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 to be independent of PD.

This traditional focus on default analysis has been partly 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 (see section 4 of this chapter). This is partly the consequence of the parallel increase in default rates and decrease of recovery rates registered during the 1999-2002 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 (Schleifer and Vishny [1992], Altman [2001], Hamilton, Gupton and Berthault [2001]).

This chapter presents a detailed review of the way credit risk models developed during the last thirty years have treated the recovery rate and highlights the main results obtained by empirical studies. Credit risk 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 two main approaches: (i)
structural-form models, and (ii) reduced-form models. These different approaches together with their basic assumptions and implications as far as LGD modeling is concerned are reviewed in section 2. Section 3 presents the main results of the recent empirical studies concerning recovery rates. Finally, the more recent studies explicitly modeling and empirically investigating the relationship between PD and RR are reviewed in section 4. Section 5 concludes.

2. Theoretical contributions

2.1. Structural form models

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\(^1\). The basic intuition behind the Merton model is relatively simple: default occurs when the market value of a firm’s assets 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.

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 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 the Merton’s theoretical framework, PD and

\(^1\) In addition to Merton (1974), first generation structural-form models include Black and Cox (1976), Geske (1977), and Vasicek (1984).
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.

Second-generation structural form models adopt the original Merton framework as far as the default process is concerned but, at the same time, remove 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 any time 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 level. These models include Kim, Ramaswamy and Sundaresan (1993), Hull and White (1995), Nielsen, Saà-Requejo, 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.

2.2. Reduced-form models

The attempt to overcome the 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 and Singleton (1999), and Duffie (1998). 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 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. More specifically, reduced-

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2 For a technical discussion of these relationships, see Altman et al. (2001).
form models take as primitives 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 a
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 for 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\(^4\). 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 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.

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\(^3\) 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.

\(^4\) However, non-zero default probabilities over infinitely small time intervals can be achieved also by
structural models by making the default barrier (e.g. the debt level) stochastic. See e.g. Falkenstein et al.
(2002).
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.

2.3. Credit Value-at-Risk Models

During the second part 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 value-at-risk (VaR) models include J.P. Morgan’s CreditMetrics® (Gupton, Finger and Bhatia [1997]), Credit Suisse Financial Products’ CreditRisk+® (1997), McKinsey’s CreditPortfolioView® (Wilson, 1998), and KMV’s CreditPortfolioManager®.

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 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 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 bank 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\(^5\). Alternatively, percentile-based risk measures are derived (Value at Risk, VaR) that estimate unexpected losses by isolating a small portion at very unfavorable scenarios.

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 losses, while economic capital is seen as a cushion for unexpected 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*, *CreditPortfolioView* and *CreditPortfolioManager*, treat the RR in the event of default as a stochastic variable – generally modeled 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 review\(^6\), it is important to highlight that all credit VaR models treat RR and PD as two independent variables.

### 3. LGD in empirical studies

Rather than on the theoretical issues surrounding LGD modeling, most of the recent contributions have focused on the estimation of recovery rates related to different types of credit assets. This section of our review focuses on different measurement techniques and on the most recent empirical evidence of default recovery rates.

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 internal rating based (IRB) models begin with estimates from public bond and private bank loan

\(^5\) Such 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.

\(^6\) For a comprehensive analysis of these models, see Crouhy, Galai and Mark (2000) and Gordy (2000).
markets. Of course, some banks will research their own internal databases in order to conform with the requirements of the Advanced IRB approach.

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 cash inflows for three years post-default was not discounted back to default date. The general conclusion from this early experience of these departments was a recovery rate on non-performing, unsecured loans of about thirty percent of the loan amount plus accrued interest. We will refer to this approach as the “ultimate recovery” since it utilizes post-defaults 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, upon 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.

Bank loans recovery rates have been analysed both by Asarnow and Edwards (1995) and by Eales and Bosworth (1998). The first study presents the results of an analysis of losses on bank large loans defaults based on 24 years of data compiled by Citibank. In the second study, the authors report the empirical results on recovery rates from another U.S. bank – Westpac Banking Corporation. The study focuses on small business loans and larger consumer loans, such as home loans and investment property loans.
More recently, Dermine and Neto de Carvalho (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.

Some more recent works present recent empirical evidence on bank loan recoveries (Emery, 2003) and on corporate bonds by seniority (Altman and Fanjul, 2004) based on the average prices of these securities just after the date of default. Not surprisingly, the highest median recovery rates were on senior secured bank loans (73.0%) followed by senior secured bonds (54.5%). 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 (42.3%) was similar, but lower than senior unsecured bank loans (50.5%), with similar standard deviations (in the mid-twenty percents). The estimates of median recoveries on the senior-subordinated and subordinated bonds were virtually the same at 32.0%. Similar recoveries on defaulted bonds can be found in Varma, et. al. (2003). For example, Altman’s mean recovery rate on almost 2000 bond default issues was 34.3% compared to Moody’s 1,239 issuer-weighted mean of 35.4%.

Altman and Fanjul (2004) further breakdown bond recoveries by original rating (fallen angels vs. original rating non-investment [“junk”] bonds) of different seniorities. For example, senior-secured bonds that were originally rated investment grade recovered a median rate of 50.5% vs. just 33.5% for the same seniority bonds that were non-investment grade when issued. This is a dramatic statistically significant difference for similar seniority securities.

7 See chapter 6 of this book for a revised version of this study.
Standard & Poor’s (Keisman, 2003) finds that during the most recent “extreme stress” default years of 1998 to 2002, the recovery rates on all seniorities declined compared to their longer 1988-2002 average. 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 and 2005) 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 about 45% in 2003 when default rates tumbled to below average annual levels of about 4.5 percent (Altman and Fanjul, 2004).

Some recovery studies have concentrated on rates across different industries. Altman and Kishore (1996) and Verde (2003) report a fairly high variance across industrial sectors. For example, Verde (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. Using data on observed prices of defaulted securities in the United States over the period 1982-1999, Acharya, Bharath and Srinivasan (2003) find that industry conditions at the time of default are robust and important determinants of recovery rates. The importance of the “industry” factor in determining LGD has also been recently highlighted by Schuemmann (2003)\textsuperscript{8} in a survey of the academic and practitioner literature.

Another issue highlighted in some studies, especially those from S&P (Van de Castle and Keisman, 1999 and Keisman, 2003), 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 tranches.

More recently, some studies have tried to estimate the entire recovery rate probability distribution rather than focusing on its expected value. These studies include Renault

\textsuperscript{8} See chapter 1 of this book for a revised version of this study
and Scaillet (2004) and Friedman and Sandow (2003). In the former, the authors analyse recovery rates on defaulted bonds in the period between 1981 and 1999. They estimate the recovery rate density function using a non parametric technique based on a beta kernel density estimator and find that bond seniority and obligor industry are crucially important for the probabilistic behavior of recovery rates. The authors then compare their technique with the usual market practice to model parametrically the recovery rates using a beta distribution and evaluate the impact of this common practice on the estimation of credit value at risk. They find that recovery rates are far from being beta distributed.

A similar approach is followed by Friedman and Sandow (2003). The authors focus on recovery rates on defaulted debt at the time of emergence from bankruptcy and estimate the conditional probability distribution of the discounted recovery rate as a function of collateral, debt below class, debt above class and economy-wide default rates. The approach followed by this study is rather unique, as it tackles the problem of maximizing the creditor’s utility function, based on a recovery rate probability distribution, conditional on information that ought to influence it, such as collateral quality and debt seniority.

4. The PD-RR relationship

During the last five years, new approaches have enriched the theoretical and empirical estimation of LGD by focusing on the relationship between PD and RR. 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 2005), Acharya, Bharath and Srinivasan (2003), and Gupton and Stein (2005).

The model proposed by Frye (2000a and 2000b) draws on the 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. Frye’s model is based on the assumption that the same economic conditions that cause defaults to rise might cause RR to decline, i.e. that the

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9 For an enhanced version of this technique, see chapter 18 in this book.
10 See chapter 19 in this book for a revised version of this study.
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 analysis. Results show a strong negative correlation between default rates and RRs for corporate bonds. This evidence is consistent with the most recent U.S. bond market data, indicating a simultaneous increase in default rates and LGDs for the 1999-2002 period. 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.

Jarrow (2001) presents a new methodology for estimating RRs and PDs implicit in both debt and equity prices. As in Frye (2000a and 2000b), 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

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11 See chapter 10 in this book for a revised version of these studies.
12 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.
13 Hamilton, Gupton and Berthault (2001) and Altman, Brady, Resti and Sironi (2003) provide clear empirical evidence of this phenomenon.
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 also find 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 note that during this short period the correlation arises 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 the Frye’s model may not adequately 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 1982-2000, which includes the relatively high-default years of 1999 and 2000, Altman, Brady, Resti and Sironi (2005)¹⁴ 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 of the variance in bond recovery rates aggregated across all seniority and collateral levels. They conclude that a simple microeconomic mechanism based on supply and demand 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

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¹⁴ See chapter 12 in this book for a revised version of this study.
exceed demand\textsuperscript{15}, thereby driving secondary market prices down. This in turn negatively affects RR estimates, as these are generally measured using bond prices shortly after default.

Altman et al. (2005)\textsuperscript{16} also highlight the implications of their results for credit risk modelling and for the issue of procyclicality\textsuperscript{17} 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 uncorrelated\textsuperscript{18}. 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.

Using Moody’s historical bond market data, Hu and Perraudin (2002) examine the dependence between recovery rates and default rates. They first standardize the quarterly recovery data 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 period. 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%.

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 preliminary evidence published by rating agencies, they force recovery rates to be negatively associated with default probability. They find some strong support for this hypothesis through the analysis of a sample of BBB-rated

\textsuperscript{15} Demand mostly comes from niche investors called “vultures”, who intentionally purchase bonds in default. These investors represent a relatively small and specialized segment of the fixed income market.

\textsuperscript{16} See chapter 14 in this book for a revised version of this analysis.

\textsuperscript{17} 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).
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 described in section 2.1 of this chapter 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 the RR. Rather, the collateral value is in turn assumed to be the only stochastic element determining recovery. Because of this assumption, the model can be implemented using an exogenous PD, so that the firm’s asset value parameters need not be estimated. In this respect, the model combines features of both structural-form and reduced-form models. Assuming a positive correlation between a firm’s asset value and collateral value, the authors obtain a similar result as Frye (2000a), that realized default rates and recovery rates have an inverse relationship.

Using data on observed prices of defaulted securities in the United States over the period 1982-1999, Acharya, Bharath and Srinivasan (2003) 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. This result is in contrast with those of Altman et al. (2005) in that there is no effect of macroeconomic conditions over and above the industry conditions and is in line those results in that the effect of industry conditions is robust to inclusion of macroeconomic factors. Acharya, Bharath and Srinivasan (2003) suggest that the linkage, highlighted by Altman et al. (2005), between bond market aggregate variables and recoveries as arising due to supply-side effects in segmented bond markets may be a manifestation of

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18 Both expected losses and VaR measures associated with different confidence levels tend to be underestimated by approximately 30%.
19 See chapter 11 in this book for a revised version of this study.
Shleifer and Vishny (1992) industry equilibrium effect: macroeconomic variables and bond market conditions appear to 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) in his survey of the academic and practitioner literature.

Following Frye (2000a), Pykhtin (2003) and Dullmann and Trapp (2004) both propose models that account for the dependence of recoveries on systematic risk. They both extend the single factor model proposed by Gordy (2001) by assuming that the recovery rate follows a log-normal (Pykhtin, 2003) or a logit-normal (Dullmann and Trapp, 2004) distribution. The second study empirically compares the results obtained using the three alternative models (Frye, 2000a, Pykhtin, 2003, and Dullmann and Trapp, 2004). The authors 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. 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.

A model that allows to deal with the dependence between recovery rates and default events has recently been proposed by Chabaane, Laurent and Salomon (2004). They study from a purely theoretical point of view the loss distributions for large credit portfolios and show that both credit losses and standard risk measures such as credit VaR and Expected Shortfall tend to increase compared to with the Basel II approach when RRs are stochastic and correlated.

Finally, a framework explicitly aimed at modeling the relationship between LGD and the state of the economy, which explicitly accommodates for default frequencies, is the one recently proposed by Moody’s KMV (Gupton and Stein, 2005). This model –

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20 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.
21 See chapter 13 in this book for a revised version of this study.
22 See chapter 15 in this book for a revised version of this study.
23 See chapter 4 in this book for a revised version of this study.
LossCalc™ - incorporates information on different factors (collateral, type of underlying credit instrument, firm, industry and country of the borrower, macroeconomy) to predict LGD. The parameters of this model have been estimated based on a dataset of over 3,000 recovery observations concerning loans, bonds and preferred stock, which includes over 1,424 defaults of both public and private firms from a wide range of industries.

5. Concluding remarks

This chapter has focused on the theoretical and empirical studies that directly or indirectly dealt with the issue of LGD. This has been done by first presenting a review of the way credit risk models developed during the last thirty years have treated the recovery rate. The attention has then moved to the main results of the recent empirical studies concerning LGD. A growing number of empirical analyses has indeed been produced in the very recent years, ranging from studies based on “market LGD” for bonds to “workout LGD” for bank loans and other types of credit assets. A significant number of these empirical studies are reported, in a reduced or revised form, in this book.

In the last section of this review, we focused on the studies dealing with the relationship between PD and RR. Indeed, 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 most used currently available 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. 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. This view seems to have been shared also by the regulators: while in the early drafts of the new Basel Accord LGD was treated as a fixed parameter, the final Accord now accepts and
underlines that it is stochastic in nature, and may jump to substantially higher levels as the credit cycle slows down\textsuperscript{24}.

\textsuperscript{24} See chapter 2 in this book for an analysis of the treatment of LGD in the Basel Capital Accord.
References


