A parametric survival analysis of fundamental factors and sentiment index towards future stock returns: a new chapter of global financial crisis 2007

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Abstract

The traditional financial theory was purposely invented to analyze the investment performance with the belief that the rational act of an investor could lead to decision making. Most of the theories developed came up with an assumption that the market is perfectly efficient. However, the evolution of the theory led many researchers to find evidence that the decision making process in investment activities could be influenced by the irrational behavior and psychology of an investor. This is called as Behavioral Finance Theory. In this study, linear regression model was used to investigate the effect of sentiment index and the fundamental factors towards future stock returns. Then a Parametric Survival Model by using Log-logistic and Weibull Hazard Model was used to observe the existence and the size of rational bubbles in the market. A time series analysis was performed by using monthly data of NYSE and NASDAQ from five sectors during Global Financial Crisis period (2007-2009). It was found that only 27% out of 30 companies are significant. The sentiment index showed a weak negative relationship towards future stock return while the fundamental factors showed a strong negative relationship towards future stock returns and remained the major contributing factors. Lastly, small in size of rational bubbles were found during the Global Financial Crisis 2008.

1.0 Introduction

Many researchers and practitioners have developed theories and application models to appraise investment performance. Some of the financial theories that have evolved are Capital Asset Pricing Model (Sharpe, 1964), Arbitrage Pricing Theory (Ros, 1976) and Modern Portfolio Theory (Markowitz, 1952). These models are based on the concept of utilizing all the informations available in the market and by considering the rational act of an investor in the decision making process, hence indicating the market is efficient. However, researchers have yet to find the exact answer to reveal the mystery of human psychology, emotion and sentiment in influencing the decision making process. Therefore, another theory is being developed to shed some light into it which is the Behavioral Finance Theory. This theory is being evolved to understand how the investor's behavior and sentiment could influence the decision making process and to some extent how it can be used as predictor tools.

The unending debate among the researchers on whether investor's sentiment has a predictive ability towards stock returns has opened up many opportunities of expanding the epistemology knowledge of behavioral finance. Thus, many studies have been conducted to enhance their arguments by using several different proxies of sentiment extraction. Some of the

sentiment proxies that were used include the surveys of investor confidence, sentiment from market variables, news and social media, and internet message boards. In this paper, we conducted an investigation to see whether investor sentiment could influence future stock return by using a model of sentiment proxies by Baker and Stein (2004) which is the trading volume of an investor. Based on this model, investors can be categorized into two main types which are rational and over-confident investors. They believed that trading volume could be an important indicator of investor sentiment. Overconfident investors will trade more as they belief they will obtain more returns. This will push the price of stock to increase and attract more trading volume. The increase in trading volume in the market reflects the increase in investor sentiment. Therefore, this paper endeavors to investigate whether the fundamental factors and investor sentiment could influence future stock returns. This research paper consists of the analysis of the body of literature relating to the fundamental factors, investor sentiment and future stock returns, hypotheses statement, data and methodology, findings and results and lastly the conclusion.

2.0 Literature Review and Hypotheses Development

2.1 Investor Sentiment

A number of past literatures had conducted studies to examine whether investor sentiment has predictability power towards future stock returns. The empirical results varied depending on the choice of the investor sentiment proxy. Previously, Kim and Kim (2012) subdivided four major groups of literatures that generally tested the relationship between investor sentiment and future stock returns based on the source of sentiment information they had extracted. The four major determinants of sentiment are (1) surveys of investor confidence; (2) sentiment from market variables; (3) news and social media; and (4) Internet message boards. For the first group of papers, most of the researchers such as Otoo (1999), Solt and Statman (1988) and Brown and Cliff (2004) agreed that there were no relationship between sentiment index and future returns. The second group of papers which extracted sentiment from market variables such as Neal and Wheatley (1998), Baker and Wurgler (2006), Baker, Wurgler and Yuan (2011) and Edelen, Marcus and Tehranian (2010) generally reported that there was a negative relationship between investor sentiment and future stock returns. The third group of papers which used sentiment proxies from news and social media such as Clarke and Statman (1998) and Fisher and Statman (2000) reported there was no relation between sentiment and future returns. However, Tetlock (2007), Tetlock, Saar-Tsechansky, and Macskassy (2008) and Chen, De, Hu, and Hwang (2011) reported that there was a negative relationship between sentiment and future stock returns where negative news could forecast firms stock returns. The fourth group of papers used internet message board as the proxies for their sentiment. Wysocki (1998), Antweiler and Frank (2004) Das and Chen (2007) found that the sentiment from internet message boards could predict stock return such as abnormal, positive and negative return.

However, the focus of this paper is to extract the investor sentiment index by using trading volume as the proxy. Several researchers defined sentiment in many sensible ways. Smidt (1968) said that sentiment could lead towards speculative bubbles, Zweig (1973) stated that sentiment comes from investor's biased expectations towards asset values, Black (1986) said that sentiment is the noise in the financial markets, Lee, Shleifer and Thaler (1991) defined it as biased expectation of the investor towards stock return that is unjustifiable by fundamental values and lastly Baker and Stein (2004) defined sentiment as investor's optimism or pessimism towards stocks. In this paper, Trading Volume Index (TVI) was used as a measure of the sentiment. TVI can be defined as the average change of the trading volume per unit of time. Previous literature suggested that trading volume is the best measure for sentiment because of

two main reasons; (1) it can explain the investor overconfidence's movement in the market as stated in Baker and Stein (2004) framework. (2) Smidt (1968) and Brown and Cliff (2004) suggested that the investor sentiment's formation occur through the process of time. This study emphasizes on conducting a preliminary test in five different sectors in which different sizes of company is taken as the sample of works during the period of Global Financial Crisis (2007-2009) as the influencing event towards the movement of investor sentiment.

2.2 Book-to-market ratio

In this study, sentiment index is not the only concern in predicting the future stock returns. There are several other variables that is believed to have predictability power towards future stock returns. Many researchers believed that book-to-market ratio is one of the dominant determinants to predict future stock returns. Some of studies which found that book-to-market ratio can predict the market returns are Fama and French (1992) which showed that the book-to-market ratio of individual stocks had the ability in explaining the variations in stock returns and Kothari and Shanken (1997) was used a Bayesian framework to investigate the ability of book-to-market ratio to predict the market returns and found that book-to-market ratio can predict negative expected return. In contrast to those finding, Fama and French (1995) came out with another finding by which they did not find any causal link between book-to-market equity ratio as factors in earnings and returns.

2.3 Market Capitalization

Other than book-to-market ratio, market capitalization is another determinant that can be used as controlling variable in predicting the future stock returns. Crain (2011) found that smaller firms can predict higher return than the larger ones. Banz (1981) reported there is a relationship between the total market value of the common stock of a firm and its return and found that for the period 1936-1975, the common stock of large firms might be a proxy for risk, therefore, a potentially important return predictor. Smaller firms, in general, are much more risky compared to larger firms, leading to lower prices and higher returns.

3.0 Data and Methodology

3.1 Data collection

The data was collected from Yahoo! Finance and Morningstar (*independent investment research*) databases. The data consists of Future Stock Returns of company (dependent variable), Market Capitalization, Book-to-Market ratio and Sentiment Index (independent variables). The sentiment index was measured by calculating the changes in trading volume twice. The data comprised of five companies from five different sectors NASDAQ and NYSE market comprises of Consumer goods, Technology, Healthcare, Services and Financial sectors. The data was based on monthly basis from 1st January 2007 to 31st December 2009. To avoid bias in selecting the data, we selected the companies from three different groups which were large cap, Medium cap and Small cap. Market Capitalization and Book to Market ratio are transformed into logarithmic form.

3.2 Diagnostic Data

3.2.1 Unit Root Test

Prior to the regression analysis, unit root test were conducted by using Augmented Dickey-Fuller (1979) (ADF Test) and Phillips-Perron (1988) (PP Test) to test the data stationary. Based on the ADF test, Futures Return and Sentiment Index for all panel data failed to reject the null hypothesis, thus indicates the data are stationary at level. Both Log Market Capitalization

and Log Book to Market ratio are stationary at first difference. All the results in PP test were consistent with the ADF test for all companies.

3.2.2 Variance Inflation Factor (VIF) Test

The VIF test was employed to identify whether there was multicollinearity problem between all the independent variables. Multicollinearity or also known as perfect collinearity can occur among the independent variables and can cause problem to understand the significance of each variable in the multiple regression model. Thus, to avoid this problem, Variance Inflation Factor was employed to measure how much the variable contributes towards the standard error in the regression. Large VIF indicated that the multicollinearity problem is existed. The formula of VIF is as follow:

$$VIF_{j} = \underbrace{1}_{1+R^{2}_{i}}$$
Equation 1

The R^2_J indicates the multiple correlation coefficients. When the value of R^2_J is 0, then the independent variables are not correlated. While if the VIF value is 1, it shows there is no multicollinearity problem exist in the variables. However, if the VIF value is more than 10, it indicates that there is a multicollinearity problem among the variables. Therefore, based on the results in this study, the centered VIF value were less than 10 for all companies which indicated that all the variables were free from multicollinearity problem.

3.2.3 Breusch-Godfrey LM Test

We employed Breusch-Godfrey LM test (1978) to detect the autocorrelation problem within the datasets. According to Gujarati and Porter (2010), this test is more general than few other tests for autocorrelation. The residual regression is shown below:

$$e_t = \alpha_1 + \beta_2 X 1_t + \beta_2 X 2_t + C_1 e_{t-1} + C_2 e_{t-2} + + Ck e_{t-k} + v_t$$
 Equation 2

The Breusch-Godfrey LM test results portray the serial correlation of the probability for all companies are greater than 0.05 ($\chi^2 > 0.05$) which reject H₀ and indicates no serial correlation existence.

3.2.4 Multiple Linear Regressions

To ascertain the first objective of this study, we applied the multiple linear regressions model. The empirical model is as follows:

$$\check{r}_{t+1} = \alpha + \beta_1 \Phi_t + \beta_2 \delta_t + \beta_3 \mu_t + \varepsilon_t$$
Equation 3

Where;

 \check{r}_{t+1} = Future stock return

 Φ = Sentiment index δ = Market Capitaliz

δ = Market Capitalization μ = Book-to-Market ratio

 α = constant

 β = Beta coefficient

 ϵ = Residual term

3.2.5 Parametric Survival Model

In order to achieve the second objective, the Parametric Survival Model was employed. We used the Log-Logistic Hazard Model (Bennet, 1983) to detect the presence of the rational

bubbles in the stock market during Global Financial Crisis 2008. Whereby, the Weibull Hazard Model (Mudhokar, Srivastava and Kolia, 1996) was used to analyse the size of the bubbles. The log-logistic survivor function is as follow:

$$S(t) = \frac{1}{1 + (\lambda t)^2}$$
 Equation 4

Where $\alpha = -\log \lambda$ and $p = 1/\sigma$. The hazard function is:

$$\lambda (t) = \frac{\lambda p (\lambda)^{p-1}}{1 + (\lambda t)^p}$$
 Equation 5

The logit of the survival function S(t) is linear in logit provides a diagnostic plot. If the straight line appears on the graph, then the survivor function is log-logistic. While the hazards itself are:

- Monotone decreasing from ∞ if p<1
- Monotone decreasing from λ if p=1, and
- Similar to the log normal if p=1

The Weibull Hazard Model (Mudhokar, Srivastava and Kolia 1996) is defined as:

$$S(t) = \exp(-at^{bt+1})$$
 Equation 6

S(t) is the likelihood of survival in a data set to at the time t. Therefore, the matching hazard function is:

$$H(t) = \alpha (\beta + 1)t^{\beta}$$
 Equation 7

Where β is the duration coefficient of the hazard function and α is the size or shape parameter of the Weibull distribution. The Weibul Hazard model basic idea is that of a linear function between the log hazard function and the log of duration, which can be simplified as:

Ln
$$[h(t)] = ln[\alpha(\beta + 1] + \beta ln(t)]$$
 Equation 8

Hypotheses to be tested were as follow:

H₁: There is significant relationship between the fundamental factors and investor sentiment towards future stock return

H₂: The rational bubbles are exist in the stock market during GFC 2008

4.0 Findings and Discussions

4.1 Results of Multiple Linear Regressions

Table 1 illustrates the results of Multiple Linear Regressions of 8 companies that showed significant relationship out of 30 companies in the sample of study. All companies displayed significant relationship towards Future Stock Return at 95% critical level except for company 124 which was significant at 99% critical level. Table 2 displays the summary of relationship between the independent variables and dependent variable. The results showed that both fundamental factors had a strong negative relationship towards future stock return. On the other hand the sentiment index only showed weak negative relationship where evidences were only found in company 105, 122 and 124 only. The results in Table 3 portrays the summary of the companies that are significant and insignificant based on different industries. Among all

industries, the services sector had the most significant companies while Technology sector did not show any significant evidence. This might be due to the Technology sector which was not much affected during the Global Financial Crisis 2008 or might be due to some other reasons.

4.2 Results of Parametric Survival Analysis

Table 4 specifies the test for duration dependence for Future Stock Returns based on the model motivated by Baker and Stein (2004). Based on the Log Logistic results, all companies produced negative alphas and positive coefficient of duration elasticity which indicated that the bubbles do exist and there was positive duration dependence among the companies. The gamma for the companies was less than one and indicated that the hazard rates were monotone decreasing. The LR test for the absence of duration dependence test suggested that all the companies in this group rejected the null hypothesis and concluded that there was positive duration dependence in the series of Future Stock Returns.

Weibull Hazard Model results expound the positive alpha values which indicated that the rational bubbles existence supports the findings of Watanapalachaikul and Sardar (2003) who claimed that rational bubbles were indicated when the beta coefficient is positive. The results generated from this model indicated the rational bubble's size were still small and showed no sign of bursting in the short period of time during the GFC period.

Table 1: Results of Multiple Linear Regressions

Company	Coefficient	t-stat	t-stat p-value		F-stat	
101		Control of the Control				
Constant	1.357277	1.090825	(0.2843)		1	
InMcap	-0.098004	-1.758114	(0.0893)*	0.231869	2.917992	
lnBM	-0.210706	-2.224616	(0.0340)++		(0.050848)++	
Sent	-0.005096	-0.962653	(0.3437)		\$5.53230312003EM	
105						
Constant	2.366467	2.503399	(0.0182)***	0.264835		
InMcap	-0.132348	-2.727408	(0.0107)***		3.482310	
InBM	0.039391	0.635926	(0.5298)		(0.028376)++	
Sent	-0.010293	-1.978197	(0.0575)**		44.50.00.00.00	
110						
Constant	-3.892772	-2.894107	(0.0071)***	0.275055	3.667673	
InMcap	0.123044	2.421526	(0.0219)**	3 (2000) (2000)	(0.023520)**	
InBM	-0.397231	-3.246098	(0.0029)***		500000000000000000000000000000000000000	
Sent	0.001506	1.614345	(0.1173)		1	
115				1		
Constant	1.076364	1.224145	(0.2307)		l	
InMcap	-0.089144	-2.415060	(0.0223)**	0.255402	3.315722	
InBM	-0.183047	-1.882209	(0.0699)*		(0.033646)**	
Sent	-0.000320	-0.213992	(0.8321)		#22500000115#U	
118					1	
Constant	1.150516	1.804394	(0.0816)*			
InMcap	-0.105664	-2.766966	(0.0097)***	0.263632	3.460833	
lnBM	-0.202291	-2.421864	(0.0219)**		(0.029004)**	
Sent	-0.000705	-0.477438	(0.6366)		- Secretary Control	
121						
Constant	1.378376	1.675022	(0.1047)		0.0000000000000000000000000000000000000	
lnMcap	-0.112720	-2.408101	(0.0226)**	0.257413	3.350891	
lnBM	-0.205936	-2.596496	(0.0146)***	Electric total	(0.032453)**	
Sent	0.001142	1.637962	(0.1122)		51 355	
122					†	
Constant	0.626834	0.884593	(0.3837)			
InMcap	-0.083021	-1.956748	(0.0601)*	0.227461	2.846190	
InBM	-0.262299	-2.046669	(0.0498)**		(0.054834)**	
Sent	0.003447	1.706918	(0.0985)*			
124						
Constant	-2.525502	-2.275634	(0.0304)**			
InMcap	0.145069	1.872111	(0.0713)*	0.298041	4.104327	
InBM	0.004801	0.045588	(0.9640)	10000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (100) (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (1000 (100) (1000 (1000 (1000 (1000 (1000 (100) (1000 (1000 (100) (1000 (1000 (1000 (100) (1000 (1000 (1000 (100) (1000 (1000 (100) (1000 (1000 (100) (1000 (1000 (100) (1000 (1000 (100) (1000 (1000 (100) (1000 (100) (1000 (100) (1000 (100) (1000 (100) (1000 (100) (1000 (100) (1000 (100) (1000 (100) (1000 (100) (1000 (100) (1000 (100) (1000 (100) (1000 (100) (1000 (100) (1000 (100) (1000 (100) (1000 (100) (1000 (100) (1000 (100) (1000 (100) (1000) (1000 (100) (1000 (100) (1000 (100) (1000 (100) (100) (1000 (100) (100) (1000 (100) (1000 (100) (100) (100) (1000 (100) (100) (100) (100) (100) (1000 (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100)	(0.015231)***	
Sent	0.002602	2.460848	(0.0201)**			

Figure in the parentheses indicates the p-value. *, ** and *** denote 90%, 95% and 99% critical value.

Table 2: Summary of Positive versus Negative Relationship

Variables	Positive Relationship	Negative Relationship		
Sentiment Index	38%	62%		
lnMcap	12%	88%		
lnBM	0%	100%		

Table 3: Results of Industry Analysis

Industry	Significant	Insignificant	
Consumer Goods	2 Companies	4 Companies	
Financial	1 Company	5 Companies	
Healthcare	2 Companies	4 Companies	
Service	3 Companies	3 Companies	
Technology	0 Company	6 Companies	
Overall	8 Companies (27%)	22 Companies (73%)	

Table 4: Results of Parametric Survival Analysis

Code/Model	Log Logistic Hazard Model				Weibull Hazard Model			
	α	β	Y	H ₀ ; β=0	α	β	Y	H₀: β=0
101	-0.4266639	0.5080211	0.0605978	(28.20)***	1.924957	0.0763697	0.1458821	(13.32)***
105	-0.4090504	0.5134788	0.0501799	(23.28)***	1.807184	0.0975212	0.1641156	(14.31)***
110	-0.3350791	0.5004538	0.0569011	(24.85)***	2.51270	0.0104096	0.0810491	(10.50)***
115	-0.2140462	0.4414599	0.1058663	(17.97)***	1.999728	0.0634909	0.1353721	(12.46)***
118	-0.3898826	0.4897584	0.0960987	(26.11)***	1.567137	0.1635444	0.2086418	(16.35)***
121	-0.3775927	0.4838925	0.0800536	(27.16)***	1.808499	0.1036901	0.1639000	(14.95)***
122	-0.4781608	0.5705871	0.0709796	(25.80)***	1.83874	0.0867776	0.1590177	(14.52)***
124	-0.5001379	0.5584854	0.0477823	(37.16)***	1.948857	0.0666445	0.1424368	(13.48)***

Notes: Figures in the parentheses are the LR (χ^2). *, ** and *** Denote significance at the 10%, 5% and 1% level respectively. The LR statistic test for the absence of duration dependence. The Log Logistic and Weibull models, the absence of duration dependence corresponds to β =0 and the LR statistic is asymptotically χ^2 with 1 degree of freedom.

5.0 Conclusion and Recommendation

In this study, we aimed on achieving two main objectives which were (1) Forecasting the relationship between the fundamental factors and sentiment index towards future returns and (2) Detecting the existence of rational bubbles in the stock market during Global Financial Crisis 2008. We were driven to conduct the study to reveal whether the future stock return was more influenced by the fundamental values or by the behavioral element which is the sentiment of an investor. Studies on sentiments are still being debated on which proxy of sentiment should be used. Therefore in this study we used trading volume index to extract the sentiment index where Baker and Stein (2004) believed as the best measurement of the sentiment. Furthermore, to enhance the level of the sentiment, we extracted the data during the period of Global Financial Crisis 2008 that could be a great contributor towards investor sentiment activity in the stock market. We conducted a Multiple Linear Regression to examine the relationship between

sentiment and the fundamental factors towards future stock return and generally found that there is a weak evidence that shows sentiment is negatively related to future stock return. Meanwhile, Market Capitalization and Book-to-Market remained the major contributor towards future stock returns. However, less than half of the sample did not show any significant effect. The results can be concluded that the measurement for the sentiment is still debatable. We also found the rational bubbles existence during the financial crisis period even though the size was small. Therefore, the main recommendation for the next study on this area of interest is to focus more on the measurement of investor sentiment. Other than that, the period of study can be more extended into pre, during and post Global Financial Crisis.

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