks, increasing the portfolio spread by one percentage point will increase non-performing C&I loans by almost 0.61 percentage points in the next quarter. Over four quarters, non-performing loans are higher by about 2 percentage points.[6] Since the mean of non-performing loans over the sample is approximately 6%, the measured effect of loan rates on non-performing loans is economically significant. When comparing the behavior of the same bank over time using the fixed effects specifications in the second column, the effects are smaller but remain statistically and economically significant. The message across the first two columns is a result that will appear many times over in the paper: changes in the portfolio interest rate for a given bank are less correlated with future performance than are differences in the portfolio interest rate across banks.

The second two columns of Panel A of table 2 illustrate the relationship between loan

5 We find similar results with up to eight lags of the interest rate.

6 The relatively short lag between (changes in) spreads and delinquency is not inconsistent with Avery and Gordons’ (1995) loan seasoning study; they find the delinquency rates on individual C&I loans is tri-modal, with one peak at six months (and others at two to four years, and over six years of age).

***Table 2.* Lagged C&I loan portfolio interest rates predict future loan performance**
The table reports coefficients and standard errors from an OLS regression of C&I loan performance measures on four lags of the average interest rate on new C&I loans and four lags of C&I loan growth. Measures of C&I loan performance and charge-offs are normalized by total C&I loans while loan provisions are normalized by total loans. A full set of time effects is not included in Panel A but is included in Panel B. Standard errors (reported in parentheses) have been corrected for heteroskedasticity and are clustered at the bank level in specifications not using bank fixed effects. The sample contains all *STBL*-reporting banks over 1984–2001.

	Problem C&I Loans		C&I Loan Charge-offs		Total Loan Provisions	
A. Not controlling for time effects						
Spread_{it-1}	0.61***	0.20***	0.07***	0.05***	0.01	0.02***
	(0.10)	(0.06)	(0.01)	(0.01)	(0.01)	(0.01)
Spread_{it-2}	0.60***	0.17***	0.06***	0.03**	0.00	0.01
	(0.10)	(0.07)	(0.02)	(0.01)	(0.01)	(0.01)
Spread_{it-3}	0.33***	−0.01	0.00	−0.02	−0.01**	0.00
	(0.10)	(0.07)	(0.01)	(0.01)	(0.01)	(0.01)
Spread_{it-4}	0.47***	0.10	0.02*	0.01	−0.01**	0.01
	(0.09)	(0.06)	(0.01)	(0.01)	(0.01)	(0.01)
$\Sigma_j\ \text{spread}_{t-j}$	2.01***	0.46***	0.15***	0.07***	−0.01***	0.04***
P-value	0.00	0.00	0.00	0.00	0.00	0.00
Bank effects	No	Yes	No	Yes	No	Yes
N	14,459	14,459	14,459	14,459	14,459	14,459
R^2	0.123	0.61	0.047	0.202	0.008	0.108
B. Controlling for time effects						
Spread_{it-1}	0.65***	0.31***	0.08***	0.07***	0.00	0.01**
	(0.11)	(0.08)	(0.02)	(0.01)	(0.01)	(0.01)
Spread_{it-2}	0.65***	0.27***	0.06***	0.04***	0.01	0.02**
	(0.11)	(0.08)	(0.02)	(0.02)	(0.01)	(0.01)
Spread_{it-3}	0.52***	0.11	0.01	0.00	−0.01**	0.00
	(0.11)	(0.07)	(0.02)	(0.01)	(0.01)	(0.01)
Spread_{it-4}	0.76***	0.25***	0.03	0.02	0.00	0.01
	(0.10)	(0.08)	(0.01)	(0.01)	(0.01)	(0.01)
$\Sigma_j\ \text{spread}_{t-j}$	2.58***	0.94***	0.18***	0.13***	0.00	0.04***
P-value	0.00	0.00	0.00	0.00	0.31	0.00
Bank effects	No	Yes	No	Yes	No	Yes
N	14,459	14,459	14,459	14,459	14,459	14,459
R^2	0.221	0.636	0.092	0.224	0.075	0.157

Significance levels are shown as *, **, *** representing 10%, 5% and 1% respectively.

interest rates and loan charge-offs, which can be more closely linked to capital charges and deposit insurance premia. The results in the third column of the table indicate that after four quarters, a one-percentage point increase in the C&I portfolio spread tends to be followed by an increase the ratio of C&I loan charge-offs to C&I loans by about 7 basis points in specifications with fixed effects. As the mean rate of C&I charge-offs is 46 basis points for the sample, the portfolio interest rate seems economically significant. On the other hand, the trade-off between risk and return is quite favorable to the bank as the increase in interest income is much larger than the increase in charge-offs.

The results in the final two columns of Panel A for loan provisions are weaker, in part because they refer to provisions for all loans and in part because banks have some ability to smooth provisions over time. In the preferred specification with bank fixed effects, an

Table 3. **Frequency of bad CAMEL ratings and CAMEL downgrades among STBL reporting Banks** The sample includes STBL-reporting banks that had CAMEL ratings of 1 or 2 as of March of the following year. Downgrades refer to banks that have their CAMEL ratings downgraded to 3, 4, or 5 between March of the following year and March two years into the future.

	CAMEL 1,2			
Years	Non-Downgrades	Downgrades	Total	CAMEL 3,4,5
1985–1987	435	12	447	139
1988–1990	559	92	651	251
1991–1993	689	2	691	212
1994–1996	798	3	801	16
1997–2000	929	10	939	29
Total	3,410	119	3,529	647

increase in the portfolio interest rate by one percentage point increases provisions by 4 basis points after four quarters. Over the sample, the rate of provisioning relative to total loans is about 0.22 percentage points. As C&I loans are 15% of the average bank loan portfolio and the rate of C&I loan non-performance is about 1.5 times the rate of total loan non-performance, a reasonable number for average provisions for C&I loans might be 5 basis points. Portfolio spreads again appear to be correlated with measures of future loss in economically significant magnitudes. Note, however, that banks do not appear to provision enough for the greater credit risk implied by higher interest rates, as charge-offs increase by about twice as much as provisions after four quarters. Under-provisioning at the time these loans are originated will end up hurting bank performance in the future.

Panel B duplicates the effort of Panel A with the assistance of a full set of time effects. Above, the exercise was to investigate the correlation between the portfolio spread and future loan performance, where a higher spread was correlated with worse future loan performance. With time effects, the exercise is to investigate the consequences of having a portfolio spread larger than the average bank in the sample by looking at loan performance relative to the average bank. From a supervisory perspective, the question is whether to be worried about high spreads or high spreads relative to other banks. The message from the first four columns is clear, the relationship between the portfolio spread and future loan performance is much tighter with time effects.

4. Do loan rates predict supervisory rating downgrades?

Here, we consider whether the information in loan spreads might be helpful to bank supervisors, particularly in their off-site surveillance of banks. Supervisors scrutinize a long list of variables from banks' most recent *Call Reports* (see table 4) to identify potential problem or ''exception'' banks whose condition might have changed substantially since their last examination and CAMEL rating assignment (Gilbert et al., 2000). Every quarter, new *Call Report* data are fed into the Federal Reserves' SEER risk rank model or its CAMEL downgrade model to predict the probability of bank failure, or

Table 4. **Summary statistics for the CAMEL downgrade samples**
The table reports sample means and standard deviations of selected variables (in parentheses) from the December *Call Reports* 1985–2000. The sample includes *STBL*-reporting banks that had CAMEL ratings of 1 or 2 as of March 1986–2001.

	Full Sample	Recent Sample
Portfolio spread (Spread_{it})	3.043	3.298
	(1.434)	(1.067)
$\Delta \ln(L^{\text{cai}})$	0.029	0.038
	(0.138)	(0.145)
Pr(DOWNGRADE)	0.036	0.010
	(0.187)	(0.101)
Ln(Assets)	13.721	14.180
	(2.239)	(2.425)
C&I lending/loans	0.151	0.161
	(0.095)	(0.107)
Real estate lending/loans	0.251	0.314
	(0.124)	(0.135)
OREO/assets	0.002	0.001
	(0.004)	(0.002)
ROA	0.011	0.012
	(0.005)	(0.005)
Securities/assets	0.253	0.233
	(0.134)	(0.126)
Equity/assets	0.081	0.090
	(0.025)	(0.030)
Large deposits/assets	0.150	0.270
	(0.138)	(0.113)
Risk		2.810
		(0.717)
Fraction (risk = 5)		0.024
		(0.073)
Fraction (risk = 4)		0.168
		(0.268)
Fraction (risk = 3)		0.484
		(0.379)
Fraction (risk = 2)		0.204
		(0.314)
Fraction (risk = .)		0.042
		(0.160)
N	3,410	779

less dramatically, a CAMEL downgrade. The model returns the expected probability of a downgrade conditional on the most recent *Call Report* data. If the probability is sufficiently high supervisors might accelerate their next on-site examination of the bank. Our strategy here is to test whether, given the roughly dozen variables already included in the SEER model and the downgrade model, inclusion of a bank's C&I loan portfolio spread helps predict the probability of a downgrade. If so, then consideration of loan spreads in the future might improve supervisors' examination strategy.

The supervisory rating data become available starting in 1985, but do not appear to cover the whole sample of *STBL*-reporting banks until 1987. We construct a data set that contains a bank's most recent CAMEL rating as of March and then attempt to forecast downgrades from CAMEL ratings of 1 or 2–3, 4, or 5 over the following year. As the most recent data that would have been available in March for forecasting is from the previous quarter, we only use December data from the *Call Reports* and November data from *STBL*.

The sample used in this analysis is described in table 3. The first column corresponds to the year prior to the measurement of a bank's most recent CAMEL rating in March (in year + 1), and is used to match to the other sources of data. The next three columns describe *STBL*-reporting banks that had CAMEL ratings of 1 or 2 as of that March. Columns (2) and (3) break out the number of these banks that were either not downgraded or downgraded to CAMEL ratings of 3, 4, or 5 by the following March (in year + 2). The final column notes the number of banks that initially had poor CAMEL ratings in March (in year $t+1$). While the sample contains 119 downgrades, note that there are only 10 downgrades since 1997 when internal risk ratings become available. Summary statistics for this sample are described in table 4. The full sample corresponds to 1985–2000 while the recent sample includes data on internal risk ratings which are available only starting in 1997.

Table 5 illustrates the results of our forecasting exercise, which involves a Probit of CAMEL downgrade on bank characteristics. The standard errors have been corrected for heteroskedasticity and clustered at the bank level. The first column highlights the main result: conditional on other variables that are used in the Federal Reserve System's SEER model, the portfolio spread on new C&I loans has highly significant marginal predictive power. The implied marginal effect of a one percentage point increase in the spread is to increase the probability of downgrade by more than 30 basis points, about 10% of the mean rate of downgrade. Controlling for the non-price terms of lending in column (2) strengthens this result a little. Interestingly, only the fraction of new loans that are small appears to have any significant explanatory power, where loans to small firms reduce the probability of a future downgrade. The third and fourth columns repeat the exercise from the first two columns, using the event of downgrade in two years, with similar results.

5. Do loan interest rates perform better than internal ratings of risk?

Since 1997, the *STBL* has included banks' own, internal risk ratings of the new loans they make each quarter. English and Nelson (1998) discuss the internal loan ratings collected from banks in the *STBL* since 1997. Using terms on the 42,000 loans reported by banks in the August 1998 *STBL*, they find the expected positive correlation between banks' loan ratings and the rates on those loans, even after controlling for the other terms of lending. On whether the ratings predict loan performance—the question we are most interested in here—their findings are ''disappointing,'' (p. 21): charge-off rates are insignificantly related to the reported share of high-risk loans and positively related to the share of low-risk loans.

This section compares the relative value of loan ratings and loan spreads in predicting (1) loan performance, and (2) CAMEL downgrades. The results of the first exercise are displayed in table 6, which simply adds to the model of loan performance above four lags of the average internal rating on new C&I loans. The first three columns employ clustering at the bank level and final three columns use bank fixed effects, and we use time fixed

***Table 5.* Current C&I portfolio interest rates predict future CAMEL downgrades**

The table reports coefficients and standard errors from a Probit of CAMEL downgrade on bank-level characteristics from the previous December. The first two columns refer to a downgrade over the next year and the final two to a downgrade in two years. Standard errors (reported in parentheses) have been corrected for heteroskedasticity and are clustered at the bank level.

	(1)	(2)	(3)	(4)
Ln(Assets)	0.0143	− 0.0275	− 0.0211	− 0.0393
	(0.0373)	(0.0418)	(0.0432)	(0.0483)
C&I loans	3.5324***	3.4381***	3.9431***	3.8819***
	(0.7721)	(0.7875)	(0.7360)	(0.7464)
Real estate loans	1.8651***	1.9424***	1.7418***	1.7460***
	(0.6339)	(0.6466)	(0.6173)	(0.6254)
OREO	1.3149	− 0.2199	− 15.0012	− 15.8514
	(13.0600)	(13.4662)	(13.4984)	(13.6452)
ROA	− 8.8186	− 8.3225	0.1957	0.5546
	(9.1872)	(9.0092)	(10.8607)	(10.7818)
Securities	− 0.8509	− 0.8584	− 1.0014	− 1.0180
	(0.6684)	(0.6776)	(0.6926)	(0.6980)
Equity	− 7.0988*	− 6.9992*	− 11.8048***	− 11.6411**
	(4.1599)	(4.2404)	(4.6033)	(4.6303)
Large CDs	− 4.3989***	− 4.4267***	− 4.5583***	− 4.6111***
	(0.8530)	(0.8571)	(0.9488)	(0.9440)
Problem C&I loans	− 0.1725	− 0.2072	0.3179	0.3138
	(0.3553)	(0.3701)	(0.3979)	(0.4003)
Problem loans	6.8905***	7.3728***	9.2139***	9.5652***
	(2.4036)	(2.3331)	(2.4407)	(2.4155)
Spread_{it}	0.1409***	0.1604***	0.1125***	0.1248***
	(0.0430)	(0.0493)	(0.0415)	(0.0457)
$\Delta\ln(L^{\text{cai}})$	− 0.7019*	− 0.6988**	0.0065	0.0204
	(0.3610)	(0.3555)	(0.3551)	(0.3476)
Fraction small		− 0.3424*		− 0.1756
		(0.1878)		(0.1927)
Fraction secured		− 0.1796		0.0207
		(0.1570)		(0.1600)
Maturity		− 0.0007		0.0005
		(0.0011)		(0.0013)
Marginal effects				
Spread_{it}	0.0034***	0.0037***	0.0047***	0.0052***
	(0.0013)	(0.0014)	(0.0020)	(0.0022)
Time until downgrade	1 year	1 year	2 years	2 years
N	3,316	3,316	2,909	2,909
R^2	0.257	0.262	0.283	0.284

Significance levels are shown as *, **, ***, representing 10%, 5% and 1% respectively.

effects in all specifications. The first column demonstrates that the relationship between portfolio spreads and loan performance persists in the more recent sample, although the relationship is a bit weaker even before conditioning on internal ratings. The second column demonstrates internal ratings add no explanatory power to the model and have

***Table 6.* C&I loan portfolio interest rates predict C&I loan performance better than internal risk ratings**
The table reports coefficients and standard errors from an OLS regression of C&I loan performance measures on four lags of the average interest rate on new C&I loans, four lags of C&I loan growth, and a full set of time effects. Columns (2) and (5) add four lags of the average internal risk rating on C&I loans, while columns (3) and (6) add four lags of the fraction of loans with a rating of 4 or 5. Standard errors (reported in parentheses) have been corrected for heteroskedasticity and are clustered at the bank level in specifications not using bank fixed effects.

	(1)	(2)	(3)	(4)	(5)	(6)
Spread_{it-1}	0.09	0.06	0.08	0.04	0.01	0.02
	(0.18)	(0.19)	(0.18)	(0.13)	(0.14)	(0.14)
Spread_{it-2}	0.25	0.23	0.26	0.10	0.09	0.10
	(0.20)	(0.23)	(0.21)	(0.12)	(0.13)	(0.13)
Spread_{it-3}	0.52**	0.51*	0.51**	0.27**	0.27**	0.27**
	(0.25)	(0.27)	(0.25)	(0.11)	(0.12)	(0.11)
Spread_{it-4}	0.49*	0.49***	0.48***	0.25**	0.22**	0.21**
	(0.14)	(0.15)	(0.15)	(0.10)	(0.11)	(0.11)
Risk_{it-1}		− 0.16			0.12	
		(0.21)			(0.16)	
Risk_{it-2}		− 0.21			0.04	
		(0.23)			(0.16)	
Risk_{it-3}		− 0.22			0.00	
		(0.26)			(0.14)	
Risk_{it-4}		− 0.20			0.11	
		(0.20)			(0.15)	
Fr(4 or 5)_{t-1}			− 0.09			0.27
			(0.29)			(0.24)
Fr(4 or 5)_{t-2}			− 0.52			− 0.14
			(0.28)			(0.22)
Fr(4 or 5)_{t-3}			− 0.21			0.11
			(0.34)			(0.25)
Fr(4 or 5)_{t-4}			0.15			0.57*
			(0.30)			(0.24)
$\Sigma_i\ \text{spread}_{t-j}$	1.35***	1.28***	1.33***	0.65***	0.60**	0.60**
P-value	0.00	0.00	0.00	0.01	0.01	0.01
$\Sigma_j\ \text{IR}_{t-j}$	NA	− 0.79***	− 0.66**	NA	0.26	0.81**
P-value	NA	0.01	0.03	NA	0.31	0.04
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank effects	No	No	No	Yes	Yes	Yes
N	2,411	2,411	2,411	2,411	2,411	2,411
R^2	0.103	0.115	0.105	0.643	0.643	0.643

Significance levels are shown as *, **, ***, representing 10%, 5% and 1% repectively.

little effect on the explanatory power of the spread. In the third column instead of the average rating we use the fraction of new loans that are rated 4 or 5, with similar results. The negative sign on most of the internal rating variables in the second and third column would suggest that banks that have a more risky loan portfolio tend to have better future loan performance.

As in table 2, the results with fixed effects are statistically weaker, but there is still a significant correlation between future loan performance and the spread. More interestingly, there does seem to be some life in internal risk ratings.[7] In column 5, the coefficients at least have the right sign, but are not statistically significant, but things look much better for the sum of coefficients in column 6 on the fraction of loans with a 4 or 5. While there is not much information across banks in internal risk ratings, there does seem to be information in the bank fixed effect specifications, implicitly using the change in risk ratings.

The results of our second horse race are displayed in table 7, which simply adds to our model of CAMEL downgrades the average internal rating on new C&I loans. Note that this specification is run only using data since 1997. The first four columns use downgrade in the next year while the second four columns use downgrade in two years. In the first column the link between the spread and CAMEL downgrades is no longer significant, but the coefficient estimate is nearly identical to that from table 5. On the other hand, even though the C&I portfolio internal risk rating had little connection with future loan performance, there is a correlation between the internal risk ratings and CAMEL downgrades. A similar relationship holds when breaking out the C&I loan portfolio into the fraction in each risk rating class. Note the monotone relationship between the fraction in a risk class and probability of downgrade. The final three columns use downgrade in two years as a dependent variable. As in the estimation over the full sample, the portfolio spread is statistically and economically significant while the explanatory power of internal risk ratings is limited.

6. Conclusion

Loan interest rates are highly significant in predicting future loan performance and in forecasting downgrades in bank CAMEL ratings. By contrast, banks' own internal risk ratings have little explanatory power in predicting future loan performance or in forecasting CAMEL downgrades once we control for the loan interest rate. Given the latter result, researchers and reformers should consider whether internal risk ratings are appropriate for setting risk-based capital requirements, and how best to use the information in loan rates to aid bank regulation and supervision. At minimum, interest rates would likely be useful in validating the ratings banks report to regulators; a highly rated loan with a high spread should attract supervisors' attention.

Will greater reliance on interest rates in supervision invite gaming by bankers—mispricing or transfer pricing—in order to minimize regulatory burden? Is our proposal subject to the Lucas Critique? Perhaps, but surely the gaming problem will be less of a problem—and easier to detect—than such problems under the ratings approach. Indeed, it was concerns about the credibility of the ratings approach—and the lack of verifiability—that motivated our suggestion of using interest rates in the first place.

Actually using the information in loan rates will require adjustments for non-price

7 See English and Nelson (1998) on the risk ratings reported in the *STBL*. Treacy and Carey (2000) describe the ratings systems at the 50 largest U.S. bank holding companies.

***Table 7.* Current C&I loan portfolio interest rates and internal risk ratings predict future camel downgrades**

The table reports coefficients and standard errors from a Probit of CAMEL downgrade on bank-level characteristics from the previous December. The second column adds the interest rate on new C&I loans, while the third and fourth columns add information about the internal risk rating on new C&I loans. The first four columns refer to downgrade in the next year while the final four columns refer to downgrade in two years. Standard errors (reported in parentheses) have been corrected for heteroskedasticity and are clustered at the bank level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(Assets)	− 0.1280	− 0.1370	− 0.1950*	− 0.1950*	− 0.1860**	− 0.1940*	− 0.2170*	− 0.2040*
	(0.0780)	(0.0950)	(0.1050)	(0.1100)	(0.0890)	(0.1120)	(0.1120)	(0.1140)
C&I Loans	1.6030	1.4470	0.6870	0.5730	3.8180**	3.6240**	3.3700*	3.6160
	(1.8230)	(1.8290)	(1.9350)	(1.9260)	(1.6460)	(1.7590)	(1.9070)	(2.2300)
Real estate loans	− 2.2310	− 2.4760	− 3.1430*	− 3.0540*	− 2.3830	− 2.4560	− 2.5400	− 2.4500
	(1.5220)	(1.7800)	(1.7590)	(1.7110)	(1.6810)	(1.7800)	(1.8050)	(1.8160)
OREO	47.1850	65.1070*	60.8360*	63.8320*	− 15.4340	3.6140	− 0.1470	4.7200
	(31.8300)	(33.5710)	(33.7910)	(35.4560)	(44.5620)	(50.6620)	(49.3230)	(43.6610)
ROA	− 38.7360	− 37.7370	− 36.7560	− 41.6880	− 21.3950	− 19.8710	− 19.6430	− 24.2930
	(23.6790)	(24.4870)	(24.0040)	(25.3440)	(31.3050)	(31.1680)	(30.5230)	(32.9490)
Securities	− 1.3710	− 1.2360	− 1.8960	− 2.0560	− 0.8220	− 0.6030	− 0.7870	− 0.8020
	(1.4270)	(1.3920)	(1.3590)	(1.4590)	(1.2060)	(1.0830)	(1.1560)	(1.4020)
Equity	− 8.1750***	− 18.4400***	− 16.5280***	− 16.3660***	− 15.4340**	− 14.6940**	− 14.0900**	− 12.8420**
	(5.2870)	(5.4510)	(5.3630)	(6.2900)	(6.8960)	(7.4920)	(7.1060)	(5.8690)
Large CDs	− 0.1360	− 0.5760	0.1190	0.0580	− 1.1360	− 1.3950	− 1.1610	− 1.4430
	(1.2210)	(1.4730)	(1.5880)	(1.5250)	(1.3140)	(1.4720)	(1.5170)	(1.5760)
Bad C&I loans	3.0340***	2.8160***	2.6720**	2.2180*	3.6920***	2.8430	2.7580	1.7480
	(1.1310)	(1.2510)	(1.2130)	(1.3420)	(1.4130)	(1.7760)	(1.7660)	(1.8090)
Bad total loans	11.0730*	12.1210**	14.5140**	16.2520**	9.6220	10.5180	11.3980	16.1120
	(6.3830)	(6.4110)	(7.3030)	(8.6060)	(8.6210)	(8.5410)	(8.9040)	(11.7020)
$Spread_{it}$	0.1310	0.1430	0.1260	0.1300	0.4950***	0.5860***	0.5720***	0.6450***
	(0.1330)	(0.1550)	(0.1690)	(0.1620)	(0.1340)	(0.1650)	(0.1590)	(0.2030)
$\Delta\ln(L^{cai})$	− 1.0320**	− 1.2390**	− 1.3360**	− 1.3710**	− 0.9460	− 1.0920	− 1.1750	− 1.1260
	(0.4970)	(0.5350)	(0.5590)	(0.5840)	(0.6560)	(0.8140)	(0.8320)	(0.9680)
Fraction small		− 0.4830	− 0.4830	− 0.5320		− 0.5150	− 0.4950	− 0.5090
		(0.4530)	(0.4490)	(0.3930)		(0.5490)	(0.5450)	(0.5450)
Fraction secured		0.9610	0.8100	0.8640		0.9050	0.8670	1.1800
		(1.1370)	(1.0430)	(1.0080)		(0.8600)	(0.8050)	(0.9620)
Maturity		− 0.0020	− 0.0030	− 0.0040		− 0.0030	− 0.0030	− 0.0040
		(0.0030)	(0.0040)	(0.0040)		(0.0040)	(0.0040)	(0.0040)
Risk Rating			0.4560*				0.1800	
			(0.2510)				(0.2150)	
Fr(Risk = 5)				3.6520**				5.2980
				(1.8890)				(3.3200)
Fr(Risk = 4)				2.4670**				2.5770
				(1.2860)				(1.5960)
Fr(Risk = 3)				2.1910*				3.0500*
				(1.0560)				(1.5540)
Fr(Risk = 2)				1.8220				3.1150*
				(1.2950)				(1.6800)
Fr(Risk = .)				− 0.1420				0.1580
				(2.0030)				(2.7210)
Marginal Effects								
$Spread_{it}$	0.0010	0.0009	0.0005	0.0003	0.0032***	0.0028***	0.0026***	0.0009***
P-value	0.322	0.357	0.454	0.423	0.000	0.000	0.000	0.001
Risk rating			0.0020**				0.0008	
P-value			0.069				0.402	
Time until downgrade	1 year	1 year	1 year	1 year	2 years	2 years	2 years	2 years
N	728	728	728	728	620	620	620	620
R^2	0.202	0.227	0.256	0.278	0.294	0.317	0.322	0.367

Significance levels are shown as *, **, ***, representing 10%, 5% and 1% respectively.

lending terms, fees, relationship pricing, etc., but those practical problems do not seem insurmountable. If those other terms introduce noise in the risk-rate relationship, supervisors will have to adjust their reliance on rates accordingly. But given our strong findings on the strength of that relationship, even with less than ideal data, the current weight on interest rates in the supervisory process—zero—can hardly be optimal.

Appendix

Theory

We sketch a simple model in order to emphasize a few fundamental points. First, the under-pricing of deposit insurance creates incentives for banks to undertake excessive risk and leverage. Second, either the risk-pricing of deposit insurance or a risk-based capital requirement could fix these incentives, but only when risk choice is observed by the regulator. Third, when risk choice is private information, banks will have every incentive to misrepresent actual risk choice to the regulator in order to reduce their capital requirements and/or deposit insurance premia. Finally, while risk choice might not be observed directly by the regulators, in principle it can be credibly revealed to the regulator through the portfolio interest rate.

Basic framework. Consider a bank that exists for three periods. At time $t = 1$, the bank finances one dollar of assets using both insured deposits d and equity e so that $e + d = 1$. We assume there is a frontier $R(x)$ which describes the efficient trade-off between the time 3 value of assets R and the time 2 choice of the probability the bank survives x. Along this frontier, the portfolio has value $R(x)$ with probability x, and with probability $(1 - x)$ it has value zero, where R is decreasing in x.[8] The choice of loan portfolios (x, R) is consequently constrained by the inequalities $R(x) \geq R \Leftrightarrow x(R) \geq x$, and the frontier is illustrated in figure 4.

At time $t = 3$, uncertainty over the value of assets is realized and all parties receive payoffs. In the good state, the sum paid to depositors and the deposit insurer is $R_d D$ and the bank receives any residual cash flows. Reflecting the current regulatory regime, we assume that R_d is simply the risk-free rate of interest R_f which implies that the deposit insurance premium is zero. In the bad state neither party receives any cash flows and the bank fails. For simplicity, all parties are risk-neutral. The net value of bank equity can be written,[9]

$$V = x[R - R_f d] - (1 - d)R_f. \tag{1}$$

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8 We place few other restrictions on the form of $R(x)$. In order for the first-order conditions to characterize the solution to the bank's maximization problem, we must assume $2\delta R/\delta x + x\delta^2 R/\delta x^2 < 0$.

9 As all cash flows occur at time 3, there is no need for discounting when characterizing optimal bank choice of risk and leverage. Assuming that bank assets have no value in the bad state is made for simplicity and is not important. If leverage d has an independent effect on the probability of survival x, then the problem becomes a bit more complicated and it is possible for leverage requirements not to bind. We ignore this complication here.

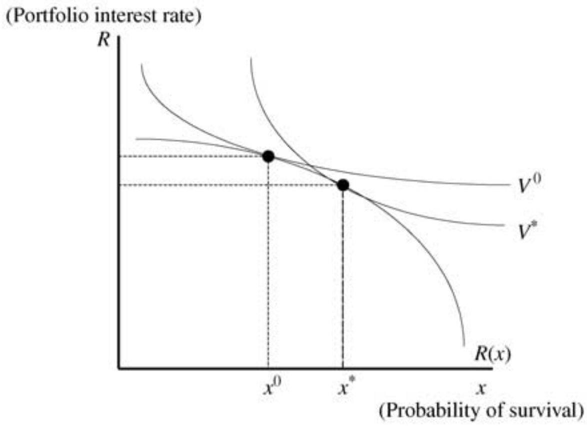

Figure 4. **Optimal risk choice.**

Note immediately that the bank will choose a combination of risk x and return R from the efficient frontier as the net value of equity is increasing in x holding constant the portfolio interest rate R. The bank wants to maximize the probability of survival x given return R, which is done by choosing a portfolio from the schedule $R(x)$.

The first-order conditions describing optimal choice of risk x at time 2 can be written,

$$\delta V/\delta x = (R - R_f d) + x(\delta R/\delta x) = 0. \tag{2}$$

Here, the marginal value of increasing the probability of survival x to the net value of equity is reduced by leverage d, implying that leverage induces the bank to assume excessive risk. The under-pricing of deposit insurance by the insurer also creates a distortion as illustrated by the first-order conditions describing optimal choice of leverage d at time 1,

$$\delta V/\delta d = R_f(1 - x) \geq 0. \tag{3}$$

Clearly, the bank will seek to maximize the time 1 choice of leverage d as long as there is a positive probability of default. As equation (2) indicates, an increase in leverage further reduces the return to safe assets, inducing the bank to assume even greater risk.

Regulatory regimes. If instead the regulator set a risk-based deposit insurance premium, the cost of deposits R_d will be equal to R_f/x. The new objective function is simply,

$$V = xR - R_f,$$

and the equivalent of the first-order conditions in equation (2) would indicate that the net value of equity no longer depends on leverage. Moreover, this efficient choice of risk would maximize the value of assets.

These points are illustrated in figure 4, where V^0 corresponds to the iso-''net value of equity'' curve in the absence of regulation and V^* in the presence of risk-priced deposit insurance. The under-pricing of deposit insurance flattens out the slope of the iso- ''net value of equity'' curve, inducing the bank to assume more risk by reducing x in order to increase the good state return R.

Alternatively consider a risk-based capital requirement that puts an upper bound on leverage so that $d(x) \geq d$. As this leverage requirement binds, the bank can no longer choose risk x and leverage d separately. First-order conditions with respect to the choice of risk now imply,

$$\delta V/\delta x = R + x(\delta R/\delta x) + R_f[(1-x)(\delta d/\delta x) - d]. \tag{5}$$

The last term of equation (5) illustrates that binding risk-based capital requirements affect risk choice relative to the efficient risk choice in two ways. An increase in the probability of survival x reduces the opportunity cost of equity by $R_f \delta d/\delta x$ and decreases the expected time 2 value of equity by $R_f[d + x\delta d/\delta x]$. Note that when $d(x) = c/(1-x)$, these two incentives are offset perfectly, implying that the bank will choose risk to maximize the value of assets. With this form of regulation, the regulator can choose c so that each bank meets a target level of leverage but makes first-best risk choice.

Gaming of regulation by banks. A natural problem for regulators is that the choice of risk x is not observed, implying that it is quite difficult to enforce risk-based capital standards or write risk-based deposit insurance premiums. Consider the possibility that banks can report risk level x^{rep} to regulators independently of their actual risk choice x. As the bank has an incentive to maximize leverage in absence of regulation, it will have every incentive to exaggerate x^{rep} in order to reduce its capital requirement. This is of course quite similar to tying capital requirements to the risk choice revealed by internal risk ratings as proposed in the *Revised Basle Accord*.

On the other hand, while bank regulators might not directly observe the actual choice of risk x, they do observe the portfolio interest rate R. By its nature, the interest rate is contractible and could be used to set deposit insurance premiums or risk-based capital requirements. As long as the efficient trade-off between risk and return $R(x)$ can be observed by regulators, the nominal interest rate on the bank's asset portfolio is a sufficient statistic for the choice of risk. This implies that the regulator can set risk-based capital standards or risk-priced deposit insurance using the inferred value of x through portfolio interest rates, either of which completely eliminate incentives for excessive leverage and risk-taking.

To make this point clear, reconsider a risk-based deposit insurance scheme. The cost of deposits is $r_d = r_f/x^{\text{hat}}(R)$, where $x^{\text{hat}}(R)$ is the regulator's mapping from the portfolio interest rate to survival probability. The marginal effect of x on the net value of equity is now

$$\delta V/\delta x = R + x(\delta R/\delta x) + d^* R_f[\varepsilon_R^{\text{hat}}/\varepsilon_R - 1]x^{\text{hat}}. \tag{6}$$

Here, $\varepsilon_R^{\text{hat}}$ is the elasticity of predicted survival probability x^{hat} to R, and is a measure of how sensitive the insurance premium is to the portfolio interest rate. On the other hand,

$\varepsilon_R(<0)$ is the elasticity of the survival probability to the portfolio interest rate defined by the efficient frontier. Note that the incentives for first-best risk choice exist when $\varepsilon_R^{\text{hat}} = \varepsilon_R$, which implies that the elasticity of the cost of deposits r_d to the portfolio interest rate should be $-\varepsilon_R$ in order to eliminate incentives for excessive risk-taking. Moreover, as long as the elasticity of the cost of deposits is at least as large as $(1 - x^{\text{hat}})\varepsilon_R$, the introduction of a risk-based deposit insurance premium reduces risk relative to a regime of zero-cost deposit insurance. This latter result is important because it implies that the deposit insurance premium does not have to be very sensitive to risk in order to reduce existing incentives for excessive risk-taking since the expected probability of default $(1 - x^{\text{hat}})$ is quite small.

The crucial element here that is missing in the current regulatory regime is an unbreakable mapping from risk to a regulatory instrument. In particular, the only way an expected profit-maximizing bank will assume more risk on a loan is through an increase in the stated interest rate. This implies that unlike the current or Revised Basle Accord, the implementation of either interest-rate based capital requirements or interest-rate based pricing of deposit insurance has the potential to actually fix the underlying agency problems that motivate a need for bank regulation in the first place.

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