# Collateral Damage:
# A Source of Systematic Credit Risk

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Should a borrower default on a loan, a bank's recovery may depend on the value of the loan collateral. The value of collateral, like the value of other assets, fluctuates with economic conditions. If the economy takes a downturn, a bank can experience a double misfortune: many obligors default, and the value of collateral is damaged.

Conventional credit models overlook the effect of economic conditions on collateral. They allow default to vary from year to year, but they hold fixed the average value of collateral and the average level of recovery.

The distinctive feature of the credit model presented here is that an economic downturn causes damage to the value of collateral. When systematic collateral damage enters the credit model, the capital allocated to a well-collateralized loan rises by a multiple.[1]

Taking collateral damage into account complicates a credit capital model. However, the results of the model can be well approximated by a function of expected loss alone. Expected loss can therefore be used as the basis of a credit capital estimate. This estimate is simpler, and can be more accurate, than using the results of a conventional credit model that ignores the role of collateral damage.

## Credit capital model

The credit capital model uses the conditional approach suggested by Michael Gordy and Christopher Finger. The variables in the model depend on a systematic risk factor, a random variable representing the good years and bad years of the economy. The co-variation between two variables stems from their mutual dependence on the systematic factor. Two variables that relate strongly to the systematic factor relate strongly to each other and therefore have a strong correlation.

Exposure of \$1.00 is assumed to each obligor $j$. At the end of a one-year analysis horizon, the value of collateral is a random number characterized by three positive parameters: its amount, $\mu_j$; its volatility, $\sigma_j$; and its sensitivity to $X$, the systematic risk factor, also known as its "loading," $q_j$:

(1) $Collateral_j = \mu_j (1 + \sigma_j C_j),$ and

(2) $C_j = q_j X + \sqrt{1 - q_j^2} Z_j,$

where $X$ and $\{Z_j\}$ have independent standard normal distributions.

Equation (2) implies that $C_j$ has a standard normal distribution. When the systematic factor exceeds zero, both $C_j$ and $Collateral_j$ tend to be greater than average, but that also depends on an idiosyncratic risk factor, $Z_j$, which affects only the collateral of obligor $j$. Equation (1) shows each unit of collateral value has a normal distribution with mean equal to 1.00 and standard deviation equal to $\sigma_j$.

The overall financial condition of the obligor, $A_j$, also depends on the systematic risk factor via a positive loading, $p_j$:

$$(3) \quad A_j = p_j X + \sqrt{1 - p_j^{\,2}}\, X_j,$$

where $\{X_j\}$ have standard normal distributions independent of each other, $X$, and $\{Z_j\}$.

When X exceeds zero, obligor $j$ tends to prosper. $A_j$ also depends on the idiosyncratic variable $X_j$, which affects the fortunes of obligor $j$ and nothing else. $A_j$ may take on a wide range of values having a standard normal distribution. This specification ignores the influences that may exist between $X_j$ and collateral, and/or between $Z_j$ and $A_j$. These nonsystematic influences have a relatively minor effect on credit capital.

The correlation between two obligors depends on their loadings on the systematic risk factor $X$:

$$(4) \quad Corr\,[A_j, A_k] = Cov\,[p_j X + \sqrt{1 - p_j^{\,2}}\, X_j, p_k X + \sqrt{1 - p_k^{\,2}}\, X_k] = p_j p_k$$

An obligor defaults if its financial condition falls below a threshold. Let $D_j$ represent the default event:

$$(5) \quad D_j = 1 \text{ if } A_j < \Phi^{-1}(PD_j);\ D_j = 0 \text{ otherwise}$$

where $PD_j$ represents the probability of default for obligor $j$, and $\Phi^{-1}$ is the inverse cumulative standard normal distribution. Equation (5) thus insures obligor $j$ defaults with probability $PD_j$: Prob [ $D_j = 1$ ] = E [ $D_j$ ] = $PD_j$.

If default occurs, the bank can recover, properly discounted and net of foreclosure expenses, no more than the loan amount:

$$(6) \quad \text{Recovery}_j = \text{Min}\,[1, Collateral_j], \text{ that is, } LGD_j = \text{Max}\,[0, 1 - Collateral_j]$$

The model allows collateral value to exceed exposure, but it does not allow the bank to recover more than exposure (though banks do experience such gains from time to time). If default occurs and collateral value exceeds exposure, the bank has no loss. This occurs often if $\mu_j$ is greater than 1.00. It is also common in banking: in many defaults, a bank experiences no loss whatsoever. If default occurs and collateral value is less than zero, the bank may lose more than \$1.00. These events are rare both in banking and in the model.[2] If $\sigma_j = 20\%$, the value of collateral becomes negative only if $C_j < -5.0$, which corresponds to a probability of 0.00003%. Taking the average of $LGD$ over all possible outcomes produces the expected loss given default, $ELGD$.

For simplicity, the model includes losses due only to default and not due to downgrade or changes in pricing spreads. The amount lost to obligor $j$ is then the product of the default event and the loss given default:

$$(7) \quad Loss_j = D_j \; LGD_j$$

Taking the sum over all $j$ equals the total credit loss. Monte Carlo simulation or other means can then determine the distribution for random realizations of the systematic factor $X$ and of the idiosyncratic factors $\{X_j\}$ and $\{Z_j\}$.

Capital models are used by some banks to target the credit ratings they receive from rating agencies. A bank that targets an investment grade rating might wish to hold enough credit capital to absorb the loss that arises in 99.90% of Monte Carlo simulation runs. We may speak of a target solvency of 99.90% or of a target insolvency of 0.10%. The latter equals $\alpha$, the final parameter of the credit capital model.

In equation (7), $D_j$ depends on $X$ and $X_j$, and $LGD_j$ depends on $X$ and $Z_j$. Conditional on a realization $X = x$, these factors are independent:

$$(8) \quad \mathrm{E}[Loss_j \mid X = x] = \mathrm{E}[D_j \mid X = x] \; * \; \mathrm{E}[LGD_j \mid X = x]$$

Thus, given a state of the economy as represented by $X = x$, the conditional expected loss for a loan equals the product of its conditional $PD$ and its conditional $ELGD$.[3] An increase in $x$ causes both conditional $PD$ and conditional $ELGD$ to decrease. Therefore, when $X$ is at percentile $\alpha$, conditional $EL$ is at percentile $(1 - \alpha)$.

We want to find the increase in target capital when a particular loan is added to the credit portfolio. Marginal capital depends on the portfolio to which the loan is added. We assume that the portfolio has the same exposure to each obligor, and that the portfolio is large enough to be fully diversified. Then the marginal capital of a loan can be treated as equal to the mathematical expectation of loss conditional on $X = \alpha$. Therefore, a bank that has an insolvency target of 0.10% can substitute the 0.10 percentile of the standard normal, $x = -3.09$, in equation (8) to obtain credit capital for a loan characterized by the five parameters $\sigma_j$, $p_j$, $q_j$, $PD_j$, and $\mu_j$. Recapping the roles played by the parameters and suppressing the subscript, we have:

| | |
|---|---|
| $\sigma$: | Standard deviation of collateral value. |
| $p$: | Sensitivity of obligor's financial condition to systematic risk factor. |
| $q$: | Sensitivity of obligor's collateral to systematic risk factor. |
| $PD$: | Probability of obligor's default. |
| $ELGD$: | Expected loss given obligor's default. |
| $\mu$: | Amount of collateral provided by obligor $j$; may be implied from $ELGD$. |
| $\alpha$: | The bank's target probability that portfolio loss exceeds credit capital. |

The novel feature of the model is that *LGD* depends on the state of the economy. This feature is not present in conventional credit models. For example, CreditMetrics® first determines obligor default and then independently determines *LGD*. Any risk in recovery is purely idiosyncratic, equivalent to forcing $q = 0$. CreditRisk+® assumes *LGD* is a known amount. The variance of recovery is zero, equivalent to forcing $\sigma = 0$. The capital model presented here can mimic these models. If $q$ is set to zero (or if $\sigma$ is set to zero), conditional *ELGD* does not respond to the state of the economy, but becomes, instead, a constant.

## Quantifying collateral damage

This section begins by finding representative values of the parameters $\sigma$, $p$, and $q$. It then demonstrates the importance of collateral damage for an example loan. Finally, it repeats the analysis for loans having a range of *ELGD*.

The parameter $\sigma$ might apply to a number of assets pledged as collateral: inventory, receivables, negotiable instruments, title documents, intangibles, and so forth. In addition to assets pledged as collateral, other assets with uncertain values may be awarded to the bank as a general creditor, and these assets are also considered "collateral" in the present analysis. For this mixture of assets no single estimate of $\sigma$ can be entirely satisfactory. Toward obtaining a representative estimate, Moody's Investors Service provides summary data for 98 senior secured bank loans. On these, average recovery equals 70.26%, with standard deviation equal to 21.33%. The implied estimate of $\sigma$ equals 21.33 / 70.26 = 30%. However, the recovery achieved on a loan is apt to be closer to the recovery expected on the same loan than to the overall average recovery. Therefore the raw estimate is apt to overstate $\sigma$. We take $\sigma = 20\%$ as the representative value, with robustness checks using $\sigma = 15\%$ and $\sigma = 25\%$.

We take 0.5 as the representative value of $p$. Equation (4) then implies that any pair of obligors has a correlation of $(0.5)^2 = 25\%$. This accords with the average level of asset correlation suggested by the CreditMetrics® Technical Document. Checks of robustness are performed at $p = 0.4$ and $p = 0.6$.

No studies known to the author provide an estimate of $q$, the loading of collateral on the systematic factor. It appears, however, that the representative value of $q$ is greater than or equal to $p$. The assets banks obtain when obligors default are, first of all, assets. All assets tend to decline with the systematic factor, whether or not they may become the source of recovery on a bank loan. If this overall systematic effect were the only channel of influence from $X$ to the value of collateral, one would suppose that $q = p$.

Two additional channels of influence increase the effect of $X$ on collateral in an economic slump. A low value of $X$ leads to financial distress for many obligors, and it leads to financial distress for some banks. An obligor in financial distress might devote fewer resources to resolving customer complaints, to maintaining equipment, and to safeguarding its fixed investments. The affected assets—accounts receivable, vehicles, and real estate—serve as collateral. Thus, the assets a bank obtains may have been already degraded by previous attempts to extract value. A bank must also anticipate the effects of its own distress in determining the appropriate level of capital. In the circumstances envisioned by the capital model, a bank has exhausted or nearly exhausted its capital cushion. It then faces unusual pressure to reduce risk and to liquidate assets even if it cannot obtain the best price. The value a bank actually realizes from collateral may therefore be even more depressed than the values of other assets. Two channels of influence—the actions of distressed obligors before they default, and the actions of the distressed bank itself after it receives collateral—make collateral values unusually sensitive to an economic slump. It is difficult to see an opposing influence that would selectively protect collateral from systematic risk.[4] We assume that representative $q$ is equal to $p$, with robustness checks of $q = p + 0.10$ and $q = p + 0.20$.

Using the representative values of the parameters $\sigma$, $p$, and $q$, we take the example of a relatively low-rated obligor that has provided a high level of collateral. Specifically, figure 1 analyzes a loan having $PD = 5\%$ and $ELGD = 10\%$. The horizontal axis is calibrated to the percentiles of $X$. Along the axis, $X$ varies from very worst to very best, and any point between is equally likely to arise. The two lines represent the two factors on the right-hand side of equation (8). Both decline as $X$ rises. The average of conditional *PD* equals the unconditional *PD* of 5%. The *PD*-weighted average of conditional *ELGD* equals the unconditional *ELGD* of 10%.

Thus, figure 1 shows how the overall levels of *PD* and *ELGD* distribute conditionally across states of the economy. For most states, one sees relatively benign levels of both variables. But in a severe economic slump, both conditional *PD* and conditional *ELGD* rise with a vengeance. To prepare for this adverse circumstance, banks hold capital.

Suppose a bank targets its own insolvency at $\alpha = 0.10\%$. In figure 1 this point appears 0.10% of the distance along the axis, almost at the extreme left. The corresponding levels of conditional *PD* and conditional *ELGD* are 45.4% and 26.1%, respectively. According to equation (8), the product of these two equals credit capital: 45.4% * 26.1% = 11.8%.

If the bank uses a conventional credit model to allocate capital for this loan, it makes a significant error. It ignores the increase in *LGD* that comes about in the economic slump. Specifically, it assigns capital equal to 45.4% * 10% = 4.5%. The accurate target is 2.61 times this allocation, because the effect of collateral damage is to increase *ELGD* from its overall value of 10% to its value in an economic slump, 26.1%. Preferable to such a prediction by a model would be statistical data on the performance of bank loans. But data do not exist regarding *LGD* in an economic slump of this severity. Until we have such data, it would be a risky course of action is to assume an economic slump has no effect on *LGD*.

The obligor with $PD = 5\%$ is further analyzed in figure 2. Of a range of values of *ELGD*, more highly collateralized loans appear further to the left. The upper line shows the error multiple made by a conventional model if a bank has a solvency target of 99.90%. Thus, for a loan with *ELGD* = 10%, the bank should hold 2.61 times the capital calculated by a conventional model. The downward slope of the line shows that when *ELGD* is lower, the conventional model makes a greater error. The lower line shows the error multiple for a bank having a lower solvency target of 99.50%. The difference between the two lines shows that a bank with a lower target solvency has less sensitivity to the effects of collateral damage.

## Capital and expected loss

This section compares the loan of figure 1 to a second loan having equal expected loss. The equality of expected loss implies a near-equality of capital. The comparison is extended to loans with a range of combinations characteristics, and the same conclusion is found. The conclusion is then checked, both for a range of values of the model parameters $\sigma$, $p$, $q$, and $\alpha$ and for a fundamental change in the specification of the model.

The loan in the previous example has *PD* = 5% and *ELGD* = 10%. Table A compares that loan to a second loan having the same *EL*, but having *ELGD* = 50%. Panel 2 shows the first loan is more affected by collateral damage. The lower the *ELGD* of a loan, the greater potential it has to rise in an economic slump. An economic slump affects the *ELGD* of each loan, but it has a greater proportional effect on the first one, having a lower *ELGD*.

The two loans also differ in *PD*. The second loan, having higher *ELGD* than the first, has lower *PD*. In an economic slump, the *PD* of the second loan rises about eighteen fold, while the *PD* of the first loan rises only about nine fold. The lower the *PD* of an obligor, the greater potential it has to rise in an economic slump. An economic slump affects the *PD* of each loan, but it has a greater proportional effect on second one, having a lower *PD*.

The economic slump raises both *ELGD*s and both *PD*s. Of the two *ELGD*s, the proportional effect is greater for the first loan. Of the two *PD*s, the proportional effect is greater for the second loan. The product of the two effects is nearly the same, and so the two loans require nearly the same capital. In fact, by a narrow margin the first loan requires greater capital (11.8%) than the second loan (11.0%). This is contrary to the verdict of a conventional model. As shown in panel 3, the conventional model reverses the ranking and presents an alarmingly rosy view of the low-*ELGD* loan.

The two loans in table A have the same *EL* and require nearly the same capital. That the two loans divide *EL* differently between *PD* and *ELGD* has relatively little importance. The relationship between *EL* and capital generalizes readily, as shown in the context of a stylized bank internal rating system.

Many banks use one-dimensional internal risk rating systems. These systems initially assign a risk rating based on the characteristics of the obligor. (The characteristics usually include a public rating, if available, financial statement analysis, projections, and so forth.) The rating might be upgraded based on the amount of collateral securing a particular loan. A collateralized loan to a poorer-rated obligor then has the same rating as an uncollateralized loan to a better-rated obligor. This resembles the relationship of the two loans in table A. The first loan has relatively lower *ELGD*, and the second loan has relatively lower *PD*. The product of *ELGD* and *PD* can therefore be nearly equal for the two loans. When this is so throughout every rating grade, the rating system can be characterized as an *EL* system, even if it is not intentionally based on expected loss.

*EL* rating systems appear to be the norm. After a thorough study, William Treacy and Mark Carey of the Federal Reserve characterize the ratings systems of nearly all large U.S. banks as measuring *EL*. (They characterize some as measuring *PD* as well, on a separate dimension.) We therefore assume the interplay between *PD* and *ELGD* results in uniform *EL* within a rating grade.

We establish grades for *EL* = 0.025%, 0.05%, 0.1%, 0.2%, 0.4%, 0.8%, and 1.6%. This range includes most bankable assets. Within any rating grade, a conventional model allocates less capital to loans having lower *ELGD*, as shown in figure 3. (The target is low investment grade, $\alpha = 0.50\%$.) The five lines depict capital for five levels of *ELGD*. The top line depicts *ELGD* = 100%, and the bottom line depicts *ELGD* = 6.25%. In the rating grade where *EL* = 0.1%, these correspond to *PD* = 0.1% and *PD* = 1.6%, respectively.

Within any *EL* grade, the conventional model allocates more capital to loans having higher *ELGD* and lower *PD*. That is because the conventional model partitions *EL* into *PD* and *ELGD*—and then looks only at the systematic risk in the *PD* fraction. In an economic slump, the greatest proportional increase in default occurs in obligors having the lowest *PD*. Therefore, within an *EL* rating grade, the conventional model concludes that *more* capital is required for loans where the probability of default is *low*.

The difference between figure 3 and figure 4 is the effect of collateral damage. The lower is *ELGD*, the more collateral and the more systematic risk is held by the bank. In an economic slump, the greatest proportional increase in *LGD* occurs in loans having the lowest *ELGD*. Therefore, the lines having the lowest *ELGD* rise the most in the transition from figure 3 to figure 4. Not only do they rise, they rise to approximately the same level. The result is that credit capital is approximately a function of expected loss alone.

Examination of figure 3 and figure 4 leads to three conclusions. First, the effect of collateral damage increases capital for all loans (except for *ELGD* = 100%) and markedly increases capital for low-*ELGD* loans. Second, the low-*ELGD* lines in figure 4 are much closer to the line representing *ELGD* = 100% than they are to their own representations in figure 3. In a conventional model it appears more accurate to adjust the inputs for a low-*ELGD* loan—to adjust *ELGD* to 100% and to adjust *PD* downward, maintaining the same level of *EL*—than it is to simply accept the results of the model using the unadjusted input. Third, a function of expected loss provides an estimate of credit capital that is more accurate than using both *PD* and *ELGD* in a conventional credit model.

These conclusions are tested for robustness. Thirty-six combinations of parameter values are used to re-create figure 3 and figure 4. Three levels of $\sigma$ (15%, 20%, and 25%) are combined with six combinations of values for $p$ and $q$ ({0.4, 0.4}, {0.4, 0.5}, {0.4, 0.6}, {0.5, 0.5}, {0.5, 0.6}, and {0.6, 0.6}) and examined at two settings of $\alpha$ (0.1% and 0.5%). Each of the thirty-six pairs of charts supports all three of the conclusions stated above.[5]

Not only are these conclusions robust for a range of parameter values, they are also robust for a change in the mathematical specification of the model. In this specification there is no explicit role for collateral. Instead, recovery is modeled directly as a beta distribution, as is done in CreditMetrics®. The model allows collateral damage to enter by *conditioning* recovery on the value of $C_j$. Specifically, replacing equation (1) we have:

$$\text{(9)} \quad \text{Recovery}_j = \text{BetaInv}[\,\Phi(C_j)\,,\; mean = \mu\,,\; s.d. = \sigma\,]$$

Figure 5 shows the results of the conditional beta recovery model. Except that the beta recovery model allocates slightly more capital to low-*ELGD* loans, figure 5 resembles the normal model of figure 4. Robustness checks of the beta recovery model also resemble the robustness checks of their normal model counterparts.[6] The conclusion—that capital depends principally on expected loss—is therefore robust with respect both to changes in parameter values and to a change in the model specification.

To account for the effects of collateral damage in a credit portfolio, the best solution would be to correctly model the effects of *PD*, *ELGD*, $\sigma$, $p$, and $q$ along the lines suggested in this article or in some other way. Most banks would find that they have neither the data nor the systems to adopt this approach in the near term. A second-best solution is to estimate capital as a function of expected loss, stratifying the portfolio by uniform $\sigma$, $p$, and $q$ as in the above.

For current users of a conventional credit model, a second-best solution appears to be an appropriate adjustment of the inputs. The suggestion is to adjust *PD* downward and to adjust *ELGD* to unity, keeping the product equal to the *EL* of the original loan.[7] The adjusted loan should contribute approximately the risk of the original loan including the risk of collateral damage. This adjustment is available to users of both CreditMetrics® and CreditRisk+®.

## Conclusion

The credit capital model presented here takes note of an effect well known to bankers:

The credit cycle can produce a double misfortune involving greater-than-average default frequency and poorer-than-average recoveries. Of the two misfortunes, conventional credit models analyze the first and ignore the second. They can therefore assign alarmingly little capital to well-collateralized loans.

The effect of economic conditions on loan recoveries complicates the capital model. However, the results of the full model are well approximated by a function of expected loss. This conclusion holds for an alternative model specification and for a robust range of parameter values.

These results contain several messages. To bank lending and credit policy officers, the results repeat a message most often heard following large credit losses: collateral should not lead to complacency, because collateral value can decline at exactly the moment that a bank gains ownership. To bank portfolio credit analysts who use models to estimate portfolio risk, the results warn that all sources of systematic risk must be included. Lacking that, the inputs to existing models should be adjusted for more accurate results. To bank supervisors attempting to assess credit risk, the results suggest that a simple estimate of credit capital can be expedient and accurate.

Naturally, bank credit models should be expanded to cover as many sources of risk as possible. An estimate based on expected loss would not be completely accurate or ideal. However, the expected loss approach may provide a better estimate than some current credit models. Until models evolve to incorporate the systematic risk of both default and recovery, a credit capital estimate based on expected loss may be the best solution.

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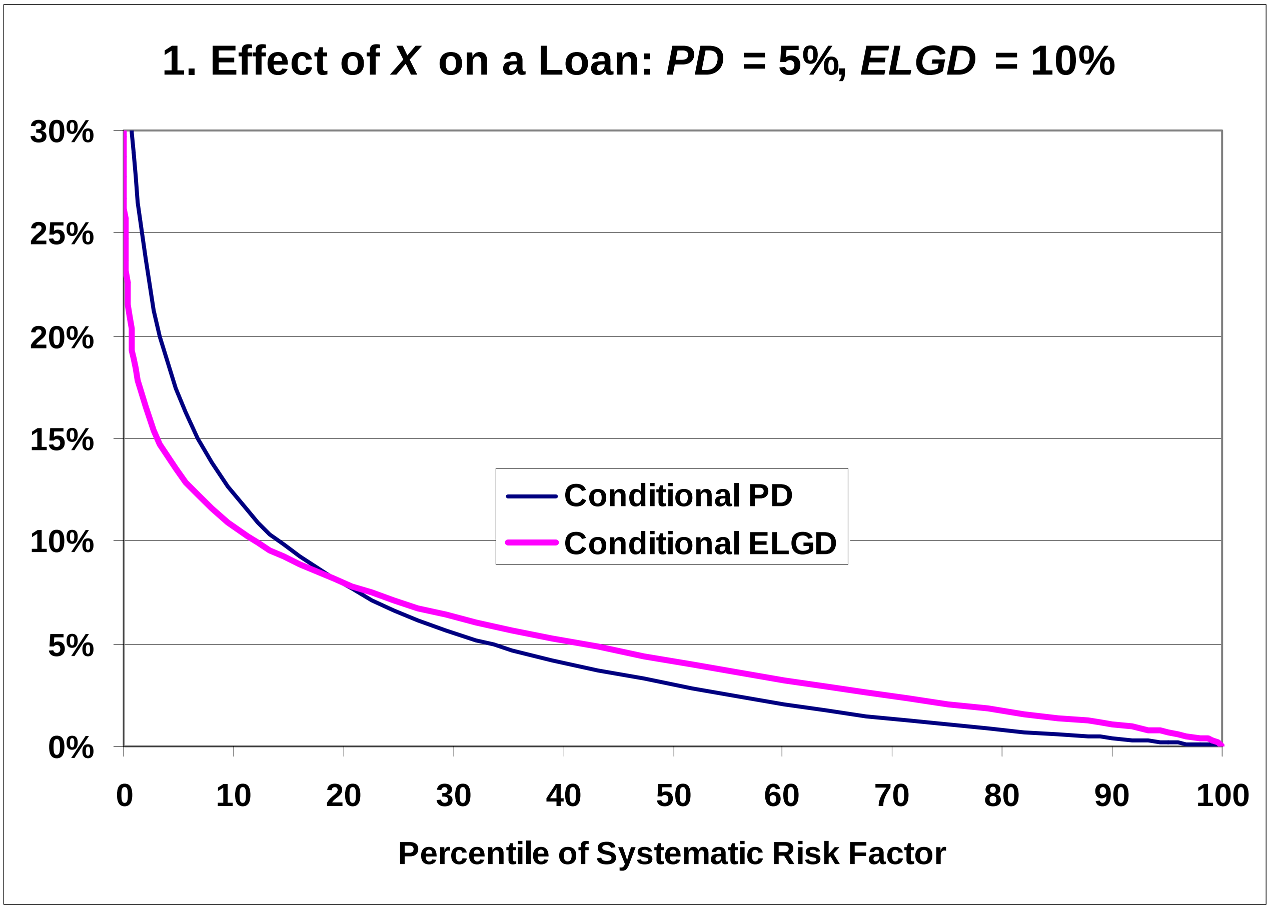
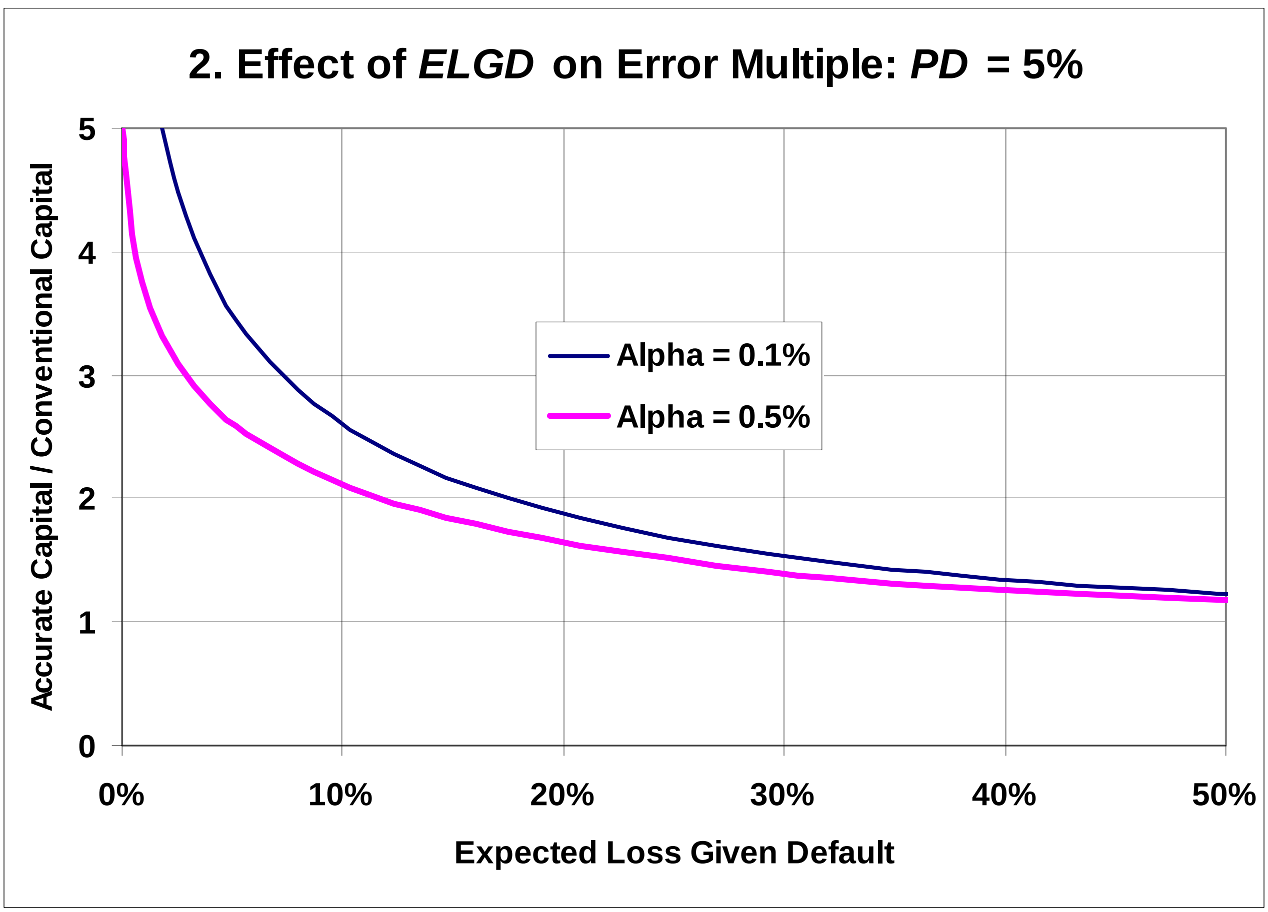
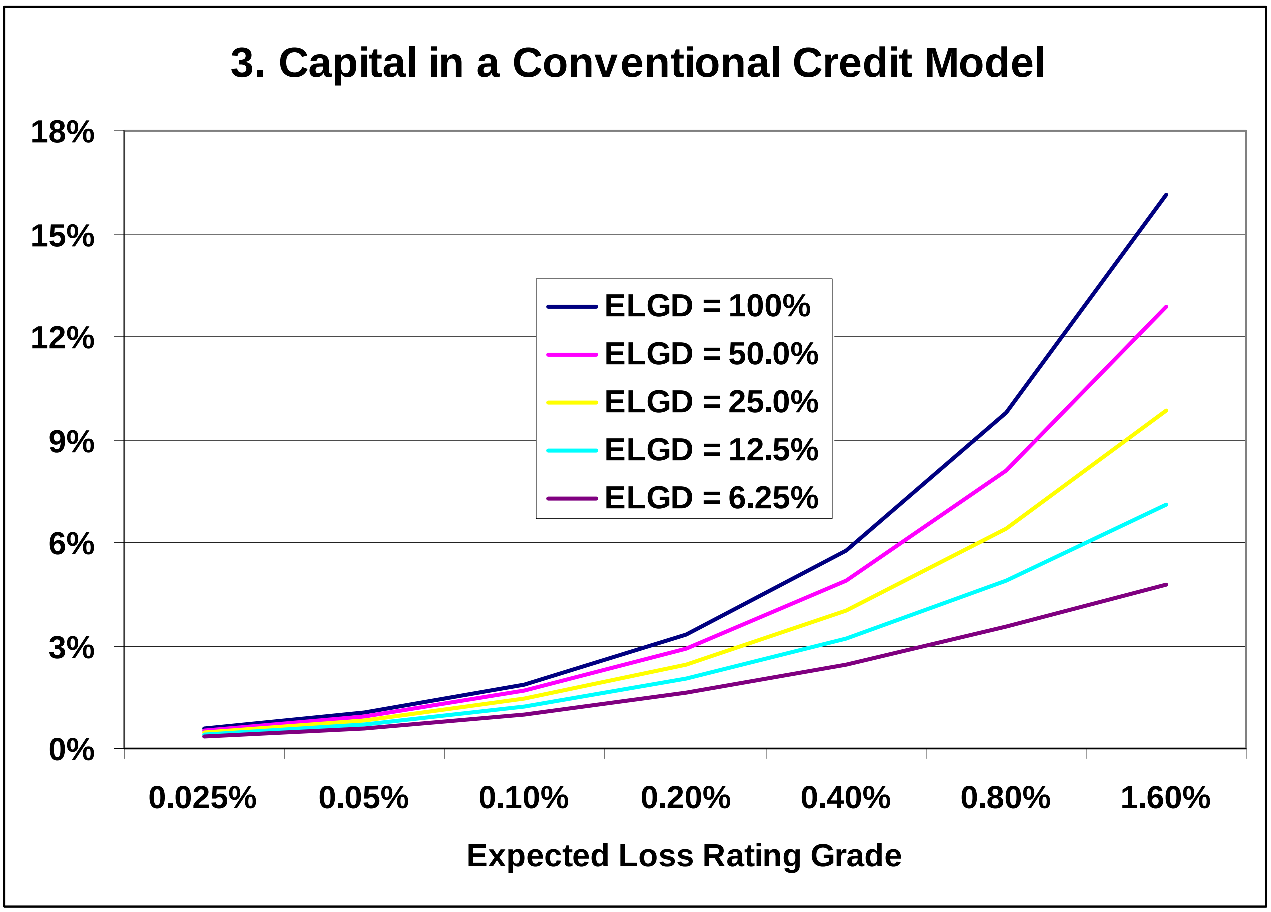
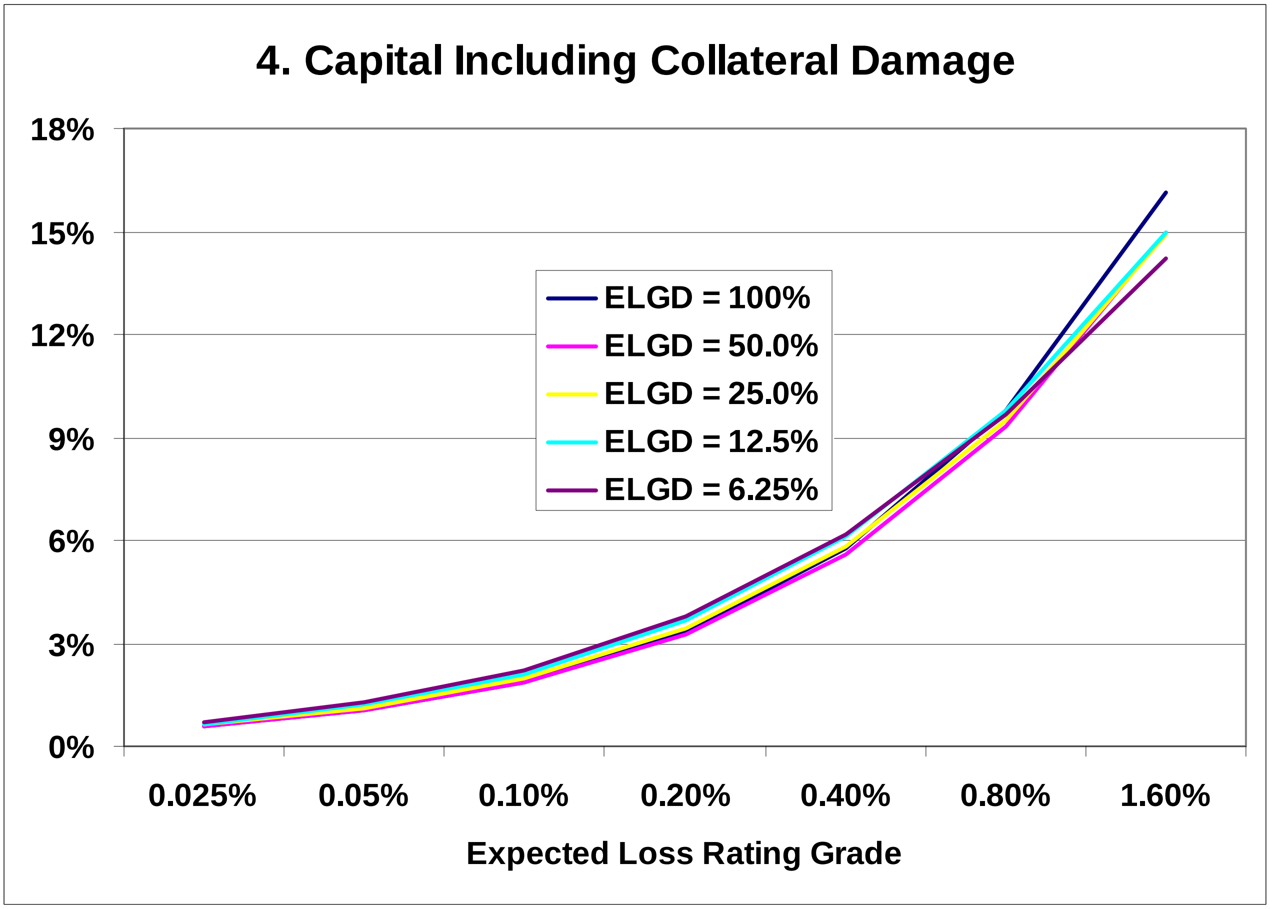
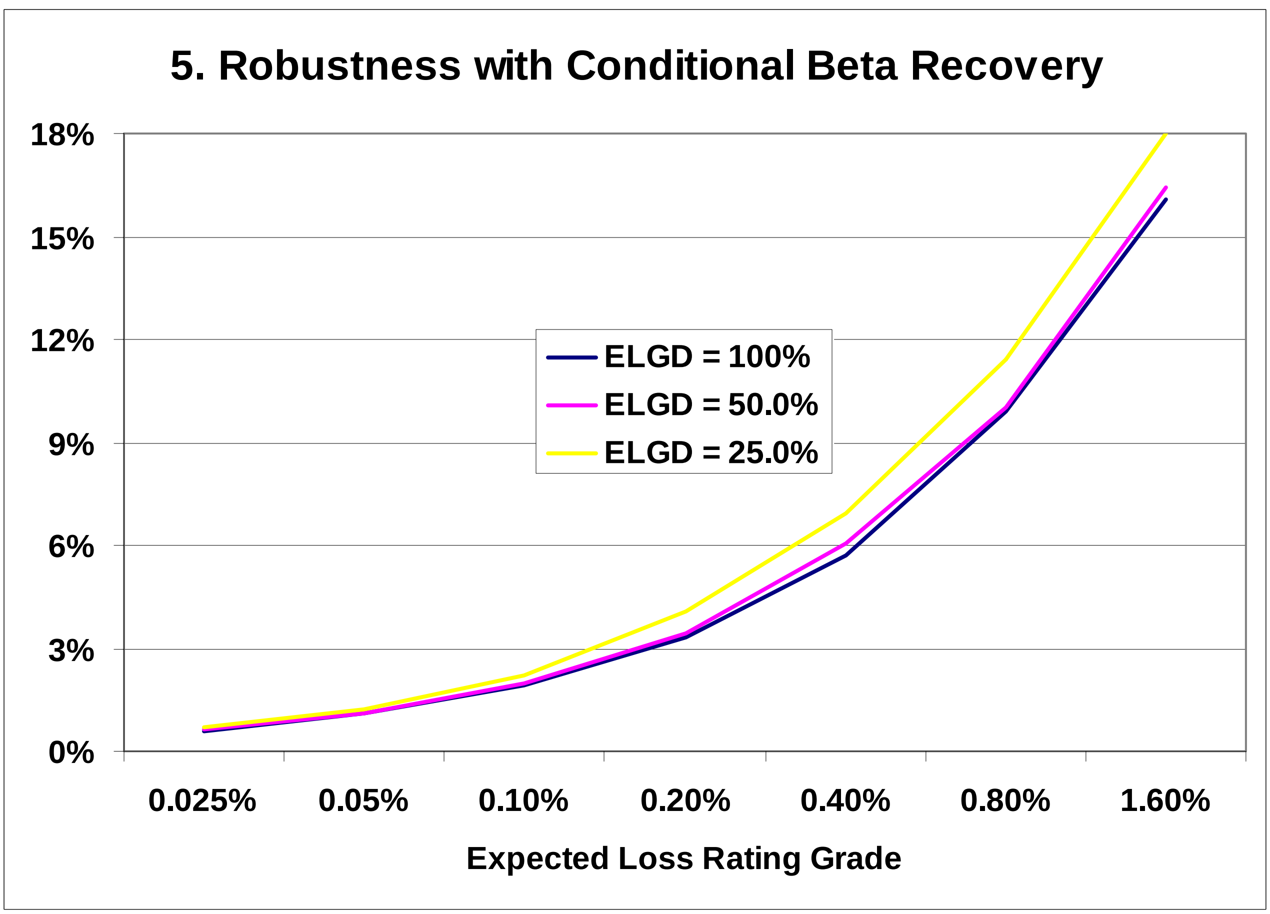

1. Effect of X on a Loan: PD = 5%, ELGD = 10%
30%
25%
20%
15%
10%
5%
0%
0
10
20
30
40
50
60
70
80
90
100
Percentile of Systematic Risk Factor
Conditional PD
Conditional ELGD


2. Effect of ELGD on Error Multiple: PD = 5%
Accurate Capital / Conventional Capital
5
4
3
2
1
0
0%
10%
20%
30%
40%
50%
Expected Loss Given Default
Alpha = 0.1%
Alpha = 0.5%

| A. Expected Performance of Two Loans | | | | | |
|---|---|---|---|---|---|
| 1. Overall Expectation | | | | | |
| | PD | x | ELGD | = | EL |
| First Loan | 5.00% | | 10% | | 0.50% |
| Second Loan | 1.00% | | 50% | | 0.50% |
| 2. Expectation in an Economic Slump; Target $\alpha$ = 0.10% | | | | | |
| | PD | x | ELGD | = | Capital |
| First Loan | 45.4% | | 26.1% | | 11.8% |
| Second Loan | 18.4% | | 60.2% | | 11.0% |
| 3. Economic Slump in a Conventional Credit Model | | | | | |
| | PD | x | ELGD | = | Capital |
| First Loan | 45.4% | | 10% | | 4.5% |
| Second Loan | 18.4% | | 50% | | 9.2% |




4. Capital Including Collateral Damage
18%
15%
12%
9%
6%
3%
0%
ELGD = 100%
ELGD = 50.0%
ELGD = 25.0%
ELGD = 12.5%
ELGD = 6.25%
0.025%
0.05%
0.10%
0.20%
0.40%
0.80%
1.60%
Expected Loss Rating Grade


5. Robustness with Conditional Beta Recovery
18%
15%
12%
9%
6%
3%
0%
ELGD = 100%
ELGD = 50.0%
ELGD = 25.0%
0.025%
0.05%
0.10%
0.20%
0.40%
0.80%
1.60%
Expected Loss Rating Grade

[1] We give broad meanings to two terms. "Collateral" here includes all the assets a bank obtains as a consequence of default, including, but not limited to, the assets pledged as collateral in a loan document. "Capital" refers to equity capital and to accumulated loan loss reserves, both of which help banks weather stressful periods.

[2] An example is a default on a real estate loan where the property is discovered to contain toxic waste that requires an expensive clean up.

[3] Conditional *EL*, conditional *PD*, and conditional *ELGD* refer to the expectation conditional on the realization of $X$. Given $X$, the expectation is taken across all $j$. When conditioning is clear from context, the modifier may be suppressed. Otherwise when the variables are not designated as "conditional," they have the usual meaning of an all-inclusive expectation.

[4] Some specific collateral, such as cash or Treasury securities, has a low value of $q$, but these cases are far from the norm.

[5] An Excel workbook with these results is available from the author: Jon.Frye@chi.frb.org

[6] Robustness checks with lower $q$ and/or lower $\sigma$ can include lower levels of *ELGD*. They reach the same conclusions about the relationship of *EL* to credit capital.

[7] Many CreditRisk+® users adjust model inputs now. They adjust *exposure* (rather than *PD*) downward as they adjust *ELGD* to unity, keeping the product equal to that of the original loan. This affects *ELGD* but not *PD*, so the *EL* of the proxy loan differs from the *EL* of the original. The difference in *EL* leads to the understatement of capital seen in figure 3. Mechanically, the understatement comes about because the downward adjustment of exposure dominates the upward adjustment of *ELGD*.