Which is More Informative in Predicting Loss-Given-Default: Firm-specific or Recovery Actions

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Ⅰ. Introduction

Historically, loss given default (LGD) did not receive as much attention as probability of default, although they are both key risk components of credit risk. However, recent regulatory reforms have attracted more interest from academia and industry toward LGD; Basel New Capital Accord allows banks to measure LGD using their internal data via advanced internal rating based approach (AIRB). Therefore, much effort has been put into estimation of LGD and it bred many empirical results in the area. However, publically available papers mostly focus on bonds; researches on LGD of loans have been rare until recently and they have been led by practitioners and followed by academic researchers. This phenomenon is due to the proprietary nature of loan data.

Since Altman (1977), there have been two streams of research regarding LGD. The first one focuses on the relationship between PD and LGD: Frye (2000) suggested a model in which the correlation between PD and LGD are derived from a common economic factor; Jokivuolle and Peura (2003) assumed a positive correlation between firm's asset value and collateral value and invented an LGD model based on an option pricing theory where LGD is determined by the stochastic collateral value. Bruche and González-Aguado (2010) showed that the correlation between PD and LGD results in a significant increase of credit loss of loan portfolios.

The second stream deals with estimation of LGD focusing on the determining factors or estimation method itself. Factors that are found significant include size of loan, collateral, seniority of bonds, product type, firm size, credit rating, financial ratios, firm age, and industry among others. However, there is no consensus on these factors except collateral, different studies suggesting different factors. See Asarnow and Edwards (1995), Hurt and Felsovalyi (1998), Thorburn (2000), Araten et al. (2004), Varma and Cantor (2005), Dermine and Neto de Carvalho (2006), Acharya et al. (2007), Chalupka and Kopecsni (2009), and Grunert and Weber (2009) for more details. The reason for this can be attributed to the differences in loan products among banks, lending and debt collection

procedures among countries, LGD measurement methods and/or sample periods.

On the other hand, there are common observations on the LGD distribution, i.e., left-skewness and bimodality. Bimodality makes OLS estimator inappropriate and yielded parametric and non-parametric models that attempt to captures bimodality. Renault and Scaillet (2004), Gourieroux and Monfort (2006), Calabrese and Zenga (2010), Bastos (2010), Qi and Zhao (2011), and Loterman et al. (2011) are included in this category. It is generally agreed that GLM (generalized linear model) is better in forecasting LGD than OLS and non-parametric methods are superior to parametric methods.

However, previous studies have ignored one important factor that relates to LGD, i.e., the legal and institutional devices that can be utilized during the course of lending or debt collection. Credit reinforcement by collateral, compulsory execution of distressed debt, and application for workout by the debtor all can significantly affect recovery of debt and LGD. Therefore, our paper aims to assess how recovery enhancing devices and other legal means related to the debtor's credit recovery can affect LGD. We first consider an LGD model that has only these "recovery related device" factors (henceforth, we will call this model 'recovery device model') and compare it with a firm specific factor model. We also combine these two models and examine which model performs best in terms of explanatory power and forecasting power. There are three types of recovery devices we consider in our analysis. The first type is legal devices that are utilized by the lender in order to compulsorily collect debts: security right, provisional seizure, and injunction are included in this category. The second type is devices designed by the lender to enhance debt collection: KODIT, of which we use recovery data for the empirical analysis, sometime allows a debtor an amortization plan when the debtor cannot repay the loan at once. The last type is devices utilized by the debtor as a means of credit recovery. Though these devices cannot be used by the lender's discretion, they are closely related to LGD and we considered these factors as well. individual workout, individual rehabilitation, and individual bankruptcy are included in this category.

This paper is organized as follows: In Section 2, the data used for empirical analysis are described, and the LGD measurement model as well as summary

statistics of the data are presented in Section 3. In Section 4, two LGD estimation models we tested are described and Section 5 is dedicated to the analysis of estimation results. Finally, concluding remarks are given in Section 6.

Ⅱ. Data

For empirical analysis, we acquired recovery data from KODIT, Korea Credit Guarantee Fund. KODIT is a public financial institution established in 1976 with the objective of leading balanced development of the national economy by extending credit guarantees for the liabilities of promising SMEs which lack tangible collateral. If a firm having a debt guaranteed by KODIT cannot honor its debt, KODIT pays the lending bank the principal and interest on behalf of the firm and takes the right to indemnity against the firm. Therefore the recovery risk is transferred to KODIT and the risk is typically high as most debts are credit debts without collateral.

Tough it might be the case that the debt collection data of banks are more comprehensive and thus contain more information, Those data are mostly either unaccessible or non-existent. On the other hand, KODIT has accumulated all the detailed debt collection process and this can serve as an invaluable resource in assessing how policies related to debt collection affect loss given default (LGD). This is especially so since, unlike banks that tends to sell the distressed debt at an early stage of recovery, KODIT being operated by government funding, in order to minimize government funding burden and maintain liquidity of itself, usually has a very long debt collection period and various recovery devices are applied during the process to increase the recovery rate.

Among the firms that KODIT subrogated the debt to the bank during January 1st, 1990 to May 31, 2011, 68,871 firms having financial data were chosen for empirical test. This set of data were then divided into two subsets, data up to 2006 for estimation and the rest for out-of-sample test.

There exist two widely used recovery rate measurement methods. The first

method is to calculate the present value of future cash flow including amount collected, legal and management cost, etc. The recovery rate estimated by this method is called discounted recovery rate or workout recovery rate. The second method is to define the value of the distressed debt as its market value. This method is called market recovery rate. The latter, though easy to calculate, has limited application as market value of a distressed debt is difficult to observe if not impossible and the market value can be influenced by the supply-demand of the debt. Therefore, discounted recovery rate is commonly used and is the only viable method that is applicable to non-traded debt. We also use discounted recovery rate to estimate LGD using the formula

$$GD \quad 1 - \frac{1}{EAD_i} \cdot \underset{t=0}{} RC_t \cdot (1+d)^{-N/365} \qquad (1)$$

where LGD_i, EAD_i are respectively the LGD and EAD of firm i, RC_it is the recovered amount at time t, d is discount rate and N is debt collection period.

To apply this formula to the guarantee asset, EAD was defined as the amount subrogated to the bank and RC as the amount collected after subrogation. Also, legal costs that are incurred by legal actions during debt collection were considered in EAD and RC.

There is not widely accepted rule to define recovery period. In practice, banks set the period as the time when 95 percent of the debt is recovered. Applying this rule to our sample yielded recovery period of 2 years and we adopt this number as the recovery period in the equation. Capital cost, contract rate, or market rate can be considered as discount rate. Calabrese and Zenga (2010) suggest to use investor required return for each economic cycle. In our analysis, we used annual average return of AA- grade corporate bonds.

Summary statistics of LGD in each year estimated by Equation (1) is presented in Table 1. As shown in the table, about 40% of the samples are distributed in 2004-2006. The average LGD of the whole sample is 73.6% and it tends to decrease being in the range of 80-90% in 1990s and 60-70% in 2000s. However, LGD is still high in 2003 and 2004 of credit crisis and 2008 of the

global economic crisis, reflecting economic recession leads to a higher LGD. Standard deviation is lower in 1990s (21.7%) compared to that in 2000s (41.0%). This is expected as LGD is very high in 1990 near the maximum value of 100%. Unlike mean, median LGD remains similar across all years.

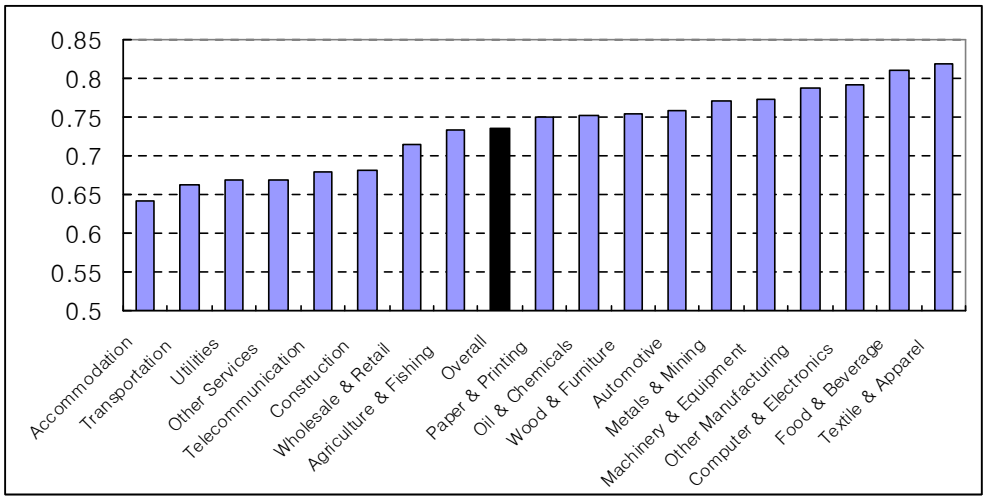
<table 1> Descriptive Statistics of LGD by year

year	Frequency	Mean	Median	Standard Deviation
1990	10	0.833	0.887	0.226
1991	176	0.926	0.996	0.167
1992	752	0.906	0.995	0.183
1993	1057	0.890	0.995	0.208
1994	1229	0.888	0.995	0.203
1995	1900	0.867	0.995	0.232
1996	1843	0.880	0.995	0.218
1997	2325	0.882	0.995	0.228
1998	4952	0.889	0.996	0.226
1999	3222	0.854	0.996	0.281
2000	2978	0.702	0.992	0.412
2001	4071	0.729	0.990	0.390
2002	3728	0.699	0.982	0.409
2003	6250	0.738	0.993	0.393
2004	7456	0.719	0.990	0.402
2005	7705	0.671	0.953	0.419
2006	6221	0.634	0.902	0.426
2007	4972	0.652	0.922	0.419
2008	5178	0.691	0.953	0.405
2009	2846	0.628	0.892	0.428
Overall	68871	0.736	0.985	0.384

LGD of each industry was also estimated and the result is displayed in Figure 1. Firms were classified into 18 industries according to Korea Standard Industry Classification. Services, Wholesale and Retail, and Construction have low LGDs while Manufacturing industries have high LGDs. Accommodation and Transportation having the lowest LGDs might be due to their physical collaterals. High LGD of manufacturing industry can be reasoned as follows: manufacturing firms are normally industry specific and might not be attractive for general

public. Thus they need be sold to other firm in the same industry. However, it is likely that other firms in the same industry suffer the same economic situation and will not buy the firm at a fair price.

<Figure 1> Mean LGD by Industry



LGD by cause of bankruptcy is shown in Table 2. Closure of business has the lowest mean and median values, 0.455 and 0.193 respectively. These numbers are remarkably lower than other values and also signifies LGD by Closure of business has a right-skewed distribution, unlike other causes that have left-skewed distributions. Closure of business does not necessarily happen due to financial distress of the firm but it can happen at the owner's discretion, in which case debt is likely to be repaid.

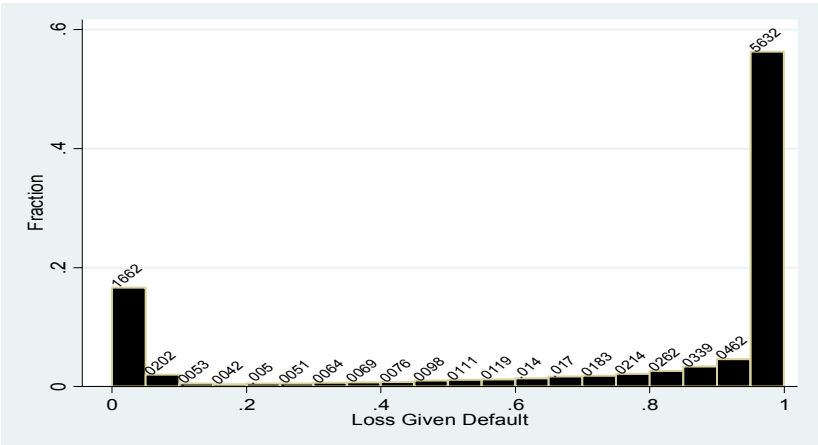
<Table 2> Mean LGD by Default Cause

Cause	Frequency	Mean	Median	Standard Deviation
Payment Overdue	24,328	0.765	0.992	0.368
Bankruptcy of Account	20,796	0.819	0.991	0.307
Deterioration of credit	12,576	0.656	0.947	0.423

Workout/file for bankruptcy	454	0.829	0.954	0.285
Closure of Business	5,398	0.455	0.193	0.466
Others	5,319	0.751	0.989	0.374

Bimodality of LGD was examined by drawing a histogram of LGD, which is displayed in Figure 2. As shown in the figure, the first mode appears close to 1 and the second mode close to 0. This confirms the prior results in the literature that LGD has a bimodal distribution. Recalling the samples have the characteristics of credit loan, we can infer that credit loans are likely to have either a very high LGD or a very low LGD.

<Figure 2> Histogram of LGD



Finally, we analyzed how LGD differs by the recovery devices utilized during the course of debt collection. Table 3 is the summary statistics of the results. When security right is present, the mean LGD is 31.2%, which is lower by 45% than the mean LGD without security right. Provisional seizure also lowers LGD by 8.4% from 75.2% to 66.8%. Unlike provisional seizure, the effect of injunction is very small, LGD being reduced by only 0.8% from 72.9%.

Allowing the debtors to pay their debt via amortization also effectively lowered LGD by a factor of 6.9% to 68%. On the other hand, the actions taken by the debtor, i.e., individual workout, individual rehabilitation, and individual bankruptcy all increased LGD as debt reduction or exemption can follow these actions.

<Table 3> Mean LGD by Recovery Institution

		Frequency	Mean	Median	Standard Deviation
Security Right	0	64890	0.762	0.990	0.366
	1	3981	0.312	0.026	0.408
Provisional seizure	0	55978	0.752	0.991	0.377
	1	12893	0.668	0.910	0.403
Injunction	0	62398	0.737	0.989	0.386
	1	6473	0.729	0.92	0.355
Individual Workout	0	68210	0.736	0.986	0.384
	1	661	0.762	0.905	0.325
Individual Rehabilitation	0	51891	0.691	0.970	0.408
	1	16980	0.876	0.994	0.247
Individual Bankruptcy	0	65914	0.732	0.986	0.387
	1	2957	0.827	0.969	0.297
Amortization	0	56279	0.749	0.991	0.387
	1	12592	0.680	0.839	0.362

Ⅳ. Estimation model and Methodology

To analyze the effects of recovery actions on LGD, we compared two models. The first model is a regression model with firm specific variables that are known to be significant in the literature and has the form

$$\begin{aligned} GD \quad & \alpha + \beta_1 Loansize_i + \beta_2 Firmsize_i + \beta_3 Firmage_i + \beta_4 Period_i \\ & + \beta_5 Rating_i + \beta_6 Cashflow_i + \beta_7 Leverage_i + \beta_8 Tangible_i + \beta_9 GDP \\ & + \sum_{k=1}^{17} Dum_{dustry} + \sum_{j=1}^{5} Dum_{cause} + \epsilon_i \end{aligned} \tag{2}$$

where Loansize is the natural log of the size of the loan and Firmsize is the natural log of the total assets in the financial statement both prior to bankruptcy. Firmage is the period between the firm establishment and bankruptcy and Period is the period between the debt initiation and bankruptcy. Rating is the credit grade rated by a proprietary credit rating system in KODIT; a number was assigned to each grade, starting with one for the lowest grade and increasing thereafter. Cashflow, Leverage, and Tangible are variables connected to the firm's financial characteristics and respectively defined as EBITDA/Total Assets, Debt Ratio, Tangible Assets/Total Assets. They were all measured using the latest financial statement prior to bankruptcy. GDP is the real GDP growth rate. Lastly, we added dummy variables for industry and cause of distress.

The other model tested is a regression model with binary variables for different recovery devices and has the form

$$\begin{aligned} GD \quad & \mu + \delta_1 Dambo_i + \delta_2 Gaap_i + \delta_3 Gabun_i + \delta_4 Pwout_i + \delta_5 Phsan_i \quad (3) \\ & + \delta_6 Pasan_i + \delta_7 Bunhl + \sum_{k=1}^{17} Dum_{dustry} + \sum_{j=1}^{5} Dum_{cause} + \omega_i \end{aligned}$$

where Dambo, Gaap, Gabun, Pwout, Phsan, Pasan, Bunhl are binary variables corresponding to security right, provisional seizure, injunction, individual workout, individual rehabilitation, individual bankruptcy, and amortization, respectively. A variable has the value of one if the corresponding recovery device was utilized during the course of debt collection. We also added dummy variables for industry and the cause of distress.

Once a debt becomes insolvent, not only the primary debtor but also others related to the debt e.g., a joint surety, are subject to the responsibility for debt repayment. In this regard, we considered all the recovery actions taken to those responsible for debt repayment as well as the primary debtor. For example, if a joint surety's asset was put under provisional seizure, we set Gaap to 1 regardless of the debtor's asset being under provision seizure.

LGD models in Equation (2) and (3) were estimated via GLM and OLS.

log-log type link function was adopted for GLM to ensure LGD to line in [0, 1]. log-log link function has the form

$$X\beta) = \exp[-\exp(-X\beta)] \tag{4}$$

As in Papke and Wooldridge(1996), we employed quasi-maximum likelihood estimator (QML) to estimate GLM.

Ⅴ. Result

We first calculated the descriptive statistics and the correlations of the independent variables of the first model (Table 4, 5). All financial ratios were winsorsized at 99%, i.e., any values exceeding 99 percentile were replaced by the 99 percentile value. Being sampled from distressed firms, Leverage has a very wide range of values and extremely low minimum value.

<Table 4> Descriptive Statistics of Input Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Loansize	68294	18.38	1.16	13.57	24.48
Firmsize	68870	6.16	1.49	0.00	13.95
Firmage	68525	8.04	4.96	0.04	66.80
Period	68690	4.70	3.09	0.01	25.18
Rating	67884	6.24	3.25	1.00	21.00
Cashflow	68871	14.79	14.91	-4.19	82.46
Leverage	68476	52.09	1448.27	-10377.05	3376.92
Tangible	68871	27.28	25.17	0.00	100.00
GDP	68871	4.30	3.63	-5.70	10.70

Table 5 show the correlations between variables. Loansize, Firmsize, Firmage, and Period have relatively high positive correlations while correlations between other variables are low.

<Table 5> Correlation Coefficients between Independent Variables

The numbers in the parentheses are the p-values.

	Loansize	Firmsize	Firmage	Period	Rating	Earning	Leverage	Tangible	GDP
Loansize	1	0.407 (0.000)	0.161 (0.000)	0.169 (0.000)	-0.049 (0.000)	-0.100 (0.000)	0.017 (0.000)	-0.030 (0.000)	-0.027 (0.000)
Firmsize		1	0.146 (0.000)	0.092 (0.000)	-0.038 (0.000)	-0.066 (0.000)	-0.009 (0.019)	-0.011 (0.003)	-0.026 (0.000)
Firmage			1	0.621 (0.000)	0.119 (0.000)	-0.048 (0.000)	-0.009 (0.017)	0.086 (0.000)	-0.085 (0.000)
Period				1	0.095 (0.000)	-0.065 (0.000)	-0.003 (0.456)	0.047 (0.000)	-0.109 (0.000)
Rating					1	0.220 (0.000)	0.060 (0.000)	0.005 0.194	-0.036 (0.000)
Earning						1	0.029 (0.000)	0.080 (0.000)	-0.001 (0.725)
Leverage							1	-0.031 (0.000)	0.000 (0.980)
Tangible								1	0.037 (0.000)
GDP									1

Estimation results of the models using GLM and OLS are presented in Table 6. Model 1 and 4 are results of the firm specific model, Model 2 and 5 are results of the recovery device model, and Model 3 and 6 are results of a model that includes all the variables in the two models.

When we first look at the results of GLM, Model 4 has a slightly higher pseudo R-squared compared to Model 1, 0.038 vs. 0.037, signifying, though marginally, the recovery device model has a higher explanatory power. The relationship between LGD and each variable is mostly consistent with our expectation: Loansize is positively correlated with LGD, which may mean that debtors with smaller debts are more willing/able to repay the loan. Firmsize is negatively related to LGD. Information asymmetry is less severe for large firms and therefore LGD of these firms is lower. Both Firmage and Loanage are also negatively related to LGD. Firms with longer history tend to be more transparent and try to preserve the accumulated firm value, that results in more effort to

repay the loan. Among financial ratios, EBITDA/Total Assets and Leverage are positively related to LGD. This supports the hypothesis that high leverage causes conflicts between creditors due to the complexity of restructuring and leads to a high LGD. Economic growth is negatively related to LGD, which is consistent with previous findings that recovery rate is high in the period of economic expansion. Credit rating is not significant in Model 1 but significantly positively related to LGD in Model 3. Firms with high credit grades normally have loans of bigger size and once they undergo bankruptcy, loss of credit loans can be very large.

In Model 2, security right is significantly negatively related to LGD. This is expected as it gives a privilege on the debtor's property. Provisional seizure also lowers LGD as expected while injunction is not statistically significant. All the credit recovery devices have a positive relationship with LGD. This is because the repayment obligation can be relieved or entirely eliminated through these devices. Finally, amortization that allows the debtor to repay the loan through smaller divided amount over several times, is negatively related to LGD. This implies amortization plan relieves the burden of repaying the loan at once and increases recovery in the end.

<table 6> Regression result from GLM and OLS

The numbers in parentheses are heteroscedasticity robust standard error. ***, **, and * denote 1%, 5%, and 10% levels of significance, respectively.

	Generalized Linear Model			Ordinary Least Squares		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
constant	-3.293(0.218) ***	0.048(0.159)	-3.474(0.223) ***	-0.252(0.049) ***	0.440(0.036) ***	-0.230(0.047) ***
Loansize	0.210(0.010) ***		0.205(0.010) ***	0.042(0.002) ***		0.039(0.002) ***
Firmsize	-0.018(0.009) **		-0.005(0.009)	-0.005(0.002) ***		-0.002(0.002)
Firmage	-0.008(0.002) ***		-0.004(0.002) **	-0.001(0.000) ***		-0.001(0.000) *
Period	-0.021(0.003) ***		-0.018(0.003) ***	-0.005(0.001) ***		-0.004(0.001) ***
Rating	0.001(0.002)		0.008(0.002) ***	0.169(0.495)[a]		0.002(0.000) ***
Cashflow	0.001(0.001) **		0.001(0.001) **	0.298(0.118)[a] **		0.288(0.113)[a] **
Leverage	0.014(0.000)[a] ***		0.019(0.000) ***	0.004(0.001)[a] ***		0.004(0.001)[a] ***

Tangible	-0.032(0.034)		0.018(0.034)	-0.007(0.007)		-0.001(0.007)
GDP	-0.017(0.002) ***		-0.014(0.002) ***	-0.003(0.000) ***		-0.002(0.000) ***
dambo		-1.245(0.029) ***	-1.298(0.030) ***		-0.375(0.008) ***	-0.381(0.008) ***
gaap		-0.170(0.026) ***	-0.204(0.026) ***		-0.039(0.005) ***	-0.046(0.005) ***
gabun		0.034(0.033)	-0.034(0.033)		0.002(0.007)	-0.010(0.007)
pwout		0.391(0.072) ***	0.502(0.073) ***		0.085(0.015) ***	0.109(0.015) ***
phsan		0.876(0.020) ***	0.816(0.020) ***		0.142(0.003) ***	0.129(0.003) ***
pasan		0.531(0.045) ***	0.591(0.046) ***		0.095(0.008) ***	0.108(0.008) ***
bunhl		-0.068(0.018) ***	-0.042(0.018) **		-0.022(0.004) ***	-0.019(0.004) ***
new_1	0.289(0.219)	0.404(0.221) *	0.371(0.226) *	0.057(0.048)	0.073(0.045)	0.070(0.046)
new_2	0.323(0.169) *	0.479(0.169) ***	0.372(0.174) **	0.057(0.039)	0.080(0.037) **	0.063(0.037) *
new_3	0.456(0.161) ***	0.518(0.161) ***	0.478(0.166) ***	0.081(0.038) **	0.087(0.036) **	0.082(0.036) **
new_4	0.112(0.167)	0.162(0.167)	0.157(0.171)	0.019(0.039)	0.025(0.037)	0.025(0.037)
new_5	0.110(0.164)	0.146(0.164)	0.153(0.169)	0.022(0.039)	0.024(0.036)	0.029(0.037)
new_6	0.078(0.173)	0.199(0.172)	0.145(0.177)	0.013(0.040)	0.033(0.038)	0.025(0.039)
new_7	0.148(0.161)	0.231(0.161)	0.194(0.165)	0.027(0.038)	0.039(0.036)	0.033(0.036)
new_8	0.231(0.165)	0.342(0.165) **	0.270(0.170)	0.042(0.039)	0.057(0.036)	0.046(0.037)
new_9	0.180(0.160)	0.249(0.160)	0.226(0.165)	0.032(0.038)	0.042(0.036)	0.039(0.036)
new_10	0.076(0.167)	0.217(0.167)	0.140(0.172)	0.015(0.039)	0.036(0.037)	0.025(0.038)
new_11	0.220(0.160)	0.330(0.161) **	0.282(0.165) *	0.040(0.038)	0.056(0.036)	0.049(0.036)
new_12	-0.299(0.204)	-0.111(0.202)	-0.201(0.208)	-0.066(0.048)	-0.029(0.045)	-0.048(0.046)
new_13	-0.300(0.160) *	-0.129(0.160)	-0.191(0.165)	-0.066(0.038) *	-0.037(0.036)	-0.046(0.036)
new_14	0.007(0.159)	0.060(0.158)	0.058(0.163)	0.000(0.038)	0.006(0.035)	0.007(0.036)
new_16	-0.118(0.167)	-0.093(0.166)	-0.088(0.172)	-0.035(0.039)	-0.032(0.037)	-0.029(0.038)
new_17	-0.141(0.167)	-0.091(0.167)	-0.083(0.172)	-0.035(0.039)	-0.034(0.037)	-0.029(0.038)
new_18	-0.164(0.161)	-0.103(0.161)	-0.093(0.166)	-0.042(0.038)	-0.034(0.036)	-0.030(0.037)
bs_1	1.122(0.026) ***	1.087(0.027) ***	1.049(0.027) ***	0.322(0.007) ***	0.295(0.006) ***	0.287(0.007) ***
bs_2	1.319(0.028) ***	1.335(0.027) ***	1.210(0.029) ***	0.355(0.007) ***	0.336(0.007) ***	0.312(0.007) ***
bs_3	0.759(0.028) ***	0.708(0.028) ***	0.721(0.029) ***	0.238(0.007) ***	0.210(0.007) ***	0.213(0.007) ***
bs_4	1.320(0.141) ***	1.351(0.142) ***	1.157(0.147) ***	0.348(0.026) ***	0.335(0.025) ***	0.297(0.025) ***
bs_6	1.014(0.037) ***	1.050(0.036) ***	0.972(0.037) ***	0.300(0.008) ***	0.287(0.008) ***	0.271(0.008) ***
pseudo-likl.	-26001.37	-25669.71	-24534.49	-	-	-

pseudo R^2	0.037	0.038	0.039	-	-	-
AIC	52066.73	51399.41	49146.98	42003.57	39644.22	37683.31
BIC	52351.4	51667.34	49493.92	42288.24	39912.14	38030.26
F-value	-	-	-	174.30^{***}	333.75^{***}	272.75^{***}
adjusted R^2	-	-	-	0.091	0.148	0.161
No. of obs	53961	55875	53961	53961	55875	53961

OLS estimation results are given the last three columns of Table 6. Unlike GLM, Recovery device model (Model 5) shows a much higher explanatory power with adjusted R-squared of 0.148 compared to 0.091 of the firm specific model (Model 4). The coefficients of most independent variables have the same sign as those of GLM results.

Most industry dummy variables are not significant in all models while all cause of distress dummy variables are significant in all models. The causes directly related to bankruptcy such as bankruptcy of checking account turn out to have higher LGDs.

The estimation results were utilized to forecast LGD of the out-of-sample data and mean absolute error (MAE) and root mean square error (RMSE) were calculated as reported in Table 7. Both Model 2 and Model 5 have lower MAE and RMSE than Model 1 and Model 4, respectively, which implies recovery devices are more useful in forecasting LGD.

Model 3 and 6 have the lowest estimation errors in each estimator implying that the combined model of the firm specific model and the recovery device model can forecast LGD better. GLM is better than OLS in terms of forecasting errors but the difference is only marginal.

<table 7> Out of sample predictive accuracy

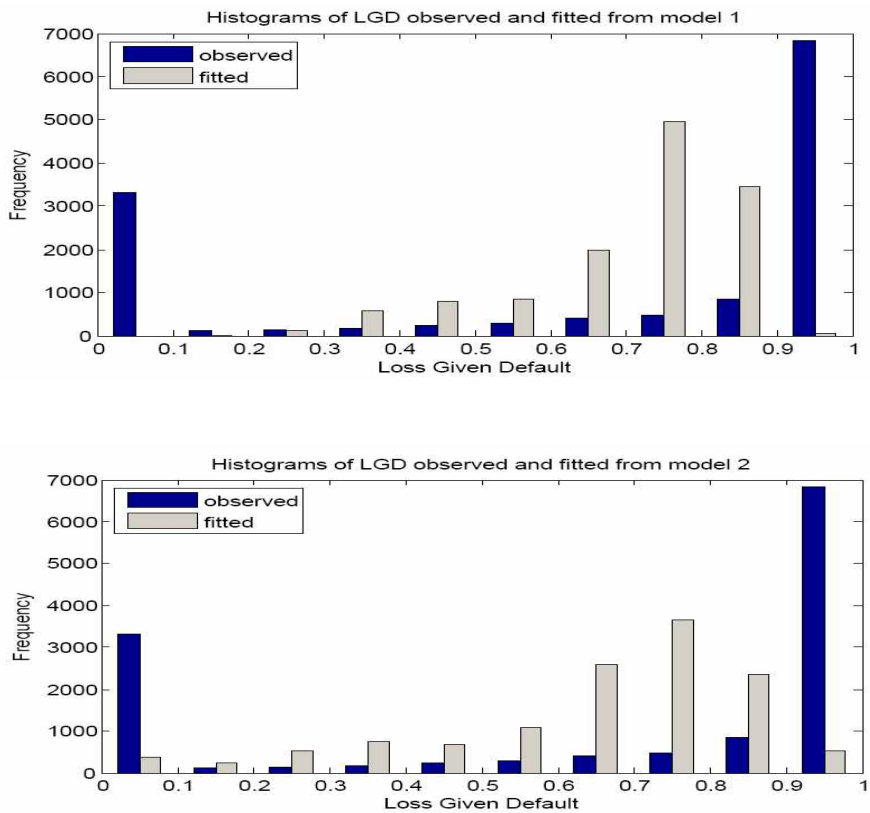
$$AE \quad \frac{1}{N} \quad |LGD_i - LGD_i|, \ \mathrm{RMSE} = \quad \frac{1}{\mathrm{N}}\sum_{\mathrm{i}}(\mathrm{LGD_i} - \mathrm{LGD_i})^2$$

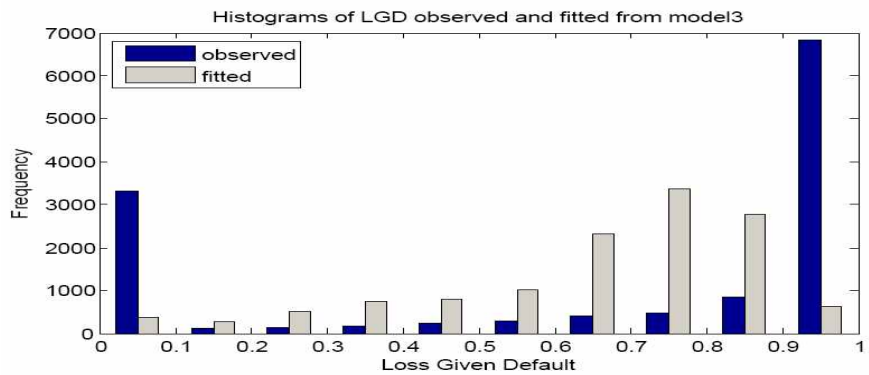
		Generalized Linear Model			Ordinary Least Squares		
		Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
In sample	MAE	0.289	0.272	0.270	0.289	0.275	0.273

	RMSE	0.356	0.344	0.341	0.356	0.345	0.344
Out of sample	MAE	0.334	0.301	0.292	0.336	0.307	0.302
	RMSE	0.402	0.365	0.356	0.402	0.367	0.361

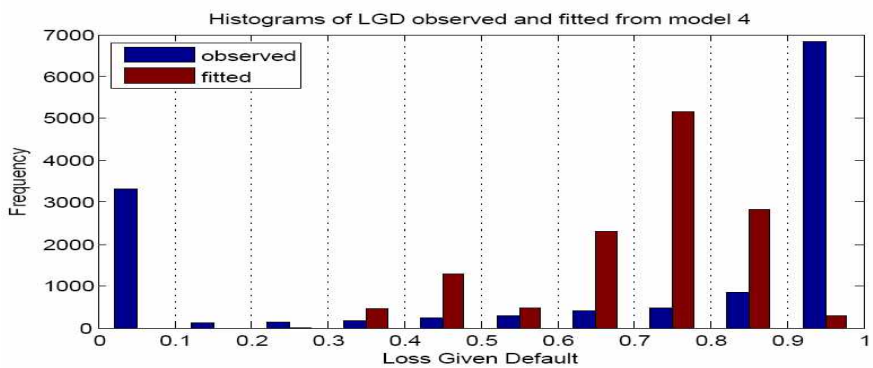
We draw a histogram of the forecast LGD to examine if bimodality is observed. Although bimodality were not present in any models tested, we can clearly see that the recovery action model describes the actual LGD distribution more closely, yielding more extreme LGDs near 0 and 1. The distribution of forecast LGD of all models are left-skewed as the actual distribution.

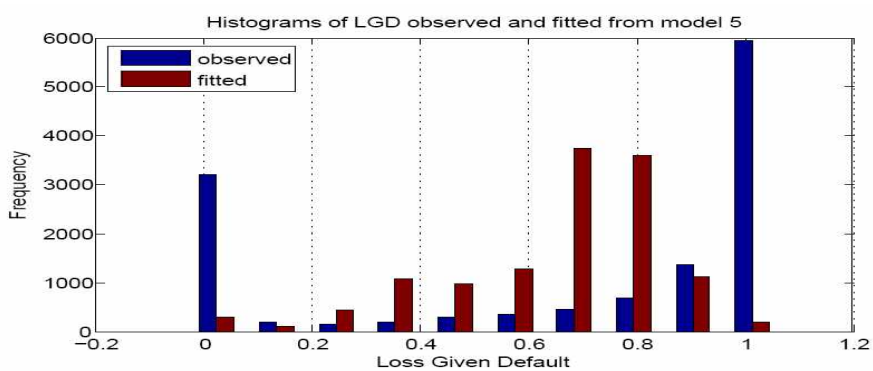
<Figure 3> Histogram of LGD observed and fitted from GLM

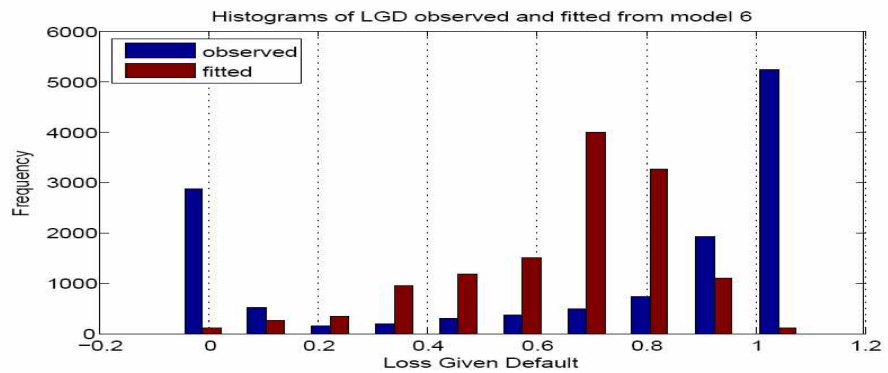




<Figure > Histogram of LGD observed and fitted from OLS







Ⅵ. Concluding Remarks

In this paper, we proposed an LGD model that takes recovery devices into account. Although these devices significantly affect debt collection process and thus LGD, they have been ignored in the previous literature. Therefore the main contribution of this paper lies in that 1) we proposed a totally new LGD model from legal and institutional perspective, 2) compared it with a more widely used firm specific model using actual data, and 3) found it can be combined with the firm specific model to improve both explanatory and forecasting power.

Empirical analysis proved that the recovery device model is superior to the firm specific model in forecasting LGD. Also, when the two models are combined, forecasting power was improved further. This implies that the recovery device factors can explain LGD difference of firms that cannot be explained by the firm specific factors.

One might argue that the recovery devices can be utilized only after the firm is bankrupt and it cannot be used to forecast LGD before bankruptcy actually happens. However, we believe forecasting LGD of already insolvent loans is as important to forecast future cash flow and to manage credit risk. Also, our results suggest a method to assess the cost and benefit of those recovery devices: If reduction in LGD is less than the cost involved in utilizing a recovery

device, especially for some types of loans, banks had better go without this recovery device for those loans.

We tested only some recovery devices that are used in KODIT. Other banks must have their own devices and testing their effect on LGD will give an opportunity to further improve their existing LGD model and more accurately forecast LGD.

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