Credit Portfolio Loss Forecasts for Economic Downturns

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Recent studies find a positive correlation between default and loss given default rates of credit portfolios. In response, financial regulators require financial institutions to base their capital on 'Downturn' loss rates given default which are also known as Downturn LGDs. This article proposes a concept for the Downturn LGD which incorporates econometric properties of credit risk as well as the information content of default and loss given default models. The concept is compared to an alternative proposal by the Department of the Treasury, the Federal Reserve System and the Federal Insurance Corporation. An empirical analysis is provided for US American corporate bond portfolios of different credit quality, seniority and security.

I. INTRODUCTION

Economic downturns, such as the US subprime mortgage crisis in 2007, translate into unexpected losses to financial institutions as the number of borrowers who are unable to meet payment obligations increases and financial institutions are unable to recover these receivables. Generally speaking, financial institutions have a good understanding of default rates. However, recoveries or LGDs and therefore loss forecasts are often uncertain. It is the aim of this paper to develop a quantitative framework for deriving credit portfolio loss forecasts for economic downturns.

This exercise is important to financial institutions for meeting regulatory requirements. As a matter of fact, the Internal Ratings-Based (IRB) approach of the proposals of the Basel Committee on Banking Supervision derives the regulatory capital from a Value-at-Risk model in which individual credit risk parameters are based on economic downturn scenarios. As a result, probabilities of default (PDs) are based on a worst-case scenario of a single systematic factor and a conservative assumption of their sensitivities which are known as asset correlations. In addition, exposures at default and loss rates given default (LGDs) are modeled based on an economic downturn condition (see Basel Committee on Banking Supervision 2006, paragraph 468):

> 'A bank must estimate a LGD for each facility that aims to reflect economic downturn conditions where necessary to capture the relevant risks. This LGD cannot be less than the long-run default-weighted average loss rate given default calculated based on the average economic loss of all observed defaults within the data source for that type of

> facility. In addition, a bank must take into account the potential for the LGD of the facility to be higher than the default-weighted average during a period when credit losses are substantially higher than average [. . .].'

These requirements have recently caused confusion in the industry. They are considered to be vague which was only partially mitigated by the issue of a guidance note in relation to the process for assessing the affects of economic downturns and the appropriate discount rate for future recovery cash flows (see Basel Committee on Banking Supervision 2005).

In the past, various approaches to model LGDs were developed. The first generation of contributions identified the factors driving the values including correlations between PDs and LGDs (compare Carey 1998, Altman et al. 2005, Cantor & Varma 2005, Schuermann 2005, Acharya et al. 2007). The second generation developed and empirically applied frameworks to quantify the correlation between PDs and LGDs (compare Frye 2000, Pykhtin 2003, Tasche 2004, Düllmann & Trapp 2005, Rösch & Scheule 2005, Hamerle et al. 2007) and the latest generation derives concepts to stress LGDs for economic downturns. This stream of literature is relatively new as the analysis of economic downturns is traditionally done on a portfolio level and not a parameter level. However, the recent proposals by the Basel Committee on Banking Supervision have created the need to stress the loss given default or in other words calculate the 'Downturn LGD'. Barco (2007) extends work by Miu & Ozdemir (2006) empirically by first calculating the economic capital (based on the dependence structure between LGDs and PDs) and then deriving the Downturn LGD (based on the assumption of independence between LGDs and PDs). The findings are that a Downturn LGD depends on the expected LGD, correlation between PDs and LGDs and the confidence level at which the economic capital is sufficient to cover future credit losses.

In the US, the Department of the Treasury, the Federal Reserve System and the Federal Deposit Insurance Corporation (FDIC) propose a linear relationship between the Downturn LGD (BLGD) and the Expected LGD (ELGD) with a floor of 8% and a cap of 100% (compare Department of the Treasury, Federal Reserve System and Federal Insurance Corporation 2006):

$$BLGD_t = 0.08 + 0.92 \times ELGD_t \tag{1}$$

Banks often rely on this approach which will serve as a benchmark in this study.

This article builds upon these previous contributions by deriving an alternative proposal in which the loss given default is stressed in a manner consistent with the existing regulations and based on the business cycle as well as the dependence structure between PDs and LGDs. An analysis shows that empirical correlations between the two systematic risk drivers of default probabilities and LGDs are positive but less than perfect. The positive correlation may result from the asset value of a company which drives both the default and recovery process. Other factors may include timing differences of default and recovery processes, seniority levels and the nature of securities.

This contribution extends the existing literature by deriving a concept for Downturn LGDs which results in a practical formula in relation to the current proposals by the Basel Committee on Banking Supervision. This concept has the following advantages in comparison to previous initiatives:

- The degree to which risk segments are exposed and loss models reflect systematic risk is taken into account. Loss models may be based on estimates of long-run averages (known as through-the-cycle models) as well as estimates which include the future state of the business cycle (known as point-in-time models). Both approaches are accepted under the current regulations.
- The model is based on two latent correlated systematic risk drivers - one for the PDs and one for the LGDs. These random variables take into account that PDs and LGDs may be correlated.
- The availability of market prices is not required. Note that with regard to the model framework, a discussion on the accuracy of reduced form versus structural models exists. The models presented in this contribution are derived from a structural theory but applied as reduced form models which is consistent with the commercial banking industry where the availability of market prices for debt or equity is limited. According to the FDIC (www.fdic.org) commercial and industrial loans account for less than 20% of total loans of regulated US banks. In addition, only a fraction of the commercial and industrial loans may be linked to market prices for debt or equity.
- The approach is based on the expected loss given default and does not require the prior specification of the Value-at-Risk as suggested by previous contributions.

The rest of the paper is structured as follows. The next section develops the risk model for the PDs, the LGDs and the correlations between the two parameters based on the factor model which underlies the Basel IRB approach and is based on Gordy (2000) and Gordy (2003). The model estimation and application in a portfolio context is shown. The third section provides an empirical analysis on US American corporate bond portfolios and analyzes the impact on the economic and regulatory capital of financial institutions. The last section concludes and discusses the results and limitations of the presented research as well as extensions for future research.

II. FRAMEWORK

Parameters of the Default and Loss Given Default Process

Following work by Heitfield (2005), Rösch & Scheule (2005), McNeil & Wendin (2007) and Koopman & Lucas (2008), the default process and recovery process are based on an asset value model in which a default event occurs if the asset value return falls below a threshold. This article focuses on the default events, the recoveries given default and the correlations between these credit risk measures. It is common in literature to estimate the risk parameters given observable and unobservable information. Thus, conditional (ex post) as well as unconditional (ex ante) credit risk measures are differentiated.

The conditional probability of default (CPD) is based on an intercept γ_0, a vector of systematic risk drivers z_{t-1}^D and a standard normally distributed unobservable systematic factor F_t:

$$CPD_t(F_t) = \Phi\left(\frac{\gamma_0 + \gamma z_{t-1}^D - \omega F_t}{\sqrt{1-\omega^2}}\right) \tag{2}$$

F_t may be interpreted as the contemporaneous systematic information which is not captured by z_{t-1}^D. Therefore, F_t represents an additional source of uncertainty in the CPD which takes different states of the economy into account. This specification suggests that a favorable economic scenario, represented by positive realizations of F_t, reduces the CPD and vice versa. The sensitivity ω may be interpreted as the co-movement of the CPDs for given time periods.

$\sqrt{1-\omega^2}$ represents the variance of the standard normally distributed asset value return and $\Phi(\cdot)$ is the respective cumulative distribution function.

The unconditional PD is the expected value of Equation (2) and is given by

$$PD_t = \int_{-\infty}^{\infty} \Phi\left(\frac{\gamma_0 + \gamma z_{t-1}^D - \omega f_t}{\sqrt{1-\omega^2}}\right) d\Phi(f_t) = \Phi\left(\gamma_0 + \gamma z_{t-1}^D\right) \tag{3}$$

Note that it can be shown that ω^2 is the correlation between the asset returns which is also known as asset correlation (compare Rösch & Scheule 2005).

Similarly, the conditional recovery rate is based on an intercept β_0, systematic risk drivers z_{t-1}^R and a standard normally distributed unobservable systematic factor X_t:

$$R_t(X_t) = \Phi\left(\beta_0 + \beta z_{t-1}^R + bX_t\right) \tag{4}$$

Other contributions such as Schönbucher (2003), Düllmann & Trapp (2005) and Rösch & Scheule (2005) assume a logistic normal process for the recovery rates. The results of models which are based on the logistic transformation are comparable (see Hamerle et al. 2006). The conditional loss rate given default (CLGD) is then defined as

$$CLGD_t(X_t) = 1 - R_t(X_t) = 1 - \Phi\left(\beta_0 + \beta z_{t-1}^R + bX_t\right) \tag{5}$$

The unconditional loss rate given default (LGD) is given by

$$
\begin{aligned}
LGD_t &= 1 - \int_{-\infty}^{\infty} \Phi\big(\beta_0 + \beta z_{t-1}^R + bx_t\big)\, d\Phi(x_t) \\
&= 1 - \Phi\left(\big(\beta_0 + \beta z_{t-1}^R\big) \cdot \sqrt{\tfrac{1}{1+b^2}}\right)
\end{aligned} \tag{6}
$$

Extensions may incorporate additional borrower information into Equation (2) to Equation (6). Note that the parameters will change due to the nonlinear standard normal distribution function and heterogeneity of idiosyncratic information. For example, the inclusion of an idiosyncratic standard normally distributed risk driver $Z_i(i \in N$, where N is the set of borowers under consideration) with sensitivity δ results in a reparameterization of a systematic risk driver Y_t by a factor of $\frac{1}{\sqrt{1-\delta^2}}$:

$$
\Phi(Y_t) = \mathrm{E}\left(\Phi\left(\frac{Y_t + \delta \cdot Z_i}{\sqrt{1-\delta^2}}\right)\right) \tag{7}
$$

For simplicity, this paper focuses on economic downturns, i.e., systematic credit risk, and does not include idiosyncratic risk.

Downturn Loss Given Default

The Basel Committee on Banking Supervision (2006) provides in its Internal Ratings-Based Approach for retail and corporate credit exposures, a formula for the CPD based on Equation (2) and the assumption of a 'worst case' realization of the systematic random variable $f_t = 0.999$:

$$
CPD_t\big(f_t = \Phi^{-1}(0.999)\big) = \Phi\left(\frac{\Phi^{-1}(PD_t) + \omega\Phi^{-1}(0.999)}{\sqrt{1-\omega^2}}\right) \tag{8}
$$

Please note that the contemporaneous random factor enters the model with a positive sign and that a positive factor implies an economic downturn. Unfortunately, no formula is given for LGD which is to be modeled given an economic downturn scenario (Downturn LGD) as the model implies the independence of PDs and LGDs (compare Gordy 2000).

Therefore, we propose to base the Downturn LGD (DLGD) on the assumption for F_t in Equation (8), i.e., the 99.9th percentile of a standard normal distributed random variable. This implies that given this assumption, PDs and LGDs are independent and the VaR can be derived by a multiplication of CPD and DLGD as proposed by the Basel Committee on Banking Supervision (2006). Note that this definition results in the required independence between PDs and LGDs and implies that the regulatory capital covers the 99.9$^{\text{th}}$ percentile of future unexpected losses in the presence of a correlation between PDs and LGDs. Alternatively, the Downturn LGD may be derived based on the joint specification of a 'worst-case' realization of X_t which may require a reformulation of the existing Basel II framework.

The link between the recovery and default process is introduced by modeling the dependence of the two systematic risk factors F_t and X_t which are marginally normally distributed. We model their dependence by assuming that they are bivariately normally distributed with correlation parameter ρ. Alternatively, a copula which is different from the Gaussian copula may be assumed. The correlation equals one in the special case that a single systematic factor drives both the default events as well as the recovery rates given these events.

Therefore, according to the law of conditional expectation, the expected loss rate given default conditional on a 'worst case' realization of F_t is

$$DLGD_t(f_t) = 1 - \Phi\left(\mu(f_t) \cdot \sqrt{\frac{1}{1+\sigma(f_t)^2}}\right) \tag{9}$$

with the conditional mean of the average transformed recovery rate

$$\mu(f_t) = \beta_0 + \beta z_{t-1}^R + b\rho f_t \tag{10}$$

and the conditional standard deviation of the average transformed recovery rate

$$\sigma(f_t) = b\sqrt{1-\rho^2} \tag{11}$$

Figure 1 shows the resulting CPD, LGD and CLGD for a risk segment which is analyzed in Section 3. The conditional loss rates given default (CLGD) is higher (lower) than LGD for a low (high) f_t, i.e., during economic downturns (upturns).

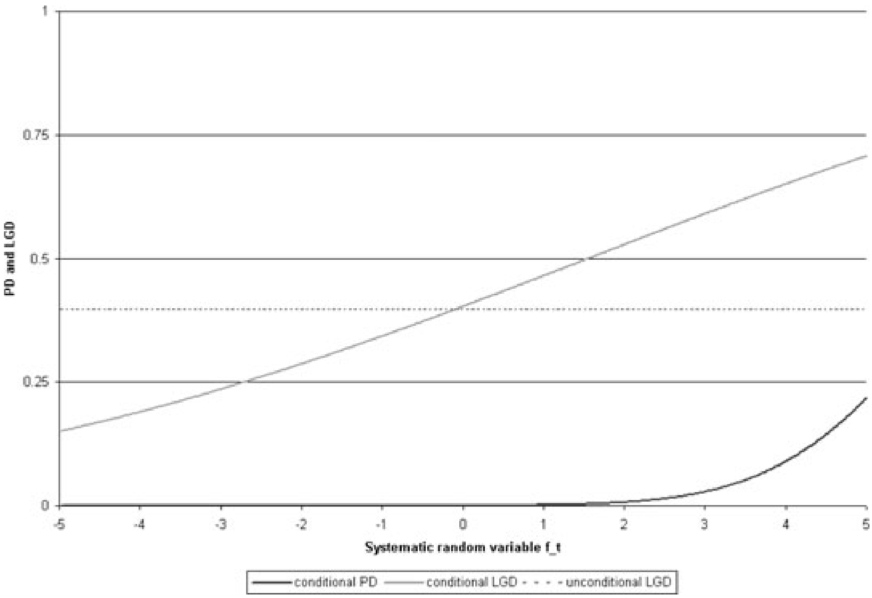
Equation (9) can be expressed in terms of the unconditional LGD which may be more practical for an implementation in the proposals by the Basel Committee on Banking Supervision:

$$\begin{aligned} &DLGD_t(f_t = \Phi^{-1}(0.999)) \\ &= \Phi\left(\left(\Phi^{-1}(LGD_t) \cdot \sqrt{1+b^2} + b\rho\Phi^{-1}(0.999)\right) \cdot \sqrt{\frac{1}{1+b^2(1-\rho^2)}}\right) \end{aligned} \tag{12}$$

Generally speaking, Equation (12) is based on a bank's loan risk characteristics, simple to implement and consistent with the existing proposed regulatory regime. Regulators may assist financial institutions in the specification of the sensitivity of the unknown systematic risk drivers b as well as the correlation ρ in instances where data may limit the estimation of these parameters (compare Basel Committee on Banking Supervision 2005). For example, a conservative solution may involve a ρ which is equal to one.

Parameter Estimation

The described model consists of a limited set of parameters (γ_0, β_0, γ, β, ω, b and ρ). These parameters can be estimated from observable data by maximizing



Notes: Based on the through-the-cycle modeling methodology, investment grade rated issuers and senior secured issues of the data set analyzed in Section 3 (i.e., $\hat{\gamma}_0 = -3.133$, $\hat{\omega} = 0.491$, $\hat{\beta}_0 = 0.245$, $\hat{b} = 0.362$ *and* $\hat{\rho} = 0.702$*).*

Figure 1: Conditional probability of default, unconditional loss rate given default and conditional loss rate given default given the realization f_t.

the log-likelihood over all borrowers and periods using adaptive Gauss-Hermite-quadrature (compare Pinheiro & Bates 1995, Rabe-Hesketh et al. 2002).

The log-likelihood is

$$LL = \sum_{t=1}^{T} \ln\left(\int_{-\infty}^{\infty} LL^D(f_t) \cdot LL^R(f_t) d\Phi(f_t)\right) \tag{13}$$

The likelihood in relation to the observed default rate is

$$LL^D(f_t) = \binom{n_t}{d_t} CPD(f_t)^{d_t} (1 - CPD(f_t))^{n_t - d_t} \tag{14}$$

where n_t denotes the number of entities, and d_t denotes the number of defaulters within year t. The likelihood in relation to the observed recovery rate is

$$LL^R(f_t) = \frac{1}{\sigma(f_t)\sqrt{2\pi}} \exp\left\{ - \frac{\left[\Phi^{-1}(RR_t) - \mu(f_t)\right]^2}{2[\sigma(f_t)]^2} \right\} \tag{15}$$

with CPD(f_t) from Equation (2), $\mu(f_t)$ from Equation (10) and $\sigma(f_t)$ from Equation (11). Note that the distribution of X_t is explicitly included in the log-likelihood function.

Credit Portfolio Risk Model

Credit portfolio risk may be measured as the expectation (Expected Loss) or a percentile of future credit portfolio losses (Value-at-Risk). The distribution of future credit portfolio losses is based on a risk model with parameters such as the PD, LGD, exposure at default as well as correlations between the respective random risk parameters. Additional measures for credit portfolio risk such as Unexpected Loss (i.e., the difference between the Value-at-Risk and Expected Loss) or Expected Shortfall (i.e., the expected value of losses exceeding the Value-at-Risk) may be derived.

In the empirical section, the resulting Basel II Value-at-Risk is compared to the economic Value-at-Risk. The later is derived from a model which generates a distribution for the future credit loss. In this model, the portfolio is infinitely granular and the portfolio loss rate depends only on the systematic risk factors (as well as observable information):

$$L_t(F_t, X_t) = CPD_t(F_t) \times LGD_t(X_t) \tag{16}$$

The Figures 2 and 3 show the density distributions and the resulting credit portfolio losses for the random systematic variables for a risk segment which is analyzed in Section 3:

The density and loss distributions for the random systematic variables F_t and X_t may be aggregated to a loss distribution. Figure 4 shows the resulting loss distribution and derived measures for credit portfolio risk such as Expected Loss or Value-at-Risk.

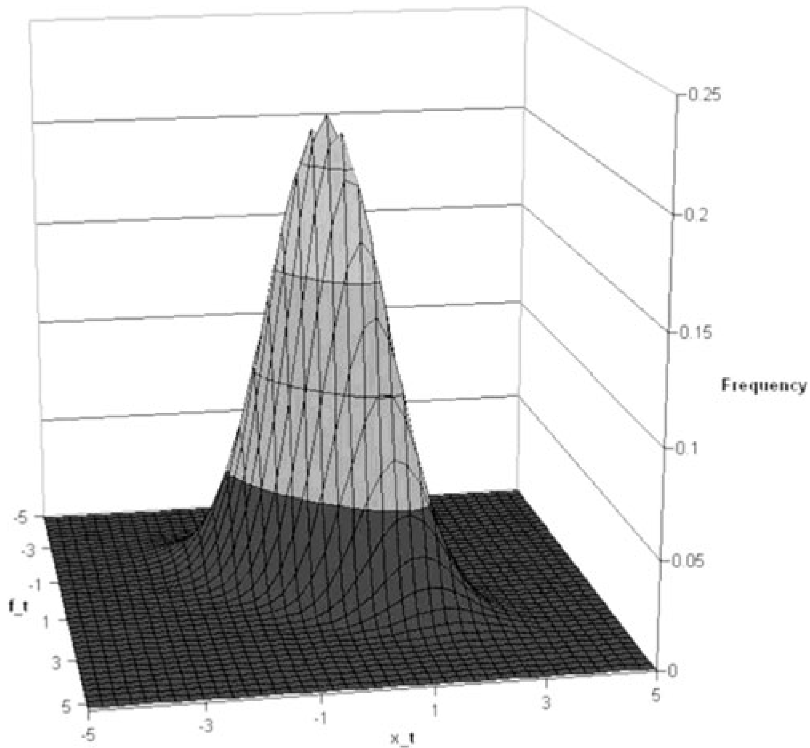
III. US AMERICAN CORPORATE BOND PORTFOLIOS

Data

The empirical analysis is based on the global corporate bond issuer default and bond issue recovery rates published by Moody's (2007). In this data set, default rates are calculated as the ratio of defaulted and total number of rated issuers for a given period. A default is in essence recorded if

- Interest and/or principal payments are missed or delayed,
- Chapter 11 or Chapter 7 bankruptcy is filed, or
- Distressed exchange such as a reduction of the financial obligation occurs.

A default rate is defined as the ratio of the number of issuers who defaulted during the year and the total number of issuers at the beginning of the year. The default rates are published for different rating categories such as investment grade (i.e.,

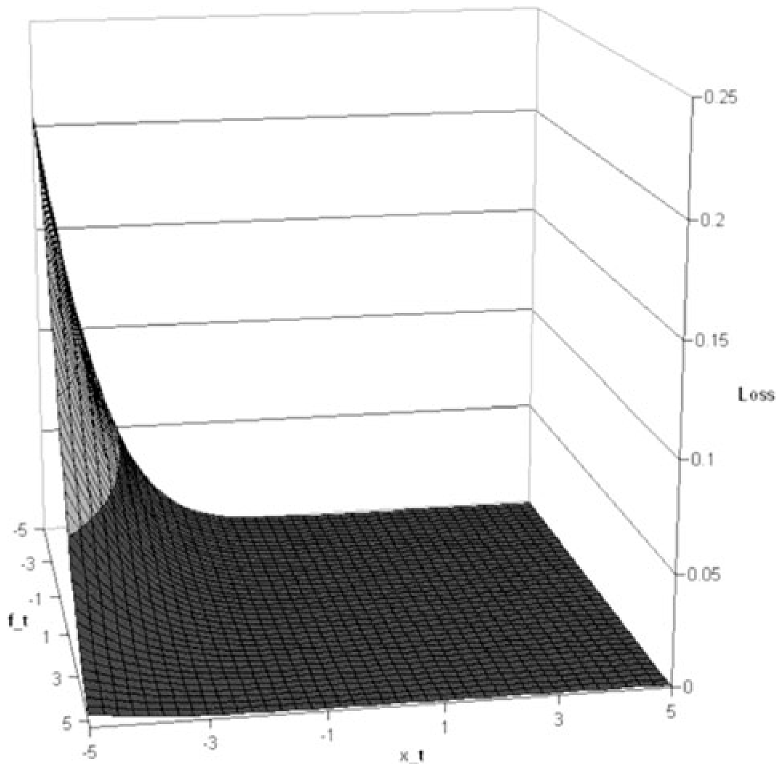


Notes: Based on the through-the-cycle modeling methodology, investment grade rated issuers and senior secured issues of the data set analyzed in Section 3 (i.e., $\hat{\gamma}_0 = -3.133$, $\hat{\omega} = 0.491$, $\hat{\beta}_0 = 0.245$, $\hat{b} = 0.362$ *and* $\hat{\rho} = 0.702$*).*

Figure 2: Frequency distributions for the systematic random variables F_t and X_t.

rating Baa or better; abbreviated 'IG'), Ba, B, Caa to C. Figure 5 shows the number of issuers rated by Moody's rating agency per rating category.

Most defaults are related to publicly traded debt issues. Therefore, Moody's defines a recovery rate as the ratio of the price of defaulted debt obligations after 30 days of the occurrence of a default event and the par value. The recovery rates are published for different levels of seniority and security such as senior secured (SSEC), senior unsecured (SUSEC), senior subordinated (SSUB), subordinated (SUB) and junior subordinated debt. We excluded junior subordinated recovery rates from the analysis due to a high number of missing values. Figure 6 shows the default and recovery rates for all issuers and defaulted issues. The variables fluctuate in opposite directions over time. This signals that defaults and recoveries and therefore LGDs show considerable systematic risk which may be explained by time-varying variables.

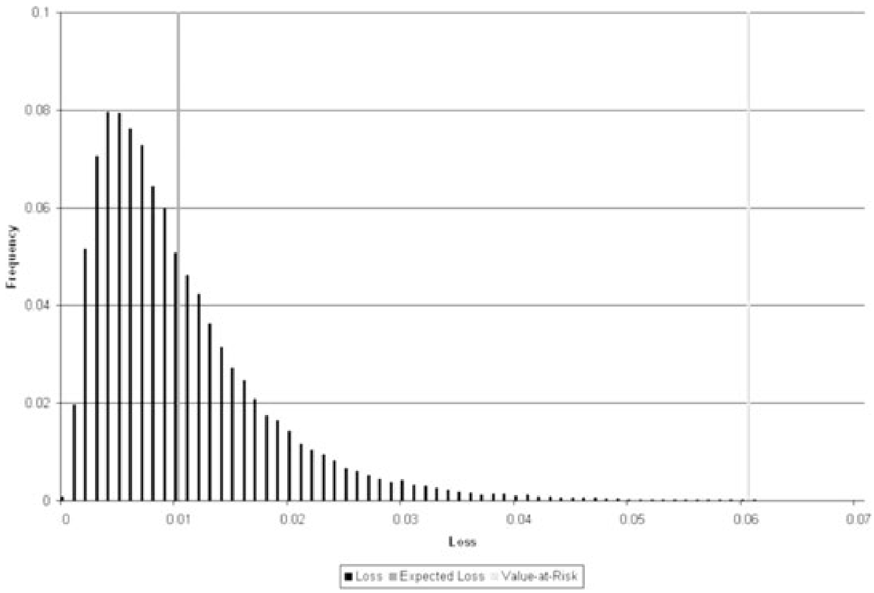


Notes: Based on the through-the-cycle modeling methodology, investment grade rated issuers and senior secured issues of the data set analyzed in Section 3 (i.e., $\hat{\gamma}_0 = -3.133$, $\hat{\omega} = 0.491$, $\hat{\beta}_0 = 0.245$, $\hat{b} = 0.362$ *and* $\hat{\rho} = 0.702$*).*

Figure 3: Loss distribution for the systematic random variables F_t and X_t.

Following Rösch & Scheule (2005), the composite indices published by The Conference Board (www.tcb-indicators.org) were chosen as macroeconomic systematic risk drivers, i.e., the

- Index of 4 coincident indicators (COINC) which measures the current state of the U.S. economy. The index includes the number of employees on non agricultural payrolls, personal income less transfer payments, index of industrial production and manufacturing as well as trade sales.
- Index of 10 leading indicators (LEAD) which measures the future state of the U.S. economy. The index includes average weekly hours in manufacturing, average weekly initial claims for unemployment insurance, manufacturers' new orders of consumer goods and materials, vendor performance, manufacturer's new orders of non-defense capital goods, building permits for new



Notes: Expected Loss is the expected value and the Value-at-Risk is the 99.9th percentile of the random variable loss. Based on the through-the-cycle modeling methodology, investment grade rated issuers and senior secured issues of the data set analyzed in Section 3 (i.e., $\hat{\gamma}_0 = -3.133$, $\hat{\omega} = 0.491$, $\hat{\beta}_0 = 0.245$, $\hat{b} = 0.362$ *and* $\hat{\rho} = 0.702$*).*

Figure 4: Loss distribution.

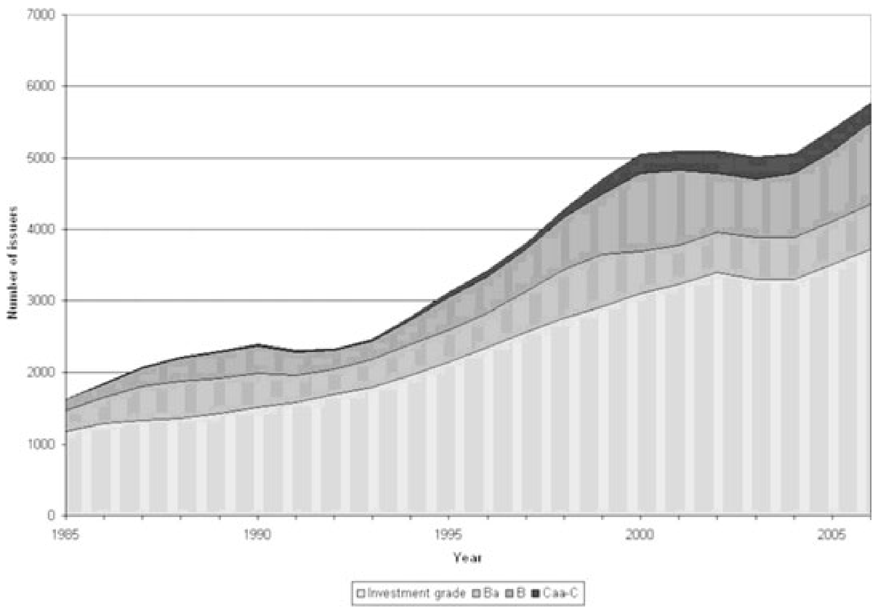
private housing units, stock price index, money supply, interest rate spread of 10-year treasury bonds less federal funds and consumer expectations.

These indices are generally recognized as indicators for the U.S. business cycle. Note that for the analysis, growth rates of the indices were calculated and lagged by three months. Due to a limited number of defaults in previous years, the compiled data set was restricted to a time period from 1985 to 2006. Table 1 includes descriptive statistics of the variables.

It can be seen that default rates increase with lower credit quality and that recovery rates decrease with a lower level of credit protection by seniority or security. The default rates for different rating classes as well as the recovery rates for different seniority/security classes are positively correlated while default and recovery rates are negatively correlated.

Parameter Estimation

In the first step, a model without any time-varying risk drivers is estimated. Since no time-varying information is included, PDs and recoveries given default are



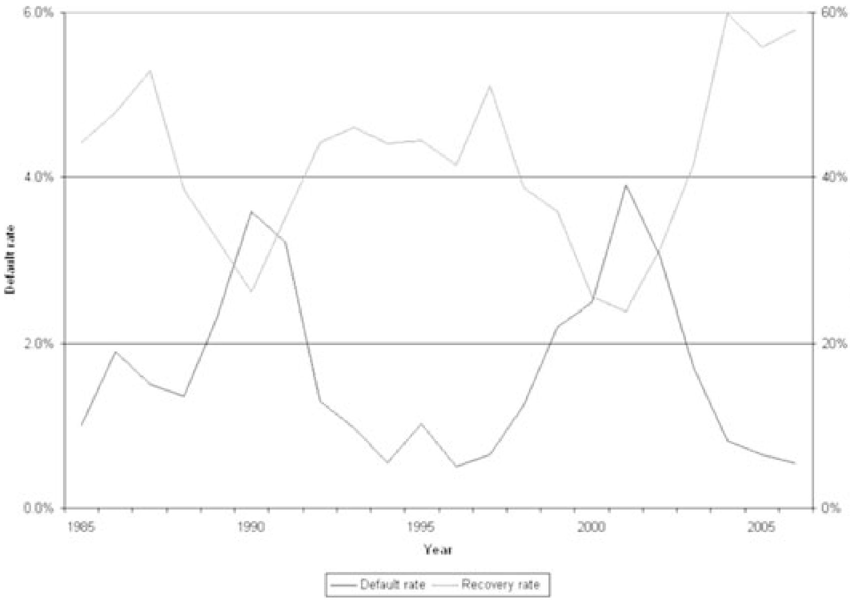
Notes: Alphanumeric rating categories are aggregated; investment grade: ratings Aaa to Baa3, Ba: ratings Ba1 to Ba3, B: ratings B1 to B, Caa-C: ratings Caa1 to C.

Figure 5: Number of issuers rated by moody's per rating category.

averaged over the business cycle. Such a model is often called a through-the-cycle model. In the second step, the default rates and LGDs will be modeled by time-lagged macroeconomic risk drivers. Such a model is often called a point-in-time model. In order to compare credit portfolio risk measures from a through-the-cycle and a point-in-time model, it is assumed that the realizations of the observable systematic risk drivers equal the historic average (compare Table 1).

The following discussion is based on the degree of the macroeconomic impact on credit risk which is not reflected by observable information in the models and therefore captured by the random variables F_t and X_t and the sensitivity of the default process ω, the sensitivity of the recovery process b and the correlation ρ. These parameters are shown in the Tables 2, 3 and 4. The complete parameter sets with standard errors and significance are included in Section 5 (Appendix).

It can be seen that a point-in-time methodology reduces the exposure to the unknown systematic risk factors (ω and b) while the correlations ρ may change in either direction. The correlations between the asset value returns and the transformed recovery rates are generally positive with values between -0.071 and 0.851. The dependence between the default and recovery process is highest for investment grade and Caa-C issuers and senior issues.



Notes: Default rates are ratios of the number of defaulted issuers and the total number of issuers. Recovery rates are ratios of the price of defaulted debt obligations after 30 days of the occurrence of a default event and the par value.

Figure 6: Default rates for all issuers and recovery rates for all defaulted issues.

One combination with high estimates for b and ρ is the rating category Caa-C and seniority/security class SSEC. The following section will return to this point.

Implications on the Economic and Regulatory Capital of Financial Institutions

The PDs and CPDs are calculated. The conditional probabilities are based on a worst-case scenario for the systematic random variable, i.e., $f_t = -\Phi^{-1}$ (0.999) and the empirical asset correlations as well as the asset correlations proposed by the Basel Committee on Banking Supervision (Basel II CPD). Table 5 shows the PDs. Asset correlations for the different rating classes are shown in Table 6.

It is consistent with previous literature that PDs are increasing with lower credit quality and LGDs are increasing with lower seniority or security. The asset correlations are lower for the point-in-time than for the through-the-cycle modeling methodology. Both the PDs and LGDs are similar for the two methodologies as the point-in-time models are based on average realizations for the macroeconomic variables. However, a point-in-time model will lead in an economic recession to higher-than-average probabilities of default as well as lower-than-average recovery rates and vice versa for an economic boom.

Table 1: Descriptive statistics of variables; US corporate bonds

Variable	Mean	Median	Max.	Min.	Std.	Skew.	Kurt.
IG	0.001	0.001	0.005	0.000	0.001	2.644	7.437
Ba	0.013	0.009	0.054	0.001	0.013	1.707	3.221
B	0.062	0.059	0.162	0.008	0.043	0.808	0.309
CaaC	0.211	0.203	0.588	0.001	0.127	1.053	2.481
SSEC	0.591	0.610	0.836	0.357	0.137	0.039	−1.111
SUSEC	0.460	0.460	0.628	0.218	0.117	−0.496	−0.328
SSUB	0.372	0.367	0.519	0.203	0.097	−0.166	−1.180
SUB	0.356	0.347	0.829	0.123	0.160	1.048	2.420
LEAD	0.032	0.039	0.076	−0.037	0.028	−0.885	0.708
COINC	0.023	0.024	0.049	−0.017	0.017	−0.772	0.039

Notes: IG, Ba, B and Caa-C are default rates; SSEC, SUSEC, SSUB and SUB are recovery rates; LEAD and COINC are time-lagged growth rates of macroeconomic indicators.

Table 2: Estimates for parameter ω for different rating categories, seniority/security categories and rating methodologies

	SSEC	SUSEC	SSUB	SUB
Through-the-cycle				
IG	0.491	0.467	0.457	0.468
Ba	0.347	0.361	0.354	0.352
B	0.355	0.357	0.358	0.358
Caa-C	0.364	0.291	0.314	0.313
Point-in-time				
IG	0.465	0.450	0.425	0.442
Ba	0.295	0.304	0.292	0.296
B	0.323	0.325	0.325	0.325
Caa-C	0.282	0.237	0.262	0.254

Notes: All parameter estimates with standard errors and significance are included in Section 5 (Appendix).

The LGDs are calculated based on three definitions: LGD according to Equation (6), CLGD according to Equation (12) (CLGD) and the benchmark loss rate given default according the proposal by Department of the Treasury, Federal Reserve System and Federal Insurance Corporation (2006) which is shown in Equation (1) (BLGD). Table 7 displays these values for different modeling methodologies and seniority/security classes.

The LGDs for ELGD are lower than for BLGD which are lower than for CLGD. The charts in Figure 7 compare CLGD and BLGD in dependence of ELGD as well as the sensitivity to the random systematic risk driver b (first column) and the correlation between the default and loss given default process ρ (second column).

Table 3: Estimates for parameter b for different rating categories, seniority/security categories and rating methodologies

	SSEC	SUSEC	SSUB	SUB
Through-the-cycle				
IG	0.362	0.302	0.260	0.455
Ba	0.362	0.302	0.260	0.455
B	0.362	0.302	0.260	0.455
Caa-C	0.378	0.302	0.260	0.456
Point-in-time				
IG	0.306	0.285	0.239	0.395
Ba	0.306	0.285	0.239	0.395
B	0.306	0.285	0.239	0.395
Caa-C	0.308	0.285	0.239	0.395

Notes: All parameter estimates with standard errors and significance are included in Section 5 (Appendix).

Table 4: Estimates for parameter ρ for different rating categories, seniority/security categories and rating methodologies

	SSEC	SUSEC	SSUB	SUB
Through-the-cycle				
IG	0.702	0.566	0.456	0.372
Ba	0.510	0.391	0.158	0.409
B	0.547	0.455	0.203	0.468
Caa-C	0.810	0.766	0.297	0.528
Point-in-time				
IG	0.851	0.586	0.502	0.327
Ba	0.330	0.248	−0.071	0.216
B	0.414	0.365	0.041	0.327
Caa-C	0.705	0.744	0.111	0.362

Notes: All parameter estimates with standard errors and significance are included in Section 5 (Appendix).

The first chart for a given column shows that according to the framework presented in this paper, CLGD is an increasing nonlinear function of ELGD, b and ρ. The second chart for a given column shows that BLGD is an increasing linear function of ELGD with a cap of 8% and a maximum of 100%. The third chart shows the difference between CLGD and BLGD. It can be seen that CLGD exceeds BLGD in most instances, particularly where

- The sensitivity to the random systematic risk driver b (first column) is high;
- The correlation between the default and loss given default process is high; and
- The loss given default rates are close to 50%.

Table 5: Unconditional, conditional and conditional Basel II probabilities of default

	IG	Ba	B	Caa-C
Through-the-cycle				
PD	0.001	0.013	0.061	0.202
CPD	0.030	0.105	0.313	0.622
Basel II CPD	0.031	0.156	0.314	0.600
Point-in-time				
PD	0.001	0.011	0.058	0.190
CPD	0.020	0.075	0.273	0.497
Basel II CPD	0.023	0.149	0.308	0.582

Notes: PD is calculated using Equation (3). CPD is calculated using Equation (2). Basel II CPD is calculated by replacing the estimated parameter $\hat{\omega}$ by the square root of the asset correlation proposed by the Basel Committee on Banking Supervision. The numbers are based on the through-the-cycle as well as point-in-time modeling methodology for senior secured bonds.

Table 6: Empirical and Basel II asset correlations; point-in-time modeling methodology

	IG	Ba	B	Caa-C
Through-the-cycle				
Empirical asset correlation	0.241	0.121	0.126	0.132
Basel II asset correlation	0.235	0.184	0.126	0.120
Point-in-time				
Empirical asset correlation	0.216	0.087	0.104	0.079
Basel II asset correlation	0.237	0.188	0.127	0.120

Notes: Empirical asset correlations are calculated by $\hat{\omega}^2$. The numbers are based on the through-the-cycle as well as point-in-time modeling methodology for senior secured bonds.

In other words, financial institutions may consider applying an econometric definition for the Downturn LGDs such as CLGD for risk segments which show these characteristics. Examples may be corporate loans to cyclical industries or retail credit card loans.

In the next step, the Expected Loss and Value-at-Risk are calculated based on the estimated parameters and shown in Table 8 and Table 9.

It is the requirement of regulators that the equity and provisions of a financial institution should cover the Value-at-Risk. Note that the Expected Loss should be covered by provisions. The difference between Value-at-Risk and Expected Loss which is also known as Credit-Value-at-Risk should be covered by Tier I

Table 7: Estimated loss rates given default

	SSEC	SUSEC	SSUB	SUB
Through-the-cycle				
ELGD	0.409	0.541	0.628	0.640
CLGD	0.700	0.732	0.754	0.801
BLGD	0.456	0.578	0.658	0.670
Point-in-time				
ELGD	0.407	0.541	0.629	0.643
CLGD	0.710	0.728	0.756	0.772
BLGD	0.455	0.578	0.658	0.670

Notes: ELGD is based on Equation (6), CLGD is based on Equation (12) and BLGD is based on Equation (1). The numbers are based on the through-the-cycle as well as point-in-time modeling methodology for investment grade rated issuers.

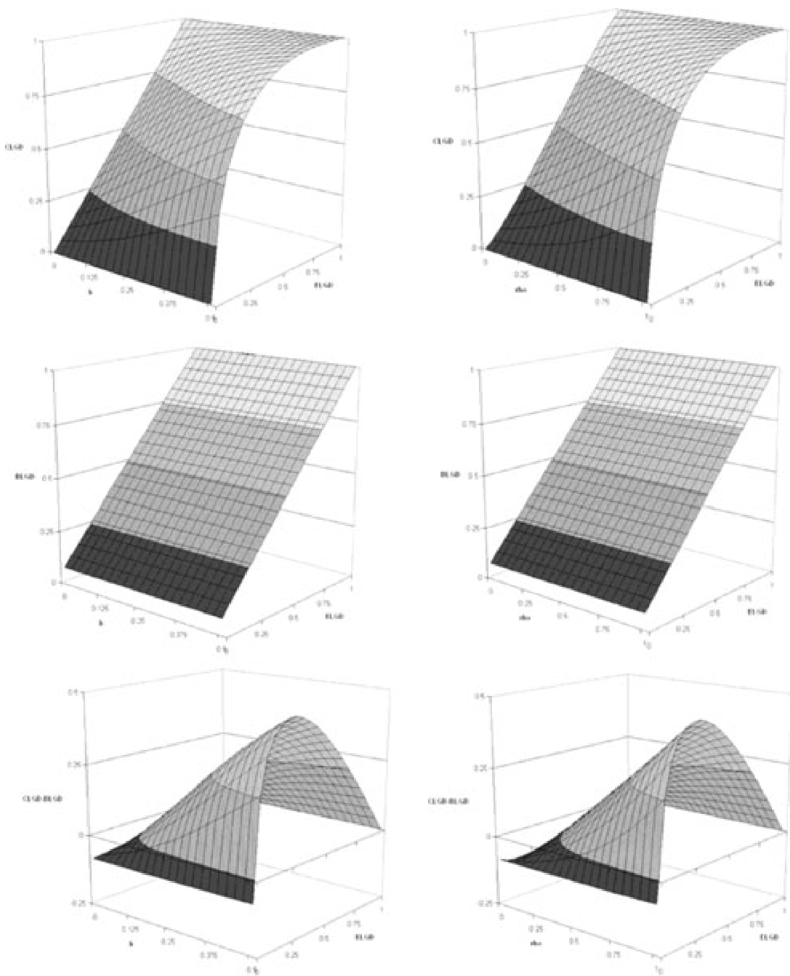
and Tier II capital (compare Laeven & Majnoni 2003). It is interesting to analyze whether the Basel II Value-at-Risk based on ELGD, BLGD and CLGD covers the Value-at-Risk. All three concepts involve a miss-specification embedded in the CPDs and/or the LGDs:

- All Basel II Value-at-Risk definitions: Asset correlations are pre-specified by Basel Committee on Banking Supervision (2006) and may not reflect the empirical values. As a results the CPDs may be miss-specified;
- Basel II Value-at-Risk based on ELGD: ELGD does not reflect the positive correlation between the default and loss rate given default processes;
- Basel II Value-at-Risk based on BLGD: BLGD is a linear increase of the loss rates based on the observation that LGDs should be higher in economic downturns and bounded between 8% and 100%.

Therefore, it is interesting to identify the LGD concept which covers the Value-at-Risk best. Table 10 shows the Basel II Value-at-Risk for ELGD, Table 11 for CLGD and Table 12 for BLGD. The results are reported for the different combinations of rating and seniority/security classes.

Due to the lower systematic uncertainty of a point-in-time model, the Value-at-Risk is lower than in a through-the-cycle model. This is generally not true for the Basel II regulatory capital where the sensitivities to systematic risk are pre-specified and therefore independent of the modeling methodology. Table 13 compares the differences between the different Basel Value-at-Risk definitions and the Value-at-Risk.

The percentages of Value-at-Risk shortfalls, i.e., instances where the Basel-II Value-at-Risk does not cover the Value-at-Risk, are 50% (ELGD), 12.5% (CLGD) and 42.5% (BLGD). All frameworks perform generally better for point-in-time



Notes: The first column shows the Downturn LGD in dependence of the expected LGD (ELGD) and the sensitivity to the business cycle b (assumption $\rho = 1$); the second column shows the Downturn LGD in dependence of the expected LGD and the correlation between the default and loss process rho (assumption $b = 1$); the first row shows that the conditional loss rate given default (CLGD) is a nonlinear function of ELGD and b and ρ; the second row shows that the proposal by the Department of the Treasury, Federal Reserve System and Federal Insurance Corporation (2006) is a linear function of ELGD and independent of b. The third row shows the difference between CLGD (first row) and BLGD (second row).

Figure 7: Comparison of different downturn LGD definitions in dependence of the expected LGD, b and ρ.

Table 8: Expected Loss

	SSEC	SUSEC	SSUB	SUB
Through-the-cycle				
IG	0.001	0.001	0.001	0.001
Ba	0.006	0.007	0.008	0.009
B	0.028	0.035	0.039	0.042
Caa-C	0.095	0.104	0.126	0.135
Point-in-time				
IG	0.000	0.000	0.000	0.000
Ba	0.005	0.006	0.007	0.008
B	0.026	0.033	0.037	0.040
Caa-C	0.084	0.101	0.123	0.128

Notes: Assumption of a portfolio exposure of one and an infinitely granular portfolio. The numbers are based on the through-the-cycle as well as point-in-time modeling methodology for different combinations of rating and seniority/security classes.

Table 9: Value-at-Risk

	SSEC	SUSEC	SSUB	SUB
Through-the-cycle				
IG	0.021	0.020	0.017	0.022
Ba	0.072	0.077	0.076	0.092
B	0.213	0.242	0.226	0.281
Caa-C	0.488	0.401	0.406	0.487
Point-in-time				
IG	0.014	0.015	0.011	0.015
Ba	0.044	0.050	0.047	0.059
B	0.164	0.200	0.184	0.228
Caa-C	0.346	0.336	0.330	0.386

Notes: Assumption of a portfolio exposure of one and an infinitely granular portfolio. The numbers are based on the through-the-cycle as well as point-in-time modeling methodology for different combinations of rating and seniority/security classes.

models. As a result, CLGD may dominate the other loss concepts in accuracy and may therefore be of interest to financial institutions and regulators.

IV. DISCUSSION

Financial institutions are faced with the challenge of forecasting future credit portfolio losses. It is common practice to focus on a limited set of parameters, such as the probability of default, asset correlation, loss rate given default or exposure at default. Risk models are developed for the credit portfolio loss as well as the underlying parameters (probabilities of default and loss rates given default).

Table 10: Basel II Value-at-Risk; loss rate given default definition: ELGD

	SSEC	SUSEC	SSUB	SUB
Through-the-cycle				
IG	0.013	0.015	0.018	0.019
Ba	0.064	0.085	0.098	0.100
B	0.128	0.170	0.198	0.202
Caa-C	0.249	0.306	0.371	0.382
Point-in-time				
IG	0.009	0.013	0.014	0.015
Ba	0.061	0.081	0.094	0.096
B	0.125	0.167	0.194	0.199
Caa-C	0.238	0.304	0.369	0.377

Notes: The Basel II Value-at-Risk is calculated by multiplying the conditional Basel II PD and ELGD. The numbers are based on the through-the-cycle as well as point-in-time modeling methodology for different combinations of rating and seniority/security classes.

Table 11: Basel II Value-at-Risk; loss rate given default definition: CLGD

	SSEC	SUSEC	SSUB	SUB
Through-the-cycle				
IG	0.022	0.021	0.021	0.024
Ba	0.097	0.106	0.106	0.128
B	0.200	0.219	0.217	0.263
Caa-C	0.454	0.448	0.421	0.510
Point-in-time				
IG	0.016	0.018	0.016	0.018
Ba	0.078	0.093	0.091	0.109
B	0.171	0.204	0.198	0.238
Caa-C	0.385	0.435	0.387	0.460

Notes: The Basel II Value-at-Risk is calculated by multiplying the conditional Basel II PD and CLGD. The numbers are based on the through-the-cycle as well as point-in-time modeling methodology for different combinations of rating and seniority/security classes.

The paper developed a framework which resulted in a closed-end, consistent and simple definition of the Downturn LGD. This concept was compared to the LGDs and an alternative definition put forward by the Department of the Treasury, Federal Reserve System and Federal Insurance Corporation (2006). The results provide evidence for the accuracy of this proposal. Remaining inaccuracies were attributed to the miss-specification of asset correlations.

The empirical analysis may be limited as data was only available for portfolios of borrowers but not for individual borrowers. It has been pointed out that the LGDs depend on many factors such as default criteria, degree of subordination,

Table 12: Basel II Value-at-Risk; loss rate given default definition: BLGD

	SSEC	SUSEC	SSUB	SUB
Through-the-cycle				
IG	0.014	0.016	0.019	0.020
Ba	0.071	0.091	0.103	0.105
B	0.143	0.182	0.208	0.211
Caa-C	0.277	0.327	0.389	0.399
Point-in-time				
IG	0.011	0.014	0.014	0.016
Ba	0.068	0.087	0.098	0.100
B	0.140	0.178	0.204	0.207
Caa-C	0.265	0.325	0.387	0.394

Notes: The Basel II Value-at-Risk is calculated by multiplying the conditional Basel II PD and BLGD. The numbers are based on the through-the-cycle as well as point-in-time modeling methodology for different combinations of rating and seniority/security classes.

Table 13: Average differences between regulatory (Basel II Value-at-Risk) and economic (Value-at-Risk) credit portfolio risk as well as Basel II shortfalls

	Value-at-Risk difference	Basel II shortfall (#)
Through-the-cycle		
ELGD	−0.045	12
CLGD	0.007	5
BLGD	−0.035	9
Point-in-time		
ELGD	−0.004	8
CLGD	0.031	0
BLGD	0.005	8

Notes: Value-at-Risk difference is the difference between the average risk segment weighted Basel II Value-at-Risk and Value-at-Risk. Basel II shortfall is the number of risk segments in which the Basel II Value-at-Risk does not cover the Value-at-Risk.

value of collateral, industry and the business cycle. The present study focused on categories of seniority and security and may be refined by future research. The framework is open to any level of information as long as data on historic default and recovery rates are available.

It should be noted that banks may have to exercise caution when deriving Expected Losses for provisioning and regulatory capital. Specific and general provisioning aim to cover the Expected Losses while regulatory capital aims to cover the Unexpected Losses (i.e., the difference between the Value-at-Risk and the Expected Loss). This implies that regulatory capital and provisioning may have to be based on the same loss model.

With regard to the stability of the financial system, these models have to be approved by regulators who have an interest in a conservative assessment of the credit portfolio risk and require stress-testing of risk estimates. The development of a stress-test framework may complement the downturn definition (and thus the Value-at-Risk concept) and may be a new and interesting area of research.

A potential implementation of the proposed formula (Equation 12) may need the guidance by the regulator by specifying parameters which may require a sufficient loss history in relation to the time dimension. Therefore, we would like to encourage fellow researchers to conduct similar empirical studies for other borrower and/or product types and share their experience, feedback and results.

V. APPENDIX

THROUGH-THE-CYCLE MODELING METHODOLOGY

Estimated parameters: through-the-cycle modeling methodology

Rating	**Seniority**	$\hat{c}$	$\hat{w}$	$\hat{\beta}_0$	$\hat{b}$	$\hat{\rho}$
IG	SSEC	−3.133	0.491	0.245	0.362	0.702
		0.182	0.114	0.077	0.055	0.157
		***	***	***	***	***
	SUSEC	−3.166	0.466	−0.108	0.302	0.566
		0.168	0.112	0.064	0.046	0.179
		***	***		***	***
	SSUB	−3.168	0.457	−0.337	0.260	0.456
		0.163	0.110	0.056	0.039	0.212
		***	***	***	***	**
	SUB	−3.151	0.468	−0.395	0.455	0.372
		0.171	0.114	0.097	0.069	0.257
		***	***	***	***	0.000
Ba	SSEC	−2.241	0.347	0.245	0.362	0.510
		0.092	0.062	0.077	0.055	0.186
		***	***	***	***	**
	SUSEC	−2.235	0.361	−0.108	0.302	0.391
		0.096	0.066	0.064	0.046	0.199
		***	***		***	*
	SSUB	−2.236	0.354	−0.337	0.260	0.158
		0.094	0.064	0.056	0.039	0.231
		***	***	***	***	0.000
	SUB	−2.237	0.352	−0.395	0.455	0.409
		0.093	0.063	0.097	0.069	0.207
		***	***	***	***	*
B	SSEC	−1.549	0.355	0.245	0.362	0.547
		0.084	0.051	0.077	0.055	0.161
		***	***	***	***	***

(Continued)

(Continued)

Rating	Seniority	$\hat{c}$	$\hat{w}$	$\hat{\beta}_0$	$\hat{b}$	$\hat{\rho}$
	SUSEC	−1.548	0.357	−0.108	0.302	0.455
		0.085	0.051	0.064	0.046	0.176
		***	***		***	**
	SSUB	−1.544	0.358	−0.337	0.260	0.203
		0.085	0.051	0.056	0.039	0.211
		***	***	***	***	0.000
	SUB	−1.545	0.358	−0.395	0.455	0.468
		0.085	0.051	0.097	0.069	0.175
		***	***	***	***	**
Caa-C	SSEC	−0.834	0.364	0.229	0.378	0.810
		0.050	0.059	0.063	0.058	0.100
		***	***	***	***	***
	SUSEC	−0.913	0.291	−0.106	0.302	0.766
		0.069	0.049	0.062	0.044	0.131
		***	***		***	***
	SSUB	−0.853	0.314	−0.337	0.260	0.297
		0.075	0.055	0.055	0.039	0.241
		***	***	***	***	0.000
	SUB	−0.844	0.313	−0.397	0.456	0.528
		0.073	0.059	0.095	0.069	0.179
		***	***	***	***	***

*Notes: First row: Parameter estimates, second row: standard errors, third row: significance; *: significant at 10%-level, **: significant at 5%-level, ***: significant at 1%-level.*

Point-in-time Modeling Methodology

Estimated parameters: point-in-time modeling methodology

Rating	Seniority	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{w}$	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{b}$	$\hat{\rho}$
IG	SSEC	−2.937	−9.686	0.465	0.032	6.746	0.306	0.851
		0.201	4.969	0.113	0.085	1.705	0.046	0.114
		***	*	***		***	***	***
	SUSEC	−3.094	−4.102	0.450	−0.220	3.541	0.285	0.585
		0.200	6.396	0.115	0.087	1.968	0.043	0.184
		***		***	**	*	***	***
	SSUB	−3.011	−8.215	0.425	−0.454	3.671	0.239	0.502
		0.206	6.346	0.110	0.074	1.713	0.036	0.210
		***		***	***	**	***	**
	SUB	−3.050	−5.745	0.442	−0.644	7.856	0.395	0.327
		0.210	6.799	0.114	0.126	2.966	0.060	0.259
		***		***	***	**	***	

(Continued)

(Continued)

Rating	**Seniority**	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{w}$	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{b}$	$\hat{\rho}$
Ba	SSEC	−2.078	−6.310	0.295	0.024	6.972	0.306	0.330
		0.109	2.583	0.062	0.099	2.353	0.046	0.226
		***	**	***		***	***	
	SUSEC	−2.079	−6.144	0.304	−0.223	3.649	0.285	0.247
		0.111	2.639	0.065	0.092	2.189	0.043	0.231
		***	**	***	**		***	
	SSUB	−2.078	−6.258	0.292	−0.456	3.740	0.239	−0.071
		0.108	2.558	0.063	0.077	1.836	0.036	0.249
		***	**	***	***	*	***	
	SUB	−2.075	−6.355	0.296	−0.651	8.106	0.395	0.216
		0.109	2.592	0.063	0.128	3.038	0.060	0.242
		***	**	***	***	**	***	
B	SSEC	−1.39	−5.6	0.323	0.024	6.97	0.31	0.414
		0.112	2.639	0.049	0.099	2.36	0.05	0.19
		***	**	***		***	***	**
	SUSEC	−1.39	−5.53	0.325	−0.22	3.65	0.28	0.365
		0.111	2.596	0.049	0.092	2.19	0.04	0.193
		***	**	***	**		***	*
	SSUB	−1.39	−5.56	0.325	−0.46	3.74	0.24	0.041
		0.113	2.655	0.049	0.077	1.84	0.04	0.221
		***	**	***	***	*	***	
	SUB	−1.39	−5.62	0.325	−0.65	8.11	0.4	0.327
		0.11	2.551	0.049	0.128	3.03	0.06	0.2
		***	**	***	***	**	***	
Caa-C	SSEC	−0.64	−7.4	0.281	0.01	7.36	0.31	0.705
		0.08	2.293	0.064	0.09	2.27	0.05	0.152
		***	***	***		***	***	***
	SUSEC	−0.71	−6.64	0.237	−0.22	3.65	0.28	0.744
		0.105	2.406	0.051	0.093	2.21	0.04	0.152
		***	**	***	**		***	***
	SSUB	−0.64	−7.13	0.262	−0.46	3.74	0.24	0.111
		0.113	2.626	0.058	0.077	1.84	0.04	0.269
		***	**	***	***	*	***	
	SUB	−0.65	−6.87	0.254	−0.65	8.1	0.4	0.362
		0.108	2.56	0.056	0.128	3.04	0.06	0.215
		***	**	***	***	**	***	

*Notes: First row: Parameter estimates, second row: standard errors, third row: significance; *: significant at 10%-level, **: significant at 5%-level, ***: significant at 1%-level.*

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