7

A Critical Parameter: Loss Given Default

INTRODUCTION

As discussed in Chapter 5, the loss given default (LGD) is a critical parameter used together with the probability of default (PD) to estimate expected credit losses, calculated as PD times LGD. The LGD can be defined as one minus the recovery rate (RR) on defaulted debt instruments. Despite its importance in credit risk measurement, LGD estimation is less developed than PD modeling. In this chapter, we describe how some of the credit risk models described in earlier chapters estimate LGD.

ACADEMIC MODELS OF LGD

Even if PD is relatively high, expected credit losses may be low if recovery rates are high. Thus, for example, if a loan is fully secured with marketable securities which can be sold at full value upon default, there may be no loss at all. Table 7.1 shows that even low-grade debt issues may experience low expected loss rates because LGD is substantially lower than 100 percent. That is, even if there is a default, some value is recovered (the RR is greater than zero, and LGD = 1 – RR).

Different types of debt instruments have different recovery rates. For example, more senior securities tend to have higher recovery rates than subordinated securities, all else equal. Figure 7.1 uses the recovery history included in the Moody's KMV database to show that the highest (lowest) LGD is for preferred stock and junior subordinated bonds (industrial revenue bonds, senior secured bonds, and senior secured loans).

Early models of credit risk tended to assume a fixed or nonstochastic LGD. The Basel Committee assessed a fixed 45 percent LGD on secured

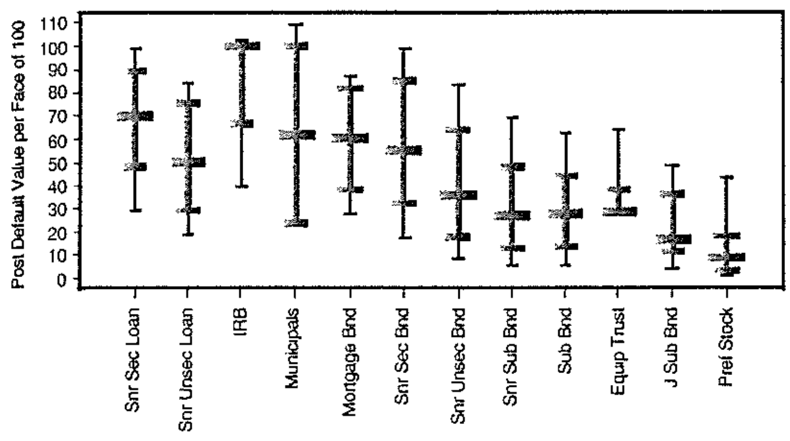

FIGURE 7.1 Box Plots of Post Default Price by Debt Type
Notes: The solid center line represents the median, the inner whiskers represent the interquartile range, and the outer whiskers represent the 10th to 90th percentile range of the distribution.
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loans if fully secured by physical, non-real-estate collateral, and 40 percent if fully secured by receivables (for the Basel II Internal Ratings-Based Foundation model, see Chapter 13). However, there is evidence suggesting that these fixed LGD rates may be too high for bank loans. A Citibank study of 831 defaulted corporate loans and 89 asset-based loans for 1970–1993 found recovery rates of 79 percent (or equivalently LGD equal to 21 percent). Similarly, high recovery rates were found in a Fitch Investor Service report in October 1997 (82 percent) and a Moody's Investor Service Report of June 1998 (87 percent), see Asarnow (1999). Carey and Gordy (2004) find an average LGD on bank debt of 23 percent.

However, Table 7.2 shows that using a large sample of Italian loans, Caselli et al. (2008) find an average (median) LGD of 54 percent (56 percent) and a standard deviation of 43 percent for the sample of 11,649 loans. The LGD for small and medium enterprises (SMEs) averaged 52 percent, but households had an average (median) LGD of 55 percent (68 percent) and a standard deviation of 45 percent This suggests that there is a wide dispersion in recovery rates across loans made to different industries and between different countries. Caselli et al. (2008) document one element of this dispersion by breaking down the loans by sector and find that the

TABLE 7.1 Mortality Loss Given Default by Original Rating—All Rated Corporate Bonds: 1971–2004

		Years after Issuance[a]									
		1	2	3	4	5	6	7	8	9	10
AAA	Marginal	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	Cumulative	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AA	Marginal	0.00	0.00	0.05	0.05	0.01	0.01	0.00	0.00	0.03	0.02
	Cumulative	0.00	0.00	0.05	0.10	0.11	0.12	0.12	0.12	0.15	0.17
A	Marginal	0.00	0.03	0.01	0.04	0.03	0.06	0.02	0.04	0.08	0.00
	Cumulative	0.00	0.03	0.04	0.08	0.11	0.17	0.19	0.23	0.31	0.31
BBB	Marginal	0.25	2.25	1.10	0.77	0.46	0.27	0.10	0.11	0.07	0.24
	Cumulative	0.25	2.49	3.57	4.31	4.75	5.00	5.10	5.21	5.27	5.50
BB	Marginal	0.69	1.44	2.55	1.16	1.46	0.60	0.90	0.38	0.84	1.28
	Cumulative	0.69	2.13	4.62	5.72	7.10	7.66	8.48	9.83	9.60	10.76
B	Marginal	1.83	4.75	5.18	5.72	4.06	2.41	2.54	1.34	1.02	0.64
	Cumulative	1.83	6.50	11.34	14.41	19.80	21.73	23.72	24.75	25.51	25.99
CCC	Marginal	5.33	11.68	14.67	9.32	3.10	7.28	4.31	2.52	0.00	3.22
	Cumulative	5.33	16.39	28.65	35.31	37.31	41.88	44.38	45.78	45.78	47.53

[a]Rated by S&P at issuance based on 1,604 issues.
Source: Altman and Hotchkiss (2006), Table 7.13, page 172.

TABLE 7.2 Relationship between Distance to Default and Recovery for U.S. Senior Unsecured Bonds

Loan Type	Number of Loans	Percent of Total	Mean LGD	Median LGD	Standard Deviation LGD
Small/Medium Businesses	6,034	51.80	0.52	0.52	0.41
Households	5,615	48.20	0.55	0.68	0.45
Entire Sample	11,649	100	0.54	0.56	0.43

Source: Caselli et al. (2008), page 8.

average (median) LGD for loans to SMEs range from 23 percent (4 percent) to 68 percent (98 percent). Similarly, the average (median) LGD for loans to households ranges from 15 percent (2 percent) to 79 percent (100 percent). Helwege et al. (2009) state that recovery rates on senior secured bonds between 1982 and 2007 ranged between 38 percent and 80 percent, with an average of 52 percent. In contrast, the credit default swap auction process yielded average recoveries of only 30 percent on senior bond auctions (see Chapter 12). Similarly, loan auctions during 2009 yielded low recovery rates (averaging 31 percent), perhaps demonstrating the distressed nature of the market during the time period.

An important distinction that may account for the disparity in estimates across studies is how the LGD is measured. Many studies use bond prices around the time of default as a measure of the recovery rate. For example, Moody's measures recoveries using the bid prices on defaulted bonds 30 days after the default occurs. Acharya et al. (2007) use trading prices of defaulted debt instruments just prior to the bankruptcy petition, or earliest available trading prices of the instruments received in a settlement or liquidation (e.g., acquisition, refinancing, distressed exchange, etc.). Debt prices around the default date are considered to be a measure of the recovery value of the debt if there is a market for the instrument. However, if there is no demand for these securities, or if the market is thin, the prices may be inaccurate or nonexistent.

In contrast, therefore, Caselli et al. (2008) use actual recovery data from bank loan workouts for their sample in order to measure the loss experienced by the lender upon default. Here the issues become quite practical. Specifically, what are the estimated recovery cash flows? Over what period of time are they to be collected? What is the estimated termination date for recoveries? And what is the discount rate to be applied to those cash flows? Each of these issues becomes relevant if the workout cost measure for recovery estimation is used by banks in the context of the Basel II IRB Advanced Model.

More fundamentally, academic research has shown that there is a stochastic component to LGD. That is, LGD is not fixed and may indeed fluctuate with both company-specific and economywide factors. Allen and Saunders (2004) survey the academic literature and note two areas of consensus. First, there is a positive correlation between asset and collateral values, thereby causing LGD (RR) to increase (decrease) as collateral values decrease. Altman (1989) finds significant positive correlations between recovery rates and external credit ratings just prior to default. Schuermann (2004) surveys evidence that recovery rates fluctuate over time and are negatively correlated with short-term default-risk-free interest rates because increases in interest rates (usually consistent with economic downturns) generally depress asset prices, thereby reducing recovery rates and increasing LGD. Calem and LaCour-Little (2004) estimate loss probability distributions for portfolios of mortgage loans and find that loan-specific characteristics (such as original loan to value ratios, measuring collateral, and borrower FICO scores) are important determinants of portfolio loss rates. Thus, LGD is a function of the underlying collateral value, which fluctuates over time.

The second area of consensus in the academic literature is that time-varying LGD has a systematic risk component—in other words, there is a cyclical component to LGD. Both historical evidence and the academic literature support this and suggest that systematic market factors affect both LGD and PD. Altman and Kishore (1996) find that recovery rates are time-varying. Maclachlan (1999) finds that credit spreads are highest and therefore bond prices are lowest during low points in the business cycle. This suggests a negative correlation between LGD and macroeconomic conditions because bond prices for distressed debt can be viewed as a lower bound on recovery amounts. Bangia, Diebold, and Schuermann (2002) use National Bureau of Economic Research (NBER) designations of contractions and expansions to find that economic capital is 30 percent higher in a contraction year than in an expansion year, suggesting that expected loss rates (that is, PD × LGD) are procyclical.

In addition to economywide factors impacting LGD, researchers have found that LGD depends on industry conditions. Acharya et al. (2007) find that RR in a distressed industry (i.e., an industry for which the median annual stock return for the three-digit SIC code is less than −30 percent) is reduced by $0.10 to $0.15 on the dollar as compared to the LGD of defaulted debt in nondistressed industries. Moreover, they find that this effect is exacerbated when industry assets are more specific (less generally usable by other firms in other industries) and the industry is more concentrated (reducing the demand for defaulted firm assets). These factors contribute to the fire sale price reductions required to dispose of defaulted firm assets, thereby reducing the recovery rate realized by creditors.

Many of the previously cited papers examining the systematic components in LGD do not generally consider whether LGD is correlated with PD. However, if LGD and PD are both impacted by the same factors, then the systematic component in LGD could be either exacerbated or mitigated. That is, if PD and LGD both increase in economic downturns and decrease in economic upturns, then the cyclical effect (as measured by both default correlations and LGD correlations) will be more pronounced. If, however, PD and LGD are negatively correlated (move in the opposite directions), then the cyclical effect in LGD may be reduced.

The question of the correlation between PD and LGD is an empirical one. Houweling and Vorst (2005) use a reduced form model to show that default swap prices are insensitive to the assumption of recovery values, although they do find a positive correlation between recovery rates and PD. Jokivuolle and Peura (2000) also model the recovery rate as a function of the PD and show that the expected LGD is a decreasing function of the growth rate in the value of collateral, an increasing function of the volatility of the collateral value, and an increasing function of the correlation between the collateral value and the value of the borrower firm's total assets. Moreover, the expected LGD is a decreasing function of the default probability of the borrower, given that the correlation between the collateral and the firm values is positive. This counterintuitive result obtains because of the use of an options-theoretic structural model to depict default. That is, low-PD firms must experience abnormally large negative shocks to asset values to enter the default region and therefore the value of their collateral is quite impaired. In contrast, high-PD firms (with a low distance to default) are thrown into default by only slight declines in asset values. Thus, the recovery rates of low-credit-quality firms tend to be higher than recovery rates in high-credit-quality firms in the Jokivuolle and Peura (2000) simulations.

Altman, Resti, and Sironi (2002) and Altman et al. (2005) exhaustively investigate the correlation between both ex post realized and simulated default rates and recovery rates. They find strong evidence of an inverse relationship such that recovery rates fall (rise) when PD increases (decreases). The explanation for this result stems from supply and demand considerations in the market for distressed debt. When default rates increase, for instance in cyclical downturns, there are likely to be more defaulted bonds available for sale on the distressed debt market. The demand for such below-investment-grade instruments is relatively inelastic since buyers are restricted to *vulture* funds and the relatively few financial intermediaries

(e.g., hedge funds and sovereign wealth funds) that are permitted to invest in this paper.

Altman (1993) attempts to measure the size of demand in this market for "alternative investments" and estimates that the vulture funds had at least $7 billion under management in the 1991 recessionary period. In contrast, the supply of distressed and defaulted public and private bonds (selling at a credit spread at least 1,000 basis points over 10-year Treasury bond rates) was approximately $300 billion during the 1990–1991 period. Given the 10-to-1 disparity in size between the supply and demand sides of the market, Altman, Resti, and Sironi (2002) contend that even dramatic increases in demand would not be sufficient to absorb the increased supply during cyclical downturns. Thus, since supply increases during cyclical downturns whereas demand is relatively stable, the price of distressed debt declines, thereby reducing recovery values when defaults increase. However, explicitly controlling for macroeconomic effects (using variables like GDP and changes in GDP) yields insignificant and inconsistent results in the Altman, Resti, and Sironi (2002) model.

Supporting the previously cited findings, Frye (2000, 2003, and 2005) examines 859 bonds and loans that defaulted from 1983 to 2001 and finds a significant inverse (direct) relationship between PD and recovery rates (LGD). However, the empirical findings in Acharya et al. (2007) refute the hypothesis of a direct relationship between PD and LGD. They find that the PD is a significant factor explaining LGD only when industry factors are left out. However, when they incorporate a measure of industry distress, the impact of PD becomes statistically insignificant. Therefore, the correlation between PD and LGD that has been found in some empirical models may be an artifact of omitted variables. Thus, the relationship between PD and LGD is still an open question in the academic literature.

However, what seems to be clear from the literature is that LGD is a function of macroeconomic conditions. For example, Unal, Madan, and Guntay (2003) decompose the difference between the prices of senior versus junior debt in order to estimate the risk-neutral mean recovery rates on senior debt relative to junior debt that are independent of default probabilities. Thus, their model is an alternative to the use of either defaulted debt prices or post-default expected cash flows to measure LGD. The recovery rate in their risk-neutral valuation model is conditioned on the business cycle (measured using macroeconomic factors) and firm-specific information. Furthermore, Caselli et al. (2008) use a sample of 11,649 bank loans to pinpoint the macroeconomic explanatory variables for LGD on loans to both households and businesses (small and medium enterprises, or SMEs). They find that for households, the LGD is sensitive to the unemployment rate and household consumption patterns. For SMEs, LGD is sensitive to the total number of employed people and the GDP growth rate. They interpret their results as support for the Basel Committee's insistence that the LGD assumptions input into the Basel II capital model be estimated for downturns separately, so as to incorporate these cyclical patterns (see the discussion in Chapter 13). Levy and Hu (2007) develop a theoretical framework to account for LGD procyclical dynamics that incorporates increases in LGD during economic downturns.

The sensitivity of LGD to industry and macroeconomic factors is impacted by the debt structure. That is, senior secured debt may have a lower LGD than subordinated unsecured debt. However, Acharya et al. (2007) find that it is senior unsecured debt (as opposed to bank debt and subordinated debt) that is most exposed to the impact of fire sale increases in LGD when the borrower's industry is in distress. Thus, bank debt and collateralized debt have high recovery rates even during an industrywide crisis, except when the collateral consists of industry-specific assets. Chatterjee and Yan (2008) document the existence of contingent value rights (CVRs), which are put options that pay additional cash or securities when the issuer's share price falls below a prespecified trigger level. These instruments can be used in reorganizations and restructurings to increase RR if the firm experiences financial distress.[1] Thus, the structure of the firm's debt may be an important determinant of LGD.

DISENTANGLING LGD AND PD

It is standard practice in both the academic literature and in commercial risk management products to jointly estimate LGD and PD. That is, since the default risk premium is composed of the product of PD and LGD (i.e., expected loss EL = PD × LGD), one input must be fixed in order to economically identify the other. Typically, it is the LGD that is assumed fixed so as to estimate PD. As noted in Pan and Singleton (2008), this identification problem occurs when contracts are priced under the "fractional recovery of market value convention (RMV)" (see, e.g., Duffie and Singleton [1999]). Under this scenario, the LGD and the PD are inseparable, since the recoverable market value is itself a function of PD. Alternatively, however, pricing may take place under the "fractional recovery of face value (RFV)" method, in which case the LGD and the PD in the default risk premium are separable. Pan and Singleton (2008) use sovereign credit default swap (CDS) spreads for Mexico, Korea, and Turkey in order to separately identify PD and LGD, assuming RFV.[2]

Pan and Singleton (2008) use different maturities (1, 2, 3, 5, and 10 years) of sovereign CDSs in order to estimate the LGD over the period from March 19, 2001, through August 10, 2006. They find sufficient sample sizes to reliably estimate LGD separately from PD. They estimate the hazard functions of PD and LGD for each of the four credit events specified in the ISDA standardized sovereign CDS contract: (1) obligation acceleration, (2) failure to pay, (3) restructuring, and (4) repudiation/moratorium.[3] They find that CDS spreads are sensitive to the LGD estimate for the 5-year and 10-year maturities, but not for the one-year contract. They view this as the result of "a liquidity or supply/demand premium . . . [in which] large institutional money management firms often use the short-dated CDS contract as a primary trading vehicle for expressing views on sovereign bonds." Thus, the presence of a liquidity risk premium may inject noise into the reduced form estimation of credit risk components.

Practitioners in the sovereign CDS market typically assume an LGD equal to 75 percent. Pan and Singleton's (2008) model supports this assumption for Korea, but not for Mexico and Turkey, for which they find LGD estimates in the region of 25 percent. They find that when their model is estimated for the less turbulent 2003–2006 period (i.e., with lower bid-ask spreads, implying more liquid CDS markets), the estimated LGD was close to 75 percent for Mexico, but still less than 50 percent for Turkey. They point to other credit-sensitive derivative products that could be used to solve for LGD in the presence of illiquidity problems that distort the pricing of credit spreads. Independently, Levy and Hu (2007) incorporate systematic risk into the recovery process, as well as the correlation between PD and LGD, and find that estimated spreads increase by 14 percent for a typical bond, and by 30 percent in some cases. Thus, there is still quite a bit of analytical work remaining in understanding and modeling the loss process.

MOODY'S KMV'S APPROACH TO LGD ESTIMATION

Moody's KMV LGD estimator, called LossCalc™, is a forward-looking estimator of recovery rates (i.e., postdefault debt prices) that incorporates an inverse relationship (negative correlation) between PD and RR, consistent with the work of Altman et al. (2005) and Frye (2005). Figure 7.2 shows that the RR for high-risk firms (with distance to default, DD, greater than 0.28) is lower than for low-risk firms.

The Moody's KMV LossCalc™ model consists of a linear regression involving more than 4,000 recovery observations that occurred over more than 20 years.[4] Regression variables include PD (or Moody's KMV EDF™—see Chapter 4), collateral, debt type, seniority class, borrower location, and industry. The model can solve for a spot one-year LGD or a

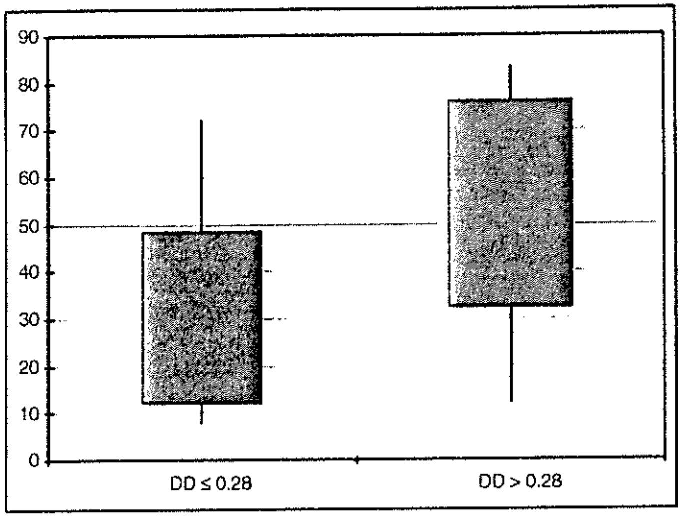

FIGURE 7.2 Relationship between Distance to Default and Recovery for U.S. Senior Unsecured Bonds
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five-year term structure of LGDs. Incorporating macroeconomic conditions, Moody's KMV estimates a stressed LGD, as if the economy was at either a 10-year or 25-year low. Industry distress is also incorporated (see the earlier discussion of Acharya and Bharath [2007]) using the median distance to default by region, industry sector, and date (see Chapter 4).

The most important determinant of LGD in the Moody's KMV LossCalc™ model is debt seniority, in both absolute and relative terms.[5] However, the model's R^2 measure of explanatory power ranges between 30 and 35 percent for the one-year and longer-term models. Thus, more than two-thirds of the variation in LGD is idiosyncratic and unexplained by the model. Because of this, it is necessary to include a measure of uncertainty about LGD into any credit risk analysis. That is, since there is a dispersion of possible values around the expected LGD, the error term of the basic regression should be considered. In the Moody's KMV LossCalc™ model the variance of the error term is higher for low-LGD securities than for high-LGD securities. To incorporate this and other factors, the model uses the beta distribution to represent the variance in the LGD estimate. A similar

type of beta distribution assumption has been employed in J.P. Morgan's CreditMetrics model.

The Moody's KMV LossCalc™ model is based on post-default debt prices. However, the model is validated using a sample of 1,323 observations of actual recovery rates. The correlation coefficient between recovery rates and post-default debt prices was 95 percent in this subsample, suggesting that the database proxies accurately for recovery rates. However, the test of any model is to determine how it performs out-of-sample. Moody's KMV performs a test of the model as compared to lookup tables of LGD (RR) historically used by bankers. Lookup tables specify the RR for each type of debt, industry or collateral, using average historical RR for each specification. Table 7.3 shows that the Moody's KMV LossCalc™ models

TABLE 7.3 Walk-Forward Analysis: Instantaneous Model

	LossCalc™ v3.0 In-Sample	LossCalc™ v3.0 Out-of-Sample	Best Lookup Table	Out-of-Sample Lookup Table
Correlation with actual recovery	0.602	0.545	0.521	0.462
Average error	−$0.13	$0.01	$1.70	$3.64

Walk-Forward Analysis: One-Year Model

	LossCalc™ v3.0 In-Sample	LossCalc™ v3.0 Out-of-Sample	Best Lookup Table	Out-of-Sample Lookup Table
Correlation with actual recovery	0.569	0.513	0.521	0.462
Average error	$0.55	$0.85	$1.70	$3.64

Walk-Forward Analysis: Long-Run Model

	LossCalc™ v3.0 In-Sample	LossCalc™ v3.0 Out-of-Sample	Best Lookup Table	Out-of-Sample Lookup Table
Correlation with actual recovery	0.550	0.497	0.521	0.462
Average error	$1.10	$2.75	$1.70	$3.64

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TABLE 7.4 Comparison of the Recovery of Face Value Estimates for the Economic and Recorded Default Dates

N = 73	Economic Default	Recorded Default
Mean	0.4879	0.5283
Median	0.45	0.5782
Standard deviation	0.3044	0.3151
First quartile	0.2	0.2225
Third quartile	0.76	0.8425

Source: X. Guo, R. A. Jarrow, H. Lin, "Distressed Debt Prices and Recovery Rate Estimation," January 26, 2009, Kamakura Research Paper, 17.

(focused on different time frames) each outperform the out-of-sample lookup table estimates over the period from 1996 to 2008. However, the long-run model underperforms the best lookup table, which is tabulated using a regression analysis.[6]

KAMAKURA'S APPROACH TO LGD ESTIMATION

Reduced form models (such as Kamakura's Risk Manager) model default as a sudden drop in debt value (a negative jump) at default. In contrast, structural models (such as Moody's KMV) model default as a gradual reduction (or negative diffusion) in a firm's values until the default point is reached. Guo et al. (2009) examine risky debt prices and find that the actual date of default does not always correspond to the date that the market first prices *impending* default. They define an *economic default date*, which more accurately models recovery rates. This date is the first date that the market prices the bond at the present value of its price on the *official* default date. Out of 96 debt issues in their sample, 73 experience economic default prior to actual default. Table 7.4 illustrates that the measure of the recovery rate is significantly different if the economic default date is used rather than the actual default date. Thus, Kamakura recommends modeling the recovery process from the economic default date, rather than the actual default date.

SUMMARY

In this chapter, we consider the other half of the expected loss calculation, the loss given default (LGD), or one minus the recovery rate (RR). Expected

losses (EL) are calculated by multiplying the probability of default (PD) by LGD. LGD is usually measured using observed debt prices around the default date. However, another measure of LGD is to consider actual recoveries from defaulted debt workouts or from an options-theoretic model. In this chapter, we have shown that LGD is sensitive to macroeconomic conditions, industry factors, debt priority structure, and the treatment of the default date. Since this area has been less studied than the estimation of PD, many open questions remain, such as the relationship between PD and LGD and the best model specification of LGD forecasts.