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Credit Losses in Economic Downturns - Empirical Evidence for Hong Kong Mortgage Loans

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Abstract

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 the 'Downturn' loss rate given default which is also known as Downturn LGD. 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 Hong Kong mortgage loan portfolios.

Keywords: Basel II, Business Cycle, Capital Adequacy, Correlation, Credit Risk, Economic Downturn, Expected Loss, Fixed Income, Loss Given Default, Probability of Default, Value-at-Risk
JEL Classification: G20; G28; C51

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1. 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, which was only partially mitigated by the issue of a guidance note in relation to the process for assessing the effects 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 correct 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):

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

Unfortunately, this approach does not take into account the degree to which risk segments are exposed to systematic risk and to which loss models reflect systematic risk. Due to its popularity, this approach 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 develops 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 extends the existing literature as follows:

- The degree to which risk segments are exposed and loss models reflect systematic risk is taken into account. The framework is able to incorporate loss models which are based on estimates of long-run averages (known as through-the-cycle models) as well as loss models which include the future state of the business cycle (known as point-in-time models). Both approaches are accepted under the current regulations and a lively discussion exists on whether the state of the business cycle should be incorporated into regulatory models. The concern is that cycle-dependent regulatory capital may amplify the stress on financial institutions during economic downturns.

- 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 US commercial 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 specification of the Value-at-Risk as suggested by previous contributions. This is important as the Downturn LGD relates to the Basel II requirements for all deposit-taking institutions and does not require the existence of a credit portfolio model. Approaches which derive the LGD from the Value-at-Risk are in essence limited to large financial institutions which possess the necessary quantitative skills.

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 Hong Kong mortgage loan portfolios. The last section concludes and discusses the results and limitations of the presented research as well as extensions for future research.

2. Framework

2.1 Parameters of the Default and Loss Given Default Process

Following work by Heitfield (2005), Rösch & Scheule (2005) and McNeil & Wendin (2007), 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 the literature to estimate the risk parameters given observable and unobservable information and conditional (ex post) as well as unconditional (ex ante) credit risk measures.

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

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

F_t may be interpreted as the contemporaneous systematic information which is not captured by $\boldsymbol{z}_{t-1}^D$. 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. 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

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

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 $\boldsymbol{z}_{t-1}^{R}$ and a standard normally distributed unobservable systematic factor X_t:

$$R_t(X_t) = \Phi(\beta_0 + \boldsymbol{\beta z}_{t-1}^{R} + bX_t) \tag{4}$$

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

$$CLGD_t(X_t) = 1 - R_t(X_t) = 1 - \Phi(\beta_0 + \boldsymbol{\beta z}_{t-1}^{R} + bX_t) \tag{5}$$

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

$$LGD_t = 1 - \int_{-\infty}^{\infty} \Phi(\beta_0 + \boldsymbol{\beta z}_{t-1}^{R} + bx_t) d\Phi(x_t) = 1 - \Phi\left((\beta_0 + \boldsymbol{\beta z}_{t-1}^{R}) \cdot \sqrt{\frac{1}{1+b^2}} \right) \tag{6}$$

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 borrowers under consideration) with sensitivity δ results in a reparameterization of a systematic risk driver Y_t by a factor of $\frac{1}{\sqrt{1-\delta^2}}$:

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

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

2.2 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:

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

No formula is given for LGD which is to be modeled given an economic downturn scenario (Downturn LGD). However, the Basel II model is based on the assumption of an infinitely granular portfolio and 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 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 99.9th 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. 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

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

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 rate given default (CLGD) is higher (lower) than LGD for high (low) f_t, i.e. during economic downturns (upturns).

Equation (9) can be expressed in terms of the unconditional, i.e., 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 ρ to equal one.

2.3 Parameter Estimation

The described model consists of a limited set of parameters (γ_0, β_0, $\boldsymbol{\gamma}$, $\boldsymbol{\beta}$, ω, b and ρ). These parameters can be estimated from observable data by maximizing 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

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

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

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

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

2.4 Credit Portfolio Risk Model

Credit portfolio risk is generally measured by a percentile of the distribution of future credit portfolio losses, which is known as the Value-at-Risk. This distribution is based on a risk model with parameters such as the PD, LGD, exposure at default or the correlation between the respective 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.

A risk model is assumed which generates a forecast distribution for the credit loss in the forecast period T + 1. In this model, the portfolio is infinitely granular and the portfolio loss rate depends only on the systematic risk factors

$$L_{T+1}(F_{T+1}, X_{T+1}) = CPD_{T+1}(F_{T+1}) \times LGD_{T+1}(X_{T+1}) \tag{16}$$

The Expected Loss is given by

$$\begin{aligned} l_{T+1} &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} CPD_{T+1}(f_{T+1}) \times LGD_{T+1}(x_{T+1}) f(f_{T+1}, x_{T+1}) df_{T+1} dx_{T+1} \\ &= CPD_{T+1} - \Phi(\Phi^{-1}(CPD_{T+1}), \Phi^{-1}(1 - ELGD_{T+1}), -\rho \cdot w \cdot b/\sqrt{1 - b^2}) \end{aligned} \tag{17}$$

where $f(f_{T+1}, x_{T+1})$ is the joint density of the systematic risk factors and $\Phi(\cdot,\cdot,\xi)$ is the two dimensional standard normal cumulative density function with correlation ξ. This risk model can be empirically specified by substituting its unknown parameters with the Maximum-Likelihood parameter estimates from Section 2.3. Equation (17) represents a closed-form expression for the portfolio loss given the PD and the expected recovery rate and may have important implications for other credit portfolio loss applications.

3. Hong Kong Mortgage Loan Portfolios

3.1 Data

The empirical analysis is based on Hong Kong mortgage loans as i) data on economic downturns, namely the South East Asian financial crisis is available and ii) the recent US subprime mortgage crisis has revealed that little is known on the modeling of financial risks in relation to retail loan exposures.

Unfortunately, financial institutions generally do not publish default and loss given default rates and the respective data histories are unavailable to external researchers. However, delinquency rates as well as asset prices are generally available. The paper takes the ratio of loans which are overdue for more than three months to total loans as a proxy for default rates and a transformation of the inflation adjusted property price index as a proxy for the security value and therefore recovery rates:

$$RR_t = min\left(\frac{S_t}{S_{t-1}} \cdot k, 1\right) \tag{18}$$

with the inflation adjusted property price index S_t and devaluation ratio k = 0.2, 0.4, 0.6, 0.8 and 1.0. This formula assumes that all defaulted loans were originated in period t-1, no capital was repaid and that the security value is equal to a certain percentage of the market average. The devaluation ratio represents the difference between the outstanding loan and the security value after workout costs. Figure 8 shows the resulting default and recovery rate (for k = 0.5 and k = 1.0): (Please see Figure 2)

In response to the South-East Asian Financial Crisis in 1997, the default rate peaks in 1999 while property values bottom in 1998. This suggests that asset markets may reflect changes in the economy earlier than credit markets. The growth rate of the Hong Kong GDP which is time-lagged by six months is used as a macroeconomic variable. Table 1 includes descriptive statistics of the variables.

3.2 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 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 parameters are shown in Table 2 for the through-the-cycle and Table 3 for the point-in-time model:

It can be seen that a point-in-time methodology reduces the exposure to the unknown systematic risk factors ω and b as well as the correlations ρ.

3.3 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 4 shows the PDs and asset correlations.

The asset correlations are lower for the point-in-time than for the through-the-cycle modeling methodology.

Table 5 and 6 show the LGDs, Expected Losses, Value-at-Risks and Basel II Value-at-Risks for the different LGDs.

The PDs and ELGDs 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.

The LGDs are calculated based on three definitions: ELGD according to Equation (6), CLGD according to Equation (12) and BLGD according the proposal by the Department of the Treasury, the Federal Reserve System and the Federal Insurance Corporation (2006) which is shown in Equation (1). ELGD is generally lower than BLGD which is lower than CLGD. The charts in Figures 3 compare CLGD and BLGD in dependence of ELGD as well as b (first column) and ρ (second column).

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 miniumum 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.

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 and Tier II capital (compare Laeven & Majnoni 2003). It is important to understand that the reported Value-at-Risk is the correct value given that the respective model is correct which is expected to be the claim of the presenting financial institution. It is interesting to our analysis 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 misspecification 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 misspecified;

- 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 an arbitrary increase of the loss rates based on the observation that LGDs should be higher in economic downturns and bounded by a theoretical value of 100%.

Therefore, it is interesting to identify the LGD concept which covers the Value-at-Risk best. 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), 0% (CLGD) and 40% (BLGD). All frameworks perform generally better for point-in-time models. As a result, CLGD clearly dominates the other loss concepts in accuracy.

4. 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, LGD 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).

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, the Federal Reserve System and the Federal Insurance Corporation (2006). The results provide evidence for the accuracy of the new framework.

The empirical analysis for Hong Kong mortgage loans 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, value of collateral, industry and the business cycle. The framework is open to any level of information as long as data on historic defaults and recoveries 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 concept.

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 be independent of the downturn definition and a new and interesting area of research.

A potential implementation of the proposed formula may need the guidance by the regulator by specifying parameters. 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.

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Table 1. Descriptive Statistics of Variables; Hong Kong Mortgage Loans

Variable	Mean	Median	Max.	Min.	Std.	Skew.	Kurt.
PD	0.034	0.028	0.082	0.007	0.023	0.817	2.817
RR (k=1.0)	0.933	0.950	1.000	0.673	0.090	-1.779	5.953
RR (k=0.8)	0.799	0.760	1.000	0.538	0.130	-0.046	2.510
RR (k=0.6)	0.603	0.570	0.780	0.404	0.104	0.156	2.576
RR (k=0.4)	0.402	0.380	0.520	0.269	0.069	0.156	2.576
RR (k=0.2)	0.201	0.190	0.260	0.135	0.035	0.156	2.576
GDP	0.039	0.051	0.073	-0.045	0.036	-1.032	3.032

Notes: Default rates are ratios of loans overdue more than three months to total loans. Recovery rates are derived from the inflation adjusted property price index based on Equation (18) and different values for k. GDP is the annual growth rate with a time lag of six months.

Table 2. Estimated Parameters; Hong Kong Mortgage Loans: Through-the-Cycle Modeling Methodology

	$\hat{c}$	$\hat{w}$	$\hat{\beta}_0$	$\hat{b}$	$\hat{\rho}$
k=1.0	-1.823	0.278	2.332	1.242	0.671
	0.081	0.054	0.332	0.235	0.159
	***	***	***	***	***
k=0.8	-1.823	0.278	1.190	1.084	0.373
	0.081	0.054	0.289	0.205	0.244
	***	***	***	***	
k=0.6	-1.823	0.277	0.271	0.271	0.533
	0.081	0.053	0.072	0.051	0.204
	***	***	***	***	**
k=0.4	-1.823	0.278	-0.252	0.175	0.540
	0.081	0.054	0.047	0.033	0.201
	***	***	***	***	**
k=0.2	-1.823	0.278	-0.844	0.120	0.540
	0.081	0.054	0.032	0.023	0.201
	***	***	***	***	**

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

Table 3. Estimated Parameters; Hong Kong Mortgage Loans: Point-in-Time Modeling Methodology

	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{w}$	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{b}$	$\hat{\rho}$
k=1.0	-1.656	-5.008	0.221	1.576	19.456	1.041	0.504
	0.094	1.789	0.045	0.419	8.008	0.197	0.218
	***	**	***	***	**	***	**
k=0.8	-1.656	-5.006	0.222	0.685	13.000	0.985	0.159
	0.094	1.788	0.046	0.396	7.570	0.186	0.282
	***	**	***			***	
k=0.6	-1.656	-5.011	0.222	0.105	4.260	0.227	0.293
	0.094	1.799	0.045	0.091	1.741	0.043	0.263
	***	**	***		**	***	
k=0.4	-1.656	-5.012	0.222	-0.361	2.796	0.145	0.297
	0.095	1.809	0.045	0.058	1.115	0.027	0.262
	***	**	***	***	**	***	
k=0.2	-1.656	-5.013	0.222	-0.919	1.932	0.099	0.296
	0.094	1.792	0.046	0.040	0.764	0.019	0.262
	***	**	***	***	**	***	

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

Table 4. Unconditional, Conditional and Conditional Basel II Probabilities of Default and Asset Correlations; Hong Kong Mortgage Loans

	Through-the-Cycle	Point-in-Time
PD	0.034	0.035
CPD	0.159	0.124
Basel II CPD	0.238	0.240
Empirical asset correlation	0.077	0.049
Basel II asset correlation	0.142	0.141

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

Table 5. Estimated Loss Rates Given Default, Expected Losses, Value-at-Risk and Basel II Value-at-Risk; Hong Kong Mortgage Loans: Through-the-Cycle Modeling Methodology

	k=1.0	k=0.8	k=0.6	k=0.4	k=0.2
ELGD	0.072	0.210	0.397	0.598	0.799
CLGD	0.571	0.517	0.568	0.705	0.851
BLGD	0.146	0.273	0.445	0.630	0.815
Expected Loss	0.004	0.009	0.015	0.021	0.028
Value-at-Risk	0.118	0.109	0.101	0.113	0.135
BII Value-at-Risk (ELGD)	0.017	0.050	0.095	0.142	0.191
BII Value-at-Risk (CLGD)	0.136	0.123	0.135	0.168	0.203
BII Value-at-Risk (BLGD)	0.035	0.065	0.106	0.150	0.194

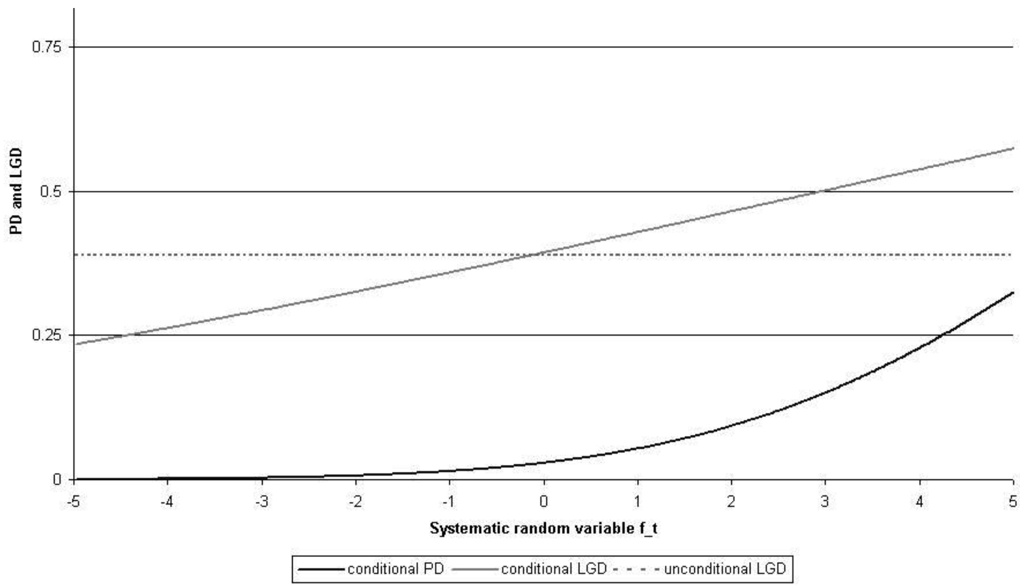
Notes: ELGD is based on Equation (6), CLGD is based on Equation (12) and BLGD is based on Equation (1). Value-at-Risk is defined as the 99.9th percentile of the random variable loss. The Basel II Value-at-Risk is calculated by multiplying the conditional Basel II PD and ELGD. Assumption of a portfolio exposure of one and an infinitely granular portfolio. The numbers are based on the through-the-cycle modeling methodology.

Table 6. Estimated Loss Rates Given Default, Expected Losses, Value-at-Risk and Basel II Value-at-Risk; Hong Kong Mortgage Loans: Point-in-Time Modeling Methodology

	k=1.0	k=0.8	k=0.6	k=0.4	k=0.2
ELGD	0.065	0.217	0.407	0.606	0.804
CLGD	0.336	0.330	0.486	0.656	0.828
BLGD	0.139	0.280	0.455	0.638	0.819
Expected Loss	0.003	0.008	0.015	0.022	0.028
Value-at-Risk	0.072	0.076	0.068	0.083	0.103
BII Value-at-Risk (ELGD)	0.016	0.052	0.098	0.146	0.193
BII Value-at-Risk (CLGD)	0.081	0.079	0.117	0.158	0.199
BII Value-at-Risk (BLGD)	0.034	0.067	0.109	0.153	0.197

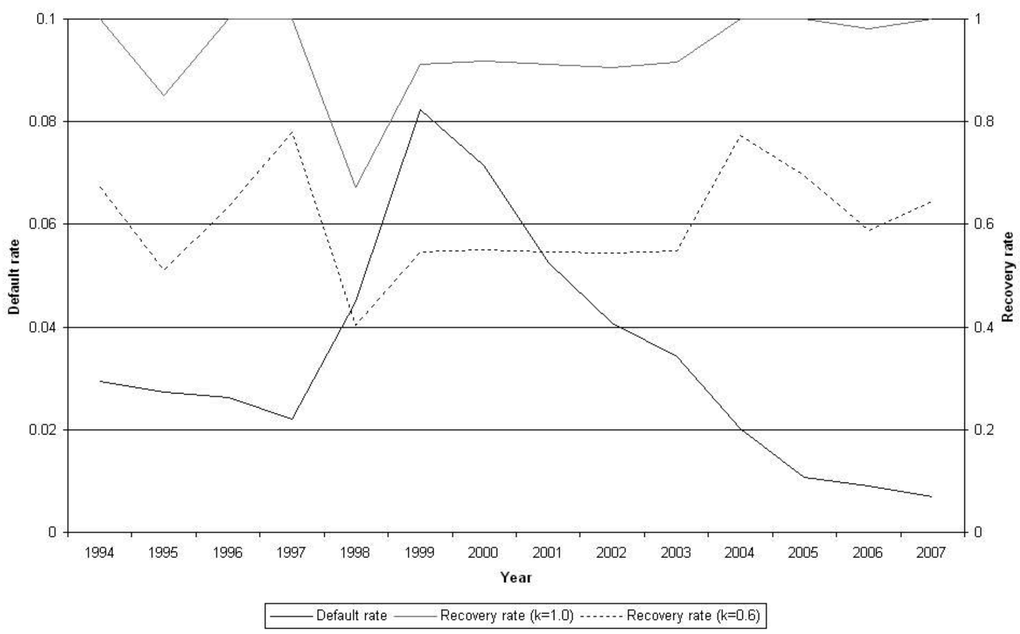
Notes: ELGD is based on Equation (6), CLGD is based on Equation (12) and BLGD is based on Equation (1). Value-at-Risk is defined as the 99.9th percentile of the random variable loss. The Basel II Value-at-Risk is calculated by multiplying the conditional Basel II PD and ELGD. Assumption of a portfolio exposure of one and an infinitely granular portfolio. The numbers are based on the point-in-time modeling methodology.

Figure 1. Conditional Probability of Default, Unconditional Loss Rate Given Default and Conditional Loss Rate Given Default Given the Realization f_t



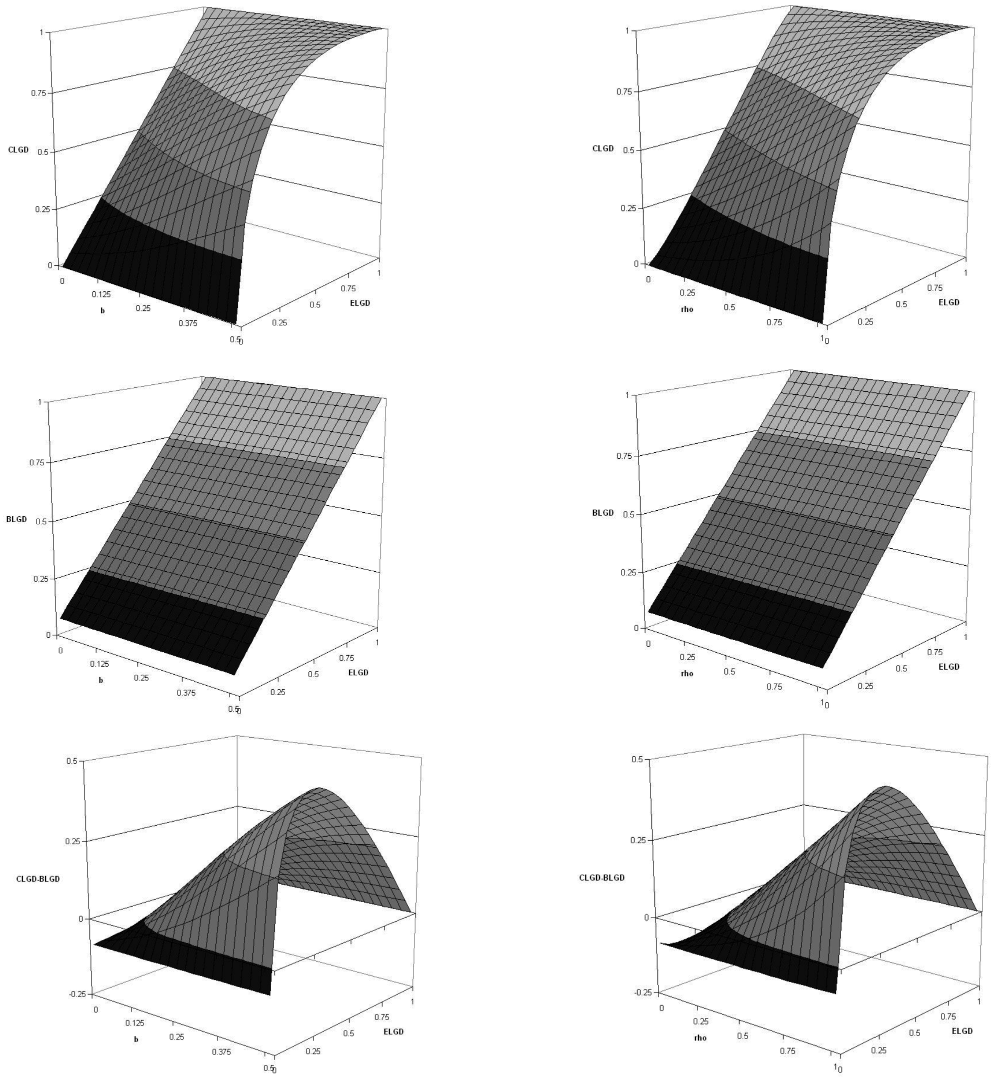
Notes: Based on the through-the-cycle modeling methodology and the data set analyzed in Section 3 (with parameter k=0.6).

Figure 2. Default Rates and Recovery Rates for Hong Kong Mortgage Loans



Notes: Default rates are ratios of loans overdue more than three months to total loans. Recovery rates are derived from the inflation adjusted property price index based on Equation (18).

Figure 3. Comparison of Different Downturn LGD Definitions in Dependence of the Expected LGD, b and ρ



Notes: The first column shows the Downturn LGD in dependence of the expected LGD (ELGD) and the sensitivity to the business cycle b (assumption ρ = 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 ρ = 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).