

Default Recovery Rates and LGD in Credit Risk Modeling and Practice

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Abstract

Evidence from many countries in recent years suggests that collateral values and recovery rates on corporate defaults can be volatile and, moreover, that they tend to go down just when the number of defaults goes up in economic downturns. This link between recovery rates and default rates has traditionally been neglected by credit risk models, as most of them focused on default risk and adopted static loss assumptions, treating the recovery rate either as a constant parameter or as a stochastic variable independent from the probability of default. This traditional focus on default analysis has been partly reversed by the recent significant increase in the number of studies dedicated to the subject of recovery rate estimation and the relationship between default and recovery rates. This paper presents a detailed review of the way credit risk models, developed during the last thirty years, treat the recovery rate and, more specifically, its relationship with the probability of default of an obligor. We also review the efforts by rating agencies to formally incorporate recovery ratings into their assessment of corporate loan and bond credit risk and the recent efforts by the Basel Committee on Banking Supervision to consider “downturn LGD” in their suggested requirements under Basel II. Recent empirical evidence concerning these issues and the latest data on high-yield bond and leverage loan defaults is also presented and discussed.

Keywords: credit rating, credit risk, recovery rate, default rate

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1. Introduction

Three main variables affect the credit risk of a financial asset: (i) the probability of default (PD), (ii) the “loss given default” (LGD), which is equal to one minus the recovery rate in the event of default (RR), and (iii) the exposure at default (EAD). While significant attention has been devoted by the credit risk literature on the estimation of the first component (PD), much less attention has been dedicated to the estimation of RR and to the relationship between PD and RR. 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 therefore to be independent of PD.

This traditional focus only on default analysis has been reversed by the recent increase in the number of studies dedicated to the subject of RR estimation and the relationship between the PD and RR (Fridson, Garman and Okashima [2000], Gupton, Gates and Carty [2000], Altman, Resti and Sironi [2001], Altman, Brady, Resti and Sironi [2003 and 2005], Frye [2000a, 2000b and 2000c], Hu and Perraudin (2002), Hamilton, Gupton and Berthault [2001]), Jarrow [2001]), Jokivuolle and Peura [2003] and Acharya, Bharath and Srinivasan (2007). This is partly the consequence of the parallel increase in default rates and decrease of recovery rates registered during a substantial part of the 1999-2009 period. More generally, evidence from many countries in recent years suggests that collateral values and recovery rates can be volatile and, moreover, they tend to go down just when the number of defaults goes up in economic downturns. Indeed, first half results in 2009 (8.0% year-to-date) indicate that the default rate on high-yield bonds will reach a record high level in 2009 and recovery rates will fall to perhaps the lowest level in history, at least in the modern high yield bond era (22.5% year-to-date, Altman and Karlin (2009) and Keisman and Marshella (2009).

This chapter presents a detailed review of the way credit risk models, developed during the last thirty years, have treated the recovery rate and, more specifically, its

relationship with the probability of default of an obligor. These models can be divided into two main categories: (a) credit pricing models, and (b) portfolio credit value-at-risk (VaR) models. Credit pricing models can in turn be divided into three main approaches: (i) “first generation” structural-form models, (ii) “second generation” structural-form models, and (iii) reduced-form models. These three different approaches together with their basic assumptions, advantages, drawbacks and empirical performance are reviewed in sections 2, 3 and 4. Credit VaR models are then examined in section 5. The more recent studies explicitly modeling and empirically investigating the relationship between PD and RR are reviewed in section 6. In Section 7, we discuss BIS efforts to motivate banks to consider “downturn LGD” in the specification of capital requirements under Basel II. Section 8 reviews the very recent efforts by the major rating agencies to provide explicit estimates of recovery given default. Section 9 revisits the issue of procyclicality and Section 10 presents some recent empirical evidence on recovery rates on both defaulted bonds and loans and also on the relationship between default and recovery rates. Section 11 concludes.

2. First generation structural-form models: the Merton approach

The first category of credit risk models are the ones based on the original framework developed by Merton (1974) using the principles of option pricing (Black and Scholes, 1973). In such a framework, the default process of a company is driven by the value of the company’s assets and the risk of a firm’s default is therefore explicitly linked to the variability of the firm’s asset value. The basic intuition behind the Merton model is relatively simple: default occurs when the value of a firm’s assets (the market value of the firm) is lower than that of its liabilities. The payment to the debtholders at the maturity of the debt is therefore the smaller of two quantities: the face value of the debt or the market value of the firm’s assets. Assuming that the company’s debt is entirely represented by a zero-coupon bond, if the value of the firm at maturity is greater than the face value of the bond, then the bondholder gets back the face value of the bond. However, if the value of the firm is less than the face value of the bond, the shareholders get nothing and the bondholder gets back the market value of the firm. The payoff at maturity to the bondholder is therefore equivalent to the face value of the bond minus a put option on the value of the firm, with a

strike price equal to the face value of the bond and a maturity equal to the maturity of the bond. Following this basic intuition, Merton derived an explicit formula for risky bonds which can be used both to estimate the PD of a firm and to estimate the yield differential between a risky bond and a default-free bond.

In addition to Merton (1974), first generation structural-form models include Black and Cox (1976), Geske (1977), and Vasicek (1984). Each of these models tries to refine the original Merton framework by removing one or more of the unrealistic assumptions. Black and Cox (1976) introduce the possibility of more complex capital structures, with subordinated debt; Geske (1977) introduces interest-paying debt; Vasicek (1984) introduces the distinction between short and long term liabilities which now represents a distinctive feature of the KMV model¹.

Under these models, all the relevant credit risk elements, including default and recovery at default, are a function of the structural characteristics of the firm: asset levels, asset volatility (business risk) and leverage (financial risk). The RR is therefore an endogenous variable, as the creditors' payoff is a function of the residual value of the defaulted company's assets. More precisely, under Merton's theoretical framework, PD and RR tend to be inversely related. If, for example, the firm's value increases, then its PD tends to decrease while the expected RR at default increases (*ceteris paribus*). On the other side, if the firm's debt increases, its PD increases while the expected RR at default decreases. Finally, if the firm's asset volatility increases, its PD increases while the expected RR at default decreases, since the possible asset values can be quite low relative to liability levels.

Although the line of research that followed the Merton approach has proven very useful in addressing the qualitatively important aspects of pricing credit risks, it has been less successful in practical applications². This lack of success has been attributed to

¹ In the KMV model, default occurs when the firm's asset value goes below a threshold represented by the sum of the total amount of short term liabilities and half of the amount of long term liabilities.

² The standard reference is Jones, Mason and Rosenfeld (1984), who found that, even for firms with very simple capital structures, a Merton-type model is unable to price investment-grade corporate bonds better than a naive model that assumes no risk of default.

different reasons. First, under Merton's model the firm defaults only at maturity of the debt, a scenario that is at odds with reality. Second, for the model to be used in valuing default-risky debts of a firm with more than one class of debt in its capital structure (complex capital structures), the priority/seniority structures of various debts have to be specified. Also, this framework assumes that the absolute-priority rules are actually adhered to upon default in that debts are paid off in the order of their seniority. However, empirical evidence, such as in Franks and Torous (1994), indicates that the absolute-priority rules are often violated. Moreover, the use of a lognormal distribution in the basic Merton model (instead of a more fat tailed distribution) tends to overstate recovery rates in the event of default.

3. Second-generation structural-form models

In response to such difficulties, an alternative approach has been developed which still adopts the original Merton framework as far as the default process is concerned but, at the same time, removes one of the unrealistic assumptions of the Merton model; namely, that default can occur only at maturity of the debt when the firm's assets are no longer sufficient to cover debt obligations. Instead, it is assumed that default may occur anytime between the issuance and maturity of the debt and that default is triggered when the value of the firm's assets reaches a lower threshold level³. These models include Kim, Ramaswamy and Sundaresan (1993), Hull and White (1995), Nielsen, Saà-Requejo, and Santa Clara (1993), Longstaff and Schwartz (1995) and others.

Under these models, the RR in the event of default is exogenous and independent from the firm's asset value. It is generally defined as a fixed ratio of the outstanding debt value and is therefore independent from the PD. For example, Longstaff and Schwartz (1995) argue that, by looking at the history of defaults and the recovery rates for various classes of debt of comparable firms, one can form a reliable estimate of the RR. In their model, they allow for a stochastic term structure of interest rates and for some correlation between defaults and interest rates. They find that this correlation between default risk and

³ One of the earliest studies based on this framework is Black and Cox (1976). However, this is not included in the second-generation models in terms of the treatment of the recovery rate.

the interest rate has a significant effect on the properties of the credit spread⁴. This approach simplifies the first class of models by both exogenously specifying the cash flows to risky debt in the event of bankruptcy and simplifying the bankruptcy process. The latter occurs when the value of the firm's underlying assets hits some exogenously specified boundary.

Despite these improvements with respect to the original Merton's framework, second generation structural-form models still suffer from three main drawbacks, which represent the main reasons behind their relatively poor empirical performance⁵. First, they still require estimates for the parameters of the firm's asset value, which is non-observable. Indeed, unlike the stock price in the Black and Scholes formula for valuing equity options, the current market value of a firm is not easily observable. Second, structural-form models cannot incorporate credit-rating changes that occur quite frequently for default-risky corporate debts. Most corporate bonds undergo credit downgrades before they actually default. As a consequence, any credit risk model should take into account the uncertainty associated with credit rating changes as well as the uncertainty concerning default. Finally, most structural-form models assume that the value of the firm is continuous in time. As a result, the time of default can be predicted just before it happens and hence, as argued by Duffie and Lando (2000), there are no "sudden surprises". In other words, without recurring to a "jump process", the PD of a firm is known with certainty.

4. Reduced-form models

The attempt to overcome the above mentioned shortcomings of structural-form models gave rise to reduced-form models. These include Litterman and Iben (1991), Madan and Unal (1995), Jarrow and Turnbull (1995), Jarrow, Lando and Turnbull (1997), Lando (1998), Duffie (1998). and Duffie and Singleton (1999). Unlike structural-form models, reduced-form models do not condition default on the value of the firm, and parameters related to the firm's value need not be estimated to implement them. In addition to that, reduced-form models introduce separate explicit assumptions on the dynamic of both PD

⁴ Using Moody's corporate bond yield data, they find that credit spreads are negatively related to interest rates and that durations of risky bonds depend on the correlation with interest rates.

and RR. These variables are modeled independently from the structural features of the firm, its asset volatility and leverage. Generally speaking, reduced-form models assume an exogenous RR that is independent from the PD and take as basics the behavior of default-free interest rates, the RR of defaultable bonds at default, as well as a stochastic process for default intensity. At each instant, there is some probability that a firm defaults on its obligations. Both this probability and the RR in the event of default may vary stochastically through time. Those stochastic processes determine the price of credit risk. Although these processes are not formally linked to the firm's asset value, there is presumably some underlying relation. Thus Duffie and Singleton (1999) describe these alternative approaches as reduced-form models.

Reduced-form models fundamentally differ from typical structural-form models in the degree of predictability of the default as they can accommodate defaults that are sudden surprises. A typical reduced-form model assumes that an exogenous random variable drives default and that the probability of default over any time interval is nonzero. Default occurs when the random variable undergoes a discrete shift in its level. These models treat defaults as unpredictable Poisson events. The time at which the discrete shift will occur cannot be foretold on the basis of information available today.

Reduced-form models somewhat differ from each other by the manner in which the RR is parameterized. For example, Jarrow and Turnbull (1995) assumed that, at default, a bond would have a market value equal to an exogenously specified fraction of an otherwise equivalent default-free bond. Duffie and Singleton (1999) followed with a model that, when market value at default (i.e. RR) is exogenously specified, allows for closed-form solutions for the term-structure of credit spreads. Their model also allows for a random RR that depends on the pre-default value of the bond. While this model assumes an exogenous process for the expected loss at default, meaning that the RR does not depend on the value of the defaultable claim, it allows for correlation between the default hazard-rate process and RR. Indeed, in this model, the behavior of both PD and RR may be allowed to depend on firm-specific or macroeconomic variables and therefore to be correlated.

⁵ See Eom, Helwege and Huang (2001) for an empirical analysis of structural-form models.

Other models assume that bonds of the same issuer, seniority, and face value have the same RR at default, regardless of the remaining maturity. For example, Duffie (1998) assumes that, at default, the holder of a bond of given face value receives a fixed payment, irrespective of the coupon level or maturity, and the same fraction of face value as any other bond of the same seniority. This allows him to use recovery parameters based on statistics provided by rating agencies such as Moody's. Jarrow, Lando and Turnbull (1997) also allow for different debt seniorities to translate into different RRs for a given firm. Both Lando (1998) and Jarrow, Lando and Turnbull (1997) use transition matrices (historical probabilities of credit rating changes) to price defaultable bonds.

Empirical evidence concerning reduced-form models is rather limited. Using the Duffie and Singleton (1999) framework, Duffie (1999) finds that these models have difficulty in explaining the observed term structure of credit spreads across firms of different credit risk qualities. In particular, such models have difficulty generating both relatively flat yield spreads when firms have low credit risk and steeper yield spreads when firms have higher credit risk.

A recent attempt to combine the advantages of structural-form models – a clear economic mechanism behind the default process - and the ones of reduced-form models – unpredictability of default - can be found in Zhou (2001). This is done by modeling the evolution of firm value as a jump-diffusion process. This model links RRs to the firm value at default so that the variation in RRs is endogenously generated and the correlation between RRs and credit ratings reported first in Altman (1989) and Gupton, Gates and Carty (2000) is justified.

5. Credit Value-at-Risk Models

During the second half of the nineties, banks and consultants started developing credit risk models aimed at measuring the potential loss, with a predetermined confidence level, that a portfolio of credit exposures could suffer within a specified time horizon (generally one year). These were mostly motivated by the growing importance of credit risk management especially since the now complete Basel II was anticipated to be proposed

by the BD. These value-at-risk (VaR) models include J.P. Morgan's *CreditMetrics*® (Gupton, Finger and Bhatia [1997] now provided by the Risk Metrics Group), *Credit Suisse Financial Products' CreditRisk+*® (1997), McKinsey's *CreditPortfolioView*® (Wilson, 1998), Moody's KMV's *CreditPortfolioManager*®, and Kamakura's *Risk Manager*®.

Credit VaR models can be gathered in two main categories: 1) Default Mode models (DM) and 2) Mark-to-Market (MTM) models. In the former, credit risk is identified with default risk and a binomial approach is adopted. Therefore, only two possible events are taken into account: default and survival. The latter includes all possible changes of the borrower creditworthiness, technically called "credit migrations". In DM models, credit losses only arise when a default occurs. On the other hand, MTM models are multinomial, in that losses arise also when negative credit migrations occur. The two approaches basically differ for the amount of data necessary to feed them: limited in the case of default mode models, much wider in the case of mark-to-market ones.

The main output of a credit risk model is the probability density function (PDF) of the future losses on a credit portfolio. From the analysis of such a loss distribution, a financial institution can estimate both the expected loss and the unexpected loss on its credit portfolio. The expected loss equals the (unconditional) mean of the loss distribution; it represents the amount the investor can expect to lose within a specific period of time (usually one year). On the other side, the unexpected loss represents the "deviation" from expected loss and measures the actual portfolio risk. This can in turn be measured as the standard deviation of the loss distribution. Such a measure is relevant only in the case of a normal distribution and is therefore hardly useful for credit risk measurement: indeed, the distribution of credit losses is usually highly asymmetrical and fat-tailed. This implies that the probability of large losses is higher than the one associated with a normal distribution. Financial institutions typically apply credit risk models to evaluate the "economic capital" necessary to face the risk associated with their credit portfolios. In such a framework, provisions for credit losses should cover expected losses⁶, while economic capital is seen as a cushion for unexpected losses. Indeed, Basel II in its final iteration (BIS, June 2004)

separated these two types of losses.

Credit VaR models can largely be seen as reduced-form models, where the RR is typically taken as an exogenous constant parameter or a stochastic variable independent from PD. Some of these models, such as *CreditMetrics*[®], treat the RR in the event of default as a stochastic variable – generally modelled through a beta distribution – independent from the PD. Others, such as *CreditRisk*⁺[®], treat it as a constant parameter that must be specified as an input for each single credit exposure. While a comprehensive analysis of these models goes beyond the aim of this review⁷, it is important to highlight that all credit VaR models treat RR and PD as two independent variables.

6. Recent contributions on the PD-RR relationship and their impact

During the last several years, new approaches explicitly modeling and empirically investigating the relationship between PD and RR have been developed. These models include Bakshi et al. (2001), Jokivuolle and Peura (2003). Frye (2000a and 2000b), Jarrow (2001), Hu and Perraudin (2002), and Carey and Gordy (2003), Altman, Brady, Resti and Sironi (2001, 2003 and 2005), and Acharya, Bharath and Srinivasan (2007).

Bakshi et al. (2001) enhance the reduced-form models presented in section 4 to allow for a flexible correlation between the risk-free rate, the default probability and the recovery rate. Based on some 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.

A rather different approach is the one proposed by Jokivuolle and Peura (2003). 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 triggers the event of default. However, the firm's asset value does not determine

⁶ As discussed in Jones and Mingo (1998), reserves are used to cover expected losses.

⁷ For a comprehensive analysis of these models, see Crouhy, Galai and Mark (2000) and Gordy (2000).

the RR. Rather, the collateral value is in turn assumed to be the only stochastic element determining recovery⁸. 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 similar result as Frye (2000a, b), that realized default rates and recovery rates have an inverse relationship.

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. These models are based on the assumption that the same economic conditions that cause defaults to rise might cause RRs to decline, i.e. that the distribution of recovery is different in high-default periods from low-default ones. In Frye's model, both PD and RR depend on the state of the systematic factor. The correlation between these two variables therefore derives from their mutual 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 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.

While the model 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 period were used for the empirical analysis⁹. Results show a strong negative

⁸ Because of this simplifying assumption the model can be implemented using an exogenous PD, so that the firm asset value parameters need not be estimated. In this respect, the model combines features of both structural-form and reduced-form models.

⁹ Data for the 1970-1981 period have been eliminated from the sample period because of the low number of default prices available for the computation of yearly recovery rates.

correlation between default rates and RRs for corporate bonds. This evidence is consistent with U.S. bond market data, indicating a simultaneous increase in default rates and LGDs for the 1999-2002 period¹⁰. 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. In all cases, Frye, and others, compare defaults and recoveries just after default, not the ultimate recovery after the restructuring, or recovery period.

Jarrow (2001) presents a new methodology for estimating RRs and PDs implicit in both debt and equity prices. As in Frye, RRs and PDs are correlated and depend on the state of the macroeconomy. 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 dataset. In addition to that, the methodology explicitly incorporates a liquidity premium in the estimation procedure, which is considered essential in light of the high variability in the yield spreads between risky debt and U.S. Treasury securities.

Using four different datasets (Moody's Default Risk Service database of bond defaults and LGDs, Society of Actuaries database of private placement defaults and LGDs, Standard & Poor's database of bond defaults and LGDs, and Portfolio Management Data's database of LGDs) ranging from 1970 to 1999, Carey and Gordy (2003) analyze LGD measures and their correlation with default rates. Their preliminary results contrast with the findings of Frye (2000b): estimates of simple default rate-LGD correlation are close to zero. They find, however, that limiting the sample period to 1988-1998, estimated correlations are more in line with Frye's results (0.45 for senior debt and 0.8 for subordinated debt). The authors postulate that during this short period the correlation rises not so much because LGDs are low during the low-default years 1993-1996, but rather because LGDs are relatively high during the high-default years 1990 and 1991. They therefore conclude that the basic intuition behind Frye's model may not adequately

¹⁰Hamilton, Gupton and Berthault (2001) and Altman, Brady, Resti and Sironi (2003, 2005) provide clear

characterize the relationship between default rates and LGDs. Indeed, a weak or asymmetric relationship suggests that default rates and LGDs may be influenced by different components of the economic cycle.

Using defaulted bonds' data for the sample period 1982-2002, which includes the relatively high-default years of 2000-2002, Altman, Brady, Resti and Sironi (2005), following Altman, Resti and Sironi (2001), find empirical results that appear consistent with Frye's intuition: a negative correlation between default rates and RRs. However, they find that the single systematic risk factor – i.e. the performance of the economy - is less predictive than Frye's model would suggest. Their econometric univariate and multivariate models assign a key role to the supply of defaulted bonds (the default rate) and show that this variable, together with variables that proxy the size of the high-yield bond market and the economic cycle, explain a substantial proportion (close to 90%) of the variance in bond recovery rates aggregated across all seniority and collateral levels. They conclude that a simple market mechanism based on supply and demand for the defaulted securities drives aggregate recovery rates more than a macroeconomic model based on the common dependence of default and recovery on the state of the cycle. In high default years, the supply of defaulted securities tends to exceed demand¹¹, thereby driving secondary market prices down. This in turn negatively affects RR estimates, as these are generally measured using bond prices shortly after default. During periods of low defaults, as we have observed in the 2004-2006 cycle, recoveries increase.

The coincident relationship between high-yield bond default rates and recovery rates is shown in Figure 1. This graph shows the association of weighted average default rates and recovery rates over the period 1982-2009, using four bi-variate regression specifications. The actual regressions are based on data from 1982-2003 and the subsequent five years (2004-2009) are inserted to show the regressions estimate compared to the actual. Note that the degree of explanatory power is excellent with as much as 65%

empirical evidence of this phenomenon.

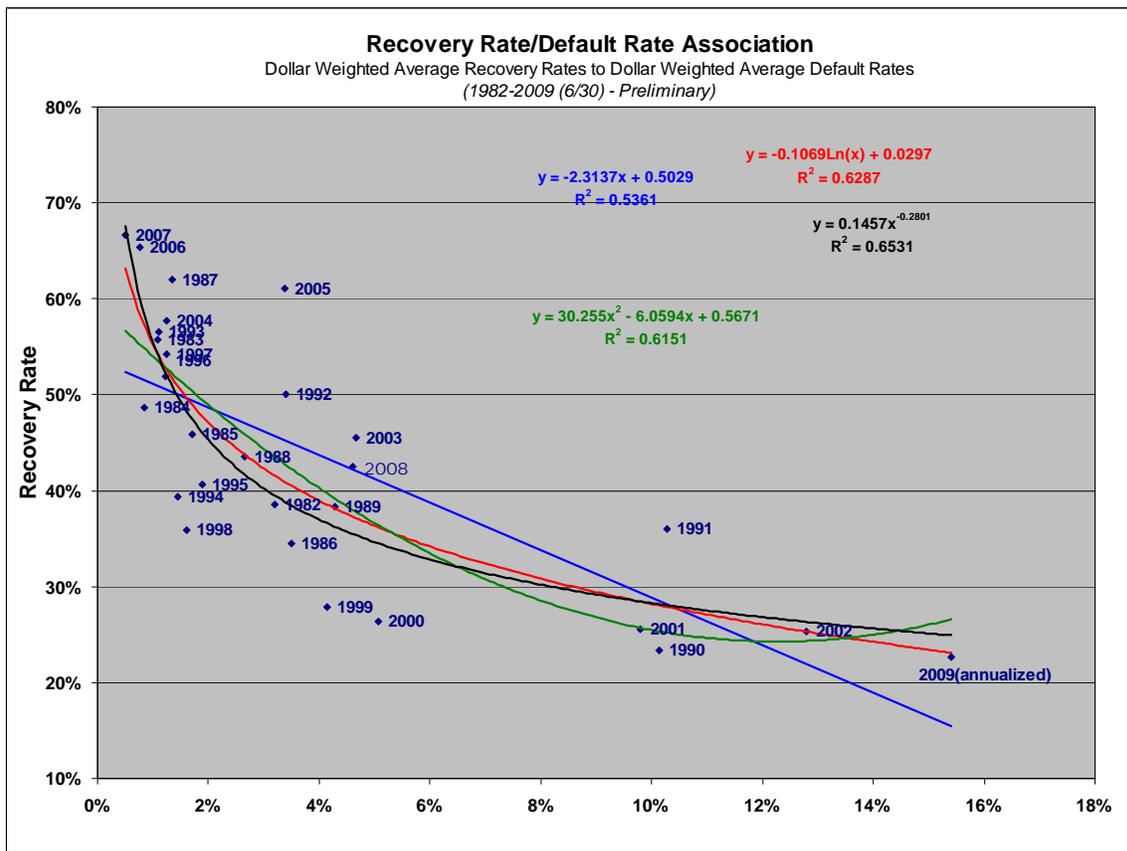
¹¹ Demand mostly comes from niche investors called “vultures”, who intentionally purchase bonds in default. These investors represented a relatively small (perhaps \$100 billion) and specialized segment of the debt market. This hedge-fund sector grew considerably, however, in the 2003-2006 period, perhaps more than doubling in size (author estimates).

of the variation in aggregate bond recovery rates explained by just one variable - - the aggregate default rate. These regressions include linear (53.6%), quadratic (61.5%), log-linear (62.9%) and power function (65.3%) structures. The clear negative relationship between default and recovery rates is striking with periods of excess supply of defaults relative to demand resulting in unusually low recoveries in such years as 1990, 1991, 2001 and 2002.

One can also observe, however, that the most recent years, 2005 and 2006, which are part of an extremely low default cycle, show estimates which are far below the actual results. For example, our model would have predicted an above average recovery rate of about 56% in 2006. Instead, the actual rate was almost 73% as of the end of the third quarter. And the 2005 estimate of about 45% compares to the actual recovery rate of over 60%. Either the model has performed poorly or the default market has been influenced by an unusual amount of excess credit liquidity, and perhaps other factors, which have changed, perhaps temporarily, the dynamics in the credit markets.

A recent article (Altman, 2007), argues that there was a type of “credit bubble” causing seemingly highly distressed firms to remain non-bankrupt when, in more “normal” periods, many of these firms would have defaulted. This, in turn, produced an abnormally low default rate and the huge liquidity of distressed debt investors bid up the prices of both existing and newly defaulted issues. As we had predicted, a regression to the long-term mean, i.e., lower recoveries, and a huge increase in default rates began in 2008 and culminated in record high first-half 2009 defaults and near record low recovery rates (Altman and Karlin, 2009).

Figure 1



Source: E. Altman, et. al., "The Link Between Default and Recovery Rates". Journal of Business (2005) and Altman and Karlin (2009).

Using Moody's historical bond market data, Hu and Perraudin (2002) also examine the dependence between recovery rates and default rates. They first standardize the quarterly recovery data in order to filter out the volatility of recovery rates due to changes over time in the pool of rated borrowers. They find that correlations between quarterly recovery rates and default rates for bonds issued by US-domiciled obligors are 0.22 for post-1982 data (1983-2000) and 0.19 for the 1971-2000 periods. Using extreme value theory and other non-parametric 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%.

7. Correlation Results' Impact and Downturn LGD

The impact of the Altman et al. studies of 2001, 2003, as well as the Hu and Perraudin (2002) and Frye (2000a, b, and c) studies, was almost immediate, resulting in suggested changes in Basel II's pillar I's guidelines. Specifically, the final BIS Accord (2004) suggested, via its paragraph 468 declaration, a "downturn," or "stressed" LGD for banks. According to this document, IRB banks are required to use estimates of LGD parameters, where necessary, to capture the relevant risks. The guidelines were in general terms only and left specific details of the quantification process to supervisors to develop in collaboration with the banking industry. The underlying theory was that recovery rates on defaulted exposures may be lower during economic downturns than during more normal conditions and that a capital rule be realized to guarantee sufficient capital to cover losses during these adverse circumstances. Paragraph 468 also stated that loss severities may not exhibit such cyclical variability, especially if based on ultimate recoveries, and therefore LGD estimates of downturn LGD may not differ materially from the long-run weighted average.

Many banks reacted negatively to this conservative approach and proposed more modest adjustments. Indeed, Araten et al. (2004) suggested that correlations are not usually material. All of this discussion and debate resulted in a set of more explicit guidelines and principles in the BIS (2005) "Guidance on Paragraph 468 of the Framework Document." In this report, the BIS found (1) that there is a potential for realized recovery rates to be lower than average during times of high default rates and failing to account for this could

result in an understatement of the capital required to cover unexpected losses; (2) that data limitations pose a difficult challenge to the estimation of LGD in general and particularly in downturns; and (3) there is little consensus with respect to appropriate methods for incorporating downturn conditions in LGD estimates. The BIS was careful to state that any principles be flexible enough to allow for a range of sound practices and to encourage continued refinements. In other words, while requiring analysis and reports about “downturn LGD” amongst its members, banks appear to be free to specify if there should be any penalty or not to their average assessments of LGD parameters.

The principles (2005) were that banks must have a rigorous and well documented process for assessing, if any, economic downturn’s impact on recovery rates and that this process must consist of (1) the identification of appropriate downturn conditions for each asset class, (2) identification of adverse dependencies, if any, between default and recovery rates and (3) incorporating them to produce LGD estimates. The recovery cash flows should utilize a discount rate that reflects the costs of holding defaulted assets over the workout period, including an appropriate risk premium. These costs should be consistent with the concept of economic loss, not an accounting concept of economic loss (e.g., not the interest rate on the old loan). This can be accomplished either with a discount rate based on the risk-free rate plus a spread appropriate for the risk of recovery and cost of cash flows or by converting the cash flows to certainty equivalents (described in footnote 3 in BIS (2005) and discounting these by the risk-free rate, or, by a combination of these adjustments to the discount rate.

By specifically referring to the stream of cash flows over the restructuring period, the BIS, and banks, are embracing the use of ultimate recoveries and not recoveries at the time of default. As such, the correlation between default and recovery rates observed in the bond markets by several researchers, discussed earlier, may not imply a negative correlation between default and ultimate recovery rates. Indeed, there is a timing disconnect which may be important, especially if the distressed loan market is not efficient and the discounted values of ultimate recoveries are materially different from the recovery values at the time of default. Finally, the BIS principles refer to the possibility that stress tests performed under normal expected values of recoveries will not produce different

results than downturn LGD estimates under paragraph 468. It remains to be seen how bank regulators will respond to efforts by banks to assess downturn LGD estimates.

One regulator in the United States, the Federal Reserve System, has suggested that IRB banks in the US use a simple formula to specify downturn LGD, of the form:¹²

$$\mathbf{LGD\ in\ Downturn = .08 + .92\ LGD,}$$

Where LGD = long-term LGD average. So, where the long-term LGD equals, for example, 0.3 (i.e., recovery rates of 0.7), the downturn LGD would increase modestly to 0.33 (about 10%). If this modification were applied to Foundation Basel II banks, not possible in the US, then the downturn LGD = 0.494 on unsecured exposure, $(.08 + .92 (.45) = .494)$, again an increase of about 10% of the normal conditions' expected recovery. For secured loans, the analysis requires a stress test on the collateral itself.

Miu and Ozdemir (2006) analyze this downturn LGD requirement and suggest that the original LGD assessment by banks, without considering PD and RR correlation, can be appropriately adjusted by incorporating a certain degree of conservatism in cyclical LGD estimates within a point-in-time modeling framework. They find even greater impacts on economic capital than even Altman, Resti and Sironi (2001) did - - with as much as an increase of 35% - 45% in corporate loan portfolios and 16% for a middle-market portfolio to compensate for the lack of correlations. Altman et al. had found, through simulations of loan portfolios that about 30% needed to be added. Both studies, however, suggest that banks determine these penalties, if any, without abandoning the point-in-time, one-year perspective as to estimating LGD.

Some Final References

A number of related studies on LGD can be found in Altman, Resti and Sironi's (2005) anthology. These include Chabane, Laurent and Salomon's credit risk assessment of stochastic LGD and correlation effects, Friedman and Sandow's conditional probability distribution analysis of recovery rates, Laurent and Schmit's estimation of distressed LGD on leasing contracts, DeLaurentis and Riani's further analysis of LGD in the leasing industry, Citron and Wright's investigation of recovery rates on distressed management

¹² From http://federalreserve.gov/GeneralInfo/Basel2/NPR_20060905/NPR/.

buyouts and Dermine and Neto de Carvalho's empirical investigation of recoveries' impact on bank provisions. Schuermann provides an overview on what we know and do not know about LGD, as well, in the volume.

Gupton and Stein (2002) analyze the recovery rate on over 1800 corporate bond, loan and preferred stock defaults, from 900 companies, in order to specify and test Moody's LossCalc® model for predicting loss given default (LGD). Their model estimates LGD at two points in time – immediately and in one year – adding a holding period dimension to the analysis. The authors find that their multifactor model, incorporating micro variables (e.g., debt type, seniority), industry and some macroeconomics factors (e.g., default rates, changes in leading indicators) outperforms traditional historic average methods in predicting LGD.

Using data on observed prices of defaulted securities in the United States over the period 1982-1999, Acharya, Bharath and Srinivasan (2007) find that seniority and security are important determinants of recovery rates. While this result is not surprising and in line with previous empirical studies on recoveries, their second main result is rather striking and concerns the effect of industry-specific and macroeconomic conditions in the default year. Indeed, industry conditions at the time of default are found to be robust and important determinants of recovery rates. They show that creditors of defaulted firms recover significantly lower amounts in present-value terms when the industry of defaulted firms is in distress and also when non-defaulted firms are rather illiquid and if their debt is collateralized by specific assets that are not easily redeployable into other sectors. Also, they find that there is little effect of macroeconomic conditions over and above the industry conditions and the latter is robust even with the inclusion of macroeconomic factors. ABH suggest that the linkage, again highlighted by Altman et al. (2005), between bond market aggregate variables and recoveries arises due to supply-side effects in segmented bond markets, and that this may be a manifestation of Shleifer and Vishny's (1992) industry equilibrium effect. That is, macroeconomic variables and bond market conditions may be picking up the effect of omitted industry conditions. The importance of the "industry" factor in determining LGD has been recently highlighted by Schuermann (2003 and 2005) in a survey of the academic and practitioner literature.

Frye (2000a), Pykhtin (2003) and Dullmann and Trapp (2004) all propose a model that accounts for the dependence of recoveries on systematic risk. They extend the single factor model proposed by Gordy (2000), by assuming that the recovery rate follows a log-normal (Pykhtin, 2003) or a logit-normal (Dullmann and Trapp, 2004) one. The latter study empirically compares the results obtained using the three alternative models (Frye, 2000a, Pykhtin, 2003, and Dullmann and Trapp, 2004). They use time series of default rates and recovery rates from *Standard and Poor's Credit Pro* database, including bond and loan default information in the time period from 1982 to 1999. They find that estimates of recovery rates based on market prices at default are significantly higher than the ones obtained using recovery rates at emergence from restructuring. The findings of this study are in line with previous ones: systematic risk is an important factor that influences recovery rates. The authors show that ignoring this risk component may lead to downward biased estimates of economic capital.

8. Recovery Ratings

There has been a debate in the practitioner literature about how recovery rates impact bond ratings ascribed to default risk estimates from the various major rating agencies. One agency, Moody's, has always maintained that it explicitly considered recoveries in the bond rating of a particular corporate issue. Others (S&P and Fitch), typically adjusted, through "notching," the senior unsecured issuer rating based on whether the particular issue was investment grade or speculative grade given a certain seniority priority. For example, a subordinated issue of an investment grade company was typically "down-notched" by one notch and a speculative grade issue was penalized by two notches if subordinated. The Moody's assertion was questionable since prior to the 1990's there simply was no reliable database on recoveries available.

Regardless of the "ancient" approaches used, all three rating agencies have recently recognized the heightened importance of recoveries for a number of applications including Basel II, structured products, the credit default swap market, as well as traditional default analysis, and have introduced "Recovery Ratings" as a complementary risk rating indicator.

Table 1 reviews these "Recovery Ratings," first introduced by S&P on US senior bank loans in December 2003 and discussed in Chew & Kerr in Altman et. al. (2005). Fitch then introduced, in late 2005, their recovery analysis on all highly speculative grade issues rated B or below. Finally, Moody's in September 2006 introduced their rating of US non-financial speculative grade issues and expected to do the same in Europe in 2007. We expect that all of the rating agencies will expand their coverage if the market deems this information valuable.

As shown in Table 1, each of the recovery rating classes, six in each case, has a quantitative estimate of the proportion of the issue that can be expected to be recovered given a default. These range from as high as 100% down to estimates of 0-10%. In addition to the recovery percentage estimates, Table 1 reviews each rating agency's methodology for arriving at their estimate. Fundamental valuation techniques are employed followed by priority analysis of each issue under consideration.

[Table 1 Here]

In all cases, the recovery ratings are available in addition to the traditional default ratings. It remains to be seen as to the market's acceptance of this second set of ratings and whether they will form a material part of their investment decisions.

9. Recovery Rates and Procyclicality

Altman et al. (2005) also highlight the implications of their results for credit risk modelling and for the issue of procyclicality¹³ of capital requirements. In order to assess the impact of a negative correlation between default rates and recovery rates on credit risk models, they run Montecarlo simulations on a sample portfolio of bank loans and compare the key risk measures (expected and unexpected losses). They show that both the expected loss and the unexpected loss are vastly understated if one assumes that PDs and RRs are uncorrelated¹⁴. 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.

As far as procyclicality is concerned, they show that this effect tends to be exacerbated by the correlation between PDs and RRs: 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. The impact of such a mechanism was also assessed by 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 main results emerged

¹³ 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).

from this simulation exercise: (i) the procyclicality effect is driven more by up- and downgrades, rather than by default rates; in other words, adjustments in 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); (ii) when RRs are permitted to fluctuate with default rates, the procyclicality effect increases significantly.

10. Further Empirical Evidence

This section focuses on different measurements and the most recent empirical evidence of default recovery rates. Most credit risk models utilize historical average empirical estimates, combined with their primary analytical specification of the probability of default, to arrive at the all-important Loss-Given-Default (LGD) input. Since very few financial institutions have ample data on recovery rates by asset-type and by type of collateral, model builders and analysts responsible for Basel II inputs into their internal rate based (IRB) models begin with estimates from public bond and private bank loan markets. Of course, some banks will research their own internal databases in order to conform to the requirements of the Advanced IRB approach.

Early Empirical Evidence

Published data on default recovery rates generally, but not always, use secondary market bond or bank loan prices. The first empirical study, that we are aware of, that estimated default recovery rates was in Altman, Haldeman and Narayanan's (1977) ZETA® model's adjustment of the optimal cutoff score in their second generation credit scoring model. Interestingly, these bank loan recovery estimates did not come from the secondary loan trading market -- they did not exist then -- but from a survey of bank workout-department experience (1971-1975). The general conclusion from this early experience of these departments was a recovery rate on non-performing, unsecured loans of only about thirty percent of the loan amount plus accrued interest. The cash inflows for three years post-default was not discounted back to default date. We will refer to this

¹⁴ Both expected losses and VaR measures associated with different confidence levels tend to be underestimated by approximately 30%.

experience as the “ultimate nominal recovery” since it utilizes post-default recoveries, usually from the end of the restructuring period.

In later studies, ultimate recovery rates refer to the nominal or discounted value of bonds or loans based on either the price of the security at the end of the reorganization period (usually Chapter 11) or the value of the package of cash or securities upon emergence from restructuring. For example, Altman and Eberhart (1994) observed the price performance of defaulted bonds, stratified by seniority, at the time of the restructuring emergence as well as the discounted value of these prices. They concluded that the most senior bonds in the capital structure (senior secured and senior unsecured) did very well in the post-default period (20-30% per annum returns) but the more junior bonds (senior subordinated and subordinated) did poorly, barely breaking even on a nominal basis and losing money on a discounted basis. Similar, but less extreme, results were found by Fridson, et. al., (Merrill Lynch (2001) when they updated (1994-2000) Altman & Eberhart’s earlier study which covered the period 1981-1993.

Other studies that analyzed bank loans recovery rates were by Asarnow and Edwards (1995) and Eales and Bosworth (1998). The first study presents the results of an analysis of losses on bank-loan defaults based on 24 years of data compiled by Citibank; their database comprises 831 commercial and industrial (C&I) loans, as well as 89 structured loans (highly collateralized loans that contain many restrictive covenants). Their results (based on “ultimate” recoveries) indicate a LGD of about 35% for C&I loans (with larger loans, above US\$ 10 million, showing a somewhat lower loss rate of 29%); unsurprisingly, the LGD for structured loans is considerably lower (13%), due to the role played by collateral and covenants in supporting the early default-detection and recovery processes. In the second study, the authors report the empirical results on recovery rates from a foreign bank operating in the United States – Westpac Banking Corporation. The study focuses on small business loans and larger consumer loans, such as home loans and investment property loans.

Neto de Carvalho and Dermine (2003) analyze the determinants of loss given default rates using a portfolio of credits given by the largest private Portuguese bank,

Banco Comercial Portugues. Their study is based on a sample of 371 defaulted loans to small and medium size companies, originally granted during the period June 1985-December 2000. The estimates of recovery rates are based on the discounted cash flows recovered after the default event. The authors report three main empirical results which are consistent with previous empirical evidence: (i) the frequency distribution of loan losses given default is bi-modal, with many cases presenting a 0% recovery and other cases presenting a 100% recovery, (ii) the size of the loan has a statistically significant negative impact on the recovery rate, (iii) while the type of collateral is statistically significant in determining the recovery, this is not the case for the age of the bank-company relationship.

More Recent Evidence

In Table 2, we present recent empirical evidence on bank loan recoveries (Keisman, Moody's, 2009) and on corporate bonds by seniority (Altman and Karlin, 2009) based on the average prices of these securities just after the date of default. Surprisingly, the highest mean recovery rates were on senior unsecured bonds (60%) and bank loans (59.4%) followed by senior secured loans (56.3%).¹⁵ Although the data from Moody's and Altman were from different periods and samples, it is interesting to note that the recovery on senior unsecured bonds (45.9%) was significantly lower than senior unsecured bank loans (59.4%). The estimates of median recoveries on the senior-subordinated and subordinated bonds were very similar. Similar recoveries on defaulted bonds can be found in Varma, et. al. (Moody's, 2003). Altman and Karlin's value weighted mean recovery rate on over 2,300 bond default issues was 37.8%.

¹⁵ Interestingly, the comparable median for defaults through 2003 was about 4.5% lower (54.5%), showing the considerable increase in default recovery rates on bonds in the period 2004-2009. This recovery rate was actually higher through 2008. Also, it is surprising that senior unsecured loans recovered more than senior secured loans, at least in terms of arithmetic average metrics. Ultimate recoveries, however (Table 4), demonstrate the expected hierarchy, with senior secured bank debt recovering far more than unsecured loans.

[Table 2 Here]

Altman and Karlin (2009) further breakdown bond recoveries just after the default date by analyzing recoveries based on the original rating (fallen angels vs. original rating non-investment grade [“junk”] bonds) of different seniorities. For example, in Table 3, we observe that senior-secured bonds, that were originally rated investment grade, recovered a median rate of 50.5% vs. just 39.0% for the same seniority bonds that were non-investment grade when issued. These are statistically significant differences for similar seniority securities. Since fallen angel defaults are much more prominent in some years in the United States (e.g., close to 50% in dollar amount of defaults in 2001 and 2002 were fallen angels prior to default), these statistics are quite meaningful. Note that for senior-subordinated and subordinated bonds, however, the rating at issuance is of little consequence, although the sample sizes for investment grade, low seniority bonds were very small. Varma, et. al., (2003) also conclude that the higher the rating prior to default, including the rating at issuance, the higher the average recovery rate at default. Apparently, the quality of assets and the structure of the defaulting company’s balance sheets favor higher recoveries for higher quality original issue bonds.

[Table 3 Here]

In Table 4, we again return to the data on ultimate recoveries and the results are from Moody’s (2009) assessment of bank loan and bond recoveries. These results show the nominal and discounted (by the loan’s pre-default interest rate) ultimate recovery at the end of the restructuring period for well over 3,000 defaulted loans and bonds over the period 1988-2009. Several items are of interest. First, the recovery on senior bank debt, which is mainly secured, was quite high at 87.3% and 77.2% for nominal and discounted values respectively. Senior secured and senior unsecured notes, which include loans and bonds, had lower recoveries and the more junior notes (almost all bonds) had, not surprisingly, the

lowest recoveries. Note, the differential between the nominal and discounted recovery rates diminish somewhat at the lower seniority levels.

[Table 4 Here]

Standard & Poor's (Keisman, 2004) also finds, not shown in any Table, that during the "extreme stress" default years of 1998 to 2002, the recovery rates on all seniorities declined compared to their longer 1988-2002 sample period. Since 1998 and 1999 were not really high default years, the results of S&P for 2000-2002 are consistent with Altman, Brady, Resti and Sironi's (2001, 2003) predictions of an inverse relationship between default and recovery rates. Indeed, recovery rates were a relatively low 25% in the corporate bond market for both 2001 and 2002 when default rates were in the double-digits but increased to almost 70% in 2006 when default rates tumbled to well below average annual levels and then fell to about 22.5% in 2009 (2Q) as defaults surged (Altman and Karlin, 2009).

Some recovery studies have concentrated on rates across different industries. Altman and Kishore (1996) and FITCH (2003) report a fairly high variance across industrial sectors. For Example, Verde (FITCH, 2003) reports that recovery rates in 2001 vs. 2002 varied dramatically from one year to the next (e.g., Gaming, Lodging and Restaurants recovered 16% in 2001 and 77% in 2002, Retail recovered 7% in 2001 and 48% in 2002, while transportation recovered 31% in 2001 and 19% in 2002) but returned to more normal levels in 2003.

Another issue highlighted in some studies, especially those from S&P, (e.g., Van de Castle and Keisman, 1999 and Keisman, 2004) is that an important determinant of ultimate recovery rates is the amount that a given seniority has junior liabilities below its level; the greater the proportion of junior securities, the higher the recovery rate on the senior tranches. The theory being that the greater the "equity cushion," the more likely there will

be assets of value, which under absolute priority, go first in liquidation or reorganization to the more senior trenches.

11. Concluding remarks

Table 5 summarizes the way RR and its relationship with PD are dealt with in the different credit models described in the previous sections of this paper. While, in the original Merton (1974) framework, an inverse relationship between PD and RR exists, the credit risk models developed during the 1990's 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. 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.

Empirical results, especially demonstrated by historical record high levels of recovery in the extreme benign credit environment of 2004-2007 and then the opposite credit market turmoil and high defaulted, low recovery environment of 2009, show the potential cyclical impact as well as the supply and demand elements of defaults and recoveries on LGD. Finally, we feel that the microeconomic/financial attributes of an individual issuer of bonds or loans combined with the market's aggregate supply and demand conditions can best explain the recovery rate at default on a particular defaulting issue. An even greater challenge is to accurately estimate the ultimate recovery rate on individual issue as well as aggregate recoveries when the firm emerges from its restructuring.

[Table 5 Here]

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Table 1

Recovery Ratings from the Rating Agencies			
Agency	Moody's	Standard & Poor's	Fitch
Ratings Type	Loss Given Default Ratings	Recovery Ratings	Recovery Ratings
Ratings Scale	LGD1 0-9% LGD2 10-29% LGD3 30-49% LGD4 50-69% LGD5 70-89% LGD6 90-100%	1+ 100% 1 100% 2 80-100% 3 50-80% 4 25-50% 5 0-25%	RR1 91-100% RR2 71-90% RR3 51-70% RR4 31-50% RR5 11-30% RR6 0-10%
Assets Rated	Non-financial corporate speculative-grade issuers in the US	US and Canadian secured bank loans to which it assigns bank loan ratings, to senior secured loans in Europe, and to any secured bonds issued along with rated bank loans	All corporate, financial institutions and sovereign issuers rated in the single B category and below
Methodology	<p>1.Establish priority of claim</p> <p>a.Jr bonds are subordinated to Sr bonds, but may or may not be subordinated to other unsecured obligations</p> <p>b.Prioritize claims across affiliates</p> <p>2.Assume a beta probability distribution for potential Enterprise Value (EV) outcomes</p> <p>a.For most issuers, assume a beta distribution of EV relative to total liabilities</p> <p>b.Corporate LGD distribution will have 50% mean and 26% standard deviation</p> <p>3.For each EV outcome, calculate LGDs for each security class implied by absolute priority</p> <p>4.Expected LGD equals the probability-weighted averages of LGDs across EV outcomes</p>	<p>1.Review transaction structure</p> <p>2.Review borrower's projections</p> <p>3.Establish simulated path to default</p> <p>4.Forecast borrower's free cash flow at default based on our simulated default scenario and default proxy</p> <p>5.Determine valuation</p> <p>6.Identify priority debt claims and value</p> <p>7.Determine collateral value available to lenders</p> <p>8.Assign recovery rating</p> <p>9.Convey the recovery analytics to the issuer and investment community</p>	<p>1.Estimate the enterprise value (EV)</p> <p>a.Establish the level of cash flow upon which it is most appropriate to base the valuation</p> <p>b.Apply a multiple reflecting a company's relative position within a sector based on actual or expected market and/or distressed multiples</p> <p>2.Estimate the creditor mass, ie identify existing claims</p> <p>a.Claims taken on as a company's fortunes deteriorate</p> <p>b.Claims necessary to the reorganization process</p> <p>c.Claims that have priority in the relevant bankruptcy code</p> <p>3.Distributing the EV</p> <p>a.The resulting value is allocated to creditors according to jurisdictional practice</p>

Source: Moody's, S&P, and Fitch (New York).

Table 2

**Recovery at Default* on Public Corporate Bonds (1978-2009-2Q)
and Bank Loans (1988-2009-2Q)**

<u>Loan/Bond Seniority</u>	<u>Number of Issues</u>	<u>Median %</u>	<u>Mean %</u>	<u>Standard Deviation %</u>
Senior Secured Loans	1034	56.74%	56.26%	27.17%
Senior Unsecured Loans	122	59.82%	59.39%	40.24%
Senior Secured Bonds	360	59.08	59.96	18.30
Senior Unsecured Bonds	1106	45.88	37.85	13.49
Senior Subordinated Bonds	443	32.79	31.03	14.23
Subordinated Bonds	255	31.00	31.14	17.52
Discount Bonds	<u>157</u>	<u>19.00</u>	<u>25.83</u>	<u>20.84</u>
Total Sample Bonds	2,321	41.78	37.81	14.04

Based on prices just after default on bonds and 30 days after default on loans.

Source: Moody's (D. Keisman, 2009) (Bank Loans) and Altman & Karlin, 2009 (Bonds).

Table 3

Investment Grade vs. Non-Investment Grade (Original Rating) Prices at Default on Public Bonds (1978 - 2008)					
Bond Seniority	Number of Issues	Median Price %	Average Price %	Weighted Price %	Standard Deviation %
Senior Secured					
Investment Grade	142	50.50	53.85	57.97	26.94
Non-Investment Grade	245	39.00	44.05	44.42	29.23
Senior Unsecured					
Investment Grade	374	43.50	44.84	38.75	24.92
Non-Investment Grade	519	32.50	36.04	34.79	23.31
Senior Subordinated					
Investment Grade	16	27.31	37.10	34.29	27.48
Non-Investment Grade	402	27.90	32.74	30.20	24.16
Subordinated					
Investment Grade	18	4.00	24.27	6.38	29.52
Non-Investment Grade	204	28.92	32.54	29.64	22.68
Discount					
Investment Grade	1	17.15	13.63	13.63	25.13
Non-investment Grade	96	18.00	27.31	26.94	23.38

Source: NYU Salomon Center Default Database

Table 4

Ultimate Recovery Rates on Bank Loan and Bond Defaults (Discounted Values, 1988-2Q 2009)				
	Observations	Ultimate Discounted Recovery	Standard Deviation	Ultimate Nominal Recovery
All Bank Debt	1156	82.24%	29.53%	92.40%
<i>Secured Bank Debt</i>	1034	85.63 %	27.17%	94.74%
<i>Unsecured Bank Debt</i>	122	56.34%	40.24%	66.05%
Senior Secured Bonds	320	62.00%	32.90%	76.03%
Senior Unsecured Bonds	863	43.80%	35.10%	59.29%
Senior Subordinated Bonds	489	30.50%	34.10%	38.41%
Subordinated Bonds	399	28.80%	34.00%	34.81%

Source: D. Keisman (Moody's Ultimate LGD Database of defaulted loans and bond issues that defaulted between 1988 – 2009. Recoveries are discounted at each instruments' pre-default interest rate.

Table 5

The Treatment of LGD and Default Rates within Different Credit Risk Models

	MAIN MODELS & RELATED EMPIRICAL STUDIES	TREATMENT OF LGD	RELATIONSHIP BETWEEN RR AND PD
<i>Credit Pricing Models</i>			
<i>First generation structural-form models</i>	Merton (1974), Black and Cox (1976), Geske (1977), Vasicek (1984), Crouhy and Galai (1994), Mason and Rosenfeld (1984).	PD and RR are a function of the structural characteristics of the firm. RR is therefore an endogenous variable.	PD and RR are inversely related (see Appendix A).
<i>Second generation structural-form models</i>	Kim, Ramaswamy and Sundaresan (1993), Nielsen, Saà-Requejo, Santa Clara (1993), Hull and White (1995), Longstaff and Schwartz (1995).	RR is exogenous and independent from the firm's asset value.	RR is generally defined as a fixed ratio of the outstanding debt value and is therefore independent from PD.
<i>Reduced-form models</i>	Litterman and Iben (1991), Madan and Unal (1995), Jarrow and Turnbull (1995), Jarrow, Lando and Turnbull (1997), Lando (1998), Duffie and Singleton (1999), Duffie (1998) and Duffee (1999).	Reduced-form models assume an exogenous RR that is either a constant or a stochastic variable independent from PD.	Reduced-form models introduce separate assumptions on the dynamic of PD and RR, which are modeled independently from the structural features of the firm.
<i>Latest contributions on the PD-RR relationship</i>	Frye (2000a and 2000b), Jarrow (2001), Carey and Gordy (2003), Altman, Brady, Resti and Sironi (2001, 2003 and 2005), Acharya Bharath and Srinivasan (2003, 2007), Miu and Ozdemir (2006).	Both PD and RR are stochastic variables which depend on a common systematic risk factor (the state of the economy).	PD and RR are negatively correlated. In the "macroeconomic approach" this derives from the common dependence on one single systematic factor. In the "microeconomic approach" it derives from the supply and demand of defaulted securities. Industry health is also a major factor. Downturn LGD studies.
<i>Credit Value at Risk Models</i>			
<i>CreditMetrics®</i>	Gupton, Finger and Bhatia (1997).	Stochastic variable (beta distr.)	RR independent from PD
<i>CreditPortfolioView®</i>	Wilson (1998).	Stochastic variable	RR independent from PD
<i>CreditRisk+®</i>	Credit Suisse Financial Products (1997).	Constant	RR independent from PD
<i>PortfolioManager®</i>	McQuown (1997), Crosbie (1999).	Stochastic variable	RR independent from PD

