A CROSS SECTIONAL STUDY OF FINANCIAL MEASURES IN PREDICTING STOCKS' RISKINESS DURING YEAR 2008 CRASH PERIOD

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ABSTRACT

The study tests the use of financial measures in predicting stocks' riskiness during 2008 crash period. The stock market witnessed a number of crashes with the most recent one in year 2008. Crashes cause instability in the stock market and a collapse of investor confidence. In a study, Bahhouth and Maysami (2009) showed evidence that Beta had a marginal effect in predicting stocks riskiness. The paper explores the ability of using financial ratios to identify stocks' riskiness (i.e. stocks that are more adversely affected during the crash periods). Analysts, practitioners and academicians used financial ratios in assessing stock returns in financial markets (Arslan, O. and Karam, M., 2009; Bhandari 1988; Basu 1977; Tze, S., and Bon H.,2009). The results showed that a set of financial measures exhibited significant predictive power in identifying stocks that were adversely affected during the year 2008 crash period.

INTRODUCTION

Several studies discussed the crash of stock markets and suggested different explanations. Roll (1989) suggested downward revised expectations for the worldwide economic activity. Others highlighted that stock prices swing from fundamental values because of the trading activities of the uninformed (Shiller, 1984). Zuckerman E. and Rao H. (2004) related the market crash of year 2000 to the main features of trading in technology stocks early in the 1990s. Investors and stock traders were not able to explain the implications of the rise and fall of the Internet stock for many years. Ofek and Richardson (2003) pointed out that during that period, the very high volume of trade in Internet stocks indicated a wide gap between the prices and their fundamental values. Demers and Lev (2001) gave two broad reasons for how Internet stocks reached unjustifiably high prices in the late 1990s and early 2000. The first focuses on the fundamental values that highlight the elements of capital gains and losses. Investors change their opinion often based on indicators rather than on fundamental values. The second suggests that fundamentals were indeed responsible for market prices but investors' interpretations of fundamentals were irrationally optimistic in making their assessments.

Ang, Tourani-Rad, and Yu (2004) in reporting their findings of 1997 south-east Asia crash period made four major remarks which are the following: 1- Price bubbles exist prior to the crash period. 2- Price momentum increases stock price prior to the crash period. 3- Price bubbles are among the most liquid and most volatile shares. 4- stock liquidity changes during crash periods. In addition, it was noticed that during normal periods, illiquid shares are priced at a discount in comparison with those of more liquid shares. The result is a negative effect on the required rates of return. Contrary to these results, during a crash period, illiquid shares experience a smaller drop in prices.

Other researchers (De Long et al., 1993; Shleifer and Vishny, 1997) explained that fundamental limitations on arbitrage might have been responsible. Ofek and Richardson (2003) described a process whereby the significant constraints on the short selling of the Internet stocks prevented the opinions of more reasonable investors from being incorporated into prices. In the early 2000, with the expiration of the lock-up period that prevented insiders from selling stocks, prices of the Internet stocks fell, which led into a price crash (Ofek and Richardson, 2003). Blodget Henry (2005) referred the market crash of year 2000 to the prevailing strategies like "buy and hold" that had been applied for more than a decade. A large number of new market traders believed that 20-percent annual return was normal. In the hindsight, the only pain that approaches the pain of losing money is the pain of not making money when everyone else is. The NASDAQ stock market, for example, did not hit 5,000 because of fraud or idiocy. It was because the majority of investors made investment decisions that they believed reasonable at that time.

This paper tests the use of fundamental measures in identifying risky stocks that are more adversely affected during the year 2008 crash period; the following is the research problem:

- *Null Hypothesis: Financial measures don't identify risky stocks during year 2008 crash period.*
- *Alternate Hypothesis: Financial measures do identify risky stocks during year 2008 crash period.*

METHODOLOGY AND DATA DESCRIPTION

This study takes a deep look into the predictive ability of financial measures in determining the stocks' riskiness during crash periods. The data is a secondary type and is taken from Compustat e-data bank. It covers a twelve-month-period ending by October 31, 2008. The data bank includes the information of the 9870 US publicly traded firms.

A binary logistic regression model (BLRM) is used to test the research problem. Logistic regression is superior to linear regression when the normality assumption of the independent variables is not met. It is simpler to read and to interpret because its values are between zero and one (Tsun-Siou, Yin-Hua & Rong-Tze, 2003; Arslan, O. and Baha, M., 2010;).

The use of the logistic regression model in this study is to evaluate the predictive power of the independent variables (fundamental measures) in classifying traded stocks into two groups (dependent variable). The dependent variable is a non-metric measure and is used to identify these two-stock groups; stocks that are adversely affected during crash periods (assigned a value = 0), and stocks that are less adversely affected (assigned a value = 1).

Data Description and Measurement

The data are of two types:

1. **Dependent variable**, which is non-metric and reflects the change in prices: 0 stands for adversely affected stocks (Risky) i.e. with a decline in price exceeding that of the overall average decline of US publicly traded firms during the 2008 crash period (An average decline of almost 50% was observed during the reported period). 1 stands for stocks that were not adversely affected (Safe) i.e. with a decline in price less than that of the average decline of US public trade firms during the reported period.
2. **Independent variables** are the financial measures and are metric ones. Financial measures were used in a number of studies; Aras and Yilmaz (2008) used price-earnings ratio, dividend yield, and market-to-book ratio to predict return on stock in emerging market. They belong to the five financial measures categories; liquidity measures (Urbanic, 2005; Arslan and Karam, 2009), profitability and return measures (Bernstein and Wild, 1999; Arslan and Karam, 2009), financing measures (De Vaney, 1994) and market measures (Mukherji et al.1997). These measures are TDE (debt / equity), EBITD (earnings before interest, taxes, and depreciation), FCF (free cash flow), PCF (price/ cash flow), DG (debt growth), PE (price / earnings), PBV(price/ book value), ROA (return on assets), ROE(return on equity), ROI (return on investment), and Z Altman measure.

DATA ANALYSIS

The testing was done using the forward method (SPSS); the most significant independent variable enters the model first, followed by those that are less significant to the limit of a 5% level of significance. The number of cases removed from the model because of incomplete data was 8,335, while the number of cases that remained in the model was 1,535.

In stage1, the summary output (table 1) showed the following results:

TABLE 1
VARIABLES IN THE MODEL: Z (STAGE 1)

Observed	Predicted		
	Financially		Percentage correct
	Safe	Risky	
Safe	005	526	00.9%
Risky	012	992	98.8%
Overall Hit Ratio			65.0%

The most significant measure was Z measure and was the 1st measure to enter the model; it explained correctly 0.9% of safe stocks, 98.8% of risky stocks, with an overall hit ratio of 65%. In stage 2, the summary output (table 2) showed the following results:

TABLE 2 VARIABLES IN THE MODEL: Z AND FCF (STAGE 2)			
Observed	Predicted		
	Financially		Percentage correct
	Safe	Risky	
Safe	009	522	01.7%
Risky	023	981	97.7%
Overall Hit Ratio			64.5%

FCF ratio exhibited significant power and entered the model along with Z measure; they both correctly classified 1.7% of safe stocks, 97.7% of risky stocks, with an overall hit ratio of 64.5%. In stage 3, the summary output (table 3) showed the following results:

TABLE 3 VARIABLES IN THE MODEL: Z, FCF AND ROE (STAGE 3)			
Observed	Predicted		
	Financially		Percentage correct
	Safe	Risky	
Safe	015	516	02.8%
Risky	022	982	97.8%
Overall Hit Ratio			65.0%

ROE ratio exhibited significant power and entered the model along with Z measure and FCF; they all correctly classified 2.8% of safe stocks, 97.8% of risky stocks, with an overall hit ratio of 65%.

Testing Reliability

In testing the reliability of the model, two measures are used.

1 Coefficient of Determination (R^2_{Logit}) is similar to that of the ordinary least squares (OLS) regression:

$$R^2_{Logit} = 1 - (2LL_0 / 2LL_1)^{1/2} \qquad (1)$$

Where $-2LL_0$ is the log-likelihood (represents unexplained variations) of the model without the independent variables. $-2LL_1$ is the log-likelihood of the research model based on the independent variables that remained in the model and exhibited significant power in explaining the two stock groups. In general, the interpretation of $R2_{logit}$ is similar to the coefficient of determination R^2 in multiple regressions. It has a value that ranges between 0 and 1. When R^2_{logit} approaches 0, the model is poor. When R^2_{logit} approaches 1, the model is a perfect predictor. The following is summary output (Table 4) of the three stage R^2_{logit}

TABLE 4 R^2_{logit} RESULTS			
Stage	Variables in the model	R^2_{Logit}	Remarks
1	Z	12.1%	Slightly significant
2	FCF and Z	12.9%	Increases
3	ROE, FCF, and Z	13.7%	Increases

2 Overall Hit Ratio: The normal Z-test for the binomial was performed to test the significance of the overall hit ratio (proportion of correctly classified cases). The following formula was applied:

$$\text{Z-test} = [P - 0.5] / [0.5\ (1 - 0.5) / N]^{1/2} \qquad (2)$$

Where P = hit ratio = proportion of correctly classified cases, N = sample size.

The Z-test tests the significance of the hit ratio from 0.5. The hit ratio measures the percentage of times the model accurately classified the cases into the two stock groups i.e. if the model completely explains the dependent variable, the overall hit ratio would be 100%. A level of significance of 5% is used. The following is the summary output (Table 5) of 3-stage overall hit significance test

TABLE 5 SIGNIFICANCE OF OVERALL HIT RATIO					
Measures	Hit Ratio %	N	Z computed	Critical Value	Result
Z	65.0	1,535	30.3	1.65	Significant
FCF and Z	64.5	1,535	29.8	1.65	Significant
ROE, FCF, and Z	65.0	1,535	30.3	1.65	Significant

Both measures showed that the model's reliability is significant.

Limitations of the study

There were two limitations in the study, which are the following: 1- Missing cases: 8,335 cases in this study had missing variables, which were removed from the study as reported in the analysis. 2- The external validity of the model was not tested.

CONCLUSIONS

The research output showed that a group of financial measures i.e. Z measure, FCF and ROE exhibited significant effect in predicting the stock's riskiness; they correctly classified 65% of the cases with R^2_{logit} of 13.7%. While on the other hand, based on a previous study done by Bahhouth and Maysami (2009), Beta and Price-earnings ratio had marginal power in predicting stock price movements by explaining less than 1% and leaving 99% of unexplained variations.

An explanation to these results is that during market down turn, investors rely more on using fundamental measures and avoid using Beta and P/E; in addition, they basically retain stocks based on the financial performance. Evidently, this argument is supported when examining the coefficient of determination, which shows that 13.7% of the total variations of price movements were explained by the group of financial measures, which are Z measure, FCF, and ROE; while in the preceding study, less than 1% of the total variations in price movements were explained by Beta and P/E. However, both models failed to explain significantly the total variation in price movement during market down turn and it is recommended to carry further studies to investigate the sources of the remaining 86.3% of these variations.

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