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The Link between Default and Recovery Rates: Theory, Empirical Evidence, and Implications*

This paper analyzes the association between default and recovery rates on credit assets and seeks to empirically explain this critical relationship. We examine recovery rates on corporate bond defaults over the period 1982–2002. Our econometric univariate and multivariate models explain a significant portion of the variance in bond recovery rates aggregated across seniority and collateral levels. We find that recovery rates are a function of supply and demand for the securities, with default rates playing a pivotal role. Our results have important implications for credit risk models and for the procyclicality effects of the New Basel Capital Accord.

I. Introduction

Credit risk affects virtually every financial contract. Therefore the measurement, pricing, and management of credit risk have received much attention from financial economists, bank supervisors and regulators, and financial market practitioners. Following the recent attempts of the Basel Committee on Banking Supervision (1999, 2001) to reform the capital adequacy framework by introducing risk-sensitive capital requirements, significant

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additional attention has been devoted to the subject of credit risk measurement by the international regulatory, academic, and banking communities.

This paper analyzes and measures the association between aggregate default and recovery rates on corporate bonds and seeks to empirically explain this critical relationship. After a brief review of the way credit risk models explicitly or implicitly treat the recovery rate variable, Section III examines the recovery rates on corporate bond defaults over the period 1982–2002. We attempt to explain recovery rates by specifying rather straightforward linear, logarithmic, and logistic regression models. The central thesis is that aggregate recovery rates are basically a function of supply and demand for the securities. Our econometric univariate and multivariate time-series models explain a significant portion of the variance in bond recovery rates aggregated across all seniority and collateral levels. In Sections IV and V, we briefly examine the effects of the relationship between defaults and recoveries on credit VaR (value at risk) models and the procyclicality effects of the new capital requirements proposed by the Basel Committee, then conclude with some remarks on the general relevance of our results.

II. The Relationship between Default Rates and Recovery Rates in Credit Risk Modeling: A Review of the Literature

Credit risk models can be divided into three main categories: (1) "first generation" structural-form models, (2) "second generation" structural-form models, and (3) reduced-form models. Rather than go through a discussion of each of these well-known approaches and their advocates in the literature, we refer the reader to our earlier report for ISDA (Altman, Resti, and Sironi 2001), which carefully reviews the literature on the conceptual relationship between the firm's probability of default (PD) and the recovery rate (RR) after default to creditors.[1]

During the last few years, new approaches explicitly modeling and empirically investigating the relationship between PD and RR have been developed. These include Frye (2000a, 2000b), Jokivuolle and Peura (2003), and Jarrow (2001). The model proposed by Frye draws from the conditional approach suggested by Finger (1999) and Gordy (2000). In these models, defaults are driven by a single systematic factor–the state of the economy–rather than by a multitude of correlation parameters. The same economic conditions are assumed to cause defaults to rise, for example, and RRs to decline. The correlation between these two variables therefore derives from their common dependence on the systematic factor. The intuition behind Frye's theoretical model is relatively simple: if a borrower defaults on a loan, a bank's recovery may depend on the value of the loan collateral. The value of the collateral, like the value of

1. See Altman, Resti and Sironi (2001) for a formal discussion of this relationship.

other assets, depends on economic conditions. If the economy experiences a recession, RRs may decrease just as default rates tend to increase. This gives rise to a negative correlation between default rates and RRs. The model originally developed by Frye (2000a) implied recovery from an equation that determines collateral. His evidence is consistent with the most recent U.S. bond market data, indicating a simultaneous increase in default rates and losses given default (LGDs)[2] in 1999–2001.[3] Frye's (2000b, 2000c) empirical analysis allows him to conclude that, in a severe economic downturn, bond recoveries might decline 20–25 percentage points from their normal-year average. Loan recoveries may decline by a similar amount but from a higher level.

Jarrow (2001) presents a new methodology for estimating RRs and PDs implicit in both debt and equity prices. As in Frye (2000a, 2000b), RRs and PDs are correlated and depend on the state of the economy. However, Jarrow's methodology explicitly incorporates equity prices in the estimation procedure, allowing the separate identification of RRs and PDs and the use of an expanded and relevant data set. In addition, the methodology explicitly incorporates a liquidity premium in the estimation procedure, which is considered essential in the light of the high variability in the yield spreads between risky debt and U.S. Treasury securities.

A rather different approach is proposed by Jokivuolle and Peura (2000). The authors present a model for bank loans in which collateral value is correlated with the PD. They use the option pricing framework for modeling risky debt: the borrowing firm's total asset value determines the event of default. However, the firm's asset value does not determine the RR. Rather, the collateral value is in turn assumed to be the only stochastic element determining recovery. Because of this assumption, the model can be implemented using an exogenous PD, so that the firm's asset value parameters need not be estimated. In this respect, the model combines features of both structural-form and reduced-form models. Assuming a positive correlation between a firm's asset value and collateral value, the authors obtain a result similar to Frye (2000a), that realized default rates and recovery rates have an inverse relationship.

Using Moody's historical bond market data, Hu and Perraudin (2002) examine the dependence between recovery rates and default rates. They first standardize the quarterly recovery data to filter out the volatility of recovery rates given by the variation over time in the pool of borrowers rated by Moody's. They find that correlations between quarterly recovery rates and default rates for bonds issued by U.S.-domiciled

2. LGD indicates the amount actually lost (by an investor or a bank) for each dollar lent to a defaulted borrower. Accordingly, LGD and RR always add to 1. One may also factor into the loss calculation the last coupon payment, which is usually not realized when a default occurs (see Altman 1989).

3. Gupton, Hamilton, and Berthault (2001) provide clear empirical evidence of this phenomenon.

obligors are 0.22 for post 1982 data (1983–2000) and 0.19 for the 1971–2000 period. Using extreme value theory and other nonparametric techniques, they also examine the impact of this negative correlation on credit VaR measures and find that the increase is statistically significant when confidence levels exceed 99%.

Bakshi, Madan, and Zhang (2001) enhance the reduced-form models presented earlier to allow for a flexible correlation between the risk-free rate, the default probability, and the recovery rate. Based on some preliminary evidence published by rating agencies, they force recovery rates to be negatively associated with default probability. They find some strong support for this hypothesis through the analysis of a sample of BBB-rated corporate bonds: more precisely, their empirical results show that, on average, a 4% worsening in the (risk-neutral) hazard rate is associated with a 1% decline in (risk-neutral) recovery rates.

Compared to the aforementioned contributions, our study extends the existing literature in three main directions. First, the determinants of defaulted bonds' recovery rates are empirically investigated. While most of the aforementioned recent studies concluded in favor of an inverse relationship between these two variables, based on the common dependence on the state of the economy, none of them empirically analyzed the more specific determinants of recovery rates. While our analysis shows empirical results that appear consistent with the intuition of a negative correlation between default rates and RRs, we find that a single systematic risk factor (the performance of the economy) is less predictive than the aforementioned theoretical models would suggest.

Second, our study is the first one to examine, both theoretically and empirically, the role played by supply and demand of defaulted bonds in determining aggregate recovery rates. Our econometric univariate and multivariate models assign a key role to the supply of defaulted bonds and show that these variables together with variables that proxy the size of the high-yield bond market explain a substantial proportion of the variance in bond recovery rates aggregated across all seniority and collateral levels.

Third, our simulations show the consequences the negative correlation between default and recovery rates would have on VaR models and the procyclicality effect of the capital requirements recently proposed by the Basel Committee. Indeed, while our results on the impact of this correlation on credit risk measures (such as unexpected loss and value at risk) are in line with the ones obtained by Hu and Perraudin (2002), they show that, if a positive correlation highlighted by bond data were to be confirmed by bank data, the procyclicality effects of "Basel II" might be even more severe than expected if banks use their own estimates of LGD. Indeed, the Basel Commission assigned a task force in 2004 to analyze "recoveries in downturns" in order to assess the significance of a decrease in activity on LGD. A report was issued in July 2005 with some guidelines for banks (¶ 468 of the framework document).

As concerns specifically the Hu and Perraudin paper, it should be pointed out that they correlate recovery rates (or percent of par, which is the same thing) with issuer-based default rates. Our models assess the relationship between dollar-denominated default and recovery rates and, as such, can assess directly the supply/demand aspects of the defaulted debt market. Moreover, in addition to assessing the relationship between default and recovery rates using ex post default rates, we explore the effect of using ex ante estimates of the future default rates (i.e., default probabilities) instead of actual, realized defaults. As will be shown, however, while the negative relationship between RR and both ex post and ex ante default rates is empirically confirmed, the probabilities of default show a considerably lower explanatory power. Finally, it should be emphasized that, while our paper and the one by Hu and Perraudin reach similar conclusions, albeit from very different approaches and tests, it is important that these results become accepted and are subsequently reflected in future credit risk models and public policy debates and regulations. For these reasons, concurrent confirming evidence from several sources are beneficial, especially if they are helpful in specifying fairly precisely the default rate/recovery rate nexus.

III. Explaining Aggregate Recovery Rates on Corporate Bond Defaults: Empirical Results

The average loss experience on credit assets is well documented in studies by the various rating agencies (Moody's, S&P, and Fitch) as well as by academics.[4] Recovery rates have been observed for bonds, stratified by seniority, as well as for bank loans. The latter asset class can be further stratified by capital structure and collateral type (Van de Castle and Keisman 2000). While quite informative, these studies say nothing about the recovery versus default correlation. The purpose of this section is to empirically test this relationship with actual default data from the U.S. corporate bond market over the last two decades. As pointed out in Section II, strong intuition suggests that default and recovery rates might be correlated. Accordingly, this section of our study attempts to explain the link between the two variables, by specifying rather straightforward statistical models.[5]

We measure aggregate annual bond recovery rates (henceforth, BRR) by the weighted average recovery of all corporate bond defaults, primarily

4. See, e.g., Altman and Kishore (1996), Altman and Arman (2002), FITCH (1997, 2001), Standard & Poor's (2000).

5. We will concentrate on average annual recovery rates but not on the factors that contribute to understanding and explaining recovery rates on individual firm and issue defaults. Unal, Madan, and Güntay (2003) propose a model for estimating risk-neutral expected recovery rate distributions, not empirically observable rates. The latter can be particularly useful in determining prices on credit derivative instruments, such as credit default swaps.

in the United States, over the period 1982–2001. The weights are based on the market value of defaulting debt issues of publicly traded corporate bonds.[6] The logarithm of BRR (BLRR) is also analyzed.

The sample includes annual and quarterly averages from about 1,300 defaulted bonds for which we were able to get reliable quotes on the price of these securities just after default. We utilize the database constructed and maintained by the NYU Salomon Center, under the direction of one of the authors. Our models are both univariate and multivariate least squares regressions. The univariate structures can explain up to 60% of the variation of average annual recovery rates, while the multivariate models explain as much as 90%.

The rest of this section proceeds as follows. We begin our analysis by describing the independent variables used to explain the annual variation in recovery rates. These include supply-side aggregate variables that are specific to the market for corporate bonds, as well as macroeconomic factors (some demand-side factors, like the return on distressed bonds and the size of the "vulture" funds market, are discussed later). Next, we describe the results of the univariate analysis. We then present our multivariate models, discussing the main results and some robustness checks.

A. Explanatory Variables

We proceed by listing several variables we reasoned could be correlated with aggregate recovery rates. The expected effects of these variables on recovery rates will be indicated by a + or − sign in parentheses. The exact definitions of the variables we use are:

BDR(−). The weighted average default rate on bonds in the high-yield bond market and its logarithm (BLDR, (−)). Weights are based on the face value of all high-yield bonds outstanding each year and the size of each defaulting issue within a particular year.[7]

6. Prices of defaulted bonds are based on the closing "bid" levels on or as close to the default date as possible. Precise-date pricing was possible only in the last 10 years or so, since market maker quotes were not available from the NYU Salomon Center database prior to 1990 and all prior date prices were acquired from secondary sources, primarily the *S&P Bond Guides*. Those latter prices were based on end-of-month closing bid prices only. We feel that more exact pricing is a virtue, since we are trying to capture supply and demand dynamics, which may affect prices negatively if some bondholders decide to sell their defaulted securities as fast as possible. In reality, we do not believe this is an important factor, since many investors will have sold their holdings prior to default or are more deliberate in their "dumping" of defaulting issues.

7. We did not include a variable that measures the distressed but not defaulted proportion of the high-yield market, since we do not know of a time-series measure that goes back to 1987. We define distressed issues as yielding more than 1,000 basis points over the risk-free 10-year Treasury bond rate. We did utilize the average yield spread in the market and found it was highly correlated (0.67) to the subsequent 1-year's default rate, hence it did not add value (see the discussion later). The high-yield bond yield spread, however, can be quite helpful in forecasting the following year's BDR, a critical variable in our model (see our discussion of a default probability prediction model in Section III.F).

BDRC(−). The 1-year change in BDR.

BOA(−). The total amount of high-yield bonds outstanding for a particular year (measured at midyear in trillions of dollars), which represents the potential supply of defaulted securities. Since the size of the high-yield market has grown in most years over the sample period, the BOA variable picks up a time-series trend as well as representing a potential supply factor.

BDA(−). We also examined the more directly related bond defaulted amount as an alternative for BOA (also measured in trillions of dollars).

GDP(+). The annual GDP growth rate.

GDPC(+). The change in the annual GDP growth rate from the previous year.

GDPI(−). Takes the value of 1 when GDP growth was less than 1.5% and 0 when GDP growth was greater than 1.5%.

SR(+). The annual return on the S&P 500 stock index.

SCR(+). The change in the annual return on the S&P 500 stock index from the previous year.

B. The Basic Explanatory Variable: Default Rates

It is clear that the supply of defaulted bonds is most vividly depicted by the aggregate amount of defaults and the rate of default. Since virtually all public defaults most immediately migrate to default from the non-investment grade or "junk" bond segment of the market, we use that market as our population base. The default rate is the par value of defaulting bonds divided by the total amount outstanding, measured at face values. Table 1 shows default rate data from 1982–2001, as well as the weighted average annual recovery rates (our dependent variable) and the default loss rate (last column). Note that the average annual recovery is 41.8% (weighted average 37.2%) and the weighted average annual loss rate to investors is 3.16%.[8] The correlation between the default rate and the weighted price after default amounts to 0.75.

C. The Demand and Supply of Distressed Securities

The logic behind our demand/supply analysis is both intuitive and important, especially since, as we have seen, most credit risk models do not formally and statistically consider this relationship. On a macroeconomic

8. The loss rate is affected by the lost coupon at default as well as the more important lost principal. The 1987 default rate and recovery rate statistics do not include the massive Texaco default, since it was motivated by a lawsuit which was considered frivolous, resulting in a strategic bankruptcy filing and a recovery rate (price at default) of over 80%. Including Texaco would have increased the default rate by over 4% and the recovery rate to 82% (reflecting the huge difference between the market's assessment of asset values versus liabilities, not typical of bankrupt companies). The results of our models would be less impressive, although still quite significant, with Texaco included.

TABLE 1 **Default Rates, Recovery Rates, and Losses**

Year	Par Value Outstanding (a) ($million)	Par Value of Defaults (b) ($million)	Default Rate	Weighted Price after Default (Recovery Rate)	Weighted Coupon	Default Loss (c)
2001	$649,000	$63,609	9.80%	25.5	9.18%	7.76%
2000	$597,200	$30,295	5.07%	26.4	8.54%	3.95%
1999	$567,400	$23,532	4.15%	27.9	10.55%	3.21%
1998	$465,500	$7,464	1.60%	35.9	9.46%	1.10%
1997	$335,400	$4,200	1.25%	54.2	11.87%	.65%
1996	$271,000	$3,336	1.23%	51.9	8.92%	.65%
1995	$240,000	$4,551	1.90%	40.6	11.83%	1.24%
1994	$235,000	$3,418	1.45%	39.4	10.25%	.96%
1993	$206,907	$2,287	1.11%	56.6	12.98%	.56%
1992	$163,000	$5,545	3.40%	50.1	12.32%	1.91%
1991	$183,600	$18,862	10.27%	36.0	11.59%	7.16%
1990	$181,000	$18,354	10.14%	23.4	12.94%	8.42%
1989	$189,258	$8,110	4.29%	38.3	13.40%	2.93%
1988	$148,187	$3,944	2.66%	43.6	11.91%	1.66%
1987	$129,557	$1,736	1.34%	62.0	12.07%	.59%
1986	$90,243	$3,156	3.50%	34.5	10.61%	2.48%
1985	$58,088	$992	1.71%	45.9	13.69%	1.04%
1984	$40,939	$344	.84%	48.6	12.23%	.48%
1983	$27,492	$301	1.09%	55.7	10.11%	.54%
1982	$18,109	$577	3.19%	38.6	9.61%	2.11%
Weighted average			4.19%	37.2	10.60%	3.16%

NOTE.—Default rate data from 1982–2001 are shown, as well as the weighted average annual recovery rates and the loss rates. The time series show a high correlation (75%) between default and recovery rates.

(a) Measured at mid-year, excludes defaulted issues.

(b) Does not include Texaco's bankruptcy in 1987.

(c) Includes lost coupon as well as principal loss.

SOURCE: Authors' compilations.

level, forces that cause default rates to increase during periods of economic stress also cause the value of assets of distressed companies to decrease. Hence the securities' values of these companies will likely be lower. While the economic logic is clear, the statistical relationship between GDP variables and recovery rates is less significant than what one might expect. We hypothesized that, if one drills down to the distressed firm market and its particular securities, we can expect a more significant and robust negative relationship between default and recovery rates.[9]

9. Consider the latest highly stressful period of corporate bond defaults in 2000–02. The huge supply of bankrupt firms' assets in sectors like telecommunications, airlines, and steel, to name a few, has had a dramatic negative impact on the value of the firms in these sectors as they filed for bankruptcy and attempted a reorganization under Chapter 11. Altman and Jha (2003) estimated that the size of the U.S. distressed and defaulted public and private debt markets swelled from about $300 billion (face value) at the end of 1999 to about $940 billion by year-end 2002. And, only 1 year in that 3-year period was officially a recession year (2001). As we will show, the recovery rate on bonds defaulting in this period was unusually low as telecom equipment, large body aircraft, and steel assets of distressed firms piled up.

The principal purchasers of defaulted securities, primarily bonds and bank loans, are niche investors called *distressed asset* or *alternative investment managers,* also called *vultures*. Prior to 1990, there was little or no analytic interest in these investors, indeed in the distressed debt market, except for the occasional anecdotal evidence of performance in such securities. Altman (1991) was the first to attempt an analysis of the size and performance of the distressed debt market and estimated, based on a fairly inclusive survey, that the amount of funds under management by these so-called vultures was at least \$7.0 billion in 1990 and, if you include those investors who did not respond to the survey and non-dedicated investors, the total was probably in the \$10–12 billion range. Cambridge Associates (2001) estimated that the amount of distressed assets under management in 1991 was \$6.3 billion. Estimates since 1990 indicate that the demand did not rise materially until 2000–01, when the estimate of total demand for distressed securities was about \$40–45 billion as of December 31, 2001 and \$60–65 billion 1 year later (see Altman and Jha 2003). So, while the demand for distressed securities grew slowly in the 1990s and early in the next decade, the supply (as we will show) grew enormously.

On the supply side, the last decade has seen the amounts of distressed and defaulted public and private bonds and bank loans grow dramatically in 1990–91 to as much as \$300 billion (face value) and \$200 billion (market value), then recede to much lower levels in the 1993–98 period, and grow enormously again in 2000–02 to the unprecedented levels of \$940 billion (face value) and almost \$500 billion market value as of December 2002. These estimates are based on calculations in Altman and Jha (2003) from periodic market calculations and estimates.[10]

On a relative scale, the ratio of supply to demand of distressed and defaulted securities was something like 10 to 1 in both 1990–91 and 2000–01. Dollarwise, of course, the amount of supply-side money dwarfed the demand in both periods. And, as we will show, the price levels of new defaulting securities was relatively very low in both periods, at the start of the 1990s and again at the start of the 2000 decade.

D. Univariate Models

We begin the discussion of our results with the univariate relationships between recovery rates and the explanatory variables described in the previous section. Table 2 displays the results of the univariate regressions

10. Defaulted bonds and bank loans are relatively easy to define and are carefully documented by the rating agencies and others. Distressed securities are defined here as bonds selling at least 1,000 basis points over comparable maturity Treasury bonds (we use the 10-year T-bond rate as our benchmark). Privately owned securities, primarily bank loans, are estimated as 1.4–1.8 $\times$ the level of publicly owned distressed and defaulted securities based on studies of a large sample of bankrupt companies (Altman and Jha 2003).

TABLE 2 **Univariate Regressions, 1982–2001: Variables Explaining Annual Recovery Rates on Defaulted Corporate Bonds**

A. Market Variables

Regression number	1	2	3	4	5	6	7	8	9	10
Dependent variable										
BRR	X		X		X		X		X	
BLLR		X		X		X		X		X
Explanatory variables: coefficients and (*t*-ratios)										
Constant	.509	−.668	.002	−1.983	.432	−.872	.493	−.706	.468	−.772
	(18.43)	(−10.1)	(.03)	(−10.6)	(24.9)	(−20.1)	(13.8)	(−8.05)	(19.10)	(−13.2)
BDR	−2.610	−6.919								
	(−4.36)	(−4.82)								
BLDR			−.113	−.293						
			(−5.53)	(−5.84)						
BDRC					−3.104	−7.958				
					(−4.79)	(−4.92)				
BOA							−.315	−.853		
							(−2.68)	(−2.95)		
BDA									−4.761	−13.122
									(−3.51)	(−4.08)
Goodness of fit measures										
R^2	.514	.563	.630	.654	.560	.574	.286	.326	.406	.481
Adjusted r^2	.487	.539	.609	.635	.536	.550	.246	.288	.373	.452
F-statistic	19.03	23.19	30.61	34.06	22.92	24.22	7.21	8.69	12.31	16.67
(p-value)	.000	.000	.000	.000	.000	.000	.015	.009	.003	.001
Residual tests										
Serial correlation LM, 2 lags (Breusch-Godfrey)	1.021	1.836	1.522	2.295	1.366	2.981	1.559	1.855	3.443	2.994
(p-value)	.600	.399	.467	.317	.505	.225	.459	.396	.179	.224
Heteroscedasticity (White, Chi square)	.089	1.585	.118	1.342	8.011	5.526	2.389	1.827	.282	1.506
(p-value)	.956	.453	.943	.511	.018	.063	.303	.401	.868	.471
N. obs.	20	20	20	20	20	20	20	20	20	20

B. Macro Variables

Regression #	11	12	13	14	15	16	17	18	19	20
Dependent variable										
BRR	X		X		X		X		X	
BLRR		X		X		X		X		X
Explanatory variables										
Constant	.364	−1.044	.419	−.907	.458	−.804	.387	−1.009	.418	−.910
	(7.59)	(−8.58)	(18.47)	(−15.65)	(15.42)	(−10.8)	(10.71)	(−11.3)	(16.42)	(−14.4)
GDP	1.688	4.218								
	(1.30)	(1.28)								
GDPC			2.167	5.323						
			(2.31)	(2.22)						
GDPI					−.101	−.265				
					(−2.16)	(−2.25)				
SR							.205	.666		
							(1.16)	(1.53)		
SRC									.095	.346
									(.73)	(1.07)
Goodness of fit measures										
R^2	.086	.083	.228	.215	.206	.220	.070	.115	.029	.060
Adjusted R^2	.035	.032	.186	.171	.162	.176	.018	.066	−.025	.007
F-statistic	1.69	1.64	5.33	4.93	4.66	5.07	1.36	2.35	.53	1.14
(*p*-value)	.211	.217	.033	.040	.045	.037	.259	.143	.475	.299
Residual tests										
Serial correlation LM, 2 lags (Breusch-Godfrey)	2.641	4.059	.663	1.418	.352	1.153	3.980	5.222	3.479	4.615
(*p*-value)	.267	.131	.718	.492	.839	.562	.137	.073	.176	.100
Heteroscedasticity (White, Chi square)	2.305	2.077	2.254	2.494	.050	.726	2.515	3.563	3.511	4.979
(*p*-value)	.316	.354	.324	.287	.823	.394	.284	.168	.173	.083
Number of observations	20	20	20	20	20	20	20	20	20	20

NOTE.—The table shows the results of a set of univariate regressions carried out between the recovery rate (BRR) or its natural log (BLRR) and an array of explanatory variables: the default rate (BDR), its log (BLDR), and its change (BDRC); the outstanding amount of bonds (BOA) and the outstanding amount of defaulted bonds (BDA); the GDP growth rate (GDP), its change (GDPC), and a dummy (GDPI) taking the value of 1 when the GDP growth is less than 1.5%; the S&P 500 stock-market index (SR) and its change (SRC).

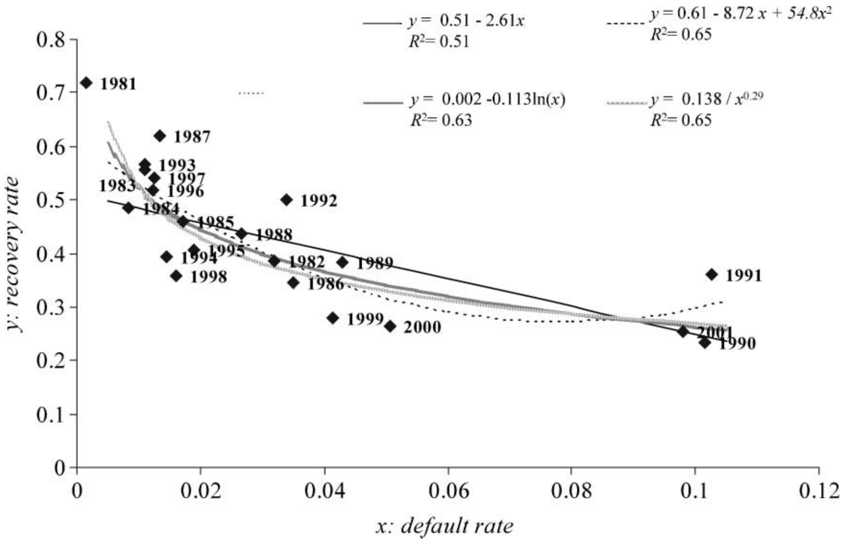

FIG. 1.—Univariate models. Results of a set of univariate regressions carried out between the recovery rate (BRR) or its natural log (BLRR) and the default rate (BDR) or its natural log (BLDR). See table 2 for more details.

carried out using these variables. These univariate regressions, and the multivariate regressions discussed in the following section, were calculated using both the recovery rate (BRR) and its natural log (BLRR) as the dependent variables. Both results are displayed in table 2, as signified by an X in the corresponding row.

We examined the simple relationship between bond recovery rates and bond default rates for the period 1982–2001. Table 2 and figure 1 show several regressions between the two fundamental variables. We find that one can explain about 51% of the variation in the annual recovery rate with the level of default rates (this is the linear model, regression 1) and 60% or more with the logarithmic and power[11] relationships (regressions 3 and 4). Hence, our basic thesis that the rate of default is a massive indicator of the likely average recovery rate among corporate bonds appears to be substantiated.[12]

The other univariate results show the correct sign for each coefficient, but not all of the relationships are significant. BDRC is highly

11. The power relationship (BRR $= e^{b0} \times \text{BDR}^{b1}$) can be estimated using the following equivalent equation: BLRR $= b_0 + b_1 \times$ BLDR (“power model”).

12. Such an impression is strongly supported by a -80% rank correlation coefficient between BDR and BRR (computed over the 1982–2001 period). Note that rank correlations represent quite a robust indicator, since they do not depend upon any specific functional form (e.g., log, quadratic, power).

TABLE 3 Correlation Coefficients among the Main Variables

	BDR	BOA	BDA	GDP	SR	BRR
BDR	1.00	.33	*.73*	*−.56*	−.30	*−.72*
BOA		1.00	*.76*	.05	−.21	*−.53*
BDA			1.00	−.26	−.49	*−.64*
GDP				1.00	−.02	.29
SR					1.00	.26
BRR						1.00

NOTE.—The table shows cross-correlations among our regressors (and between each of them and the recovery rate BRR); values greater than 0.5 are italicized. A strong link between GDP and BDR emerges, suggesting that default rates, as expected, are positively correlated with macro growth measures.

negatively correlated with recovery rates, as shown by the very significant t-ratios, although the t-ratios and R^2 values are not as significant as those for BLDR. Both BOA and BDA, as expected, are negatively correlated with recovery rates, with BDA being more significant on a univariate basis. Macroeconomic variables do not explain as much of the variation in recovery rates as the corporate bond market variables; their poorer performance is also confirmed by the presence of some heteroscedasticity and serial correlation in the regression's residuals, hinting at one or more omitted variables. We will come back to these relationships in the next paragraphs.

E. Multivariate Models

We now specify some more complex models to explain recovery rates, by adding several variables to the default rate. The basic structure of our most successful models is

$$\text{BRR} = f(\text{BDR}, \text{BDRC}, \text{BOA}, \text{or BDA})$$

Some macroeconomic variables will be added to this basic structure, to test their effect on recovery rates.

Before we move on to the multivariate results, table 3 reports the cross-correlations among our regressors (and between each of them and the recovery rate, BRR); values greater than 0.5 are highlighted. A rather strong link between GDP and BDR emerges, suggesting that, as expected, default rates are positively correlated with macro growth measures. Hence, adding GDP to the BDR/BRR relationship is expected to blur the significance of the results. We also observe a high positive correlation between BDA (absolute amount of all defaulted bonds) and the default rate.

We estimate our regressions using 1982–2001 data to explain recovery rate results and predict 2002 rates. This involves linear and log-linear structures for the two key variables, recovery rates (dependent) and default rates (explanatory), with the log-linear relationships somewhat more significant. These results appear in table 4.

TABLE 4 Multivariate Regressions, 1982–2001

	Linear and Logarithmic Models										Logistic Models				
Regression number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Dependent variable															
BRR	X		X		X		X		X		X	X	X	X	X
BLRR		X		X		X		X		X					
Explanatory variables: coefficients and (*t*-ratios)															
Constant	.514	−.646	.207	−1.436	.482	−1.467	.529	−1.538	.509	−1.447	−.074	−.097	.042	.000	.000
	(19.96)	(−11.34)	(2.78)	(−8.70)	(20.02)	(−6.35)	(11.86)	(−9.07)	(14.65)	(−8.85)	(−.64)	(−.92)	(.44)	(.00)	(.00)
BDR	−1.358	−3.745			−1.209		−1.513		−1.332		12.200	6.713	5.346	7.421	6.487
	(−2.52)	(−3.13)			(−1.59)		(−2.28)		(−2.33)		(4.14)	(2.82)	(1.55)	(2.59)	(2.64)
BLDR			−.069	−.176		−.167		−.222		−.169					
			(−3.78)	(−4.36)		(−2.94)		(−4.64)		(−4.17)					
BDRC	−1.930	−4.702	−1.748	−4.389	−2.039	−4.522	−1.937	−4.415	−1.935	−4.378		8.231	8.637	8.304	8.394
	(−3.18)	(−3.50)	(−3.39)	(−3.84)	(−3.03)	(−3.35)	(−3.11)	(−4.05)	(−3.09)	(−3.87)		(3.339)	(3.147)	(3.282)	(3.315)
BOA	−.164	−.459	−.141	−.410			−.153	−.328	−.162	−.387		.742		.691	.736
	(−2.13)	(−2.71)	(−2.12)	(−2.78)			(−1.86)	(−2.20)	(−2.03)	(−2.63)		(2.214)		(1.927)	(2.136)
BDA					−1.203	−3.199							8.196		
					(−.81)	(−1.12)							(1.064)		
GDP							−.387	−2.690						1.709	
							(−.43)	(−1.62)						(.473)	
SR									.020	.213					−.242
									(.192)	(1.156)					(−.56)

Goodness of fit measures															
R^2	.764	.819	.826	.867	.708	.817	.767	.886	.764	.878	.534	.783	.732	.786	.787
Adjusted R^2	.720	.785	.793	.842	.654	.782	.704	.856	.702	.845	.508	.742	.682	.729	.731
F-stat	17.250	24.166	25.275	34.666	12.960	23.752	12.320	29.245	12.168	26.881	20.635	19.220	14.559	13.773	13.876
(p-value)	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
Residual tests															
Serial correlation LM, 2 lags (Breusch-Godfrey)	3.291	2.007	1.136	.718	1.235	.217	3.344	.028	5.606	1.897	1.042	2.673	1.954	2.648	5.899
(p-value)	.193	.367	.567	.698	.539	.897	.188	.986	.061	.387	.594	.263	.376	.266	.052
Heteroscedasticity (White, Chi square)	5.221	5.761	5.049	5.288	12.317	12.795	5.563	4.853	6.101	6.886	.008	5.566	9.963	5.735	5.948
(p-value)	.516	.451	.538	.507	.055	.046	.696	.773	.636	.549	.996	.474	.126	.677	.653
Numbers of observations	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

NOTE.—The table shows the results of a set of multivariate regressions based on 1982–2001 data. Regressions 1 through 6 build the "basic models": most variables are quite significant based on their t-ratios. The overall accuracy of the fit goes from 71% (65% adjusted R^2) to 87% (84% adjusted); the model with the highest explanatory power and lowest "error" rates is the power model in regression 4. Macroeconomic variables are added in columns 7–10, showing a poor explanatory power. A set of logistic estimates (cols. 11–15) is provided, to account for the fact that the dependent variable (recovery rates) is bounded between 0 and 1.

Regressions 1 through 6 build the "basic models": most variables are quite significant based on their *t*-ratios. The overall accuracy of the fit goes from 71% (65% adjusted R^2) to 87% (84% adjusted).

The actual model with the highest explanatory power and lowest "error" rates is the power model[13] in regression 4 of table 4. We see that all of the four explanatory variables have the expected negative sign and are significant at the 5% or 1% level. BLDR and BDRC are extremely significant, showing that the level and change in the default rate are highly important explanatory variables for recovery rates. Indeed, the variables BDR and BDRC explain up to 80% (unadjusted) and 78% (adjusted) of the variation in BRR based simply on a linear or log-linear association. The size of the high-yield market also performs very well and adds about 6–7% to the explanatory power of the model. When we substitute BDA for BOA (regressions 5 and 6), the latter does not look statistically significant, and the R^2 of the multivariate model drops slightly to 0.82 (unadjusted) and 0.78 (adjusted). Still, the sign of BDA is correct (+). Recall that BDA was more significant than BOA on a univariate basis (table 2).

Macro variables are added in columns 7–10: we are somewhat surprised by the low contributions of these variables since several models have been constructed that utilize macro variables, apparently significantly, in explaining annual default rates.[14]

As concerns the growth rate in annual GDP, the univariate analyses presented in tables 2 and 3 had shown it to be significantly negatively correlated with the bond default rate (−0.78, see table 3); however, the univariate correlation between recovery rates (both BRR and BLRR) and GDP growth is relatively low (see table 2), although with the appropriate sign (+). Note that, when we utilize the change in GDP growth (GDPC, table 2, regression 5 and 6), the significance improves markedly.

When we introduce GDP to our existing multivariate structures (table 4, regressions 7 and 8), not only is it not significant, but it has a counterintuitive sign (negative). The GDPC variable leads to similar results (not reported). No doubt, the high negative correlation between GDP and BDR reduces the possibility of using both in the same multivariate structure.

We also postulated that the return of the stock market could affect the prices of defaulting bonds in that the stock market represented investor expectations about the future. A positive stock market outlook could imply lower default rates and higher recovery rates. For example, earnings of all companies, including distressed ones, could be reflected

13. Like its univariate cousin, the multivariate power model can be written using logs: e.g., $\mathrm{BLRR} = b_0 + b_1 \times \mathrm{BLDR} + b_2 \times \mathrm{BDRC} + b_3 \times \mathrm{BOA}$ becomes $\mathrm{BRR} = \exp[b_0] \times \mathrm{BDR}^{b1} \times \exp[b_2 \times \mathrm{BDRC} + b_3 \times \mathrm{BOA}]$ and takes its name from BDR being raised to the power of its coefficient.

14. See, e.g., Jonsson and Fridson (1996), Fridson, Garman, and Wu (1997), Helwege and Kleiman (1997), Keenan, Sobehart, and Hamilton (1999), and Chacko and Mercier (2001).

in higher stock prices. Table 4, regressions 9 and 10, show the association between the annual S&P 500 Index stock return (SR) and recovery rates. Note the insignificant *t*-ratios in the multivariate model, despite the appropriate signs. Similar results (together with low values of R^2) emerge from our univariate analysis (table 2), where the change in the S&P return (SRC) was also tested.

Since the dependent variable (BRR) in most of our regressions is bounded by 0 and 1, we also ran the same models using a logistic function (table 4, columns 11–15). As can be seen, R^2 and *t*-ratios are broadly similar to those already shown. The model in column 12, including BDR, BDRC, and BOA, explains as much as 74% (adjusted R^2) of the recovery rate's total variability. Macroeconomic variables, as before, tend to have no evident effect on BDR.

F. Robustness Checks

This section hosts some robustness checks carried out to verify how our results would change when taking into account several important modifications to our approach.

Default probabilities. The models shown previously are based on the actual default rate experienced in the high yield, speculative-grade market (BDR) and reflect a coincident supply/demand dynamic in that market. One might argue that this ex post analysis is conceptually different from the specification of an ex ante estimate of the default rate.

We believe both specifications are important. Our previous ex post models and tests are critical in understanding the actual experience of credit losses and, as such, affect credit management regulation and supervision, capital allocations, and credit policy and planning of financial institutions. On the other hand, ex ante probabilities (PDs) are customarily used in VaR models in particular and for risk-management purposes in general; however, their use in a regression analysis of recovery rates might lead to empirical tests that are inevitably limited by the models used to estimate PDs and their own biases. The results of these tests might therefore not be indicative of the true relationship between default and recovery rates.

To assess the relationship between ex ante PDs and BRRs, we used PDs generated through a well-established default rate forecasting model from Moody's (Keenan et al. 1999). This econometric model is used to forecast the global speculative grade issuer default rate and was fairly accurate ($R^2 = 0.8$) in its explanatory model tests.[15]

15. Thus far, Moody's has tested its forecasts for the 36-month period 1999–2001 and found that the correlation between estimated (PD) and actual default rates was greater than 0.90 (Hamilton et al. 2003). So, it appears that there can be a highly correlated link between estimated PDs and actual BDRs. By association, therefore, one can infer that accurate PD models can be used to estimate recovery rates and LGD.

The results of using Moody's model to explain our recovery rates did demonstrate a significant negative relationship but the explanatory power of the multivariate models was considerably lower (adjusted $R^2 = 0.39$), although still impressive with significant *t*-tests for the change in PD and the amount of bonds outstanding (all variables had the expected sign). Note that, since the Moody's model is for global issuers and our earlier tests are for U.S.-dollar-denominated high-yield bonds, we did not expect that their PD model would be nearly as accurate in explaining U.S. recovery rates.

Quarterly Data. Our results are based on yearly values, so we wanted to make sure that higher-frequency data would confirm the existence of a link between default rates and recoveries. Based on quarterly data,[16] a simple, univariate estimate (see table 5) shows that (1) BDR is still strongly significant and shows the expected sign; (2) R^2 looks relatively modest (23.9% versus 51.4% for the annual data), because quarterly default rates and recovery rates tend to be very volatile (due to some "poor" quarters with only very few defaults).

Using a moving average of 4 quarters (BRR4W, weighted by the number of defaulted issues), we estimated another model (using BDR, its lagged value and its square, see the last column in table 5), obtaining a much better R^2 (72.4%). This suggests that the link between default rates and recovery is somewhat "sticky" and, although confirmed by quarterly data, is better appreciated over a longer time interval.[17] Note that the signs of the coefficients behave as expected; for example, an increase in quarterly BDRs from 1% to 3% reduces the expected recovery rate from 39% to 31% within the same quarter, while a further decrease to 29% takes place in the following 3 months.

Risk-free rates. We considered the role of risk-free rates in explaining recovery rates, since these, in turn, depend on the discounted cash flows expected from the defaulted bonds. We therefore added to our "best" models (e.g., columns 3 and 4 in table 4) some "rate" variables (namely, the 1-year and 10-year U.S. dollar Treasury rates taken from the Federal Reserve Board of Governors, the corresponding discount rates, or alternatively, the "steepness" of the yield curve, as measured by the difference between 10-year and 1-year rates). The results are disappointing, since none of these variables ever is statistically significant at the 10% level.[18]

16. We had to refrain from using monthly data simply because of missing values (several months show no defaults, so it is impossible to compute recovery rates when defaulted bonds amount to zero).

17. This is confirmed by the equation residuals, which look substantially autocorrelated.

18. This might also be because one of our regressors (BOA, the amount of outstanding bonds) indirectly accounts for the level of risk-free rates, since lower rates imply higher market values and vice versa. Even removing BOA, however, risk-free rates cannot be found to be significant inside our model.

TABLE 5 Quarterly Regressions, 1990–2002

Dependent Variable	BRR	BRR4W
Explanatory variables: coefficients and (t-ratios)		
Constant	45.48 (17.61)	48.12 (39.3)
BDR	−5.77 (−3.92)	−8.07 (−4.24)
BDR(−1)		−2.62 (−2.87)
BDRSQ		1.10 (2.87)
Goodness of fit measures		
R^2	.239	.724
Adjusted R^2	.223	.705
F-stat	15.36	38.47
(p-value)	.000	.000
Residual tests		
Serial correlation LM, 2 lags (Breusch-Godfrey)	1.129	10.456
(p-value)	.332	.000
Heteroscedasticity (White, Chi square)	4.857	1.161
(p-value)	.012	.344
Number of observations	51	48

Note.—The table shows univariate estimates based on quarterly data. It appears that (1) BDR is strongly significant and has the expected sign; (2) R^2 looks relatively modest, because quarterly default rates and recovery rates tend to be very volatile; (3) expressing recovery rates as the moving average of four quarterly data (BRR4W) improves R^2, suggesting that the link between default rates and recovery is somewhat "sticky."

Returns on defaulted bonds. We examined whether the return experienced by the defaulted bond market affects the demand for distressed securities, thereby influencing the "equilibrium price" of defaulted bonds. To do so, we considered the 1-year return on the Altman-NYU Salomon Center Index of Defaulted Bonds (BIR), a monthly indicator of the market-weighted average performance of a sample of defaulted publicly traded bonds.[19] This is a measure of the price changes of existing defaulted issues as well as the "entry value" of new defaults and, as such, is affected by supply and demand conditions in this "niche" market.[20] On a univariate basis, the BIR shows the expected sign (+) with a t-ratio of 2.67 and explains 35% of the variation in BRR. However, when BIR is included in multivariate models, its sign remains correct, but the marginal significance is usually below 10%.

Outliers. The limited width of the time series on which our coefficient estimates are based suggests that they might be affected by a small number of outliers. We checked for this by eliminating 10% of the observations, choosing those associated with the highest residuals,[21]

19. More details can be found in Altman (1991) and Altman and Jha (2003). Note that we use a different time frame in our analysis (1987–2001), because the defaulted bond index return (BIR) has been calculated only since 1987.

20. We are aware that the average recovery rate on newly defaulted bond issues could influence the level of the defaulted bond index and vice versa. The vast majority of issues in the index, however, usually comprise bonds that have defaulted in prior periods. And, as we will see, while this variable is significant on an univariate basis and does improve the overall explanatory power of the model, it is not an important contributor.

21. This amounts to 2 years out of 20, namely, 1987 and 1997.

and running our regressions again. The results (not reported to save room) totally confirm the estimates shown in table 4. For example, for model 3, the coefficients associated with BLDR (−0.15), BDRC (−4.26), and BOA (−0.45) are virtually unchanged, and remain significant at the 1% level; the same happens for model 4 (the coefficients being, respectively, −0.15, −4.26, and −0.45).

GDP dummy and regime effects. We saw, in our multivariate results, that the GDP variable lacks statistical significance and tends to have a counterintuitive sign when added to multivariate models. The fact that GDP growth is highly correlated with default rates, our primary explanatory variable, looks like a sensible explanation for this phenomenon. To try to circumvent this problem, we used a technique similar to Helwege and Kleiman (1997): they postulate that, while a change in GDP of say 1% or 2% was not very meaningful in explaining default rates when the base year was in a strong economic growth period, the same change was meaningful when the new level was in a weak economy. Following their approach, we built a dummy variable (GDPI) which takes the value of 1 when GDP grows at less than 1.5% and 0 otherwise. The univariate GDPI results show a somewhat significant relationship with the appropriate negative sign (table 2); however, when one adds the "dummy" variable GDPI to the multivariate models discussed previously, the results (not reported) show no statistically significant effect, although the sign remains appropriate.

We further checked whether the relationship between default rates and recoveries outlined in table 4 experiences a structural change depending on the economy being in a "good" or "bad" regime. To do so, we reestimated equations 1–4 in the table after removing recession years (simply defined as years showing a negative real GDP growth rate); the results (not reported), widely confirmed the results shown in table 4; this suggests that our original estimates are not affected by recession periods.

Seniority and original rating. Our study considers default rates and recoveries at an aggregate level. However, to strengthen our analysis and get some further insights on the PD/LGD relationship, we also considered recovery rates broken down by seniority status and original rating.

Table 6 shows the results obtained on such data for our basic univariate, translog model. One can see that the link between recovery rates and default frequencies remains statistically significant for all seniority and rating groups. However, such a link tends to be somewhat weaker for subordinated bonds and junk issues. Moreover, while the sensitivity of BRR to the default rate looks similar for both seniority classes, recovery rates on investment-grade bonds seem to react more steeply to changes in the default rate. In other words, the price of defaulted bonds with an original rating between AAA and BBB decreases more sharply as defaults become relatively more frequent. Perhaps the reason for this is that original issue investment grade defaults tend to be larger than

TABLE 6 Univariate Regressions on Data Broken by Seniority Status and Original Rating

	Data Broken by Seniority Status		Data Broken by Original Rating†	
Dependent Variable	RR on Senior* Bonds (Log)	RR on Subordinated** Bonds (Log)	RR on Investment-Grade Bonds (Log)	RR on Junk‡ Bonds (Log)
Explanatory variables: coefficients and (t-ratios)				
Constant	2.97	2.58	2.70	2.70
	(13.91)	(8.79)	(9.77)	(10.99)
BLDR	−.24	−.23	−.31	−.23
	(−4.30)	(−2.90)	(−4.16)	(−3.41)
Goodness of fit measures				
R^2	.507	.319	.519	.421
Adjusted R^2	.479	.281	.489	.385
F-statistic	18.487	8.431	17.291	11.652
(p-value)	.000	.009	.001	.004
Residual tests				
Serial correlation LM, 2 lags				
(Breusch-Godfrey)	.6674	1.66	4.0302	.162
(p-value)	.5268	.2213	.0415	.852
Heteroskedasticity				
(White, Chi square)	.719	.2001	.4858	.4811
(p-value)	.5015	.8205	.6245	.6273
Number of observations	20	20	18	18

NOTE.—The table shows a set of univariate regressions, based on recovery rates broken down by seniority status and original rating. The link between recovery rates and default frequencies remains statistically significant for all seniority and rating groups. However, it grows weaker for subordinated bonds and junk issues. Moreover, recovery rates on investment-grade bonds seem to react more steeply to changes in the default rate.

* Senior-secured and senior-unsecured bonds.

** Senior-subordinated, subordinated, and discount bonds.

† Years 1993 and 1994 are not included because no default took place on investment-grade issues.

‡ Including unrated bonds.

noninvestment-grade failures and the larger amounts of distressed assets depresses the recovery rates even greater in difficult periods.

IV. Implications for Credit VaR Models, Capital Ratios, and Procyclicality

The results of our empirical tests have important implications for a number of credit-risk-related conceptual and practical areas. This section reviews two key areas that can be affected significantly when one factors in that, in fact, default rates are negatively correlated with recovery rates. These are (1) credit VaR models and (2) the potential impact of our findings on the procyclicality of capital requirements debated by the Basel Committee.[22]

22. We simply summarize here our conclusions based on several simulation analyses, discussed in greater detail in Altman, Resti and Sironi (2001).

A. VaR Models

As noted earlier, most credit VaR models treat recovery rates as deterministic (like in the CreditRisk+model proposed by Credit Suisse Financial Products 1997) or stochastic but independent from default probabilities (like in the Creditmetrics framework; Finger, Gupton, and Bhatia 1997). The impact of a negative correlation between recovery rates and default rates is generally overlooked. To assess this impact, we ran Monte Carlo simulations on a sample portfolio of bank loans and compared the key risk measures (expected and unexpected losses) obtained by the two aforementioned models to those generated when recovery rates are treated as stochastic and negatively correlated with PDs.

The results of our simulations are revealing, indicating that both the expected and unexpected losses are vastly understated if one assumes that PDs and RRs are uncorrelated.[23] As long as the PDs used in VaR models can be thought of as ex ante estimates of actual DRs, this implies that the risk measures generated by such models are biased.

Summing up, if default rates (and PDs, which can be thought of as ex ante estimates of actual DRs) are found to be correlated with RRs, then not only the risk measures based on standard errors and percentiles (i.e., the unexpected losses) could be seriously underestimated, but the amount of expected losses on a given credit portfolio (on which banks' provisioning policies should be based) could also be misjudged. Therefore, credit models that do not carefully factor in the negative correlation between PDs and RRs might lead to insufficient bank reserves and cause unnecessary shocks to financial markets.

B. The RR/PD Link and Procyclicality Effects

Procyclicality involves the sensitivity of regulatory capital requirements to economic and financial market cycles. Since ratings and default rates respond to the cycle, the new internal ratings-based (IRB) approach proposed by the Basel Committee risks increasing capital charges and limiting credit supply when the economy is slowing (the reverse being true when the economy is growing at a fast rate).

Such procyclicality effects might be thought to be exacerbated by the correlation between DRs and RRs found in our study (and in some of the contributions quoted in Section II); in other words, low recovery rates when defaults are high would amplify cyclical effects. This results from the negative correlation between default rates and recovery rates, which would lead to more sensitive capital requirements. For example, in a recession period with increasing default rates, recovery rates would decrease, leading to higher credit losses. This, in turn, would lead to higher capital requirements and, correspondingly, possibly to a decrease

23. Both expected losses and VaR measures associated with different confidence levels tend to be underestimated by approximately 30%.

in the supply of bank credit to the economy, thereby exacerbating the recession. On the other side, in a strong economic growth period with decreasing default rates, recovery rates would increase leading to lower credit losses and lower bank capital requirements. This, in turn, would allow an expansion of bank credit, thereby favoring economic growth.

This procyclicality effect would be especially true under the so-called advanced IRB approach, where banks are free to estimate their own recovery rates and might tend to revise them downward when defaults increase and ratings worsen.

The impact of such a mechanism was assessed, for example, in Resti (2002), based on simulations over a 20-year period, using a standard portfolio of bank loans (the composition of which is adjusted through time according to S&P transition matrices). Two results of these simulations are worth mentioning. First, the procyclicality effect is driven more by upgrades and downgrades than by default rates; in other words, adjustments in the credit supply needed to comply with capital requirements respond mainly to changes in the structure of weighted assets and only to a lesser extent to actual credit losses (except in extremely high default years). Second, when RRs are permitted to fluctuate with default rates, the procyclicality effect increases significantly. Moreover, bank and credit derivative spreads, too, become more volatile, since revisions in short-term RR estimates are factored into prices.

One might object that, in these simulations, banks basically react to short-term results, and regulation should encourage "advanced" IRB systems to use long-term average recovery rates. However, while the use of long-term RRs would make the procyclicality effects less marked, it would also force banks to maintain a less updated picture of their risks, thereby substituting stability for precision.

V. Concluding Remarks

This paper analyzed the link between aggregate default rates/probabilities and the loss given default on corporate bonds, from both a theoretical and an empirical standpoint. As far as the theoretical aspects are concerned, most of the literature on credit-risk-management models and tools treats the recovery rate variable as a function of historic average default recovery rates (conditioned perhaps on seniority and collateral factors) but in almost all cases as independent of expected or actual default rates. This appears rather simplistic and unrealistic in the light of our empirical evidence.

We examined the recovery rates on corporate bond defaults, over the period 1982–2002, by means of rather straightforward statistical models. These models assign a key role to the supply of defaulted paper (default rates) and explain a substantial proportion of the variance in bond recovery rates aggregated across all seniority and collateral levels.

These results have important implications for portfolio credit-risk models, for markets that depend on recovery rates as a key variable (e.g., securitizations, credit derivatives), and for the current debate on the revised BIS guidelines for capital requirements on bank assets.

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