Debt Default Probability, Asset Diversification and New Capital Accord: Implication for Islamic Banks

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ABSTRACT

The internal ratings-based (IRB) approach advocated by the new Basel relies on banks to assign default probabilities for their borrowers. However, these probabilities depend on current information on the borrower's equity price and book liabilities. Business cycle effects will surely impact asset valuations, which, in turn, will affect the loan default probabilities. Therefore, banks may be induced to implement a procyclical loan rating scheme, so as to shift the cost of recessions to the rest of the economy, thus exacerbating the business cycle effect. The higher probability of default may increase the unexpected debt losses that may induce bank to alter their portfolio from heavily weighted risk assets such as debt and corporate bonds into unweighted assets such as government bonds. Using a panel of Islamic bank balance sheets for financial years 1996-2004, this study will produce the evidence that: first, an increase in both expected and unexpected losses are negatively correlated with default probabilities. and second, bank asset portfolios are strongly affected by the total regulatory capital ratio.

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1. Introduction

The new Basle Accord introduces a standardized and an internal ratings-based (IRB) approach for assessing credit risk. This simple rule based approach is designed to address some of the most blatant shortcomings of the current Accord. Compared to the current Accord, the IRB approach is fundamentally different in concept, design, and implementation and is intended to produce a capital requirement more closely linked to each bank's actual credit risks – a lower-quality portfolio will face a higher capital charge, a higher-quality portfolio a lower capital charge. Such an approach is essential to creating the correct incentives for both banks and supervisors.

The IRB at heart provides a continuous mapping from the basic set of four input parameters (probability of default (*PD),* loss given default (*LGD),* exposure at default *(EAD)* and Maturity (*M*),, plus some other observables such as borrower type, to a minimum capital requirement. A critical issue with respect to the IRB approach is the reliability of the credit risk parameters supplied by banks, upon which the capital charges are based. This mapping is based on the same analytical framework as most credit portfolio models.

However, the significant attention has only been devoted by the credit risk literature on the estimation of the first parameter, much less attention has been dedicated to the estimation of RR and especially to the relationship between RR and PD. This is mainly the consequence of two related factors. First, credit pricing models and risk management applications tend to focus on the systematic risk components of credit risk, as these are the only ones that attract risk-premia. Second, credit risk models traditionally assumed RR to be dependent on individual features (e.g. collateral or seniority) that do not respond to systematic factors, and to be independent of PD. Therefore, the aim of this study is to produce an additional empirical evidence on the link between probability of default and recovery rate. A better understanding of how both variables are related and how they vary across banks and over time may help us to understand the need for and effect of provisioning regulation.

The remaining of this chapter is divided into six sections. In section 2, we will review on the modeling of credit risk. In section 3, we build the univariate and multivariate model aimed at providing the basis for an empirical estimation. The data sources and descriptions are given in section 4. Section 5 produces the results. Section 6 summarizes the conclusions.

2. Prior Studies

The literature on credit risk modeling is extensive and starts in the 1960's with research by Altman (1971). Following Altman, a number of authors have estimated various types of default risk models on cross-sectional data sets. See for example Altman (1973), Altman (1984), Frydman, Altman and Kao (1985), Li (1999), and Shumway (2001). These papers all have a single focus on the analysis of (credit) risk and the prediction of bankruptcy at the firm level.

In the last decade, a whole range of modeling techniques has been developed to analyze portfolio credit risk. Broadly viewed, there are three groups of portfolio credit risk models. The first group is 'structural' and based on Merton's (1974) model of firm capital structure: individual firms default when their assets' value fall below the value of their liabilities. Examples of such a microeconomic causal model are CreditMetrics and KMV's PortfolioManager. The second group consists of econometric factor risk models, like McKinsey's CreditPortfolioView. McKinsey's model is basically a logistic model where default risk in 'homogeneous' subgroups is determined by a macroeconomic index and a number of idiosyncratic factors. These two model types apply similar Monte Carlo simulations to calculate portfolio risk, as both are 'bottom-up' models that compute default rates at either the individual firm level or at sub-portfolio level. Both thus require a similar kind of aggregation. The third group contains 'top-down' actuarial models, like Credit Suisse's CreditRisk+, that make no assumptions with regard to causality.

Koyluoglu and Hickman (1998) provide an elaborate description of the above mentioned types of portfolio credit risk models. They note that all model types, despite their differences, are built on three more or less general components to calculate portfolio loss distributions. First, they contain some process that generates conditional default rates for each borrower in each state of nature and a measure of co-variation between borrowers in different states of nature. Second, their set-up allows for the calculation of conditional default rate distributions for sets of homogeneous sub-portfolios (e.g., rating classes) as if individual borrower defaults are independent, since all joint behavior is accounted for in generating conditional default rates. Third, unconditional portfolio default distributions are obtained by aggregating homogeneous sub-portfolios' conditional distributions in each state of nature; then conditional distributions are averaged using the probability of a state of nature as the weighting factor.

Gordy (2000) confirms the general insights of Koyluoglu and Hickman in a thorough comparison of two influential benchmarks for credit risk models, CreditMetrics and CreditRisk+. He concludes that they have very similar mathematical structures and that the prime sources of discrepancies in predictions are differences in distributional assumptions and functional forms. Gordy's findings suggest some general insights into the workings of these credit risk models. Among other things, he concludes that the models are highly sensitive to both the average default correlations in the model - that in turn determine default rate volatility - and the shape of the implied distribution of default probabilities. Since the work on the reform of the Basel Accord started, a number of efforts have been made to apply credit risk models to the ultimate goal of calculating capital requirements under a variety of alternative systems. Estrella (2001), for example, contains a theoretical model of optimal bank capital. He finds that a regulatory minimum capital requirement based on VaR is likely to be procyclical and suggests some ways to remedy this procyclicality.

Gordy (2000) examines the relation between portfolio models of credit VaR and ratings-based bucket models. He concludes that the latter can be reconciled with the general class of credit VaR models and that even portfolio credit VaR models imply marginal capital charges that depend only on an asset's own characteristics under some very general assumptions. Carey (1998) contains a new non-parametric methodology to estimate loss rates in the bad tail of the credit loss distribution. Calem and LaCour-Little (2001) estimate a survival time model for mortgage loan data and apply Carey's method to simulate PD distributions. They find that capital charges vary substantially with loan or borrower characteristics. They also conclude that capital charges are generally below the current standard - thereby providing some empirical support for the occurrence of securitization.

Hamerle et al. (2002) follow another approach and model the (unconditional) PD's by means of a non-linear random effects probit and logit model. Carey and Hrycay (2001) empirically examine the properties of the most commonly used methods to estimate average PD's by rating class. They find that the mapping and scoring-model methods are potentially subject to bias, instability and gaming. As a result of the interest that the reform of the Basel rules has generated, a number of authors have also examined the design of banks' internal ratings systems and the consequences that their design have for the functioning of the Basel II. Treacy and Carey (1998), for example, describe the ratings systems of large U.S. banks and collect some statistics on the distribution of loans over rating classes and the related loss rates and risk profiles. Carey (2000) finds, based on simulated data, which the success of the IRB approach will depend on the extent to which it will take into account differences in assets and portfolio properties, such as granularity, risk properties and remaining maturities.

Other papers emphasize the potential for cyclical impacts to arise from sources other than the rated credit quality of the asset. This is particularly relevant to banks that intend to apply the advanced IRB approach, where they potentially can determine the values of other variables that enter into the risk-weight formula (especially LGD, but also variables such as EAD and M). Lowe (2002) provides an extensive analysis of cyclical effects that could arise, in particular owing to changes in expected loss (or LGD) at different points in the cycle. However, it is also emphasized that the way in which regulators chooses to implement Basel II (for example, to what extent they require banks to maintain typical levels of capital above the Basel minimum requirements) will influence importantly the degree of cyclicality. While Lowe concludes that VAR models implemented under the advanced IRB approach have the potential to introduce substantial level changes and volatility into expected default rates, this may be mitigated by other factors, such as improvements in credit-risk management, capital buffers over regulatory minimums, and changes in supervisory practices.

Allen and Saunders (2003) suggest that the growing use of credit-risk measurement models (e.g., Merton-type models) may accentuate the procyclical tendencies that already exist within the banking sector, regardless of what is required by Basel II. For example, these models will tend to produce "overly optimistic" estimates of default risk during booms, reinforcing the tendency to over lend. This emphasizes the important point that what is critical from the perspective of Basel II (but not necessarily from the perspective of regulators) is the additional cyclicality that it will introduce into a system that already has cyclical tendencies. As with Lowe, it is also noted that under the

IRB approach, cyclical influences can emerge from a range of variables that ultimately contribute to the estimates of default probability.

The work by Allen and Saunders, and others, stresses the particularly important impact that changes in the assumed value of LGD could have on the required capital charge. Altman, Resti, and Sironi (2002) undertake an extensive simulation exercise, applying annual ratings transition matrices over the period 1981–2000 to a somewhat stylized loan portfolio. They contrast a scenario where the value of LGD is held constant at 50 per cent, to one where LGD is correlated with changes in default rates and allowed to vary between 40 and 60 per cent. In the latter scenario, the positive correlation between LGD and default rates brings about a sharp increase in the cyclicality of capital charges under Basel II. Cave et al. (2003) also emphasize the potentially central role of LGD estimates for banks applying the advanced IRB approach. They show that, under the proposed formula, the capital charge would be directly proportional to the loan's estimated LGD. They also calculate the capital charge that would arise for an "average" portfolio and a "stressed" portfolio that draws on data from 2002, when credit quality was under downward pressure. These scenarios all produce lower minimum capital requirements than Basel I (excluding the proposed charge for operational risk), but the reduction is significantly less under the stressed scenario, which implies the presence of cyclicality.

Altman, Resti, and Sironi (2002) and Cave et al. (2003) again emphasize that supervisory involvement in the implementation of Basel II will have a significant impact on outcomes. For example, banks using the advanced IRB approach (and their regulators) may use a longer-term view of LGD that would mitigate its potential cyclical impact. As Altman, Resti, and Sironi point out, however, this could trade stability for precision, because banks maintain a less up-to-date picture of their risks. Cave et al. suggest that the intent is to use a period of financial stress to generate representative LGDs. Similarly, while PD has a one-year horizon, it is expected that banks will be encouraged to take a conservative view of PDs such that loans originating from cyclically vulnerable industries could be slotted into a lower rating grade than long-run average PDs would indicate. French (2004) estimates the capital impact of Basel II's advanced internal ratings-based approach for all FDIC-insured commercial banks. The reference period is similar to our own, 1984–2002. The author develops several scenarios for a range of risk parameters that banks might use in the capital formulae. The scenarios are conducted for four portfolios, including wholesale loans, aggregated across all banks. The net charge-off rate is used as a proxy of expected loss, from which a corresponding unexpected loss is derived. French finds that Basel II capital requirements will likely be much lower in level terms than those of Basel I; in fact, they will be "well below the levels needed for current Prompt Corrective Action (PCA) purposes." French also reports very large swings in capital ratios over the cycle for wholesale lending, in excess of five percentage points.

3. The Model

During the last three years, new approaches explicitly modeling and empirically investigating the relationship between PD and RR have been developed. These models include Frye (2000a and 2000b), Jarrow (2001), Hu and Perraudin (2002), Jokivuolle and Peura (2003), Carey and Gordy (2003), Bakshi et al. (2001), Altman, Brady, Resti and Sironi (2001 and 2004), and Acharya, Bharath and Srinivasan (2003). The model proposed by Frye (2000a and 2000b) 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. These models are based on the assumption that the same economic conditions that cause defaults to rise might cause recoveries to decline, i.e. that the distribution of recovery is different in high-default periods from low-default ones. In Frye's model, both probability of default (PD) and recovery rate (RR) depend on the state of the systematic factor. The correlation between these two variables therefore can be derived from the following univariate model:

$$RR = f(PD) \tag{1}$$

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 other assets, depends on economic conditions. If the economy experiences a recession, recoveries may decrease just as default rates tend to increase. Therefore, equation (1) can be written as the following multivariate model:

$$RR = f(PD, M3, TL, GDP) \tag{2}$$

Equations (1) and (2) give rise to a negative correlation between default rates and recoveries. Loans have a positive influence on profitability, because as a bank's core business, they are a major generator of interest income. While both models originally developed by Frye (2000a) implied recovery to be taken from an equation that determines collateral, Frye (2000b) modeled recovery directly. This allowed him to empirically test his model using data on defaults and recoveries from U.S. corporate bond data. More precisely, data from Moody's Default Risk Service database for the 1982-1997 periods were used for the empirical analysis. Results show a strong negative correlation between default rates and Recoveries for corporate bonds Frye's (2000b and 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.

While in the original Merton (1974) framework an inverse relationship between PD and RR exists, the credit risk models developed during the Nineties treat these two variables as independent. The currently available and most used credit pricing and credit VaR models are indeed based on this independence assumption and treat RR either as a constant parameter or as a stochastic variable independent from PD. In the latter case, RR volatility is assumed to represent an idiosyncratic risk which can be eliminated through adequate portfolio diversification. This assumption strongly contrasts with the growing empirical evidence - showing a negative correlation between default and recovery rates – that has been reported in the previous section of this paper and in other empirical studies (Frye [2000b and 2000c], Altman [2001], Carey and Gordy [2003], Hamilton, Gupton and Berthault [2001], Altman, Brady, Resti and Sironi [2001, 2004]). This evidence indicates that recovery risk is a systematic risk component. As such, it should attract risk premia and should adequately be considered in credit risk management applications. The potential consequences – in terms of credit risk underestimation – of the PD and RR independence assumption when these two variables are instead correlated are shown by Altman, Brady, Resti and Sironi (2004).

The RR/PD Link and Procyclicality Effects - Procyclicality involves the sensitivity of RR 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). While in the original Merton (1974) framework an inverse relationship between PD and RR exists, the credit risk models developed during the Nineties treat these two variables as independent. The currently available and most used credit pricing and credit VaR models are indeed based on this independence assumption and treat RR either as a constant parameter or as a stochastic variable independent from PD. In the latter case, RR volatility is assumed to represent an idiosyncratic risk which can be eliminated through adequate portfolio diversification.

4. Data Sources and Descriptions

To estimate equations (1) and (2), we use an unbalanced bank-level panel data set for 15 Islamic banks (i.e., two full-pledged Islamic banks and thirteen Islamic windows). The data are annual and span the period from 1994 to 2004. In this manner a full cycle of the Malaysia economy is included, a point of particular importance given that the aim of this paper is, as mentioned, to analyze whether there is a relationship between the business cycle and recovery rate. Recovery rate is defined as the total recovery over lag total provision.

We proceed by listing several explanatory variables we believe to be correlated with aggregate recovery rates. The exact definitions of the variables are as follow: the GDP variable is included to capture economic growth effects. Our observation period does not include a whole business cycle, and the effect of this variable should therefore be interpreted with care and not used to draw conclusions about business cycle effects. The total of specific and general provisions over total loans is used as proxy for default rates (PD). The total financing *(as a share of total assets)* represents the (relative) size of financing. Generally speaking, total financings have a positive influence on profitability, because as a bank's core business, they are a major generator of income. But, total financing also entails operational costs and credit losses. If costs and risks are not expressed adequately in the price of credit (*i.e.* the mark-up rate), for instance, as a result of cross subsidization, then financing becomes a loss-making business. In any case, this variable serves to characterize a bank's balance sheet. Like the variables that follow below, the financing variable is divided by total assets in order to standardize it and allow comparisons across banks and years.

5. The Results

Empirical Results

Table 1 shows the descriptive statistics of different variables to examine the bivariate relationship by comparing the average (mean) for each variable. The reported results in Table 1 show that the values of each variable deviate slightly from the standard deviation. Therefore, they are very much volatile.

Table 1: Summary Statistics

	Mean	Std. Dev	Skewness	Kurtosis	Jarque-Bera
RR_{it}	0.900	0.231	3.318	10.030	120.254*
PD_{it}	1.303	0.033	16.316	14.588	224.803*
$M3_{it}$	5.599	5.638	0.129	-0.670	2.537*
GDP_{it}	4.701	4.709	0.062	-0.222	2.592**
TL_{it}	6.190	6.326	1.138	-1.873	9.432*

- *Significant at 1% **Significant at 5%

To verify whether the sample data is normally distributed, the data will be tested using several techniques such as the skewness test, kurtosis, the Jarque bera as well as the value of mean and median. If a sample is normally distributed, then the value of skewness will be equal to zero, the value of kurtosis should be three and the value of mean should be the same as the value of its median while the value of Jarque bera should not be significant or with high value of probability. A sample data that is normally distributed should be an efficient estimator, unbiased and consistent. Based on the findings on the descriptive as shown in Table 1, the value of mean and median for all the variables are not the same while their skewness is not equal to zero. The values of kurtosis are not equal to three and the values of Jarque-Bera are significant. Therefore it can be concluded that based on the above, the Ordinary Least Squares estimation method is not a better estimation method to be used. Hence, the Generalize Least Square method is more appropriate and expected to yield a much better result.

The correlation matrix reported in Table 2 shows that there is a negative correlation coefficient between recovery and all variable. The negative correlation between PD and RR might lead to insufficient bank reserves and cause unnecessary shocks to financial markets. As far as procyclicality is concerned, show that this effect tends to be exacerbated by the correlation between RR_{it} and PD_{it} : low recovery rates when defaults are high would amplify cyclical effects. This would especially be true under the so-called "advanced" IRB approach, where banks are free to estimate their own recovery rates and might tend to revise them downwards when defaults increase and ratings worsen.

Table 2 : Correlation Matrix

	RR_{it}	PD_{it}	$M3_{it}$	ROA_{it}	GDP_{it}
RR_{it}	1.000				
PD_{it}	-0.026	1.000			
$M3_{it}$	-0.018	0.073	1.000		
GDP_{it}	-0.075	0.052	0.928	1.000	
TL_{it}	-0.104	-0.243	0.023	0.037	1.000

The standard unit root test has to be performed to check the stationarity of our data. However, it is often argued that the commonly used unit root tests such as the augmented Dickey-Fuller test and the Phillips-Perron test are not very powerful. As a response, panel unit root tests are developed. These tests are in essence motivated to increase the power through pooling information across units.

ADF-Fisher assumes individual unit root process and use chi square test statistics. Table 2 present all variable are stationary at 1% except PD_{it} and TL_{it} not stationary at level. In the first difference, Table 3 shown all variable are stationary at 1%

Levin, Lin & Chu (1993) assume common unit root process and used t-test. Based on figures reported in Tables 3, we find all variable are stationary at one percent and negatives sign. In the first difference, all variable are stationary at one percent. This finding similar ADF-Fisher test.

Table 3: Panel Unit Roots Test

Variable	ADF-Fisher (χ^2)		Levin, Lin & Chu (t)	
	At level	First Difference		At level
RR_{it}	117.82*	111.14*	-41.506*	-39.363*
PD_{it}	70.872	79.386*	-15.037*	-14.773
$M3_{it}$	208.289*	7.349*	-23.353*	3.099*
GDP_{it}	140.563*	113.34*	-14.529*	-15.133*
TL_{it}	61.047	90.409*	-5.403*	-27.913*

Note:

- *Significant at 1% **Significant at 5 %
- Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution.
- All other tests assume asymptotic normality.

Table 4 shows the result from estimation for GLS model without effect (Model 1), random effect model (Model 2) fixed effect model (Model 3) and time effect model (model 4).

As reported in column two, Table 4 the model explains the relationship between recovery and default rates. We find that a default rate is not significant and negatively related to recovery. This result is similar with the correlation matrix result.

Table 4: Univariate Result

Specification	**Parameter Estimates**			
	Non Effect MODEL 1	**Fixed Effect MODEL 2**	**Random Effect MODEL 3**	**Time Effect MODEL 4**
Constant	1.012 (5.007)*	0.4808 (15.9018)*	0.5958 (7.9672)*	0.5178 (0.8658)*
PD_{it}	-0.789E-02 (-0.300)	-0.297-E03 (-0.011)	-0.0616E-02 (-0.236)	-0.669E-02 (-0.252)
R^2	0.0003	0.179	0.0026	0.0405
$Adj\ R^2$	-0.003	0.0611	-0.0007	0.0042
$F-test$	0.090	1.515**	0.775	1.114
DW-test	2.256	2.748	2.396	2.263

Note: *Significant at 1% **Significant at 5% ***Significant at 10%

( ) t-test

From column two Table 5, the figures explain the relationship between recovery and macroeconomics variable. We find the estimated coefficient of macroeconomics factors $M3_{it}$ is significant at five percent and has a positive sign in non-effect model and random effect model. The coefficient of GDP_{it} has a negative sign and significant at difference percent in all models except time effect not significant. The coefficient of Loans is negatively related to recovery in all models but not significant. The coefficients of default rates are not significant in all model have a negative sign.

Table 5: Multivariate Result

Specification	Parameter Estimates			
	Non Effect MODEL 1	**Fixed Effect MODEL 2**	**Random Effect MODEL 3**	**Time Effect MODEL 4**
Constant	53.072 (2.311)**	4.9647 (1.2727)	50.245 (2.164)**	-11.3149 (-0.7701)
PD_{it}	-0.2119E-01 (0.748)	0.1881E-01 (0.488)	-0.1806E-01 (-0.632)	-0.1559E-01 (-0.538)
$M3_{it}$	12.957 (2.570)**	8.076 (1.492)	12.042 (2.387)**	15.567 (0.500)
GDP_{it}	-26.204 (-2.619)**	-18.652 (-1.663)***	-24.552 (-2.436)**	-18.318 (-0.629)
TL_{it}	-0.232 (-0.963)	0.595 (0.828)	-0.198 (-0.733)	-0.215 (-0.880)
R^2	0.028	0.189	0.025	0.045
$Adj\ R^2$	0.014	0.061	0.012	-0.002
$F-test$	2.105***	1.479**	1.879***	0.957
DW-test	2.319	2.749	2.410	2.293
Note:	*Significant at 1%	**Significant at 5%	***Significant at 10%	
( ) t-test				

To diagnose the result in Table 5, first, we conducted Lagrange Multiplier (LM) tests to examine the relative efficiency of the heterogeneous fixed/random-effects estimation against the homogeneous pooled OLS model. The LM Chi-square values are not significant in the models (one-tailed). This suggests the pooled cross-sectional OLS model is more efficient than that fixed/random-effects model.

Second, we performed a Hausman specification test, which is based on the differences between the coefficients estimated from fixed or random-effects models, to determine which kind of panel model fixed or random effects would be most appropriate in this study. The computed Chi-square statistic was also found to be not significant in the model indicating that the null hypothesis of zero correlation between the unobservable company-specific effects and the explanatory variables in the model can be rejected. In this case, the random-effects model can still derive consistent estimates but the fixed effects model cannot; therefore, random-effects models were used in this study. Hence, the random effect is much better than the fixed effect.

Breusch pagan tests were conducted to test for the presence of heteroscedasticity in model. The computed χ^2 values were statistically significant in the estimation ($p \leq 0.05$, one-tailed), indicating the presence of heteroscedasticity problem in the volume decision models.

Table 6: Diagnostics test.

Test	Statistic	stat	p-value
LM test for a pooled OLS model versus a random-effects model	χ^2	0.09	0.760
Hausman test for a random-effects model versus a fixed-effects model	χ^2	5.31	0.257
Breusch-pagan test for heteroscedasticity	χ^2	91.034	0.000

6. Conclusions

This paper analyzed the link between recovery rates and default rates for Islamic bank, both from a theoretical and an empirical standpoint. As far as the theoretical aspects are concerned, most of the literature on credit risk management models 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. However, in this paper, we examined the recovery rates on defaults rates, over the period 1994-2004, 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 recovery rates aggregated. These results have important implications for portfolio credit risk models, for markets which depend on recovery rates as a key variable (e.g., securitizations, credit derivatives. etc.), and for the current debate on the revised BIS guidelines for capital requirements on bank assets. This paper produces a negative correlation between default and recovery rates – that has been reported in other empirical studies (Frye [2000b and 2000c], Altman [2001], Carey and Gordy [2003], Hamilton, Gupton andBerthault [2001], Altman, Brady, Resti and Sironi [2001, 2004]). This evidence indicates that recovery risk is a systematic risk component. As such, it should attract risk premia and should adequately be considered in credit risk management applications.

The exposure at default in bank loans is important when analyzing the factors that cause a high recovery rate. If the exposure is high, the probability rises that the bank can achieve a high recovery rate. This may be due to the assumption that the bank intensifies the enquiry of the creditworthiness and the monitoring of the borrower. In contrast, precisely those factors have an impact on achieving a very low recovery rate, which even influence the whole range of recovery rate values

References

Acharya, Viral V., Sreedar T. Bharath, Anand Srinivasan, 2003, Understanding the Recovery Rates on Defaulted Securities, mimeo.

Allen, L. and A. Saunders. 2003. "A Survey of Cyclical Effects in Credit Risk Measurement Models." Bank for International Settlements Working Paper No. 126.

Altman, Edward I., Brooks Brady, Andrea Resti and Andrea Sironi, 2004, "The Link between Default and Recovery Rates: Theory, Empirical Evidence and Implications", NYU Salomon Center Working Paper Series # S-03-4, forthcoming, *Journal of Business*.

Altman, Edward I., Brooks Brady, Andrea Resti, and Andrea Sironi, 2001, *Analyzing and Explaining Default Recovery Rates*, ISDA Research Report, London, December.

Altman, Edward I. and Vellore M. Kishore, 1996, "Almost Everything You Wanted to Know About Recoveries on Defaulted Bonds", *Financial Analysts Journal*, November/December.

Bakshi, G., Dilip Madan, Frank Zhang, 2001, "Understanding the Role of Recovery in Default Risk Models: Empirical Comparisons and Implied Recovery Rates", *Finance and Economics Discussion Series*, 2001-37, Federal Reserve Board of Governors, Washington D.C.

Basel Committee on Banking Supervision, 2003, "The New Basel Capital Accord", Consultative Document, Bank for International Settlements, April.

Banerjee A., 1999. Panel Data Unit Roots and Cointegration: An Overview. *Oxford Bulletin of Economics and Statistics* 61, pp. 607–629

Black, Fischer and John C. Cox, 1976, "Valuing Corporate Securities: Some Effects of Bond Indenture Provisions", *Journal of Finance*, 31, 351-367.

Black, Fischer and Myron Scholes, 1973, "The Pricing of Options and Corporate Liabilities", *Journal of Political Economics*, May, 637-659.

Breusch, T. S., & Pagan, A. R. (1980). The LM test and its applications to model specification in econometrics. Review of Economic Studies, 47, 239 - 254.

Carey, Mark and Michael Gordy, 2003, "Systematic Risk in Recoveries on Defaulted Debt", mimeo, Federal Reserve Board, Washington.

Cave, J., J. Feid, G. French, and W. Stark. 2003. "Risk-Based Capital Requirements for Commercial Lending: The Impact of Basel II." U.S. Federal Deposit Insurance Corporation.

Finger, Chris, 1999, *Conditional Approaches for CreditMetrics□ Portfolio Distributions*, CreditMetrics□ Monitor, April.

Fisher, R.A., 1932. Statistical Methods for Research Workers, 4th Edition. Oliver & Boyd, Edinburgh.

Frye, John, 2000a, "Collateral Damage", *Risk*, April, 91-94.

Frye, John, 2000b, "Collateral Damage Detected", Federal Reserve Bank of Chicago, Working Paper, *Emerging Issues Series*, October, 1-14.

Frye, John, 2000c, "Depressing Recoveries", *Risk*, November.

Hausman, J. A. (1978). Specification tests in econometrics. Econometrica,46.

Hu, Yen-Ting, and William Perraudin, 2002, "The Dependence of Recovery Rates and Defaults", BirkBeck College, mimeo, February.

Im K.S., Pesaran, M.H., Shin, Y., 1997. Testing for unit roots in heterogeneous panels. Working paper, Department of Applied Economics, University of Cambridge

Levin A., Lin, and F. Chu, 1993. Unit root test in panel data: new results. Discussion paper 93-56, Department of Economics, University of California at San Diego.

Lowe, P. 2002. "Credit Risk Measurement and Procyclicality." Bank for International Settlements Working Paper No. 116.

Maddala G.S. and Wu, S., 1999. A comparative study of unit root tests with panel data and a new simple test. *Oxford Bulletin of Economics and Statistics* 61, pp. 631–652.

Jarrow, Robert A., 2001, "Default Parameter Estimation Using Market Prices", *Financial Analysts Journal*, Vol. 57, No. 5, pp. 75-92.

Jokivuolle, Esa and Samu Peura, 2003, "A Model for Estimating Recovery Rates and Collateral Haircuts for Bank Loans", *European Financial Management*, forthcoming.