Forecasting bank default with the Merton model: The case of US banks

Kihwan Jo [1], Gahyun Choi [1,2], Jongwook Jeong [3,*] and Kwangwon Ahn [1,2,*]

[1] Center of Finance and Technology, Yonsei University, Seoul, South Korea
[2] Department of Industrial Engineering, Yonsei University, Seoul, South Korea
[3] SK Telecom, Seoul, South Korea

* jongwook.jeong@sk.com (J.J.); k.ahn@yonsei.ac.kr (K.A.)

Abstract. This paper examines whether the probability of default (Merton, 1974) can be applied to banks' default predictions. Using the case of US banks in the post-crisis period (2010–2014), we estimate several Cox proportional hazard models as well as their out-of-sample performance. As a result, we find that the Merton measure, that is, the probability of default, is not a sufficient statistic for predicting bank default, while, with the 6-month forecasting horizon, it is an extremely significant predictor and its functional form is a useful construct for predicting bank default. Findings suggest that (i) predicting banks' defaults over a mid- to long-term horizon can be done more effectively by adding the inverse of equity volatility and the value of net income over total assets, and (ii) the role of the capital adequacy ratio is doubtful even in short-run default prediction.

Keywords: Bank Default, Prediction, Probability of Default.

1 Introduction

The sound operation of the banking sector underpins the safety of the market economy due to its role in offering liquidity to the marketplace in which industry players commonly trade goods and services in the physical market. Moreover, the default of a particular bank can quickly spread to other banks through the creditor–debtor network, resulting in a significant impact on the economy as a whole along with the globalization of the financial market. Since the global financial crisis, the need for the preemptive management of the banking sector and early warning indicators have gained much attention; the bankruptcy of individual banks has much more economic ramifications and costs than that of a corporation. As a banking crisis imposes significant social costs, it is important for regulators to establish a system that can detect prevailing risks in advance and implement an immediate response. Although there have been many prior studies on predictions of default, they are mostly focused on general enterprises rather than banks. Due to the unique nature of the banking industry, there are not many prior studies that thoroughly investigated bank default predictions.

ICCS Camera Ready Version 2022
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-08751-6_49

Merton [1] proposed a structural model for assessing the credit risk of a corporation by presuming the firm's equity as a call option on its assets. Specifically, Merton's "distance to default" (hereafter, DD) expresses the distance at which corporate values fall into debt levels in Z-score. Merton's model has been widely used; for example, Moody's KMV commercialized a corporate default prediction model. However, there are a number of opinions on the use of Merton's model for default prediction. Some studies have argued that the model outperforms Altman's Z-score and Ohlson's O-score [2], while others have provided counter-evidence that Merton's DD is not a sufficient statistic for measuring credit quality and the predictability of the reduced-form model, particularly with market value, is much more accurate [3,4]. In addition, some studies have reported evidence that the predictability of Merton's DD increases when it is used together with volatility and leverage [5]. As discussed, the assessment of Merton's DD model and the ways to improve its use are still inconclusive, even in corporate default.

However, there are still limited discussions about whether or not Merton's DD model can be useful for predicting bank default. Some studies have reported that information on credit ratings with Merton's DD model has predictability for bank default when used with bond spreads; particularly for downgrading banks [6]. Another study provided evidence that Merton's DD and its spreads are a superior measure than accounting data in default prediction in a case study of Japanese banks [7]. These studies provided an explanation of why and how Merton's DD has difficulty being used for banks' default prediction in two-fold: (i) market and funding risk stemming from high-leverage assets by short-term procurement and (ii) regulation and policy intervention in the market. Accordingly, some studies proposed the concept of "distance to capital" (hereafter, DC) by introducing the capital adequacy ratio (CAR) into Merton's DD to predict bank default [8–10],[1] and others revised the assumptions of Merton's model, such as asset value following a lognormal distribution, as it underestimates bank default risk [11]. As such, several attempts have been made to improve bank default prediction by including the CAR or relaxing the assumptions of the Merton model.

This study examines whether the probability of default (hereafter, POD) calculated using Merton's DD measure can be used for bank default prediction. Specifically, we test the three hypotheses as follows: (i) the POD is a sufficient statistic for forecasting bank default; (ii) the functional form of the Merton DD model creates useful information, like the case of a corporate, for forecasting bank default; and (iii) the POD has predictability for bank default. For this purpose, we estimate several Cox proportional hazard models and examine their out-of-sample performance for US banks in the post-crisis period (2010–2014). As a result, we find that the POD is not a sufficient statistic for forecasting default. Yet, over a 6-month forecasting horizon, the functional form of the Merton DD model is useful and Merton DD probability has

[1] In particular, Ji et al. [10] employed the time-varying volatility when calculating Merton's DD and its extension, DC, by sampling the posterior distribution and proposed an early warning indicator using the difference between DD and DC.

ICCS Camera Ready Version 2022
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-08751-6_49

significant default predictability. The findings suggest that the CAR, a unique characteristic of each bank, fails to predict bank default, even in the short-run. Yet, in over the mid- to long-term horizon, bank default predictions can be made more effectively by adding the inverse of equity volatility and the value of net income over total assets for in-sample and out-of-sample forecasts, respectively.

In this paper, Section 2 explains data and methodology, and Section 3 presents the results and discussion. Section 4 concludes.

2 Data and methodology

2.1 Data

Quarterly data of 322 US banks, including 60 failed banks, were retrieved from the COMPUSTAT database for the 2010–2014 period. The term "failed bank" is used following the definition of Fahlenbrach et al. [12]. Failed banks are categorized by their type of failure as follows: (i) banks that are on the list of failed banks maintained by the Federal Deposit Insurance Corporation (FDIC); (ii) banks that have filed under Chapter 11 and are not on the FDIC list; (iii) banks that are merged at a discount; (iv) banks that have been forced to de-list from the stock exchange; and (v) banks that have voluntarily de-listed. During the sample period, most failed banks belong to the "FDIC" and "Forced delisting" categories, and the number of failed banks decreased over time as the effects of the global financial crisis diminished. For the period from 2010 to 2011, the number of failed banks was 26 and 15, and FDIC cases were the main type of failed banks. Table 1 summarizes the annual status of failed banks by type.

Table 1. Sample Construction of Failed Banks

Year	2010	2011	2012	2013	2014	Total
FDIC	13	6	1	2	2	24
Chapter 11	4	1	1	2	0	8
Merged at a discount	3	1	0	1	0	5
Forced delisting	3	6	5	0	0	14
Voluntary delisting	3	1	0	4	1	9
Total	26	15	7	9	3	60

Note: A case filed under Chapter 11 is frequently referred to as a "reorganization" or "rehabilitation" bankruptcy.

ICCS Camera Ready Version 2022
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-08751-6_49

2.2 Hypotheses

This paper aims to investigate whether the probability of default [1] can be used for banks' default prediction. For this purpose, we estimate several Cox proportional hazard models to test the following three hypotheses:

- The first hypothesis is that the POD is a sufficient statistic for forecasting bank default, implying that any other variable in a hazard model should not be a statistically significant covariate other than the POD.
- The second hypothesis is that the functional form of the Merton DD model is useful for forecasting bank default, implying that the POD should remain statistically significant in a hazard model that includes all of the variables used to calculate the POD.
- The third hypothesis is that the POD has bank default predictability, implying that the POD should remain as a statistically significant default predictor in our hazard model, regardless of the other variables that we include in the models.

As a robustness check, we further examine the out-of-sample performance of our models.

2.3 Merton's DD probability and its extension

The Merton model makes two crucial assumptions. The first is that the asset value of a firm follows geometric Brownian motion,

$$dV_t = \mu V_t dt + \sigma V_t dW_t$$

where V_t is the asset value of the firm, μ is the continuously compounded average return on V_t, σ is the volatility of firm value, and dW_t is a standard Wiener process. The second assumption is that the firm has issued only one discount bond maturing after T periods. Under these two assumptions, the equity of the firm E_t is regarded as a European call option on the underlying asset value of the firm with the strike price being the obligated debt payment L at maturity T,

$$E_T = \max[V_T - L, 0].$$

In the end, the resulting Z-score, namely the POD, is the probability that a borrower cannot fulfill its promised payment at maturity,

$$POD = P(V_T < L) = N(-DD)$$

where $N(\cdot)$ is the cumulative density function (CDF) of the standard normal distribution and DD is the distance to default, namely Merton's DD.

In contrast to the probability of default for each firm, the insolvency risk of a financial institution can be measured by estimating the DC considering the minimum capital requirement [9,10]. The probability of undercapitalization (hereafter, POU) is conceptually similar to the well-known POD. For simplicity, we assume that capital consists completely of equity [9] and that the statutory minimum capital adequacy

ICCS Camera Ready Version 2022
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-08751-6_49

ratio is $c = 0.08$ as the threshold for undercapitalization (Basel I). Accordingly, once $V_T - L < c \cdot V_T$ holds at time T after a debt payment, the bank is presumed to be undercapitalized. In particular, the POU is modified from Merton's model [8] and measures insolvency risk rather than default risk, as follows:

$$POU = P(V_T - L < c \cdot V_T) = P(V_T < \lambda L) = N(-DC)$$

where DC is the distance to capital and λ is the correction factor for DC, as follows:

$$\lambda = \frac{1}{1-c}.$$

For the estimation strategy, we follow Ji et al. [10], presenting the sampling procedure from the posterior distribution through state filtering and parameter learning.

2.4 Hazard model

To assess the Merton DD model's accuracy, we need a method to compare the POD to alternative predictor variables. Thus, we employ a Cox proportional hazard model to test our hypotheses [13]. Proportional hazard models assume that the hazard rate $\lambda(t)$, that is, the probability of default at time t conditional on survival until time t, is as follows:

$$\lambda(t) = \lambda_0(t)\exp[Z(t)'\beta],$$

where $\lambda_0(t)$ is the baseline hazard rate and the term $Z(t)'\beta$ allows the expected time to default to vary across banks according to their covariates, $Z(t)$. The baseline hazard rate is common to all banks.

The Cox proportional hazard model does not impose any structure on the baseline hazard rate $\lambda_0(t)$. Cox's partial likelihood estimator provides a way of estimating β without requiring estimate of $\lambda_0(t)$. It can also handle censoring of observations, which is one of the features of the data. Details about estimating the proportional hazard model can be found in many sources, including [13].

3 Results and discussion

3.1 Hazard model results

Panels A and B of Table 2 summarize the results of estimating several Cox proportional hazard models with the 6- and 9-month forecasting horizons. Models 1 and 2 in both panels are univariate hazard models, which explain time to default as a function of the Merton DD probability and its extension incorporating the CAR, that is, the POD and the POU, respectively. These are simple univariate models. Yet, the fact that their explanatory variables vary over time implies that it is more complicated than it might appear. Models 1 and 2 confirm that the POD and the POU are both extremely significant predictors of default.

ICCS Camera Ready Version 2022
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-08751-6_49

Table 2. Hazard Model Estimates

Panel A: Time to default – 6 months

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
POD	2.901***		1.628***		1.562**		1.12
	(0.295)		(0.470)		(0.723)		(0.688)
POU		3.039***	1.671***			1.630***	1.495**
		(0.383)	(0.565)			(0.634)	(0.681)
$\ln E$				−0.115	0.090	0.058	0.190
				(0.125)	(0.159)	(0.151)	(0.171)
$\ln F$				0.041	−0.182	−0.129	−0.273
				(0.130)	(0.164)	(0.155)	(0.175)
$1/\sigma(E)$				−0.828***	−0.604***	−0.644***	−0.484**
				(0.181)	(0.207)	(0.188)	(0.212)
$r_{i,t-1} - r_{m,t-1}$				−0.001	0.003	0.004	0.001
				(0.001)	(0.001)	(0.001)	(0.001)
NI/TA				-0.018	−0.024	−0.038	−0.039
				(0.031)	(0.031)	(0.0.32)	(0.033)
Pseudo R^2	0.085	0.077	0.095	0.124	0.128	0.128	0.130

Panel B: Time to default – 9 months

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
POD	2.685***		1.564***		0.911		0.667
	(0.284)		(0.463)		(0.609)		(0.621)
POU		2.704***	1.446***			0.903	0.736
		(0.350)	(0.530)			(0.580)	(0.630)
$\ln E$				−0.061	0.073	0.000	0.190
				(0.120)	(0.153)	(0.152)	(0.166)
$\ln F$				0.029	−0.121	−0.097	−0.183
				(0.122)	(0.156)	(0.151)	(0.169)
$1/\sigma(E)$				−0.905***	−0.779***	−0.812***	−0.727**
				(0.156)	(0.181)	(0.170)	(0.191)
$r_{i,t-1} - r_{m,t-1}$				−0.003	−0.0009	−0.0003	0.0008

ICCS Camera Ready Version 2022
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-08751-6_49

				(0.001)	(0.001)	(0.001)	(0.001)
NI/TA				−0.016	−0.012	−0.017	−0.013
				(0.022)	(0.023)	(0.0.22)	(0.023)
Pseudo R^2	0.083	0.076	0.089	0.103	0.109	0.108	0.111

Note: There are 322 banks in total and 60 defaults in the sample. The PODs and POUs are expressed in percentage. $\ln E$ and $\ln F$ are the natural logarithms of equity (in millions of dollars) and the face value of debt (in millions of dollars), respectively. $1/\sigma(E)$ is the inverse of equity volatility measured using daily data from the previous year, $r_{i,t-1} - r_{m,t-1}$ is the stocks return over the previous year minus the market return over the same period, and *NI/TA* is the ratio of net income to total assets. A positive coefficient on a particular variable implies that the hazard rate is increasing in that value. Standard errors are in parentheses. *** and ** denote significance at the 1% and 5% levels, respectively.

Model 3 in Panels A and B combines the POD and POU in one hazard model. Both covariates are statistically significant, indicating that the Merton DD probability is not a sufficient statistic for bank default prediction resulting in the rejection of our first hypothesis for the 6- as well as 9-month forecasting horizons. While the coefficients of two covariates have similar magnitudes and statistical significance, their magnitudes are much smaller in Model 3 than in the first two models, Models 1 and 2 for both forecasting horizons. This suggests that the POU shares the information content of the POD related to predicting bank default.

Model 4 in both panels is a simple reduced-form model that employs the same inputs as the Merton DD model: the log of the bank's equity value, the log of the bank's debt, its returns over the past year, and the inverse of the bank's equity volatility. Unlike Bharath and Shumway [4], only the covariate of the inverse of the bank's equity volatility is strongly statistically significant in both forecasting horizons, implying that volatility is a strong predictor of bank default unlike corporate bankruptcy. For example, low volatility over a prolonged period leads to higher risk-taking [14].

Models 5 and 6 in both panels include all the covariates of Model 4 and also include the POD and POU, respectively. Comparing the estimates of Models 4, 5, and 6 in Panel A, we find that the POD and POU are significant predictors, even when all of the quantities used to calculate the Merton DD probability are included in the hazard model. Accordingly, Model 5 in Panel A indicates that the functional form of the POD is a useful construct for bank default forecasting in the 6-month forecasting horizon, providing strong evidence in favor of our second hypothesis. Yet, only $1/\sigma(E)$ in Model 5 of Panel B shows significant predictability in the 9-month prediction. Thus, the functional form of the Merton DD probability fails to create any meaningful information for bank default prediction when the prediction horizon is extended to 9 months. Moreover, unlike in the 6-month default prediction, the role of the CAR also disappears for bank default prediction in the 9-month forecasting horizon shown in Model 6 of Panel B.

ICCS Camera Ready Version 2022
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-08751-6_49

In Panels A and B, Model 7 adds the POU to Model 5; the POU includes information about the Merton DD probability and the CAR into a single risk metric. From the estimates of Model 7 of Panel A, we find that none of the predictors, other than the POU and $1/\sigma(E)$, is statistically significant. Yet, this cannot force to reject our third hypothesis in the 6-month prediction horizon since the POU inherits information content from the POD, in terms of its inputs as well as functional structure, and continues to be significant. This evidence suggests that the POU, that is, the POD incorporating the CAR, could deliver more meaningful information in regard to bank default prediction than the POD, in a 6-month forecasting window. In the 9-month predictions (Models 5, 6, and 7 in Panel B of Table 2), Merton's DD probability does not have predictability for bank default and including the CAR into the POD also fails to provide any meaningful information content as a default predictor.

Overall, Table 2 shows that the Merton DD probability is an extremely significant predictor but is not a sufficient statistic for predicting bank default. Moreover, at least in the 6-month prediction, it indicates that the functional form of the Merton DD model is useful for forecasting bank default and the unique characteristics of each bank could be used in bank default prediction for short-run default predictions: the POU is more important than the Merton DD probability for forecasting bank default. However, both the functional form of the Merton DD probability and even adding the CAR as an additional input for calculating the Z-score fail to produce any meaningful information for bank default prediction in the 9-month prediction.

3.2 Out-of-sample results

Table 3 documents our assessment of the out-of-sample predictability of several variables. To create the table, banks are sorted into deciles of a particular forecasting variable. Then, the number of defaults that occurred up to each decile group is tabulated in terms of the percentage. One advantage of this approach is that the default predictability of a specific variable can be summarized without estimating actual default probabilities. Even if our model for translating the distance to default (and distance to capital) into the POD (and the POU) is slightly misspecified, our out-of-sample results will remain unaffected. Specifically, the normal CDF is not the most appropriate choice.

Table 3. Out-of-Sample Forecasts

Panel A: Out-of-sample forecast – 6 months

	60 failures, 322 firm–months (6 months)				
Decile	POD	POU	E	$r_{i,t-1}-r_{m,t-1}$	NI/TA
1	53.3	53.3	46.7	51.7	51.7
2	81.7	71.7	75.0	73.3	80.0
3	90.0	85.0	85.0	81.7	88.3

ICCS Camera Ready Version 2022
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-08751-6_49

4	100	90.0	90.0	81.7	88.3
5	100	91.7	93.3	86.7	96.7
6–10	100	100	100	100	100

Panel B: Out-of-sample forecast – 9 months

	60 failures, 322 firm-months (9 months)				
Decile	*POD*	*POU*	*E*	$r_{i,t-1} - r_{m,t-1}$	*NI/TA*
1	51.7	40.0	43.3	50.0	53.3
2	76.7	68.3	65.0	61.7	78.3
3	83.3	80.0	81.7	68.3	85.0
4	88.3	86.7	85.0	71.7	90.0
5	100	90.0	90.0	71.7	90.0
6–10	100	100	100	100	100

Note: Panel A examines the accuracy over a 6-month forecasting horizon. There are 322 firms in our sample with 60 defaults. The POD (in percentage) is the Merton DD probability, the POU (in percentage) is the extension of POD incorporating the CAR information, *E* (in millions of dollars) is market equity, $r_{i,t-1} - r_{m,t-1}$ is the stock's return over the previous year minus the market's return over the same period, and *NI/TA* is the bank's ratio of net income to total assets. Panel B considers defaults in the 9-month forecasting horizon, and it includes the same forecast variables as Panel A.

Panel A compares the predictions of the Merton DD model to its extension with the CAR, market equity, past returns, and the ratio of net income to total assets in the 6-month forecasting horizon. While both the Merton DD model probability and its extension (namely, the POD and POU, respectively) are able to classify 53.3% of defaulting banks in the highest probability decile at the beginning of the quarter in which they default, the POU underperforms in terms of classifying defaulting banks in the other deciles. In particular, the POU is an even a worse predictor than E and NI/TA from the 2nd decile, indicating that the inclusion of the CAR in Merton's DD probability, in the form of the POU, even hurts the POD's out-of-sample performance, unlike the hazard models.

In the 6-month forecasting horizon, the out-of-sample performance of the POD is much better than simply sorting firms on their market equity in the entire deciles. This is consistent with the results of corporate default prediction, implying that the success of the POD does not simply reflect the predictive value of market equity [4,15]. Apparently, it is useful to form a probability measure by creating a Z-score and using a cumulative distribution to calculate its corresponding probability. Given that the POU does not perform better than the POD in out-of-sample forecasts contrary to hazard models, the functional form of the probability measure suggested by the Merton DD model appears to be a more valuable innovation than the incorporation of the CAR into the POD.

Panel B reports similar forecasting results with hazard models for a longer prediction horizon, that is, 9 months. Remarkably, the POD and POU, both of which exploit the same Z-score functional form suggested by theory, are not better at default prediction than NI/TA. Yet, both models perform quite well in classifying low-risk banks. In particular, the misclassification of risky banks into the lower risk deciles (deciles 5–10) is obviously the lowest for the POD, implying that using the functional form suggested by theory produces fewer low-risk misclassifications than any of the others considered. These results again confirm that we should reject our first hypothesis in the 9-month forecasting horizon, and the role of the CAR as a default predictor disappears regardless of the forecasting horizon.

Simply sorting banks by the value of their net income over total assets has surprisingly strong forecasting power, greater than any of the other indicators, including the POD, at least for 9-month forecasting. This is in contrast to the economic and statistical significance of the POD and NI/TA in the hazard model, in which NI/TA is not a significant predictor, as well as to the results of the out-of-sample forecasts reported in [4] in the case of firms. Thus, since the Merton DD model has no simple way to capture the innovations in the value of net income over total assets, it is difficult to believe that the POD is a sufficient statistic for default prediction.

4 Conclusion

For US banks in the post-crisis period (2010–2014), we find that the Merton DD measure is not a sufficient statistic for predicting bank default, that is, similar to the prediction of corporate default. However, particularly in the 6-month forecasting horizon, the Z-score calculated by Merton's DD is an extremely significant predictor and its functional form is a useful construct for forecasting bank default. The findings suggest that, over the mid- to long-term horizon, bank default prediction can be improved by adding the inverse of equity volatility (in-sample forecast) and the value of net income over total assets (out-of-sample forecast) in addition to the POD. Yet, the role of the capital adequacy ratio is doubtful even in short-run default prediction.

For corporate default prediction, the forecasting horizon is typically a year. However, the POD has bank default predictability only for a 6-month forecasting horizon, and it is difficult to predict bank default over a longer time horizon, even for 9 months. This is due to the fact that financial institutions are sensitive to investor confidence and the progress of default proceeds much more rapidly than with firms. In conclusion, social costs can be minimized by early diagnosis and rapid response to banks' default by paying attention to the POD. The role of equity volatility and the value of net income over total assets should not be overlooked in bank default prediction. In addition, we could (i) extend Merton's framework by adopting stochastic volatility and (ii) propose an early warning indicator for banks' credit risk for future studies.

ICCS Camera Ready Version 2022
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-08751-6_49

Acknowledgements

This research was supported by the Future-leading Research Initiative at Yonsei University (Grant Number: 2021-22-0306; K.A.).

References

1. Merton, R.C.: On the pricing of corporate debt: The risk structure of interest rates. Journal of Finance 29(2), 449–470 (1974).
2. Hillegeist, S.A., Keating, E.K., Cram, D.P. & Lundstedt, K.G.: Assessing the probability of bankruptcy. Review of Accounting Studies 9(1), 5–34 (2004).
3. Du, Y. & Suo, W.: Assessing credit quality from equity markets: Can a structural approach forecast credit ratings? Canadian Journal of Administrative Sciences 24,212–228 (2007).
4. Bharath, S.T. & Shumway, T.: Forecasting default with the Merton distance to default model. Review of Financial Studies 21(3), 1339–1369 (2008).
5. Campbell, J.Y., Hilscher, J. & Szilagyi, J.: In search of distress risk. Journal of Finance 63(6), 2899–2939 (2008).
6. Gropp, R., Vesala, J. & Vulpes, G.: Equity and bond market signals as leading indicators of bank fragility. Journal of Money, Credit and Banking 38(2), 399–428 (2006).
7. Harada, K., Ito, T. & Takahashi, S.: Is the Distance to Default a good measure in predicting bank failures? A case study of Japanese major banks. Japan and the World Economy 27, 70–82 (2013).
8. Chan-Lau, J.A. & Sy, A.N.: Distance–to–default in banking: A bridge too far? Journal of Banking Regulation 9(1), 14–24 (2007).
9. Ji, G., Kim, D.S. & Ahn, K.: Financial structure and systemic risk of banks: Evidence from Chinese reform. Sustainability 11, 3721 (2019).
10. Ji, G., Kong, H., Kim, W.C. & Ahn, K.: Stochastic volatility and early warning indicator. In Computational Science – International Conference on Computational Science, pp. 413–421. Springer, Cham (2020, June).
11. Nagel, S. & Purnanandam, A.: Banks' risk dynamics and distance to default. Review of Financial Studies 33(6), 2421–2467 (2020).
12. Fahlenbrach, R., Prilmeier, R. & Stulz, R.M.: This time is the same: Using bank performance in 1998 to explain bank performance during the recent financial crisis. Journal of Finance 67(6), 2139–2185 (2012).
13. Cox, D.R. & Oakes, D.: Analysis of Survival Data (Vol. 21). CRC Press. (1984).
14. Danielsson, J., Valenzuela, M. & Zer, I.: Learning from history: Volatility and financial crises. LSE SRC Discussion Paper No 57 (2018).
15. Vassalou, M. & Xing, Y.: Default risk in equity returns. Journal of Finance 59(2), 831–868 (2004).

ICCS Camera Ready Version 2022
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-08751-6_49