Forecasting the Probability of Failure of Thailand's Financial Companies in the Asian Financial Crisis*

Stephen Reynolds, Richard Fowles, James Gander, and
Wannapat Kunaporntham
University of Utah

Somchai Ratanakomut
Chulalongkorn University, Bangkok

I. Introduction

The financial crisis in Southeast Asia has gained widespread attention.[1] In particular, the financial problems in Thailand since early February 1997 have been a major focus of this attention. Even enthusiasts for the McKinnon-Shaw arguments for financial liberalization (eliminating financial repression) to accelerate economic development must be wary of liberalization and seek the knowledge to limit financial crises, if, as critics say, liberalization contributes to developing countries' periodic costs on the order of 10%–20%, even 50%, of gross domestic product (GDP) to recover from banking crises.

Briefly, the crisis occurred when banks and financial companies (financial intermediaries) borrowed heavily on a short-term basis from banks in other countries (mainly in Japan and the United States) and made overly risky loans to finance the construction of commercial and residential units. When the demand for such units was not forthcoming as expected, a domino effect occurred: the real estate investors who borrowed defaulted, their lenders defaulted, and the banks were left with foreign-currency–denominated loans requiring payment. A subsequent foreign exchange crisis followed the collapse of the real estate market. That Thailand overbuilt commercial and residential units is painfully obvious to any traveler to Bangkok. Some economists explain the risky lending by banks and financial companies by resorting to the concept of "moral hazard."[2] Had the demand for the real estate units been forthcoming from Hong Kong and South China businessmen moving to Bangkok when Beijing reasserted control over Hong Kong, as was expected, the financial crisis may never have occurred.

0013-0079/2003/5101-0011$10.00

The macro data pertaining to the Asian financial crisis—trade statistics, balance of payments accounts, and foreign direct investment flows—are abundant. Anecdotal evidence at the micro level is also plentiful. What is scarce in the literature on the topic is a microeconomic analysis of micro data, specifically Asian business firm data. A recent paper by S. Reynolds, S. Ratanakomut, and J. Gander examines the microeconomic data for major industrial firms in Thailand and six other Southeast and East Asian countries.[3] That paper dealt with the financial capital structure of firms, its relationship to certain economic characteristics (firm size, profitability, and industry sector), and the implied vulnerability of firms in the years preceding the crisis. In a related paper, both micro and macro data were used with a logit approach to estimate the probability of financial distress (firms closed down or reorganized) for firms traded on the Stock Exchange of Thailand (SET).[4]

This article examines the financial capital structure of major financial companies in Thailand over the period 1993–98. Our main focus is estimating the probability of a financial company surviving to 1997 (the start of the crisis) and the 1993–96 economic determinants of that probability. Both probit and logistic binomial regression analyses are used. In addition, we were also able to estimate the probability of a firm surviving to and operating in 1998. This estimation requires the use of a multinomial ordinal logistic model. The financial data set from balance sheets and income statements for some 91 financial companies is unique and, to our knowledge, has never been analyzed in the way that we propose to do it.

We discuss the data and the methodology in Section II. The statistical results are then presented in Section III. Some conclusions and limitations are discussed in Section IV.

II. Data and Methodology

The financial data are from the balance sheets and income statements of 91 major financial companies (intermediaries) for each of the years in the treatment period 1993–96. In 1997, only 35 of the original 91 companies survived the financial crisis; of those 35 firms, only 23 survived to 1998. In all, 68 firms were shut down by the Thai government for various reasons relating to risky lending practices. The data were obtained from the Bank of Thailand. The statistical regressions use data for the period 1993–96, giving a total of 364 time-series and cross-section observations. Table 1 provides a comparative statistical description of the variables used in the article for each subsample, survivors and nonsurvivors. Based on the mean and range values in the table, failed finance companies are not much different from the surviving companies.

Our methodology consists of postulating a relationship between the probability of a financial company surviving to 1997 (or surviving to 1998) and certain key economic determinants (firm size in terms of assets, total assets [TA], net profit, net income [NI], and borrowing and lending structures). A time variable is also included to capture any trend effect. As both the borrowing and lending structures are ratios, our model is a partial-financial-ratios model.

TABLE 1

COMPARATIVE DESCRIPTIVE STATISTICS FOR 1993–96 (Millions of Baht)

Variable	Definition	Mean	Minimum	Maximum
Finance companies closed by 1997 ($n = 56$):				
TA	Total assets	13,892	418	102,411
INVCAP	Total investment capital	1,561	37	27,840
ATHCAP	Authorized capital	291	.0+	5,559
NI	Net income (profit)	157	−771	2,000
NPL	Nonperforming loans	152.	.0+	2,550
STD	Short-term debt	11,783	279	76,657
LTD	Long-term debt	730	8	11,753
STDPLTD	Ratio of STD to LTD	34	3	148
BLD	Business lending	9,763	32	66,410
BLPATHCP	Ratio of BLD to ATHCAP	2,107	.6	170,460
BLDPICAP	Ratio of BLD to INVCAP	8	.2	20
NPLPBLD	Ratio of NPL to BLD	.02	.0+	.1
Finance companies surviving to 1997 ($n = 35$):				
TA	Total assets	16,333	279	77,378
INVCAP	Total investment capital	1,991	30	13,204
ATHCAP	Authorized capital	481	.0+	4,900
NI	Net income (profit)	331	−542	2,321
NPL	Nonperforming loans	164	.0+	886
STD	Short-term debt	13,061	134	63,297
LTD	Long-term debt	1,232	7	13,070
STDPLTD	Ratio of STD to LTD	38	1	151
BLD	Business lending	11,800	58	59,728
BLPATHCP	Ratio of BLD to ATHCAP	3,851	4	196,204
BLDPICAP	Ratio of BLD to INVCAP	8	.4	22
NPLPBLD	Ratio of NPL to BLD	.03	.0+	.6
Finance companies surviving to 1998 ($n = 23$):				
TA	Total assets	16,437	279	77,377
INVCAP	Total investment capital	2,012	30	13,204
ATHCAP	Authorized capital	489	.0+	4,900
NI	Net income (profit)	338	−119	2,321
NPL	Nonperforming loans	162	.0+	886
STD	Short-term debt	13,071	134	63,297
LTD	Long-term debt	1,387	7	13,070
STDPLTD	Ratio of STD to LTD	39	1	151
BLD	Business lending	12,092	58	59,728
BLPATHCP	Ratio of BLD to ATHCAP	4,128	4	196,204
BLDPICAP	Ratio of BLD to INVCAP	8	.4	22
NPLPBLD	Ratio of NPL to BLD	.02	.0+	.6

These ratios measure, in effect, the financial health of the firm. Our model differs from the traditional methodology used in accounting and auditing research in that the traditional approach is concerned with using financial ratios to predict firm failure (or bankruptcy), per se, and not to predict the probability of failure. The newer approach in accounting and auditing research is concerned with the probability of failure. We will discuss this point later. Since we use two probability models, we discuss the simpler binomial model first.[5]

By knowing which of the 91 companies survived to 1997, we were able to code the 91 companies existing in each year of the 1993–96 treatment period as survivors (dummy variable coded 1) or nonsurvivors (coded 0). The derived dependent (or response) variable ($Y = 0, 1$) was used in a probit and logistic model of the type: $Pr(Y = 1) = E(Y) = Pr(I^* \leq I) = F(I)$, where I^* is an unobservable threshold index, the unobservable $I = a + \boldsymbol{b}X$, and $F(I)$ is either the standardized cumulative normal distribution or its close approximation, the logistic cumulative distribution function, $1/[1 + \exp -(a + \boldsymbol{b}X)]$. Both functions give the odds of survival (i.e., the probability of $Y = 1$).

The central hypothesis is that, as firm size (assets) increases, the probability of survival decreases. The reasoning behind this hypothesis involves the nature of financial intermediaries, the market of risky borrowers, and moral hazard.

The nature of financial intermediaries is well known. As deposits (short-term borrowing) grow, so do total assets. When lending is undertaken, only the composition of assets changes. If the firm is practicing prudence in lending, it confines its lending to low-risk borrowers (or investments). As assets grow over time, the firm seeks more low-risk borrowers. The increase in firm size should then not necessarily lower the probability of survival.

If, however, the market for low-risk borrowers dries up, the firm, in seeking more highly risky borrowers, lowers its probability of survival. With Thailand's high propensity to save, finance companies generally have plenty of liquidity. Moral hazard enters when finance companies aggressively seek to increase their lending to more highly risky borrowers as their assets grow and thereby decrease the probability of survival.

The reasoning behind the moral hazard argument is based on the belief that financial companies had grown to expect to be bailed out by the government or central bank (Bank of Thailand) for any investment loans that defaulted.[6] There was, as it were, an implicit insurer of last resort. With such financial backing coupled with the fact that financial companies have very little of their own equity capital at risk, the moral hazard conjecture becomes a worthwhile hypothesis to test.

The related hypotheses are that net profit is positively related to the probability of survival; that the firm's borrowing structure (given by the ratio of short-term debt to long-term debt, STDPLTD) is inversely related to the same probability; and that the lending structure (given by the ratio of business lending to total investment capital, BLDPICAP, and the ratio of nonperforming loans to business lending, NPLPBLD) is inversely related to the probability of survival.

Net profit produces internal growth in assets to the extent that profit is retained by the firm. Among several financial uses, it provides a means to pay off short-term borrowing, reduce the risk of default by the firm, and thus increase the probability of survival.

Since the financial companies are intermediaries, their lending and borrowing structures are expected to be important determinants of their probability of surviving. They borrow (take deposits) from the public, banks, monetary institutions, and other countries and lend to businesses and households while setting aside a certain amount of their assets as reserves (as stipulated by law) for bad loans. In general, a large firm with a high STDPLTD ratio, a low net profit, a high NPLPBLD ratio, and a high BLDPICAP ratio is expected to have a low probability of surviving to 1997.

For the multinomial ordinal model, we define a three-element dependent (or response) variable.[7] Financial firms that did not survive to 1997 are coded $Y = 0$, firms that did survive to 1997 but not to 1998 are coded $Y = 1$, and firms that survived to 1998 are coded $Y = 2$. Thus, there are three probabilities, P_1, P_2, and P_3, corresponding to the three mutually exclusive ordered responses, 0, 1, and 2, for the given treatment period. A cumulative-probability–proportional-odds model is used for a logistic function. It is of the form $\log(P_1/1 - P_1) = a_1 + \boldsymbol{b}X$ and $\log\,[(P_1 + P_2)/P_3] = a_2 + \boldsymbol{b}X$, where the odds ratios are proportional and thus have common slopes given by the coefficient vector, **b.** The *X*-determinants give the probability (or the odds) of not surviving to 1997 and the probability (or the odds) of either not surviving to 1997 or to 1998. The probability of surviving to 1998 (i.e., the 23 firms) is given by P_3. Naturally, the cumulative probability (or the odds) of all three events is one. Note that, for this model, we use Y in its natural order (0, 1, 2).

The methodology of using known survivors in 1997 and 1998 after the fact as a way to identify and separate the less risky firms from the more risky firms in the earlier period (1993–96) is similar to the methodology used in revealed preference theory to analyze consumer and firm behavior and to the methodology traditionally used in accounting and auditing research.[8] The current methodology is superior to the traditional methodology of relying solely on financial ratios and discriminant analysis to predict firm failure in that we predict the probability of failure based on ratios and absolute variables.[9] In our approach, we address the dynamics of the failure process by identifying the firms that failed in 1997 and those that later failed in 1998.[10] Also, by observing which firms do in fact survive, there is a presumption that some kind of market optimizing process is working. This process selects for survival, if you will, those financial companies that have been practicing prudence in lending and borrowing and have not been guilty of "moral hazard." In this somewhat indirect way, we attempt to test the conjecture of Krugman and others. What we do by examining the economic determinants of the probability of survival is identify what it takes to be a well-managed financial company (or, conversely, an ill-managed company).

The current methodology has limitations. As indicated, our testing of the "moral hazard" conjecture is indirect. In light of alternatives, this limitation seems reasonable. A direct test would involve a case study of each financial company. Other limitations pertain to using two of the independent variables as ratios.[11] Specifically, both the borrowing and lending structures are ratios. As such, their behavior could be caused by recording errors in either the numerators or the denominators. Also, the lending structure combines business and household loans relative to invested capital, when, ideally, the numerator should be separated. The data, however, would not permit separation. In effect, we assume the same degree of risk for both types of loans.

Total invested capital, that part of the company's assets that is set aside as a reserve, has two main components: investments in government institutions (such as, in the United States, investing in government bonds) and authorized capital investment. The latter is a minimum reserve against risky assets (loans) and is set by law. We are able to separate investment capital into its two components and use as authorized capital (ATHCAP) as an alternative to total invested capital. The lending structure then has the ratio of BLD/ATHCAP = BLPATHCAP.

Last, we have no way of verifying the validity of the financial data by cross-checking it with other sources of data. Our best judgment, based on the numbers themselves and their behavior, is that the data are valid.

III. Statistical Results

The probit and logistical regression results are given in table 2. Two different runs for each of the three models of the probit and logistic regressions were made. Both runs use the lending and borrowing structures, but, in the case of the lending structure, one run uses the ratio of business lending to total investment capital (BLDPICAP) and the other uses business lending to authorized capital (set by law). Regardless of which denominator was used, the variable was not statistically significant, so only the model with total investment capital is reported.

For models 1 and 2, the probit and logistic regressions all have coefficients that are highly significant, with the exception of the coefficient for BLDPICAP. There is no heterogeneity problem. The DFBETAS test on the regression coefficients indicated one influential outlier, observation number 357 for the NPLPBLD (nonperforming loans per business loans) coefficient. In theory, this variable is an important indicator of financial problems. Runs without this observation did not change much. The value of the NPLPBLD coefficient for both models was reduced, but it remained not significant. The corresponding exp(B) value was smaller. As the other results were virtually the same, the results in the table are for the full sample. Because the results

TABLE 2

Comparative Risk-Response Models: Thailand Financial Companies, 1993–96

Variable	Model 1 (1, 0) PROBIT	Model 2 (1, 0) LOGISTIC	Model 3 (0, 1, 2) CUM LOGISTIC
Constant	−20.5	−34.0	20.1 20.8
	(−2.90)*	[8.31]*	[3.51]$^{+}$ [3.75]$^{+}$
TA	−.0004	−.00006	.00004
	(−3.64)*	[12.37]*	[5.71]*
STDPLTD	.0083	.0143	−.0143
	(2.80)*	[7.90]*	[9.44]*
NI	.0024	.0041	−.0026
	(5.19)*	[24.13]*	[16.43]*
BLDPICAP	−.0111	−.0179	.0149
	(−.57)	[.31]	[.24]
NPLPBLD	6.96	11.62	−5.52
	(2.63)*	[6.59]*	[3.83]$^{+}$
YEAR	.21	.35	−.20
	(2.80)*	[7.73]*	[3.11]
χ^2	362.7	363.7	41.17
	$p = .406$	$p = .406$	$p = .0001$
	Cannot reject	Cannot reject	Reject null $B = 0$
Classification rate, overall (%)	68.4	67.9	67.6

Note.—The ratio of coefficient to standard error is given in parentheses. The Wald χ^2 is given in brackets. The cumulative logistic model, model 3, generates two intercept values.

$^{+}$ $p < .10$.

* $p < .05$.

for both regression models are equivalent, our discussion will focus on the logistic regression.

Firm size (measured in total assets) is inversely related to the probability of survival (or odds of survival), indicating that large companies have less of a chance of surviving to 1997 than relatively smaller companies. It is interesting that others have found the same result for American nonfinancial firms during the period 1970–83.[12] This "large-firm disease" is consistent with the "moral hazard" argument and the reasoning underlying it. The coefficient for the borrowing structure is positive, indicating that the more highly risky borrowing structure has a higher probability of surviving to 1997. This is the opposite of our expectation. The profitability coefficient has the expected positive sign.

The time-variable coefficient is positive, indicating that, as time goes on, the probability of survival increases. This is a surprise. It may be because of the implicit bias in the "survival of the fittest" approach to identifying the more risky firms. Positively, it could indicate that the less risky firms became more healthy financially over time and that is why they were selected (by the market, in effect) to survive. The nonperforming loans index (NPLPBLD) has a positive coefficient, which is also the opposite of our hypothesis.

Model 3 is for the cumulative probability logistic regression. The proportional-odds hypothesis could not be rejected, and the global null hypothesis was rejected for all the regression coefficients. The intercepts for both logit functions are marginally significant ($p = .0611$ and .0529, respectively), as is the coefficient for NPLPBLD ($p = .0504$). The coefficients for the time variable (YEAR) and lending structure (BLDPICAP) are not significant. Again, as firm size increases, the probability (or the odds) of not surviving to 1997 or to 1998 increases, the large-firm disease. Also, as before, as the borrowing structure becomes more risky (the short-term to long-term debt ratio increases), the probability of not surviving to 1997 and 1998 falls, a result opposite to our expectation. The profit coefficient is negative, as expected, indicating that the probability of not surviving falls as the profitability increases.

All three models are very good predictors of firm failure and survival. The overall classification accuracy averages 68%. As an example, the logistic model 2 predicts 51 firms that would fail by 1997 (56 did fail) and 11 firms that would survive (35 did survive). There are 29 misclassifications. All in all, the models greatly underpredict the number of survivors. A year-to-year analysis has the models consistently predicting 49–51 firms failing by 1997, an 89% prediction rate. The results indicate that, as early as 1993, financial conditions were not all good in Thailand and that they remained so until 1997, when 56 finance companies were shut down.

IV. Some Conclusions

On balance, our indirect test of the conjecture of Krugman and others would seem to indicate some support for it. Small firms appear more likely to survive, perhaps because they have relatively more to lose financially and are less connected politically, and thus they are more cautious about lending. Concerning political connectivity, however, we find from informal inquiries that all the financial companies have some political connection with institutions from which they borrow. Companies with relatively more short-term debt (the deposits of customers and other borrowing) and more nonperforming loans, however, appear more likely to survive and, by implication, are more cautious about their lending practices. These results are not consistent with the moral hazard conjecture.

It appears, then, that the large financial companies with relatively less (not more) short-term debt and nonperforming loans are more apt to practice "moral hazard." This is a curious mixture of characteristics that is not easily explained. One would think that large financial companies with relatively large short-term debt and nonperforming loans would have a smaller probability of survival (or higher odds of not surviving) and would be more apt to practice "moral hazard." Overall, therefore, the firm-size results or the "large-firm disease" is consistent with the moral hazard conjecture, but the borrowing and lending structures do not lend support to the conjecture. Nevertheless, further research on testing the conjecture is indicated. In terms of public policy implications, our results suggest that smaller rather than larger financial intermediaries should be encouraged.

Notes

* We gratefully appreciate the assistance we received from personnel at the Bank of Thailand, particularly Ms. Jintana, in obtaining the financial data. Any errors are the responsibility of the authors.

1. See, e.g., Kayoko Kitamura and Tsuneo Tanaka, eds., *Examining Asia's Tigers: Nine Economies Challenging Common Structural Problems* (Tokyo: Institute of Developing Economies, 1997); Werner Baer, William R. Miles, and Allen B. Moran, "The End of the Asian Myth: Why Were the Experts Fooled?" *World Development* 27 (October 1999): 1735–47; Ross Garnaut, "The Financial Crisis: A Watershed in Economic Thought about East Asia," *Asian-Pacific Economic Literature* 12 (May 1998): 1–11; and John M. Letiche, "Causes of the Financial and Economic Crisis in Southeast Asia and the Need for National, Regional, and IMF Structural Reforms," *Journal of Asian Economics* 9 (Summer 1998): 181–91. Literally hundreds more references may be found in the abstracts on the subject in *Asian-Pacific Economic Literature* 13 (May/November 1999) and EconLit, the American Economic Association's electronic bibliography of economic literature, http://www.econlit.org/. Both Ronald I. McKinnon (*Money and Capital in Economic Development* [Washington, D.C.: Brookings Institution, 1973]) and Edward S. Shaw (*Financial Deepening in Economic Development* [New York: Oxford University Press, 1973]) challenged the then orthodox view that growth in developing countries was primarily constrained by the high cost of capital—a view that led to administered, low interest rates, and disintermediation—and emphasized the need to increase loanable funds through the positive effects of higher real interest rates on savings. Their challenge became the new orthodoxy, supported empirically in the recent examination of the consequences of financial liberalization in Pakistan by Ashfaque H. Khan and Lubna Hasan, "Financial Liberalization, Savings, and Economic Development in Pakistan," *Economic Development and Cultural Change* 46, no. 3 (April 1998): 581–97. But retreat from liberalization is counseled as the way out of the Asian crisis by Robert Wade, "From 'Miracle' to 'Cronyism': Explaining the Great Asian Slump," *Cambridge Journal of Economics* 22 (November 1998): 693–706. Assertions of the costs to the current crisis countries, e.g., Thailand, are only conjecture until recovery is complete, but estimates for Mexico of 13.5% of gross domestic product (GDP) in 1995, for Venezuela of 18% of GDP in 1994–95, and for Argentina of 55.3% of GDP in 1980–82, are reported by Edward J. Frydl, "The Length and Cost of Banking Crises," Working Paper no. 99-30 (International Monetary Fund, Washington, D.C., March 1999).

2. See, e.g., Paul Krugman, *What Happened to Asia?* available at http://web.mit.edu/krugman/www/DISINTER.htm/ (January 1998).

3. Stephen E. Reynolds, Somchai Ratanakomut, and James P. Gander, "The Private Sector in Financial Crisis: The Short-Term and Long-Term Capital Structure of Firms in Southeast and East Asia," *Journal of Asian Business* 15 (March 1999): 1–14.

4. Sunti Tirapat and Aekkachai Nittayagasetwat, "A Prediction of Firms' Financial Distress Using Macro and Micro Variables: A Case of Thailand," in *Restructuring Asian Economics for the New Millennium,* ed. Jere R. Behrman, Manoranjan Dutta, Steven L. Husted, Pitayanon Sumalee, Chirthivat Suthipand, and Paitoon Wiboonchutikula (Amsterdam: Elsevier Science, 2001).

5. James A. Ohlson, "Financial Ratios and the Probabilistic Prediction of Bankruptcy," *Journal of Accounting Research* 18 (Spring 1980): 109–30.

6. See Krugman.

7. For examples of this model, see Thomajean Johnsen and Ronale W. Melicher,

"Predicting Corporate Bankruptcy and Financial Distress: Information Value Added by Multinomial Logit Models," *Journal of Economics and Business* 46, no. 4 (1994): 269–86.

8. See, e.g., William H. Beaver, "Financial Ratios as Predictors of Failure," *Journal of Accounting Research* 4, suppl. (1966): 71–111; Edward I. Altman, "Financial Ratios, Discriminant Analysis, and the Prediction of Corporate Bankruptcy," *Journal of Finance* 23 (September 1968): 589–609; Edward B. Deakin, "A Discriminant Analysis of Predictors of Business Failure," *Journal of Accounting Research* 10 (Spring 1972): 167–79; and Paul Barnes, "The Analysis and Use of Financial Ratios: A Review Article," *Journal of Business, Finance and Accounting* 14 (Winter 1987): 449–61.

9. See Ohlson; Johnsen and Melicher; and Kay M. Poston, W. Ken Harmon, and Jeffrey D. Gramlich, "A Test of Financial Ratios as Predictors of Turnaround versus Failure among Financially Distressed Firms," *Journal of Applied Business Research* 10 (Winter 1994): 41–56.

10. Amy H. Lau, "A Five-State Financial Distress Prediction Model," *Journal of Accounting Research* 25 (Spring 1987): 127–38.

11. For a discussion of the use of ratios, see Barnes; Juha-Pekka Kallunki, Teppo Martikainen,and Jukka Perttunen, "The Proportionality of Financial Ratios: Implications for Ratio Classifications," *Applied Financial Economics* 6 (December 1996): 535–41; Aswath Damodaran, *Corporate Finance: Theory and Practice* (New York: Wiley & Sons, 1997); and Jerry L. Turner, "The Impact of Materiality Decisions on Financial Ratios," *Journal of Accounting, Auditing, and Finance* 12 (Spring 1997): 125–47.

12. See Johnsen and Melicher.