The Lahore Journal of Economics
18 : 2 (Winter 2013): pp. 147–163

Estimating Firms' Vulnerability to Short-Term Financing Shocks: The Case of Foreign Exchange Companies in Pakistan

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Abstract

Using firm-level balance sheet data for 20 of the 24 exchange companies in Pakistan for the period 2006–11, we explore the sources of firms' vulnerability to short-term financing shocks. Based on the probability estimates of a maximum likelihood binary probit model, this paper shows that the incidence and degree of vulnerability of foreign exchange companies to short-term financing shocks has risen significantly over time. If not managed opportunely, these shocks can cumulate into long-term financing shocks and even lead to corporate failure in the long run. Our regression results show that the corporate managers of these companies cannot ignore macroeconomic factors such as global changes and the macroeconomic environment (inflation and GDP growth) in addition to firm-specific factors (growth opportunities, firm size, permanent earnings, earnings volatility, and working capital management) when managing their firms' vulnerability to short-term financing shocks.

Keywords: Foreign exchange companies, vulnerability, financing shocks, Pakistan.

JEL classification: G33, G30 L80, L89.

1. Introduction

Generally, companies' financial reporting entails documenting three types of cash flows: operating, investing, and financing flows. Operating cash flows arise on account of a company's normal business operations and are crucial because they indicate a firm's capacity to generate sufficient positive cash flows to maintain and expand its operations. In case of corporate failure, firms may require external financing, consequently raising the probability of rolling over their current liabilities and becoming exposed to funding shocks.

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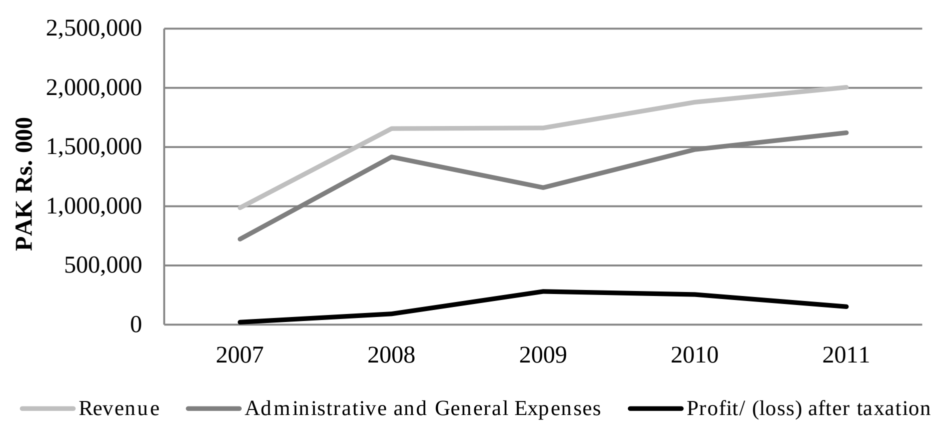
These funding shocks, if not managed well in time, can erode the firm's capital to a potentially dangerous extent (Tudela & Young, 2003b) and lead to corporate bankruptcy or failure. However, at the root of these corporate failures is the inability of firms to overcome or manage their response to short-term funding shocks. Understanding the sources of vulnerability to such shocks is, therefore, critical for corporate managers as well as for investors seeking credit exposure (see Chan-Lau & Gravelle, 2005) to such vulnerable companies. Initially, these funding shocks may weaken a firm's liquidity, but they can also affect the solvency of the corporate sector, potentially destabilizing the economy as a whole if the sector is important. Understanding the sources of vulnerability of foreign exchange companies to short-term financing shocks is crtical, given the foreign exchange exposure of the financial and real sectors in the Pakistan's current exchange rate crisis.

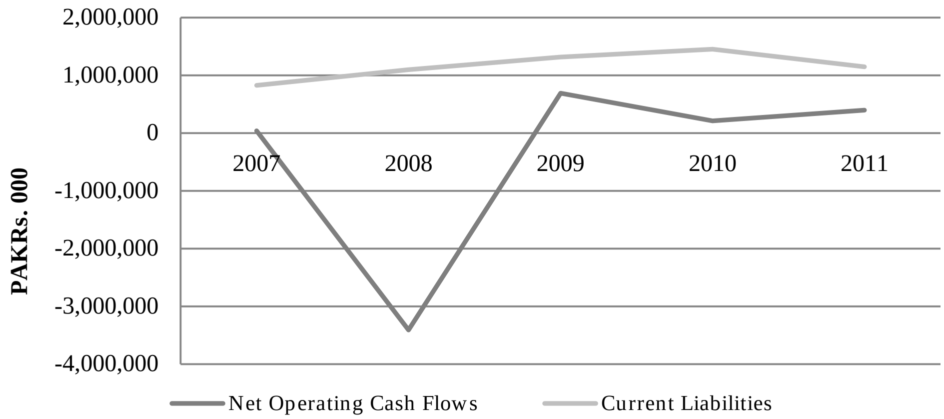
We observe a relatively significant and high degree of volatility in these firms' net operating cash flows compared to their revenue, administrative, general expense, and profit-after-tax flows during the period 2006–11 (Figures 1 and 2). Net operating cash flows are consistently below current liabilities (Figure 2) and provide evidence of the vulnerability of foreign exchange companies to short-term financing shocks in Pakistan. This evidence forms the basis for this study. Currently, there is scant literature on the vulnerability of exchange firms to short-term funding shocks and no attempt has been made to explore the sources of this vulnerability in the context of Pakistan. Accordingly, this study aims to fill this gap in the literature.

Figure 1: Selected indicators of foreign exchange industry



Note: All values are annual aggregates.
Source: State Bank of Pakistan.

Figure 2: Vulnerability of foreign exchange industry to short-term financial shocks



Note: All values are annual aggregates.

Source: State Bank of Pakistan.

The paper is organized as follows: Section 2 reviews the literature; Section 3 describes the data sources and variables employed, and discusses the study's research design and methodology; Section 4 presents our results; and Section 5 concludes the study.

2. Review of the Literature

Hong and Wu (2013) estimate a discrete-time hazard model of bank failure using data on US commercial banks for the period 1985–2004. They identify idiosyncratic and systemic funding liquidity risks as a major predictor of bank failures in 2008 and 2009.[1] Friend and Levonian (2013) conclude that using a market-based measure of capital (or leverage) allows one to predict bank failures farther in advance, thus providing more time to respond and reduce the cost of such failures.

Predictions of corporate banking failures are well documented in the literature. Among the models that attempt to develop an understanding of the factors that lead to bank failure are discriminant analysis (Stuhr & Van Wicklen, 1974; Pettway & Sinkey, 1980), factor analysis, probit and logit regression models (West, 1985; Gajewski, 1989; Thomson, 1991; Reynolds, Fowles, Gander, Kunaporntham, & Ratanakomut, 2002), event-history analysis (Looney, Wansley, & Lane, 1989), market data analysis (Demirgüç-

[1] Out-of-sample forecast.

Kunt, 1989), the proportional hazards model (Whalen, 1991), and belief networks (Sarkar & Ghosh, 1998).

Thomson (1991) uses a logit model to estimate the probability of bank failure, which, he argues, is a function of solvency, capital adequacy, asset quality, management quality, earnings performance, and the relative liquidity of the firm's portfolio. Reynolds et al. (2002) estimate the probability of failure in the context of Thailand's financial companies by applying a probit model to a panel of 91 financial firms. They relate the financial crisis to massive borrowing by banks and other financial institutions abroad and to risky housing loans.

Martin (1977) uses a logit model to estimate bank failure predictions based on data for the period 1970–76. He concludes that higher returns on assets and the capital-to-assets ratio reduce the likelihood of bank failure while a higher proportion of commercial and industrial lending raises the probability of bank default. Hanweck (1977) uses a probit model to predict bank failure based on data for the period 1973–75. He reports that the higher growth of total assets, returns on assets, and capital-to-assets ratios reduce the probability of bank failure while greater financial leverage and larger firm size raise the probability of bank default.

Similarly, Pantalone and Platt (1987) use a logit model to estimate bank failure predictions for the period 1983–85. They find that higher returns on assets and the capital-to-assets ratio reduce the likelihood of bank failure while a higher growth rate for residential lending, the proportion of commercial and industrial lending, and overall financial leverage raise the probability of bank default.

Merton (1974) introduced the idea of quantitatively modeling credit risk to show how the probability of default for an individual firm can be deduced from its market valuation. Beaver (1966) and Altman (1968) show that financial variables can be used to predict firms' liquidation. Ohlson (1980) estimates the likelihood of bankruptcy for nonfinancial firms in the US, using both logit and probit models. His results point to the statistically significant and positive impact of financial structure (total debt-to-total-liabilities ratio) and the negative impact of firm performance (return on total assets), size, and current liquidity (current ratio, working-capital-to-total-assets ratio, and the ratio of operating cash flows to current liabilities) on the probability of failure.

Gilbert, Krishnagopal, and Schwartz (1990) use the multinomial logit technique to estimate probabilities of default and then use these probabilities to classify their sample of nonfinancial firms into two groups, i.e., bankrupt and nonbankrupt. Poston, Harmon, and Gramlich (1994) similarly classify firms into three groups, i.e., turnarounds, business failures, and survivors.

A vulnerable corporate sector can transmit and/or magnify real or financial shocks to the extent that they may weaken overall macroeconomic resilience (González-Miranda, 2012). For policymakers and investors seeking credit exposure, it is therefore important to quantify the probability of such defaults (Chan-Lau & Gravelle, 2005). González-Miranda examines the corporate sector vulnerabilities of individual nonfinancial firms in a situation where their financing is brought to a halt. The study applies a probit model to a panel of 18 countries for the period 2000–11 and finds that higher leverage and maturity exposure raise a firm's probability of exposure to a funding shock, while larger firms with access to buffers are less vulnerable. Greater exchange rate flexibility, however, helps mitigate corporate vulnerability to financing shocks by encouraging hedging (see Cowan, De Gregorio, Micco, & Neilson, 2008; Patnaik & Shah, 2010; Kamil, 2012). Tirapat and Nittayagasetwat (1999) hold that macroeconomic conditions are also critical indicators of a potential financial crisis; investigating a sample of Thai listed firms, they show that the higher a firm's sensitivity to inflation, the greater will be its exposure to financial distress.

It is interesting to note that, while predictions of nonfinancial corporate default, bank failure, and overall financial distress have been widely debated in the literature, the vulnerability of firms to short-term funding shocks (which are likely to cumulate and can lead to organization failure) has received little attention, especially in the context of Pakistan. This study aims to fill this gap in the literature.

3. Methodology

This section describes the methodology, variables, and data sources used in the study.

3.1. Research Design

We use a probit model which serves well as a classification tool (see Langley & Sage, 1994). Drawing on Hanweck (1977), Martin (1977), West (1985), Pantalone and Platt (1987), Gajewski (1989), Thomson (1991), and

Reynolds et al. (2002), we take vulnerability to short-term financing shocks $[VFS_{i,t}]$ as the dependent variable, i.e., $VFS_{i,t}$ is equal to 1 when current liabilities $[CL_{i,t}]$ exceed the net operating cash flows $[NOCF_{i,t}]$ of firm i in year t and 0 when current liabilities $[CL_{i,t}]$ are either less than or equal to net operating cash flows $[NOCF_{i,t}]$.

We use this form of the dependent variable $[VFS_{i,t}]$ to estimate a maximum likelihood (ML) binary probit model because the dependent variable can then take on a binary form with respect to the presence or absence of financing shocks. This helps us in estimating the probability of a firm being subject to financing shocks. We model the probability $[Pr]$ of vulnerability to a financing shock of $[VFS_{i,t}]$ as follows:

$$\Pr\left(VFS_{i,t} = 1 \mid \mid [(X_{i,t}\beta\right), (Z_t\gamma)] = 1 - F(-X_{i,t}^{'}\,\beta - Z_t^{'}\,\gamma) \tag{1}$$

where $X_{i,t}$ is a vector of firm-specific explanatory variables that vary across firms as well as over time; $Z_t$is a vector of explanatory variables that vary only over time; and F is a continuous, strictly increasing function that takes on a real value and returns a value ranging from 0 to 1. We assume that the index specification is linear in the parameters so that it takes the form $(X_{i,t}^{'}\beta)$ and $(Z_t^{'}\gamma)$ respectively. The choice of function determines the type of binary model. It follows that:

$$\Pr(VFS_{i,t} = 0 \mid \mid [(X_{i,t}\beta),\ (Z_t\gamma)] = F(-X_{i,t}^{'}\,\beta - Z_{t\,t}^{'}\gamma) \tag{2}$$

Based on this specification, we can estimate the parameters of this model using the ML method. The likelihood function is written as:

$$l(\beta) = \sum_{i=1}^{n} VFS_{i,t} log\,[1 - F(-X_{i,t}^{'}\,\beta - Z_t^{'}\gamma)] + (1 - VFS_{i,t}\,) log[F\,(-X_{i,t}^{'}\,\beta - Z_t^{'}\gamma)] \tag{3}$$

We code the values of $VFS_{i,t}$ as follows:

$$VFS_{i,t} = \begin{cases} 1\ if\ CL_{i,t} > NOCF_{i,t} \\ 0\ if\ CL_{i,t} \le NOCF_{i,t} \end{cases} \tag{4}$$

This implies that the binary model of firms' vulnerability to financing shocks takes the form

$$VFS_{i,t} = 1 - F\left(-X_{i,t}^{'}\,\beta - \ Z_t^{'}\gamma\right) + \varepsilon_i \tag{5}$$

where $\varepsilon_i$is a residual representing the deviation of the binary $VFS_{i,t}$ from its conditional mean.

3.2. Choice and Description of Variables

We use a dummy variable for vulnerability to financing shocks [$VFS_{i,t}$], which is equal to 1 if net operating cash flows are less than current liabilities and 0 otherwise.

Permanent earnings are likely to reduce $VFS_{i,t}$ while earnings volatility will increase it. We use the return on assets as a measure of profitability (see Martin, 1977; Ohlson, 1980) calculated as follows:

$$ROA_{i,t} = \frac{NPAT_{i,t}}{TA_{i,t}} * 100 \tag{6}$$

If we view the current earnings $\left(ROA_{i,t}\right)$ of firm i at time t as the sum of permanent ($PROA_{i,t}$) and earnings volatility ().), this yields

$$ROA_{i,t} = PROA_{i,t} + RROA_{i,t} \tag{7}$$

We use the following simple technique (see Hussain, 2013) to isolate permanent earnings ($PROA_{i,t}$) from current earnings($ROA_{i,t}$):

Step 1: We regress current earnings $ROA_{i,t}$ on current earnings ($ROA_{i,t-1}$) lagged by one year ($ROA_{i,t-1}$) in the following form:

$$ROA_{i,t} = \alpha + \beta * ROA_{i,t-1} + \mu_{i,t} \tag{8}$$

where $\mu_{i,t}$ represents transitory earnings $RROA_{i,t}$

Step 2: We create a series of residuals ($\mu_{i,t}$) based on the results of equation (8) above to capture earnings volatility or the risk factor ($RROA_{i,t}$).

Step 3: We subtract the residual series [($RROA_{i,t}$)] obtained in Step 2 from the series of current earnings ($ROA_{i,t}$) to obtain the permanent component of earnings ($PROA_{i,t}$).

González-Miranda (2012) reports the negative impact of relative firm size (RFS) on the likelihood of funding shocks. Therefore, we expect a negative coefficient with size and measure it as follows:

$$RFS_{i,t} = \frac{TA_{i,t}}{\sum_{i=1}^{n} TA_{i,t}} * 100 \tag{9}$$

where $TA_{i,t}$ denotes the book value of the total assets of firm i at time t while $\sum_{i=1}^{n} TA_{i,t}$ denotes the book value of the total assets of the industry comprising *n* firms.

Better working capital management is likely to reduce funding shocks or, alternatively, to raise vulnerability (Hong & Wu, 2013). We choose the current ratio $[CR_{i,t}]$ as a proxy for working capital management, which is calculated as follows:

$$CR_{i,t} = \frac{CA_{i,t}}{CL_{i,t}} \tag{10}$$

where $CA_{i,t}$ and $CL_{i,t}$ represent the book value of current assets and current liabilities of firm *i* in year *t*.

Growing firms are likely to be more vulnerable to financing shocks on account of their larger funding needs for growth. Therefore, we expect a negative coefficient with growth opportunities [log(TA)]. We use the logarithm of the book value of assets as a proxy for growth opportunities.

In addition to firm-specific variables, we also include three macroeconomic variables (see Tirapat & Nittayagasetwat, 1999): inflation and GDP growth to capture macroeconomic effects and the nominal effective exchange rate (NEER) to capture the effect of global changes. The NEER serves as a good proxy for global changes because cash flows are likely to be highly influenced, given that most of the current assets and liabilities of foreign exchanges companies are denominated in foreign currencies.

3.3. Dataset

We use secondary data from the State Bank of Pakistan's balance sheet analysis of the financial sector. Our sample covers 20 of the 24 exchange companies operating in Pakistan for which a complete data series for the period 2006–11 is available. Four companies were dropped from the sample on account of incomplete or inconsistent data series. The data on macroeconomic indicators is derived from the State Bank of Pakistan's *Handbook of statistics on Pakistan economy 2010* and the *Statistical bulletin* for 2012.

4. Results and Discussion

Table 1 presents summary statistics that reveal some interesting facts. The NEER and current ratio of exchange companies (CR) are subject to a very high degree of volatility. When firms are exposed to funding shocks due to the volatility of exchange rates, they will fight to manage these short-term shocks by adjusting their working capital. The high degree of inflation volatility also highlights the extent of uncertainty in the economy as a whole, which, in turn, is likely to increase the exposure of exchange firms to short-term funding shocks.

Table 1: Summary statistics

	VFS	LOG (TA(-1))	RFS	PROA	RROA (-1)	D (CR)	NEER	INF (-1)	D (GDPG)
Mean	0.684	12.424	4.584	0.020	0.002	1.000	58.306	13.084	-0.961
Median	1.000	12.309	3.500	0.018	0.002	-0.040	58.777	12.000	-2.000
Maximum	1.000	13.701	14.500	0.098	0.212	242.310	70.298	20.770	1.400
Minimum	0.000	11.522	1.600	-0.115	-0.247	-376.940	50.025	7.770	-3.100
SD	0.468	0.495	2.550	0.027	0.062	62.797	7.684	4.810	1.749
Skewness	-0.789	0.673	1.828	-1.323	-0.531	-1.546	0.619	0.696	0.137
Kurtosis	1.623	3.401	6.452	11.785	9.530	21.968	1.906	2.082	1.489
Jarque-Bera	14.44	6.490	83.22	277.05	144.09	1215.80	8.98	9.16	7.76
Probability	0.001	0.039	0.000	0.000	0.000	0.000	0.011	0.010	0.021
Observations	79	79	79	79	79	79	79	79	79

Source: Author's calculations.

Categorical descriptive statistics for the explanatory variables are presented in Table A1 in the Appendix. The dependent variable frequencies given in Table A2 indicate the presence of short-term financing shocks in 68 percent of the observations in the sample. This evidence fully supports the aims of this study.

Table 2 presents the regression results of the ML-binary probit model. The estimates show that lagged growth opportunities and changes in liquidity significantly (at 10 and 5 percent, respectively) reduce the probability of firms' exposure to short-term financing shocks; larger firms, however, are more likely to face such shocks. A one-percent improvement in growth opportunities reduces vulnerability by almost 1.70 percent. Earnings volatility raises vulnerability (though insignificantly) while permanent earnings significantly (at 10 percent) reduce vulnerability to short-term funding shocks. Changes in the global and local macroeconomic environment significantly (at 5 percent) increase firms' vulnerability while inflation significantly (at 5 percent) reduces the probability of this vulnerability.

Table 2: Regression results

Method: ML-binary probit (quadratic hill climbing)				
Dependent variable: VFS				
Sample period: 2006–11				
Variable	**Coefficient**	**SE**	**z-stat.**	**Prob.**
C: constant	15.6726	10.6060	1.478	0.1395
LOG (TA (-1)): growth opportunities	-1.6988	0.8702	-1.952	0.0509
RFS: relative firm size	0.4320	0.1799	2.401	0.0163
PROA: permanent earnings	-39.9871	22.5336	-1.775	0.0760
RROA (-1): earnings volatility	14.8642	9.5469	1.557	0.1195
D (CR): liquidity	-0.0116	0.0053	-2.182	0.0291
NEER: global changes	0.1615	0.0522	3.095	0.0020
INF (-1): inflation	-0.2436	0.1065	-2.287	0.0222
D (GDPG): macroeconomic environment	1.3279	0.4287	3.097	0.0020
McFadden R-squared	0.2800	SE of regression		0.4148
LR statistic	27.6119	Log likelihood		-35.503
Prob. (LR statistic)	0.0006	Avg. log likelihood		-0.4494
		Avg. log likelihood		-0.4494
Observations with dep. = 0	25	Total obs.		79
Observations with dep. = 1	54			

***Source*:** Author's calculations.

Using the ML-binary probit model, we have estimated the vulnerability (probability) of firms to financing shocks for various years. Our estimates reveal that 16 out of 20 firms have a 5 percent or higher probability of being vulnerable to short-term financing shocks in 2011, compared to only 1 out of 20 firms in 2008 (Table A3 in the Appendix). This clearly shows that the incidence and degree of vulnerability of foreign exchange firms to short-term financing shocks has risen over time.

The results of the expectation-prediction evaluation test for the model's binary specification (Table A4 in the Appendix) show that the estimated equation yields prediction-expectation values that are 100 percent and 78.45 percent, respectively, correct for the presence of short-term financing shocks (dep. = 1) at a success cutoff rate of 5 percent or higher.

5. Conclusion and Policy Implications

Our regression results have shown that growth opportunities, permanent earnings, working capital management, and changes in inflation reduce the probability of financing shocks while firm size, and global (NEER) and macroeconomic changes have a positive and significant impact on the vulnerability of foreign exchange companies to short-term financing shocks in Pakistan. In view of these results, corporate managers of exchange rate companies cannot afford to ignore either macroeconomic and global factors or firm-specific factors in managing the vulnerability of their firms to short-term financing shocks.

About 80 percent of the firms in our sample have a 5 percent probability or higher of being vulnerable to short-term financing shocks in 2011, compared to only 1 percent in 2008. This provides evidence of a significant rise in the incidence and degree of vulnerability of foreign exchange companies to financing shocks over time.

If not managed well in time, these short-term financing shocks can cumulate into long-term shocks and lead to corporate failure of exchange rate companies in the long run through financial and real sector effects. This, in turn, can have serious impacts on an uncertain economy. Therefore, understanding the sources of vulnerability of this sector to short-term financing shocks is critical for policy advisors, investors seeking credit exposure to such vulnerable companies, and corporate managers.

References

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance*, *23*(4), 589–609.

Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research*, *4*(Suppl. Empirical research in accounting: Selected studies), 71–111.

Chan-Lau, J. A., & Gravelle, T. (2005). *The END: A new indicator of financial and nonfinancial corporate sector vulnerability* (Working Paper No. 05/231). Washington, DC: International Monetary Fund.

Cowan, K., De Gregorio, J., Micco, A., & Neilson, C. (2008). Financial diversification, sudden stops, and sudden starts. In K. Cowan, S. Edwards, R. O. Valdés, & N. Loayza (Eds.), *Current account and external financing* (vol. 12, chap. 5, pp. 159–194). Santiago, Chile: Banco Central de Chile.

Demirgüç-Kunt, A. (1989). *Modeling large commercial bank failures: A simultaneous-equation analysis* (Working Paper No. 8905). Cleveland, OH: Federal Reserve Bank of Cleveland.

Friend, K., & Levonian, M. (2013). *Predicting bank failures using a market-based measure of capital* (Mimeo). Atlanta, GA: Federal Reserve Bank of Atlanta.

Gajewski, G. R. (1989). Assessing the risk of bank failure. In *Proceedings of a conference on bank structure and competition* (pp. 432–456). Chicago, IL: Federal Reserve Bank of Chicago.

Gilbert, L. R., Krishnagopal, M., & Schwartz, K. B. (1990). Predicting bankruptcy for firms in financial distress. *Journal of Business, Finance and Accounting*, *17*, 161–171.

González-Miranda, M. (2012). *Nonfinancial firms in Latin America: A source of vulnerability?* (Working Paper No. 12/279). Washington, DC: International Monetary Fund.

Hanweck, G. A. (1977). *Predicting bank failure* (Research Papers in Banking and Financial Economics No. 19). Washington, DC: Board of Governors of the Federal Reserve System.

Hong, H., & Wu, D. (2013). *Systemic funding liquidity risk and bank failures* (Mimeo). Retrieved from http://dx.doi.org/10.2139/ssrn.2328421

Hussain, I. (2013). The paradox of rising dividend payouts in a recession: Evidence from Pakistan. *Lahore Journal of Business*, *1*(2), 97–116.

Kamil, H. (2012). *How do exchange rate regimes affect firms' incentives to hedge currency risk? Micro-evidence from Latin America* (Working Paper No. 12/69). Washington, DC: International Monetary Fund.

Langley, P., & Sage, S. (1994). Induction of selective Bayesian classifiers. In *Proceedings of the 10th conference on uncertainty in artificial intelligence* (pp. 399–406). San Mateo, CA: Morgan Kaufmann.

Looney, S. W., Wansley, J. W., & Lane, W. R. (1989). An examination of misclassifications with bank failure prediction models. *Journal of Economics and Business*, *41*(4), 327–336.

Martin, D. (1977). Early warning of bank failure: A logit regression approach. *Journal of Banking and Finance*, *1*(3), 249–276.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *Journal of Finance*, *29*(2), 449–470.

Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research*, *18*(1), 109–130.

Pantalone, C. C., & Platt, M. B. (1987, July/August). Predicting commercial bank failure since deregulation. *New England Economic Review*, 37–47.

Patnaik, I., & Shah, A. (2010). Does the currency regime shape unhedged currency exposure? *Journal of International Money and Finance*, *29*(5), 760–769.

Pettway, R. H., & Sinkey, J. F. (1980). Establishing onsite bank examination priorities: An early warning system using accounting and market information. *Journal of Finance*, *35*(1), 137–150.

Poston, K. M., Harmon, W. K., & Gramlich, J. D. (1994). A test of financial ratios as predictors of turnaround versus failure among financially distressed firms. *Journal of Applied Business Research*, *10*, 41–56.

Reynolds, S., Fowles, R., Gander, J., Kunaporntham, W., & Ratanakomut, S. (2002). Forecasting the probability of failure of Thailand's financial companies in the Asian financial crisis. *Economic Development and Cultural Change*, *51*(1), 237–246.

Sarkar, S., & Ghosh, D. (1998). Partitioning the attribute set for a probabilistic reasoning system. *INFORMS Journal on Computing*, *10*(4), 399–416.

State Bank of Pakistan. (2010). *Financial statements analysis of financial sector (2006–2010)*. Karachi, Pakistan: Author.

State Bank of Pakistan. (2011). *Handbook of statistics on Pakistan economy 2010*. Karachi, Pakistan: Author.

Stuhr, D. P., & Van Wicklen, R. (1974). Rating the financial condition of banks: A statistical approach to aid bank supervision. Federal Reserve Bank of New York, *Monthly Review*, *56*(9), 233–238.

Thomson, J. B. (1991). Predicting bank failures in the 1980s. Federal Reserve Bank of Cleveland, *Economic Review*, *27*(1), 9–20.

Tirapat, S., & Nittayagasetwat, A. (1999). An investigation of Thai-listed firms' financial distress using macro and micro variables. *Multinational Finance Journal*, *3*(2), 103–125.

Tudela, M., & Young, G. (2003a). The distribution of unsecured debt in the United Kingdom: Survey evidence. Bank of England, *Quarterly Bulletin*, *43*(4), 417–427.

Tudela, M., & Young, G. (2003b, June). Predicting default among UK companies: A Merton approach. *Financial Stability Review*, 104–114.

West, R. C. (1985). A factor-analytic approach to bank condition. *Journal of Banking and Finance*, *9*(2), 253–266.

Whalen, G. (1991). A proportional hazards model of bank failure: An examination of its usefulness as an early warning tool. Federal Reserve Bank of Cleveland, *Economic Review*, *27*(1), 21–31.

Appendix

Table A1: Categorical descriptive statistics for explanatory variables

	Mean		
Variable	**Dep. = 0**	**Dep. = 1**	**All**
C	1.000000	1.000000	1.000000
LOG (TA (-1))	12.43354	12.42026	12.42446
RFS	4.052000	4.829630	4.583544
PROA	0.023412	0.017771	0.019556
RROA (-1)	0.002351	0.001565	0.001813
D (CR)	25.48960	-10.33833	0.999620
NEER	56.34568	59.21406	58.30634
INF (-1)	13.16000	13.04944	13.08443
D (GDPG)	-0.844000	-1.014815	-0.960759
	Standard deviation		
Variable	**Dep. = 0**	**Dep. = 1**	**All**
C	0.000000	0.000000	0.000000
LOG (TA (-1))	0.342306	0.554679	0.495125
RFS	1.426861	2.907221	2.549883
PROA	0.029635	0.025801	0.027010
RROA (-1)	0.063207	0.062131	0.062068
D (CR)	70.63707	55.94860	62.79688
NEER	6.427661	8.095948	7.684488
INF (-1)	4.108864	5.138098	4.809976
D (GDPG)	1.539773	1.849366	1.749243
Observations	25	54	79

Table A2: Dependent variable frequencies

Dep. value	Count	Percent	Cumulative count	Percent
0	25	31.00	25	31.65
1	54	68.00	79	100.00

Table A3: Estimates of firms' vulnerability to financing shocks

	Probability (%)*	
Firm [a]	**2011**	**2008**
MEPL	17.2	2.8
NECL	6.4	8.9
PCECPL	6.1	2.5
NEIPL	5.9	2.4
SEC	5.8	3.0
RIECPL	5.7	2.4
WSECPL	5.6	2.7
AIMEPL	5.5	2.9
PIECPL	5.4	2.9
RECL	5.3	2.8
AECPL	5.3	2.9
DEECPL	5.3	3.5
GECPL	5.3	2.7
PECPL	5.2	4.4
RECPL	5.2	1.8
FECPL	5.0	3.2
HCEPL	4.5	3.2
HHECPL	4.4	2.6
AECPL	4.3	2.7
HQIEP	4.2	2.1

Note: * = probability (%) of being vulnerable to financing shock. [a] Acronyms have been used for the firms.

Table A4: Expectation-prediction evaluation for binary specification, Success cutoff: C = 0.05

	Estimated equation			Constant probability		
	Dep. = 0	**Dep. = 1**	**Total**	**Dep. = 0**	**Dep. = 1**	**Total**
P (dep. = 1) <= C	2.00	0.00	2.00	0.00	0.00	0.00
P (dep. = 1) > C	23.00	54.00	77.00	25.00	54.00	79.00
Total	25.00	54.00	79.00	25.00	54.00	79.00
Correct	2.00	54.00	56.00	0.00	54.00	54.00
Correct (%)	8.00	100.00	70.89	0.00	100.00	68.35
Incorrect (%)	92.00	0.00	29.11	100.00	0.00	31.65
Total gain*	8.00	0.00	2.53			
Percent gain**	8.00	NA	8.00			
	Estimated equation			**Constant probability**		
	Dep. = 0	**Dep. = 1**	**Total**	**Dep. = 0**	**Dep. = 1**	**Total**
E (# of dep. = 0)	13.46	11.64	25.10	7.91	17.09	25.00
E (# of dep. = 1)	11.54	42.36	53.90	17.09	36.91	54.00
Total	25.00	54.00	79.00	25.00	54.00	79.00
Correct	13.46	42.36	55.82	7.91	36.91	44.82
Correct (%)	53.83	78.45	70.66	31.65	68.35	56.74
Incorrect (%)	46.17	21.55	29.34	68.35	31.65	43.26
Total gain*	22.19	10.09	13.92			
Percent gain**	32.46	31.89	32.17			

Note: * = change in "% correct" from default (constant probability) specification. ** = percent of incorrect (default) predictions corrected by equation.