Market Crashes and Investor Sentiment：The Case of Taiwan

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ABSTRACT

This study examines the dynamic relations between market fluctuation and investor sentiment for the Taiwan stock market before critical crash using the LPPL (log-periodic power law) signatures. First, aftershock patterns resembling those associated with earthquakes also occurred in the Taiwan stock market before critical crashes. It exhibits the same pattern of cycles speeding up as approaching to a crash point. Second, a lead-lag relationship exists between the Taiwan stock index and investor sentiment. This study finds the variance increases of frequency on investor sentiment move ahead of the increase in stock index variance as a crash approaches. The investor sentiment variables can be used to forecast the time of a crash.

Keywords: *Market Crashes, Investors Sentiment, Log-periodic Power Law, , GARCH model, Granger causality.*

INTRODUTION

Financial crashes are major financial events both in reality and from the perspective of academic research. During the last century, several global financial crashes occurred, for example in 1929, 1962, 1987, 1998 and 2000[1]. Each of these crashes almost instantaneously destroyed years of pensions and savings. However, previous research on bubbles and crashes has mostly focused on EMH (efficient market hypothesis) or rational men (e.g.,Blanchard and Waston, 1982; Tirole, 1982; Chen et al., 2001), while investor sentiment has been relatively neglected. Interestingly, an increasing body of recent evidence supports the noise trader theory (e.g., Chen et al., 1993; Daniel et al., 1998; Hirshleifer, 2001) and market anomalies such as momentum (e.g., Jegadeesh and Titement, 1993, 2001; Lee and Swaminathan ,2002; Lasfer et al., 2003; Roberto and Christo, 2005), herding (e.g., Lakonishok et al., 1992; Nofsinger and Sias, 1999; Dennis and Strickland, 2002; Gleason et al., 2004). Moreover, Qiu and Welch (2004) see sentiment as playing an important role in financial markets. Baker and Wurgler (2004) form a composite index of sentiment and predicted that a wave of investor sentiment disproportionately affects securities whose valuations are highly subjective and difficult to arbitrage. These studies challenge the classical view of efficient and rational financial markets. Consequently, whether a wave of investor sentiment is the probably factors or process driving crash happened? If the dynamic relationship between critical crash and investor sentiment can be identified, it may help in answering the question of which factors driving crashes happened and developing indicators for tactical asset allocation or market timing before critical crashes.

Notably, the individual investors comprise over 80% of trading activity in the Taiwan stock market, far more than in most developed markets. This study investigates three crashes in the Taiwan stock market, occurring in 1990, 1997 and 2000[2], and each of which involved losses 5-8 trillion NTD. For individual investors, the fear of a crash is a

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[1] The utility industry crash occurred in 1929; the electronics industry crash occurred in 1962; the 1987 crash resulted from general market deregulation causing many new private investors to enter the market with unrealistic profit expectations; the 1998 crash is often attributed to a devaluation of the ruble and political events in Russia and also termed the Asian Currency Crisis; finally the 2000 crash result from unrealistic expectations regarding the Internet, telecommunications and other technology industries.

[2] This study investigates three crashes occurring in the Taiwan stock market: the 1990 crash resulted from the real estate bubbles and saw market capitalization lose 5.9 trillion NTD; then 1997 crash swathe stock market lose 6 trillion NTD; the 1998 crash result from the bursting of the technology bubble and saw market capitalization lose 8.5 trillion NTD.

perpetual source of stress, and its onset can have drastic consequences. Furthermore, Dennis and Strickland (2002) argue that individual investors are less sophisticated and more risk averse than institutions, and thus individual investors tend to overreact and sell during sharp market drops. Moreover, the "noise trader" theories of Black (1986) and De Long et al. (1990) propose that if some investors trade on a "noisy" signal that is unrelated to fundamentals, then asset prices will deviate from their intrinsic value. For this reason, this study uses Taiwanese data to test and verify the dynamic relations between market fluctuations and investor sentiment before critical crash.

Furthermore, a series of recent papers have presented increasing evidence that market crashes and large corrections are often preceded by speculative bubbles with one main characteristic: a power law acceleration of the market price decorated with log-periodic oscillations, which is so-called log-periodic power law (LPPL) signatures associated with speculative bubbles resulting from imitation between investors herding behavior (e.g., Zhou and Sornette, 2003). Notably, evidence that the cycle frequency speeds up as a crash approaches exists in numerous markets. Market trends best describe as the accelerating power law with log-periodic oscillation occur in markets, including the US (especially the DJIA, S&P500 and Nasdaq), German, Polish, Argentina, Brazil, Mexico, Hong-Kong and Korea stock market indices and so on (e.g., Vandewalle et al., 1999; Johanson and Sornette, 2000a, 2000b, 2001; Zou and Sornette, 2003; Sornette, 2003; Gnacinski and Makowiec ,2004). Consequently, idea that complex adaptive systems evolve towards a critical state stems can describe the states of crash.

This study, first adopts an empirical approach based on the model of LPPL signatures to describe a critical crash for the Taiwan stock index before the crash of 1997. Log-periodic patterns have been demonstrated to exist before this crash, and foreshock and aftershock patterns are known to occur not only in earthquakes but also in the Taiwan stock market crashes. Next, we elected five investor sentiment variables based previous studies, and obtains the frequency of the Taiwan stock index and investor sentiment variables based on log-periodic pattern constructed through the envelope function technique. Finally, the main focus of this study is applying the GARCH model to calculate the frequency variance and next using Granger causality with the frequency variance to test the dynamic relation between market fluctuation and investor sentiment before a crash. Interestingly, this study finds that increases in frequency variance of investor sentiment variables are ahead of those of stock index's variance increase as the time of the crash draws closer. Indeed, using the LPPL signature method, this study demonstrate that investor sentiment variables drivers precursory imprints before a crash, and can even be used to forecast market timing.

The remainder of this paper is organized as follows. Section 2 then introduces the investor sentiment variables, data and methodology. Next, section 3 describe Taiwan stock index with LPPL signatures and obtains frequency of Taiwan stock index and investor sentiment variables using the envelope function technique. GARCH model is applied to calculate the frequency variance and Granger causality model is used to test the lead-lag relationship between the Taiwan stock index and investor sentiment variables using the frequency variance. Finally, section 4 presents conclusions.

DATA AND METHODOLOGY

Measures of investor sentiment

A body of research has market anomalies like momentum, over/under-reaction and herding. DeBondt and Thaler (1985, 1987) found evidence of overreactions in stock markets. Richards (1995, 1997) used national stock market indexes to show that winners outperform losers over a six month horizon, but lowers outperform winners over three- and four-year horizons. Moreover, Jegadeesh and Titman (2001) evaluated the profitability of momentum strategies and found support for the behavioral models. Dennis and Strickland (2002) find that positive feedback herding behavior on the part of some institutions, particularly mutual and pension funds. The above studies clearly demonstrate that investors do not act like the rational individuals so beloved by economists.

The likely investor sentiment factors driving increases in log-term correlation among investors trading strategies which can be used to indicate the timing of market crashes, need to be identified. Liquidity is generally applied within fund management groups, trading desks and derivative desks. Chorida et al. (2000) formed daily time series of various measures of liquidity, such as depth and quoted and effective bid-ask spreads, and also of trading volume, such as dollar and share volume. Furthermore, Jones (2000) collects an annual time series of average quoted bid-ask spreads. Moreover, Datar et al. (1998) indicated that stocks with low turnover have higher returns than stocks with high turnover. Additionally, Amihud (2000), Lo and Wang (2000) employed turnover as a measure of liquidity. Finally, Baker and Stein (2001), and Baker and Wurgler (2004) found evidence that turnover can serve as an index of sentiment. Consequently, this study used daily Highest-Lowest spreads and turnover for Taiwan stock index as a proxy of liquidity and sentiment.

Second, investment risk magnitude could influence investor returns, in value effect respect growth stocks are more risk than value stocks. For example, Skinner and Sloan (1999) found clear evidence of an asymmetrically large reaction to earnings disappointments for high growth firms. Moreover, La Porta (1996) examined a large sample of US stocks and discovered that the stocks with the highest future returns earned significantly lower returns than those with the lowest growth forecasts. Chan et al. (2001) reached a similar conclusion that growth stocks are more risk than value stocks. These studies have demonstrate that there are numerous excellent reasons to believe the market pricing of value and growth stocks is not driven purely by risk factors, and that sentiment and psychology also play a large role. This study uses P/E ratio as a proxy of investment risk for investor sentiment.

Moreover, the structure of the Taiwan stock market with noise traders comprising over 80% of trading activity different from that in developed countries. Odean (1998) showed that one of the effects of investors over-confident was high turnover. Gervais and Odean (2001) showed that noise trader more excessively than others. Brown and Cliff (2004) used percentage change in margin borrowing and short interest as a bullish and bearish indicator related to particular types of trading activity. Therefore, this study constructs a MM ratio based on dividing margin purchases by market value as a bullish indicator, as well as SM ratio based on dividing short sales by margin borrowing to capture relative market strength.

Finally, five investor sentiment variables, Highest-Lowest spreads, turnover, P/E ratio, MM ratio and SM ratio are selected, to test and verify whether they are indicators of precursory imprints before crash.

Data

The data set comprises daily market close prices, Highest-Lowest spreads, turnover, P/E ratio, margin purchase and short sale for the Taiwan stock index. The data covers the period 07/01/1993-08/26/1997. The crash 1997 is the research event. Fig. 1 displays the movement of the Taiwan stock index for the period 10/17/1986-05/20/2004.

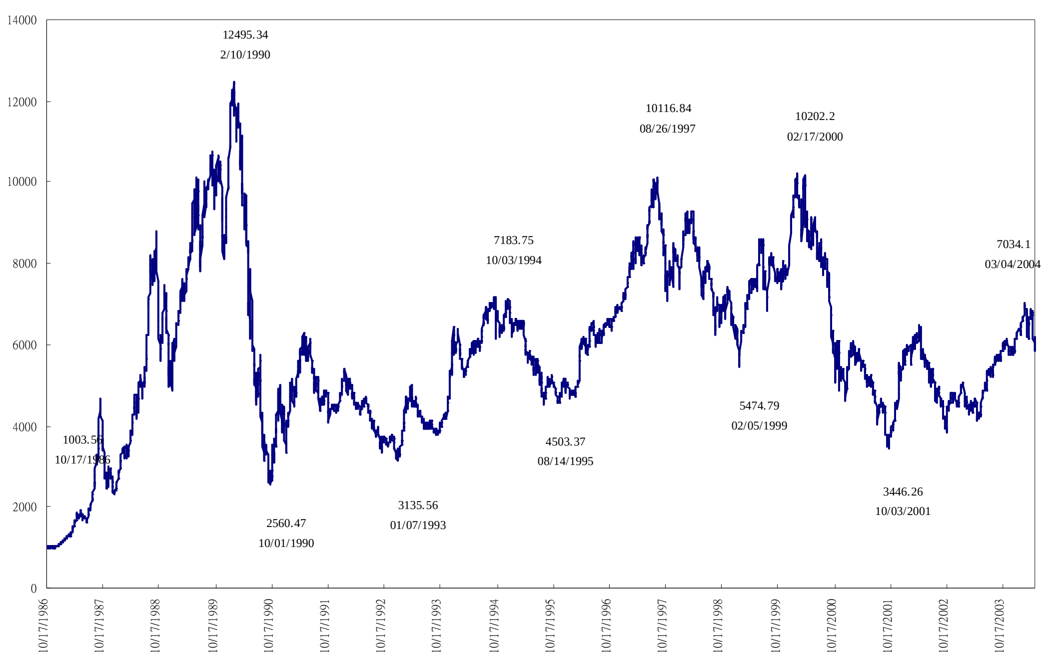


Figure 1 Taiwan Stock Index for the period 10/17/1986-05/20/2004

This study uses daily data to test and verify the dynamic relation between critical crash and investor sentiment. Since the scale of weekly or monthly data is longer than daily and thus reduces the impact of special phenomenon in stock markets, daily data can more accurately capture the relationship between market fluctuation and investor sentiment before a crash.

Methodology

Status of log-periodicity

Following the Sornette and Johansen (2001), we qualify a bubble by the existence of a regime of stock market prices well fitted by the expression

$$I(t) = A + B(t_c - t)^{-\alpha} + C(t_c - t)^{-\alpha}\cos(\omega \ln(t_c - t) - \phi) \quad \ldots \quad (1)$$

which embodies the log-periodic power law signature. Note that the phase ϕ does nothing but provide a time scale T since $\omega\ln(\tau) + \phi = \omega\ln(\tau / T)$ with the definition $\phi = -\omega \ln T$. ϕ thus disappears by the choice of T as the time unit. This stresses the fact that, if the phase is not a fundamental parameter of the fit since it can be get rid of by a suitable gauge choice, it contains nevertheless an important information on the existence of a characteristic time scale.

Log-periodic pattern

In order to prove that a log-periodic pattern appears before crashes, **Vandewalle et al. (1999)** have constructed the envelope of the index I. Two distinct curves are built: the upper envelope I_{max} and lower one I_{min}. The former represents the maximum of I in an interval $[t_i, t]$ and the latter is the minimum of I in an interval $[t, t_f]$. The interval $[t_i, t_f]$ is the full period.

We have fitted the following function:

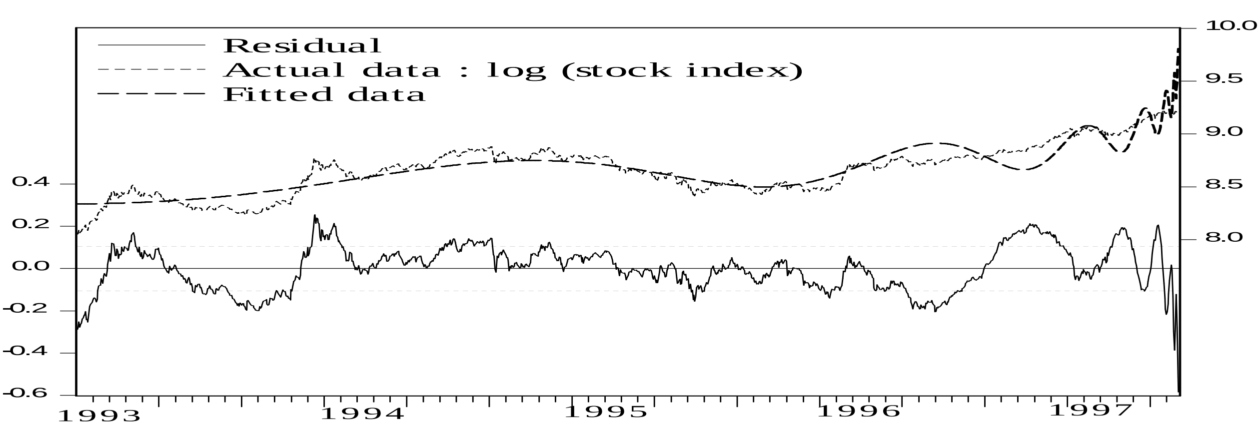
$$I_{\max} + I_{\min} = (C_1 + C_2 t)(1 - \cos(\omega \ln(t_c - t) + \phi)) \quad \ldots \quad (2)$$

where C_1 and C_2 are parameters controlling the amplitude of the oscillations. Without these parameters, a fit is still possible if an a priori single and constant amplitude (i.e. C_2=0) is presupposed.

EMPIRICAL RESULTS

Log-periodic pattern

Table 1 illustrates the coefficient estimates from log-periodic formulas Eq.(1). Consistent with previous studies, for all bubbles in most liquid markets the log-frequency $\omega / 2\pi$ has been consistently close to 1. Sornette and Johansen (2001) indicate that a survey of 20 cases including eight Hong Kong stock market, six crashes on major global stock markets and six currency crashes indicates a log-periodic component in market price evolution with a log-frequency of $\omega / 2\pi \approx 1.1 \pm 0.2$, except for the two first Hong-Kong crases of 1971 and 1973, and the global crash of April 1989, for which the value of ω was slightly lower/higher. Within the framework of power laws with complex exponents, the corresponds to a preferred scaling ratio $\lambda \fallingdotseq 2.7$: the local period of the log-periodic oscillations decreases according to a geometrical series with the ratio λ. Similar findings are repeated in other studies, such as Vandewalle et al. (1999), Johansen and Sornette (2000b), Johansen and Sornette (2001), Drozdz et al. (2003), Zhou and Sornette (2003), Johansen (2004), and so on.



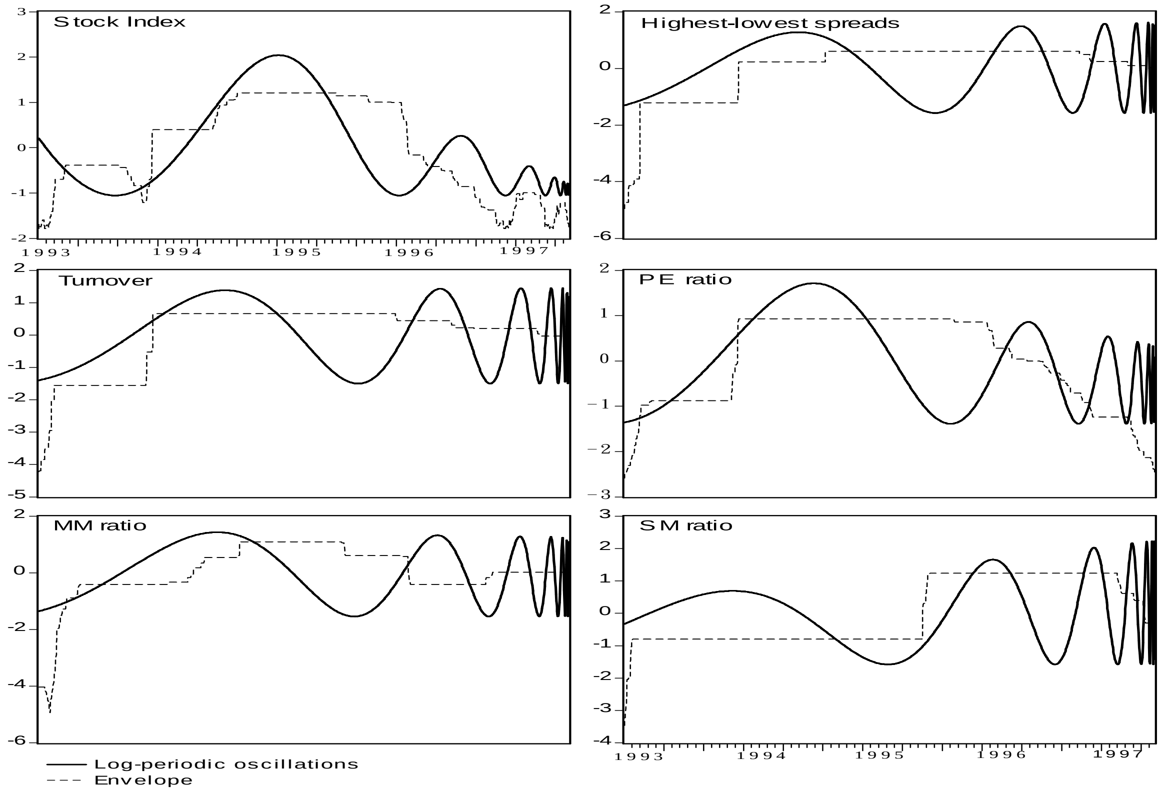


Figure 2 Taiwan Stock Index and log-periodicity of Pattern before the Crash in 1997

As shown in Fig. 2, log-periodic pattern before crash events resembles the patterns of foreshocks and aftershocks associated with earthquakes, and Table 2 lists the coefficient from Eq.(2). The top half of Fig. 2 clearly shows the accelerating power law nature of the market trend. Meanwhile, the lower section of the diagram clearly shows the log-periodic oscillations discussed previously. The cycle frequency accelerates as a crash approaches is clear. We agree with Sornette (2003): critical self-similarity is why local imitation cascades through the scales into global coordination, and a crash is most likely when the locally imitative system goes through a critical point. Besides, nor is this evidence of log-periodic pattern limited to the Taiwan stock index, have been found in investor sentiment, for example, Highest-Lowest spreads, turnover, P/E ratio, MM ratio and SM ratio which are proxy for investor sentiment.

Table 1 Taiwan Stock Index with LPPL Signatures

A Critical Crash in 1997	A	B	C	α	ω	ϕ
year	-10.10	19.83	-0.18	0.01	6.42	-14.64

Note. This table shows coefficient estimates from log-periodic formula Eq. (1).

Table 2 Log-periodic Pattern on Taiwan Stock Index and Investor Sentiment

	Index	Highest-Lowest spreads	Turnover	PE ratio	MM ration	SM ratio
C_1	2977.73	249.31	2.84	25.03	0.01	2.85
C_2	-2.13	0.04	8.16E-05	-0.01	-7.13E-07	0.01
ϕ	-1.15	-2.79	3.76	3.96	3.64	2.25

Note. This table shows coefficient estimates from Eq. (2).

Table 3 Granger Causality between Taiwan Stock Index and Investor Sentiment

Null Hypothesis	F-statistic
Stock Index does not Granger Cause Highest-Lowest spreads	5.68***
Highest-Lowest spreads doest not Granger Cause Stock Index	345.60***
Stock Index does not Granger Cause PE ratio	24.70***
PE ratio doest not Granger Cause Stock Index	118.24***
Stock Index does not Granger Cause Turnover	21.23***
Turnover doest not Granger Cause Stock Index	132.40***
Stock Index does not Granger Cause MM ratio	9.37***
MM ratio doest not Granger Cause Stock Index	115.39***
Stock Index does not Granger Cause SM ratio	1.34
SM ratio doest not Granger Cause Stock Index	22.61***

Note. This study test the lead-lag relation between Taiwan stock index and investor sentiment variables, which are Highest-Lowest spreads, PE ratio, Turnover, MM ratio and SM ratio, by using Granger causality test before critical crash in 1997. ***,**, * imply significant different from zero at 1%, 5%, and 10% levels, respectively.

Dynamic relationship between market fluctuation and investor sentiment

This empirical procedure described in this section tests whether investor sentiment is the indicator used for tactical asset allocation or market timing before critical crashes. Fig. 3 shows significant volatility clustering near a critical crash, which is the log-periodic pattern after first differentiation for the critical crash of 1997. The left half of the diagram is the whole research period and the right half of the diagram is the short-period (50 days) before the crash. This study plugs frequency with LPPL signature into the GARCH model to calculate frequency variance. From a graph showing Fig. 4, investor sentiment clearly oscillates significantly before the stock index. The priority of frequency variance is Highest-Lowest spreads, followed by PE ratio, MM ratio and Turnover, and finally SM ratio, which is synchronous with the Taiwan stock index from the right half of the diagram of Fig. 4.

This study applies Granger causality with frequency variance to test the dynamic relation between market fluctuation and investor sentiment before a crash. As shown in Table 3, investor sentiment variables and stock index have significant causality, with the exception of SM ratio. From the perspective of the F-statistic, since “the Highest-Lowest spreads doest not Granger cause Stock Index” is higher than “the Stock Index does not Granger cause the Highest-Lowest spreads” (345.60 < 5.68), frequency variance of Highest-Lowest spreads fluctuates more significantly prior to Stock Index before crash. The study next acquires the same empirical result for other investor sentiment variables, including PE ratio, turnover and MM ratio. The empirical result of the Granger causality test is as same as the description in Fig. 4.

To summarize, Fig. 4 and Table 3 clearly show that the frequency variance on investor sentiment accelerates prior to Stock Index as crash approaches. Hence this study infers that as crash approaches an increasing number of one-time investors to increase the spread of Highest-Lowest price, and then speeds up the life cycle of value and growth stocks, thus causing significant fluctuation of investment risk. When prices increase speculatively, causing wealth for some investors, other investors may be attracted by word-of-mouth, fuelling further price increases. This study thus infers that investor sentiment variables drive the increased long-range correlations among the trading strategies of investors.

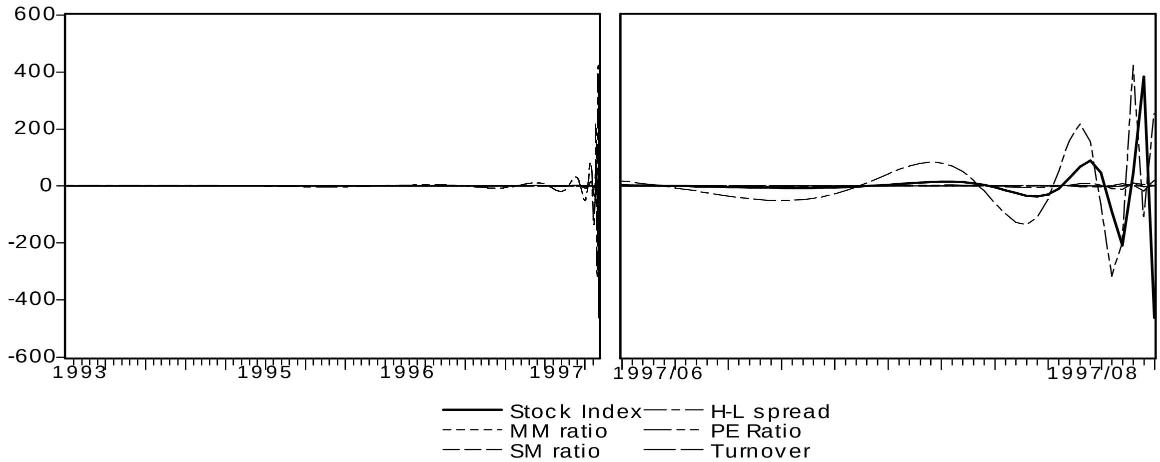


Figure 3 Log-periodic Pattern after first Differentiation

The diagram is the log-periodic pattern after first differentiation for critical crash in 1997. The left half of the diagram is the whole research period and the right half of the diagram is the short-period (50 days) before the crash.

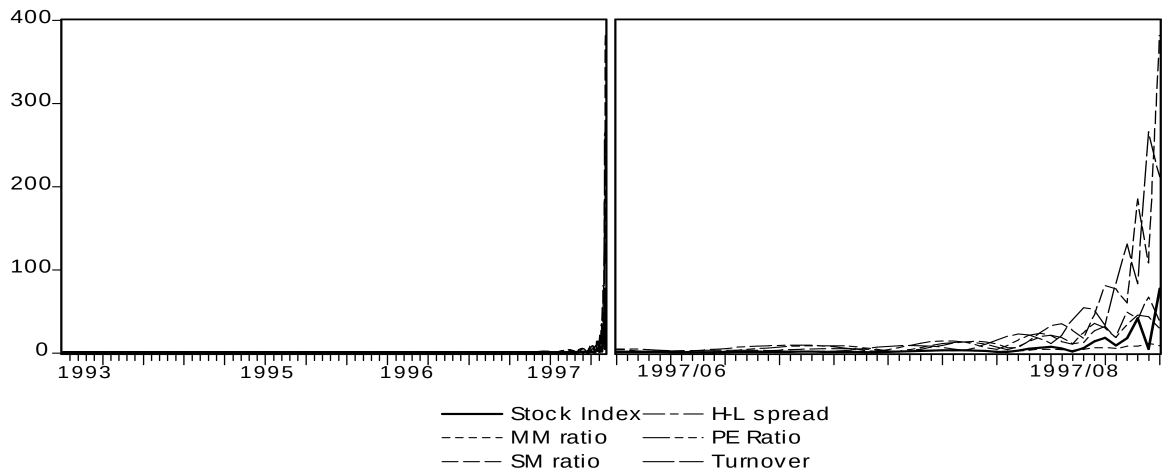


Figure 4 Frequency Variance with LPPL for Critical Crash in 1997

This study plug frequency data obtained from log-periodic pattern into GARCH model to calculate the frequency variance on Taiwan stock index and investor sentiment. The left half of the diagram is the whole research period and the right half of the diagram is the short-period (50 days) before the crash.

CONCLUSIONS

This study examined the dynamic relations between market fluctuation and investor sentiment for the Taiwan stock market before a critical crash using the LPPL(log-periodic power law) signatures. A main issue is whether indicators of investor sentiment, namely liquidity (Highest-Lowest spreads and Turnover), investment risk (PE ratio), bullish indicator (MM ratio) and relative market strength (SM ratio), are useful signals for understanding the precursory imprints before a critical crash.

Log-periodic patterns exist before crashes, and foreshock and aftershock patterns occur not only for earthquakes but also for crashes. The Taiwan stock market demonstrates the same pattern as global markets, with cycles of speeding up occurring as a crash approaches, and corresponds to a preferred scaling ratio $\lambda \fallingdotseq 2.7$. Similar finding are repeated in other studies, such as Vandewalle et al. (1999), Johansen and Sornette (2000b), Johansen and Sornette (2001), Drozdz et al. (2003), Zhou and Sornette (2003), Johansen (2004). This study supports Sornette (2003): critical self-similarity is why local imitation cascades through the scales into global coordination, and a crash is most likely when the locally imitative system goes through a critical point. LPPL can be applied to quantify stock markets, revealing patterns of complex adaptive systems

This study also found evidence of a lead-lag relationship between the Taiwan stock index and investor sentiment. From a graph illustrating figures and other data, the frequency variance of investor sentiment appears to accelerate before stock index, particularly for liquidity (Highest-Lowest spreads and Turnover), investment risk (PE ratio), and bullish indicator (MM ratio). Hence we infer that as the crash approaches an increasing number of one-time investors to increase the spread of Highest-Lowest, and then speeds up the life cycle of value and growth stocks and causing violent fluctuation of investment risk. Speculative price rises that create wealth for some investors may attract other investors, fuelling further price increases. Moreover, investors accelerate the trading speed of selling what one has bought. This study infers that investor sentiment variables drive the increased long-range correlations among investors' trading strategies.

Finally, analysis of the short periods before crashes fails to reveal the pattern of LPPL signatures, supporting the viewpoint of Sornette (2003): the underlying cause of a crash lies many years before the crash itself. Furthermore, this study fails to find the same dynamic relationships when using the traditional method with the data without transforming time-series into frequency. Indeed, LPPL signatures can help us determine the driving factor and the market timing before crashes.

This study brings up the new perspective that frequency variance of investor sentiment accelerates before stock index. Investor sentiment variables are precursory imprints before critical crashes and indicators used for market timing. This study was limited to the Taiwan stock market, and future studies could test whether global markets exhibit the same dynamic relationship between stock index and investor sentiment.

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