# What Do We Know About Loss-Given-Default?<sup>1</sup>

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**Abstract**: The New Basel Accord will allow banking organizations that are internationally active to calculate their credit risk capital requirements using an internal ratings based (IRB) approach, subject to supervisory review. One of the modeling components is loss given default (*LGD*), the credit loss incurred if an obligor of the bank defaults. The flexibility to determine *LGD* values tailored to a bank's portfolio will likely be a motivation for a bank to want to move from the foundation to the advanced IRB approach. The appropriate degree of flexibility depends, of course, on what a bank knows about *LGD* and about differentiated *LGDs* in particular; supervisors must be able to evaluate "what a bank knows." The key issues around *LGD* are: 1) What does *LGD* mean and what is its role in IRB? 2) How is *LGD* defined and measured? 3) What drives differences in *LGD*? 4) What approaches can be taken to model or estimate *LGD*? By surveying the academic and practitioner literature, with supportive examples and illustrations from public data sources, this paper is designed to provides basic answers to these questions. The factors which drive significant differences in *LGD* include place in the capital structure, presence and quality of collateral, industry and timing of the business cycle.

Keywords: New Basel Accord, credit risk

JEL Codes: G21, G28

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<sup>&</sup>lt;sup>2</sup> Any views expressed represent those of the author only and not necessarily those of the Federal Reserve Bank of New York or the Federal Reserve System.

# 1. Introduction

The new Basel Accord, expected to be implemented at year-end 2006, will require internationally active banks to use more risk sensitive methods for calculating credit risk capital requirements (Pillar 1 of the new Basel Capital Accord, or "Basel 2"). This paper discusses a key technical component of the Accord, "loss given default" (*LGD*) for corporate exposures.

The Accord allows a bank to calculate credit risk capital requirements according to either of two approaches: a standardized approach which uses agency ratings for risk-weighting assets and an internal ratings based (IRB) approach which allows a bank to use internal estimates of components of credit risk to calculate credit risk capital. Institutions using IRB need to develop methods to estimate these key components. One of these components is loss given default (*LGD*), the credit loss incurred if an obligor of the bank defaults. Since many U.S. banking organizations are likely to implement IRB, banks and supervisors alike will soon need to understand *LGD* (as well as other components), including various issues around it, to evaluate actual or planned implementations of IRB. By surveying the academic and practitioner literature, with supportive examples and illustrations from public data sources, this paper will give readers a basic understanding of *LGD* and discuss some of the key issues – which are:

- What does *LGD* mean and what is its role in IRB?
- How is *LGD* defined and measured?
- What drives differences in *LGD*?
- What approaches can be taken to model or estimate *LGD*?

This paper is designed to provide some basic answers to these questions. Since these questions do not have settled answers, this paper explores the limits of current knowledge (theoretical and empirical), including *LGD* experience using available data sources, and provides some preliminary guidance in model development and estimation.

We will start by describing the meaning and role of LGD in the new Basel Accord in Section 2 followed in Section 3 by a few stylized – i.e. commonly accepted general -- facts that drive significant differences in *LGD*, gleaned from a survey of the academic and practitioner literature. Section 4 examines in greater detail the definition and measurement of *LGD*. Since losses from bankruptcies are a major kind of loss, supervisors need to understand how the bankruptcy process affects losses and recoveries. Section 5 provides an anatomy of a bankruptcy and the role of capital structure or subordination in the amount of recoveries. Section 6 expands on the stylized facts presented in Section 3 by combining a literature review with analysis of data on defaulted bonds and (some) loans by way of illustration. Section 7 provides a more detailed discussion of *LGD* measurement and estimation. Section 8 gives a summary and concluding remarks.

# 2. LGD and the new Basel Capital Accord

The new Basel Capital Accord<sup>3</sup> is designed to better align regulatory capital with the underlying risk in a bank's credit portfolio. It allows banks to compute their credit risk capital in two ways: a revised standardized approach based on the original 1988 Capital Accord, and two versions of an internal ratings based (IRB) approach whereby banks are permitted to develop and use their own internal risk ratings. The IRB approach is based on four key parameters used to estimate credit risks:<sup>4</sup>

- 1. *PD* The probability of default of a borrower over a one-year horizon
- 2. LGD The loss given default (or 1 minus recovery) as a percentage of exposure at default
- 3. *EAD* Exposure at default (an amount, not a percentage)
- 4. *M* Maturity

For a given maturity, these parameters are used to estimate two types of expected loss (*EL*). Expected loss as an amount:

$$EL = PD \times LGD \times EAD$$

<sup>&</sup>lt;sup>3</sup> For an overview of the new Basel accord, see Basel Committee on Banking Supervision (2001b).

and expected loss as a *percentage* of exposure at default:

$$EL\% = PD \times LGD$$

IRB requires banks to disclose *PDs*, *LGDs* and *EADs* within the portfolio (Pillar 3). There are two variants of IRB available to banks, the foundation approach and the advanced approach.<sup>5</sup> They differ principally in how the four parameters can be measured and determined internally. For the foundation approach only *PD* may be assigned internally, subject to supervisory review (Pillar 2). *LGD* is fixed and based on supervisory values: 50% for senior unsecured claims and 75% for subordinated claims. *EAD* is also based on supervisory values in cases where the measurement is not clear. For instance, *EAD* is 75% for irrevocable undrawn commitments. Finally, a single average maturity of three years is assumed for the portfolio. In the advanced approach all four parameters are determined by the bank and are subject to supervisory review.

The flexibility to determine LGD values tailored to a bank's portfolio will likely be a motivation for a bank to want to move from the foundation to the advanced IRB approach. The appropriate degree of flexibility depends, of course, on what a bank knows about LGD and about differentiated LGDs in particular; supervisors must be able to evaluate "what a bank knows."

## 3. Some Stylized Facts about Recoveries and Losses

Although some banks may be able to draw on internal experience, any bank that takes the IRB approach will almost certainly need to consider common characteristics of losses and recoveries identified by a wide set of academic and industry studies. Likewise, supervisors need to be aware of these common characteristics to assess the adequacy of a bank's approach. In surveying the academic and practitioner literature, coupled with our own analysis using publicly available data, several characteristics stand out:

<sup>&</sup>lt;sup>4</sup> Section III.B, § 23 – 30, of Basel Committee on Banking Supervision (2001c).

<sup>&</sup>lt;sup>5</sup> For qualification conditions, please see Basel Committee on Banking Supervision (2001a).

- Most of the time recovery as a percentage of exposure is either relatively high (around 70-80%) or low (around 20-30%). The recovery (or loss ) distribution is said to be "bimodal" (two-humped). Hence thinking about an "average" recovery or loss given default can be very misleading.
- 2. The most important determinants of which mode a defaulted claim is likely to fall into is whether or not it is secured and its place in the capital structure of the obligor (the degree to which the claim is subordinated).
- 3. Recoveries are systematically lower in recessions, and the difference can be dramatic: about one-third lower. That is, losses are higher in recessions, lower otherwise.
- 4. Industry of the obligor seems to matter: tangible asset-intensive industries have higher recovery rates than service sector firms, with some exceptions especially in high tech and telecom.
- 5. Size of exposure seems to have no strong effect on losses.

In Section 6 we will illustrate many of these points using data from Moody's on bond and

loan recoveries from about 1970 to the end of 2001.<sup>6</sup>

# 4. Definitions of Default and Loss

# 4.1. Default

By definition, a debt instrument can experience a loss only if there has been a default. However, there is no standard definition of what constitutes a default. Different definitions may be used for different purposes. Typically a default occurs when any of the following conditions are met:

- A loan is placed on non-accrual
- A charge-off has already occurred
- The obligor is more than 90 days past due
- The obligor has filed bankruptcy

<sup>&</sup>lt;sup>6</sup> As of year-end 2001, the Moody's Corporate Default Database contains 2375 total defaults and 1622 observed recovery prices, of which 82 are loans. The data are bases on debt issues rated by Moody's, such as bank loans, corporate bonds, sovereign bonds and preferred stock from 1970 to the present.

The BIS reference definition of default for purposes of the New Basel Accord reflects many of these events:<sup>7</sup>

"A default is considered to have occurred with regard to a particular obligor when *one or more* of the following events has taken place.

- (a) It is determined that the obligor is unlikely to pay its debt obligations (principal, interest, or fees) in full;
- (b) A credit loss event associated with any obligation of the obligor, such as charge-off, specific provision, or distressed restructuring involving the forgiveness or postponement of principal, interest, or fees;
- (c) The obligor is past due more than 90 days on any credit obligation; or
- (d) The obligor has filed for bankruptcy or similar protection from creditors."

The measured loss in the event of default, and likewise the *LGD (percentage of exposure)*, will clearly depend on the definition of "default" adopted (as well as the definition of "loss"; see Section 4.2). Many instances of defaults under the definition may result in no loss incurred. For example, a firm may go 90 days past due on a loan payment and subsequently make good on all of its obligations.<sup>8</sup> This event would count as a default but would result in full recovery. A bank that ignores such events will under-estimate recovery rates since the exposure and 100% recovery won't be included in the bank's loss data. The bank's model will consequently yield an overly pessimistic picture of losses given default. To be sure, such full recovery events may in and of themselves be special and may therefore warrant separate modeling.

<sup>&</sup>lt;sup>7</sup> See Section III.F, §146 in Basel Committee on Banking Supervision (2001c).

<sup>&</sup>lt;sup>8</sup> A variation on this theme is an obligor with multiple facilities or loans being in default on only one of them. If an obligor is in default, this affects *all* of that obligor's facilities.

#### 4.2. Measurement and Estimation of LGD

*LGD* is usually defined as the ratio of losses to exposure at default, but as usual the devil is in the details (see Section 7). Once a default event has occurred, loss given default includes three types of losses.

- The loss of principal
- The carrying costs of non-performing loans, e.g. interest income foregone
- Workout expenses (collections, legal, etc.)

There are broadly three ways of measuring LGD for an instrument

- 1. Market *LGD*: observed from market prices of defaulted bonds or marketable loans soon after the actual default event
- 2. Workout *LGD*: The set of estimated cash flows resulting from the workout and/or collections process, properly discounted, and the estimated exposure
- 3. Implied Market *LGD*: *LGD*s derived from risky (but *not* defaulted) bond prices using a theoretical asset pricing model.

We will examine each in a bit more detail.

## 4.2.1. Market *LGD*

For defaulted bonds and loans which trade in the market, one may observe prices directly so long as a trade has actually occurred. The rating agency recovery studies are based on this approach. The actual prices are based on par = 100 ("cents on the dollar") and can thus be easily translated into a recovery percentage (or *LGD* as 100% minus the percentage recovery). These prices have some desirable properties since they are observed early and are a reflection of market sentiment at that time. After all, they are the result of a market transaction and hence less subject to debate about proper valuation. These prices reflect the investor's expected recovery, suitably discounted, and thus include recoveries on both discounted principal and missed interest payments

as well as restructuring costs and uncertainty of that restructuring process.<sup>9</sup> In the Moody's dataset, for example, they are observed in the market one month after the first occurrence of the default event. This price is therefore the market's expected present value of eventual recovery.

#### 4.2.2. Workout LGD

LGD observed over the course of a workout is a bit more complicated than the directly observed market LGD. Attention needs to be paid to the timing of the cash flows from the distressed asset.<sup>10</sup> Measuring this timing will impact downstream estimates of realized LGD. The cash flows should be discounted, but it is by no means obvious which discount rate to apply. In principle the correct rate would be for an asset of similar risk. Importantly, once the obligor has defaulted, the bank is an investor in a defaulted asset and should value it accordingly. Inappropriate candidates include the coupon rate (set ex ante of default, so too low) and the bank's hurdle rate (unless the bank only invests in risky assets like defaulted debt instruments, probably too low).

#### 4.2.3. Implied Market LGD

There is an entirely different approach one could take to obtain an estimate of *LGD* by looking at credit spreads on the (much larger universe of) non-defaulted risky (e.g. corporate) bonds currently traded. Although these new methods have not yet fully migrated into the bank's credit risk arena, they are used in the trading room for fixed income products and credit derivatives and as such are often used as a check against more conventional credit rating models. Moreover, some credit portfolio models require credit spreads as an input parameter.

<sup>&</sup>lt;sup>9</sup> Such as the absolute priority rule violations discussed in Section 5.

<sup>&</sup>lt;sup>10</sup> In addition, care needs to be taken to properly include the direct costs of recovery (collections staff, legal, etc.).

The spread above risk-free (i.e. Treasury) bonds is an indicator of the risk premium demanded by investors. However, this spread reflects *EL*, and thus both *PD* and *LGD*, as well as liquidity premiums. Only recently have models been developed which allow one to separately identify these two parameters from bond spreads (see, for instance, Bakshi, Madan and Zhang (2001) and Unal, Madan and Guntay (2001)). Unal, Madan and Guntay (2001) find that on average, recovery rates obtained in this way lie systematically below the "physical" recovery rates (their terminology) as implied by studies such as Altman and Kishore (1996).

#### 4.3. LGD and EAD for Facilities: LEQ

For a term loan, *EAD* is rarely ambiguous. This is not the case for facilities such as lines of credit where a borrower is theoretically able to draw down at will up to the committed line of the facility. Moreover, as financial distress worsens, a borrower will typically draw down as much as possible on existing unutilized facilities in order to avoid default. In the foundation sub-approach of IRB, *EAD* is also based on supervisory values in cases where the measurement is not clear. For instance, *EAD* is 75% for irrevocable undrawn commitments. However, under the advanced sub-approach, *EAD* may be determined by the bank via a model.

For facilities where exposure and hence LGD are uncertain, the loan equivalency factor (*LEQ*) represents a quantitative estimate of how much of the commitment will be drawn down by a defaulting borrower. *LEQ*s should be differentiated across both credit quality and facility type. Empirical work on this topic is sparse. Asarnow and Marker (1995) analyze the performance of large corporate loans at Citibank from 1988 – 1993 and show the importance of credit (debt) rating, particularly at the speculative end. Table 1 shows the average revolver utilization and *LEQ* in their sample.

Debt Rating	Avg. Revolver Utilization	<i>LEQ</i> <sup>11</sup>
AAA	0.1%	69.0%
AA	1.6%	73.4%
А	4.6%	72.3%
BBB	20.0%	72.0%
BB	46.8%	74.5%
В	63.7%	81.1%
CCC	75.0%	86.0%

Table 1: Average Revolver Utilization and *LEQ*<sup>12</sup>

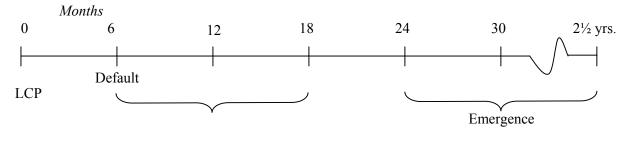
Since LEQ is expressed as a percentage much like LGD, the beta distribution is often used if a bank's credit risk or economic capital model treats *LEQ* as a random variable.

# 5. Anatomy of a Bankruptcy

While not all losses are the result of bankruptcy, many are, and so we will want to examine more closely its anatomy.<sup>13</sup> We will discuss the typical timeline as well as the capital structure and the absolute priority rule (APR).

<sup>&</sup>lt;sup>11</sup> Specifically LEQ = average revolver usage plus the usage of the normally unused commitment in the event of default. <sup>12</sup> Adapted from Exhibit 9 in Asarnow and Marker (1995). <sup>13</sup> For an overview of bankruptcy in the U.S., see White (1989) and Altman (1993).

#### 5.1. Timeline of a distressed firm



Bankruptcy Declared

A firm in distress typically goes through four stages as is illustrated in the timeline above.

- 1. LCP: the last cash paid date is known only ex post but serves as an anchor to the chronology.
- 2. **Default** is considered to occur at some later point, for bonds typically six months later. Default is often defined when a coupon or interest payment is missed. The six month delay between last cash paid and default results from coupons on bonds typically being paid twice yearly.
- 3. **Bankruptcy** (usually Chapter 11) is declared anywhere from the time of default to about a year later. A firm can default on debt obligations and still not declare bankruptcy depending on the negotiations with its creditors.
- 4. **Emergence** from bankruptcy proceedings, either via liquidation or genuine emergence as a going concern, typically occurs anywhere from two to four years after the last cash paid.

Cash flows from distressed instruments may occur throughout this process, although the bulk comes during or immediately after emergence when restructuring plans and additional financing (e.g. debtor-in-possession lending) are in place.

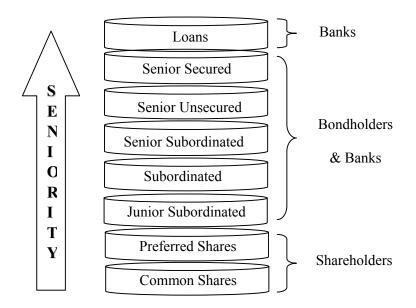
The time spent in bankruptcy can dramatically reduce the value of debt recovery. The average time spent in bankruptcy is around two years (Helwege (1999), Eberhart, Altman and Aggarwal (1998), Gupton, Gates and Carty (2000), Garbade (2001)) which is reflected in our timeline. Bond-only studies indicate that the average time in bankruptcy is a bit longer, more like  $2\frac{1}{2}$  years (Wagner (1996), Eberhart and Sweeny (1992)). Helwege (1999) finds that the presence

of contingent claims (e.g. unfunded pension liabilities) and size (a proxy for complexity) tend to lengthen bankruptcy proceedings.

As noted above, the discount rate for these cash flows is by no means obvious. The rate will depend on the riskiness of the asset at the time of cash disbursement. For example, the debt restructuring could result in the issuance of risky assets such as equity or warrants, or less risky ones such as notes, bonds or even cash.

#### 5.2. The Capital Structure and APR

The capital structure of a firm can be roughly divided as follows:



Bankruptcy law in the U.S. (and many other countries) has an important feature called the absolute priority rule (APR). Eberhart, Moore and Roenfeldt (1990 p. 1457) define the APR as:

The absolute priority rule [...] states that a bankrupt firm's value is to be distributed to suppliers of capital such that senior creditors are fully satisfied

before any distributions are made to more junior creditors, and junior creditors are paid in full before common shareholders.

However, in practice APR is routinely violated. In fact, several authors have found that in 65% to 80% of bankruptcies, even shareholders receive something without debtholders necessarily having been fully paid off (see, for instance, Eberhart and Weiss (1998) and references therein). The dominant reason is speed of resolution; creditors agree to violate APR to resolve bankruptcies faster. Some senior secured debt can become bifurcated in the course of restructuring whereby the amount of debt above the collateral value becomes junior.

Once a firm is in bankruptcy proceedings, there is a set of expenditures (claims) senior to all others. They include administrative expenses of the bankruptcy process itself such as court costs, attorneys' fees, trustee's expenses, as well as any loans incurred after the bankruptcy filing such as debtor-in-possession financing.

Valuation of a company when it is healthy is hard enough; when it is in distress, e.g. in bankruptcy, the range of valuation one might see is wider still. Unsurprisingly a claimant's valuation of the distressed firm depends on where the claims are in the distressed firm's capital structure, i.e. how senior or junior the claims are. Senior claimants have an incentive to provide conservative valuation estimates to reduce the incentives for junior claimants to hold up the bankruptcy proceedings ("There is not enough to go around, so be happy with what little you can get"). Junior claimants have the opposite incentive ("The pie is big enough for all to have a large share"). Eberhart and Sweeney (1992) show that the bond market prices are efficient in that APR violations are priced in.

# 6. What Drives Debt Recovery? Some Data

In this section we will expand on the set of stylized facts introduced in Section 3 by summarizing existing research and illustrating some of the points whenever possible with the Moody's defaulted debt dataset. Most of the published research treats recoveries of bonds rather than loans for the simple reason that that's where the data is. We would expect loans to do no worse, and probably better, than bonds, all other factors (industry, state of the business cycle, etc.) being equal. Bank loans are typically more senior in the capital structure and banks (should) more actively monitor the evolving financial health of the obligor. We will discuss distinctive loan experiences throughout the document, but the observations which follow will be drawn mainly from bonds. Note that the discussion will be in terms of recovery, and that *LGD* is just 100% minus the percentage recovery.<sup>14</sup>

One reason to expect the loan experience to be different from that of bonds is around differences in control rights between bondholders and private lenders (e.g. banks). These differences become especially important in the run-up to and during bankruptcy. Amihud, Garbade and Kahan (2000) point out that "[p]rivate loans better control the agency costs of debt through tighter covenants, renegotiation, and closer monitoring" (p. 116). Bankers are able to exploit their lending relationship to firm up their position at top of capital structure in anticipation of bankruptcy thereby raising expected recovery. The more fluid and dispersed nature of bond ownership makes it impractical for bondholders to renegotiate the core terms and conditions of the bond contract as the firm's condition changes.<sup>15</sup> Bankers are not so constrained.

#### 6.1. Recovery Distributions are Bimodal

If we look at the distribution of recoveries without regard to any factors or characteristics (seniority, industry, stage of the business cycle, etc.), we see two distinct humps or modes: Recovery and consequently LGD is either quite high or quite low (see Figure 1).<sup>16</sup>

<sup>&</sup>lt;sup>14</sup> Note also that recoveries exceeding 100% imply negative *LGD*. See Footnote 16.

<sup>&</sup>lt;sup>15</sup> See also Garbade (2001), ch. 4.

<sup>&</sup>lt;sup>16</sup> Recoveries can exceed 100% due to differences in coupon rates (high) and prevailing interest rates at time of recovery (low), i.e. if the coupon exceeds the prevailing rate.

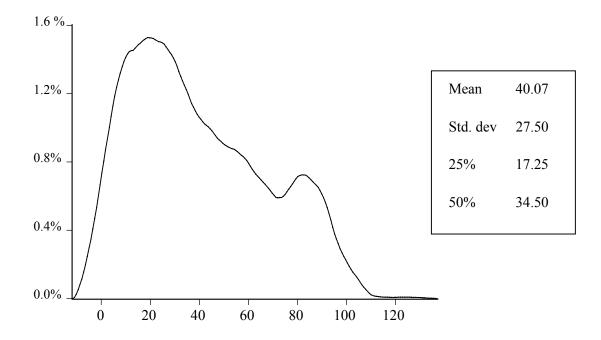


Figure 1: Moody's Recoveries, 1970-2002Q2: All Bonds & Loans

While there are indeed two modes, lower recoveries are more common (the low recovery mode is higher in the graph). What are the determinants of mode? What are the factors or variables that determine which mode the instrument will fall into? What does one need to know to predict high or low recoveries? We examine this next.

## 6.2. Seniority and Collateral Matter

Perhaps the most persistent result is that seniority and the presence of collateral (secured vs. unsecured) are the most important stratifiers of debt recovery (Altman and Kishore (1996), Gupton, Gates and Carty (2000)). It's critical to be first in line during the bankruptcy negotiations. To be concrete, Gupton, Gates and Carty (2000) report that syndicated loan recoveries for senior secured debt average 70% while senior unsecured debt average 52%. Thornburn (2000), looking at

Swedish small business bankruptcies, reports senior claims recovering on average 69% while junior claims receive only 2%. Asarnow and Edwards (1995), using Citibank lending data for the middle market and large corporate segments from 1970 to 1993, find that monitoring and structuring matters. For standard C&I lending they report the average recovery to be 65% whereas for structured lending<sup>17</sup> it is 87%.

The importance of monitoring is highlighted by Carey (1998) who looks at the performance of private placement to 13 life insurance companies relative to public debt from 1986-

1992. He finds

"...that although average loss rates on private debt are similar to those on public debt for investment grade assets (those rated BBB or better), and those rated BB, average private portfolio losses are better [lower] for the lower grades, and increasingly so as risk increases. Private default rates are slightly higher than public for the investment grades, but better [lower] loss severities have an offsetting effect on average portfolio loss rates. Both private default rates and severities are better [lower] for the risky grades, especially B and below." (pp. 1364-65).

Carey attributes the differences in performance to the closer monitoring of the higher risk

instruments.<sup>18</sup>

Using the Moody's data we can see the relationship between seniority and LGD clearly in

Figure 2 where we graph recovery by seniority. As we move down the capital structure toward

more junior positions, the mass shifts to the left meaning recovery rates become lower and lower or

LGD becomes higher.

<sup>&</sup>lt;sup>17</sup> Asarnow and Edwards (1995, p.13) state that structured loans have the following characteristics: "[1] The loans are closely monitored – the bank directly controls the company's cash receipts and disbursements. [2] The loans are highly structured and contain many restrictive covenants. [3] The loans are highly collateralized and lending is done on a formula basis, for example, having a predetermined advance rate against customer receivables as collateral."

<sup>&</sup>lt;sup>18</sup> Consequently it might be reasonable for banks to assume that their recovery experience will be better than the published results on bonds.

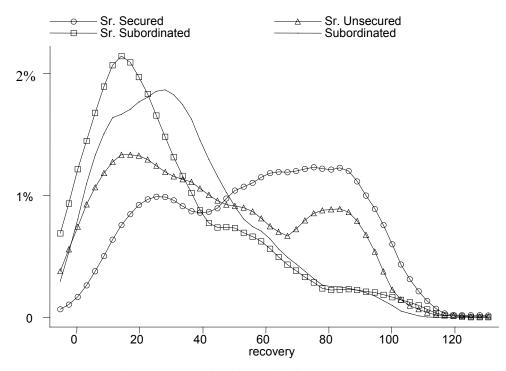


Figure 2: Recovery by Seniority (Moody's, 1970-2002Q2)

The descriptive statistics tell the same story in Table 2 where we also include junior subordinated.<sup>19</sup> We report means, standard deviations, and three quantiles: 25%, 50% (the median) and 75<sup>th</sup> percentile.

Seniority	Mean	Std. Dev.	25%	50%	75%	Ν
Sr. Secured	57.01	27.09	33.00	60.00	81.50	270
Sr. Unsecured	42.82	28.73	17.00	38.56	65.08	618
Sr. Subordinated	29.25	24.75	10.00	22.63	44.25	190
Subordinated	32.80	22.18	15.75	29.00	44.50	529
Jr. Subordinated	15.17	11.74	7.00	12.50	20.75	15

 Table 2: Recovery by Seniority (Moody's, 1970-2002Q2)

<sup>&</sup>lt;sup>19</sup> We did not include this category in the graph because of its small sample size.

A corollary to seniority is the difference in recoveries between bonds and loans. Loans are typically senior to bonds, so one would expect lenders to do better than bondholders. By and large they do (see, for instance, Van de Castle, Keisman and Yang (2000)), though Altman and Suggitt (2000) show that loan default rates are much higher over first two years of instrument life than bonds.

#### 6.3. Recoveries Across the Business Cycle

There is strong evidence that recoveries in recessions are lower, often much lower, than during expansions. Frye (2000), using Moody's data, shows that in a recession, recovery is about a third lower than in an expansion. Carey (1998), looking at private placement to thirteen life insurance companies, finds that recessions matter a lot for the tails of the loss distribution, especially for junk grade assets. Using simulation methods he finds that loss rates for sub-investment grade debt in the tails of the loss distribution (99.90 to 99.95%) during a recession are at least 50% higher than during expansions. By contrast the difference for investment grade is modest. The implication is that sub-investment grade instruments are more sensitive to systematic risk, i.e. the economy. Altman, Brady, Resti and Sironi (2002) show that when aggregate default rates are high, recovery rates are low. This result is corroborated by Hu and Perraudin (2002) who document that the correlation between recoveries and aggregate default rates for the U.S. are -20% on average and about -30% when considering only the tails, the more relevant part of the distribution for risk management.

We can illustrate this result again using our Moody's default data by graphing separately the recoveries experienced during recessions and expansions since 1970 (Figure 3).

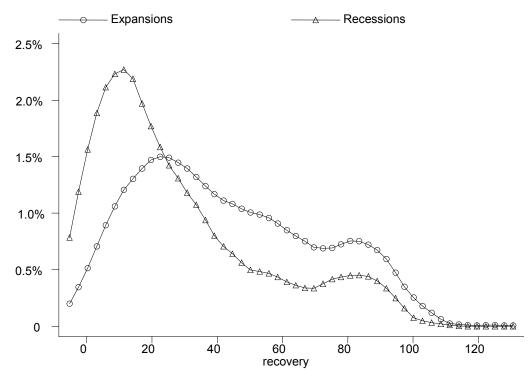


Figure 3: Recoveries across the Business Cycle (Moody's, 1970-2002Q2)

We see clearly that recessions bring with them many more instances of worse recoveries: the left mode (lower recoveries) for recessions is much higher than for expansions. Moreover, during expansions, recovery values are more evenly distributed. The numbers in Table 3 tell the same story; we reproduce the whole sample statistics for comparison.

	Mean	Std. Dev.	25%	50%	75%	Ν
Recessions	27.85	25.67	8.00	20.00	40.00	322
Expansions	43.10	27.11	21.00	38.56	63.00	1300
All	40.07	27.50	17.25	34.50	61.37	1622

Table 3: Recoveries across the Business Cycle (Moody's, 1970-2002Q2)

It is striking that the median recovery value during an expansion (38.56) is close to the 75<sup>th</sup> percentile in recession (40.00), and the recession median (20.00) corresponds to the 25<sup>th</sup> percentile in expansions (21.00).

# 6.4. The Impact of Industry

Industry matters -- sometimes. For corporate bonds, Altman and Kishore (1996) find evidence indicating that tangible asset-intensive industries such as utilities do better than asset-light industries such as services. Their study spans a long period: 1971–1995. These broad findings are corroborated using more recent data by Grossman et al. (2001) with Fitch rated bonds and loans from 1997-2000. We reproduce some of their findings here in Table 4 and Table 5. The difference in recovery rates for similar industries between loans and bonds is quite striking in the Grossman et al. (2001) study. Looking at Table 4, bonds from service oriented firms have surprisingly low recovery rates (3%) compared to loans (42%). Of course, we have no information here about seniority, so one should take these results with a grain of salt. Moreover, since these are averages, any bimodality in the recovery distribution, a phenomenon we know to be important, is obscured.

Industry, Asset Type	Avg. Recovery
Asset rich, loan	95%
Asset rich, bond	60%
Service oriented, loan	42%
Service oriented, bond	3%
Supermarket & Drug Stores, loan	89%

Table 4: Industry Impact (from Grossman et al. (2001))

The Altman and Kishore (1996) study on bonds only has somewhat less dramatic results (see Table 5).<sup>20</sup>

Industry	Avg. Recovery	Industry	Avg. Recovery
Utilities	70%	Communication	37%
Services	46%	Financial Institutions	36%
Food	45%	Construction, Real Estate	35%
Trade	44%	General Stores	33%
Manufacturing	42%	Textile	32%
Building	39%	Paper	30%
Transportation	38%	Lodging, Hospitals	26%

Table 5: Industry Impact (from Altman and Kishore (1996))

There is some disagreement over the impact of industry on *LGD* in studies looking only at loans. Brennan, McGirt, Roche and Verde (1998), using Fitch rated loans, find supporting

<sup>&</sup>lt;sup>20</sup> Some credit risk software such as CreditMetrics<sup>TM</sup> actually has embedded as choice parameters for *LGD* the results from the Altman and Kishore (1996) and Carty and Lieberman (1996) studies.

evidence for the differentiating effect of industry while Gupton, Gates and Carty (2000), using Moody's rated loans, do not.

#### 6.5. Size Probably Doesn't Matter

While size is an important determinant in models of default (PD),<sup>21</sup> once default occurs, size seems to have no strong effect on losses. Asarnow and Edwards (1995) look at Citibank's middle market and large corporate lending from 1970–93 and find no relation between loss given default and size of loan. Carty and Lieberman (1996) using Moody's data on syndicated lending to arrive at a similar negative result. Thornburn (2000), in her study of Swedish small business bankruptcies, also found that firm size doesn't matter in determining *LGD*. In a fairly narrow study, Eales and Bosworth (1998) look at Australian small business and larger consumer loans such as home loans and investment property loans and conclude that size does matter, at least a little. They report an average severity of 30% with a median of 20% (their distribution too is bimodal). Interestingly they find that loss recovery is U-shaped<sup>22</sup> with the trough of around A\$100-500k. They note that business bankruptcy almost always results in higher severity than consumer bankruptcies.

#### 7. LGD Modeling at Banks

The reforms under Basel 2 will allow banks to develop their own internal risk estimates of key parameters, including (under the advanced IRB approach) *LGD*. Under Basel 2, *PD* needs to be modeled at the obligor level, *LGD* at the facility level.

Any modeling effort will depend on the availability of historical data reflecting the bank's lending experience. In Section 4 we discussed some of the subtleties around measuring past *LGD* 

<sup>&</sup>lt;sup>21</sup> Typically banks build credit scoring (default) models by size segment, e.g. small business, middle market and large corporate.

(and more below), including the proper recording of defaults resulting in full recoveries (LGD = 0), market sales of distressed assets (yielding a mark-to-market based loss that is conceptually the same as LGD) and the proper recording and discounting of the cash flows resulting from a workout process.

The factors (or drivers or explanatory variables) included for any LGD model will likely come from the set of factors we found to be important determinants for explaining the variation in LGD. They include factors such as place in the capital structure, presence and quality of collateral, industry and timing of the business cycle.<sup>23</sup>

Any model would likely work with data having the structure where an observation is LGD for instrument *i* at time *t*. Table 6 at the end of this document provides details on the range of modeling approaches. The most basic model would simply be a contingency or "look-up" table containing LGD averages by certain characteristics. For example, a cell in this table might be LGD for Sr. unsecured loans for the automotive industry during a recession. These tables have the advantage of being relatively easy to build (no sophisticated modeling skills are needed) and easy to use. However, with enough cuts one quickly runs out of data; many cells in this table will likely go unfilled or have only very few observations on which to base an average.

For each cell in the table, an *LGD* estimate would be calculated as some version of the average ratio of losses to exposure at default. Broadly there are three approaches to obtain average *LGD* for a portfolio: dollar-weighting, default-weighting and time-weighting.

1. Dollar-weighting: for a given period (say one year)

total \$ lost total \$ exposure of defaulted loans

<sup>&</sup>lt;sup>22</sup> U-shaped: small loans and large loans both have higher recovery rates than those in the middle.

<sup>&</sup>lt;sup>23</sup> In fact an industry model, LossCalc<sup>TM</sup> from Moody's, uses most of these factors (Gupton and Stein (2002)).

2. Default-weighting: for a given period (say one year) assuming the *LGDs* of the instruments in the portfolio are known:

$$\frac{\sum LGDs}{\# \text{ of } LGDs}$$

3. Time-weighting: the average over time of either dollar-weighted or default-weighted *LGDs* of the instruments in the portfolio.

Of the three, the last (time-weighting) is the least desirable as it smoothes out high LGD years with low ones and may therefore understate expected LGD. There is substantial evidence that default and LGD are positively correlated (see Section 6.3), and time-weighting will mask this correlation. A drawback of default-weighting is that loan size information is averaged out (and hence lost). However, as we saw in Section 6.5, size does not seem to matter in the determination of LGD.

More sophisticated approaches involve formal modeling using regressions or more complicated techniques such as neural networks. By using a model to impose structure on the data, the data quantity problem from the contingency table approach is mitigated, but building, implementing and maintaining the more sophisticated models can be a challenge. Highly complex models are often prone to overfitting, meaning that "field" or out-of-sample performance can be quite poor relative to model fit (or in-sample performance). Basic regression models tend to be more robust than complex approaches but at the cost of lower accuracy.

Defaults resulting in 100% recovery (0% *LGD*) are probably somewhat special and should be modeled separately. Put differently, it is likely that there may be different factors driving this process, or that the factors should be weighted differently.

#### 8. Conclusion

The New Basel Accord will allow banking organizations that are internationally active to calculate their credit risk capital requirements using an internal ratings based (IRB) approach, subject to supervisory review. One of the modeling components is loss given default (*LGD*), the credit loss incurred if an obligor of the bank defaults. The flexibility to determine *LGD* values

tailored to a bank's portfolio will likely be a motivation for a bank to want to move from the foundation to the advanced IRB approach. The appropriate degree of flexibility depends, of course, on what a bank knows about *LGD* and about differentiated *LGDs* in particular; supervisors must be able to evaluate "what a bank knows."

The key issues around *LGD* are:

- What does *LGD* mean and what is its role in IRB?
- How is *LGD* defined and measured?
- What drives differences in *LGD*?
- What approaches can be taken to model or estimate *LGD*?

This paper is designed to provide some basic answers to these questions. The factors which drive significant differences in *LGD* include place in the capital structure, presence and quality of collateral, industry and timing of the business cycle. These factors would likely play a key role in any bank *LGD* estimates or models.

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Sophistication Level	Type	Details	Plus	Minus
Low	Contingency or Look-Up Table	A cell might be: <i>LGD</i> for Sr. unsecured loans for the automotive industry during a recession	Easy to build and use	Very data intensive to completely fill a possibly very large table
Medium	Basic regression	<i>LGD</i> <sub>it</sub> regressed on dummies for Sr/Jr, collateral quality, if any (say 3 buckets), industry group (say 6-12), expansion/recession	Relatively easy to build, flexible on data quantity, could easily be converted into a "scorecard"	Grouping/bucketing must be done with care
Medium-high	Advanced regression	As above, but with separate regression models, as warranted, for place in capital structure, collateral quality, expansion/recession; allow for different functional forms (e.g. non-linearity)	Better fit to data	Requires more sophisticated modeling knowledge; somewhat prone to overfitting and datamining
High	High Neural nets, tree methods, machine learning	Variety of methods which are often better suited for categorical variables (e.g. place in capital structure, industry) than ordinary regression	Even better fit to data	Even more sophistication; prone overfitting and datamining

Table 6: LGD Modeling Summary