Rational or Irrational? A comprehensive Studies on Stock Market Crashes

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Abstract

This study attempts to illustrate the contributing factors for different patterns of crashes. In addition to the fundamental macro-economic factors, this paper argues that the existence of herding behavior as well as the level of investor attention are also important factors affecting the pattern of stock price fluctuations. By differentiating the rational component and irrational component of these behavioral factors, more insight concerning financial crisis can be drawn.

Patterns of crashes are defined by three dimensions, which are the cumulative decline, the speed of decline, as well as the duration of the crash. Innovative measures and comprehensive analyses are conducted based on three sets of explanatory factors : macroeconomic factors, market microstructure factors and behavioral factors. Results of partial R^2 show that behavioral factors are the most influential factors explaining the magnitude as well as the duration of crash; while the speed of decline is mainly related to market microstructure factor. Our results show that investors' irrational behavior is more important than fundamental factors in explaining or predicting market crashes.

The contribution of this study are threefold: First, crashes in 40 markets are defined, measured and categorized into eight types of crash patterns, providing interesting statistics for international market crashes. Secondly, we differentiate between rational and irrational components of behavioral factors in explaining the causes of market crashes, which are largely neglected in past literatures. Thirdly, threshold of each explanatory variable of market crash are estimated. The results of this paper can provide policy makers, fund managers and investors valuable information in risk management and pre-warning system.

Keywords: stock market crash, macro-economics, market microstructure, herding behavior, investor attention, rational and irrational components, heterogeneous agent model, network analysis

1. Introduction

Why or when stock markets crash has always been a major concern of the academia and practitioners. One of the most overlooked and crucial questions is what exactly is a stock market crash? Definitions of market crash in past literatures vary from study to study; in general, they may be summarized into the following categories: below a certain threshold of the long term moving average, a tail percentile of the cumulative decline, or deviation of stock prices from the fundamental value. For example, Patel and Sarkar (1998) and David Le Bris (2010) define stock market crash period as the worst fall during a specific period of time (CMAX), usually below a certain threshold such as two standard deviation of return. Mishkin and White (2002) define crash to be the situation when the cumulative decline rate reaches 20%. Thijs Markwat (2009) state that a market is under crash if return falls below the fifth percentile of the return distribution. On the other hand, Smith, Suchanek and Williams (1988) and Siegel (2003) define crash as long term deviation of market price below fundamental value.

Defining the crash event with a fixed decline rate might be problematic in international comparison, considering the differences in volatility and market structure between each market. Using rolling standard deviation may cause other problems such as insensitivity to detect subsequent decline after crash. For example, if one uses rolling standard deviation and rolling mean return to estimate the threshold as in CMAX, short term market crashes may be neglected. It may be sensible to define crash as the period when market price falls short of the fundamental value; however, as bubbles usually pre-exist crashes, using this fundamental value deviation approach to define crash will not be able to detect properly the starting time of a crash as the market price is typically above the fundamental value at the beginning of a crash. After considering the pros and cons of the above crash definitions, this study proposes an improved and practical definition of stock market crash that can capture most of the major crash events in various markets. A crash event is defined as a period when the cumulative decline rate exceeds a threshold, and rather than being a fixed level the threshold is adjusted according to the volatility of the specific market.

Furthermore, despite the fact that crashes come in various patterns, some exhibits steep drop and takes longer to recover while others may be less steep and recover sooner, past studies have treated crashes as a homogeneous group of events. We posit that different patterns of crashes may have different contributing factors. For example, the duration and speed of crashes driven mainly by behavioral factors may be different from those driven by fundamental factors. No study has tried to differentiate the types of crashes, to the best of our knowledge. One innovation of this study is to classify crashes from three dimensions: the degree of price decline, the duration of crash, and the speed of price fall, and we examine in depth the causes for different types of crashes.

The center question of this study is: what are the causes for stock market crash? Are crashes caused by rational reaction to information as we would expect in an efficient market environment? Or are they mainly driven by irrational panic herding? If the latter is the main cause, preventive measures may be taken to dampen the damage of irrational herding. Past literatures examined stock market crashes either from an informational perspective or from a behavioral perspective. The informational factors are usually proxied by economic fundamentals and market microstructure variables; while the behavioral factors may include herding tendency judged by various measures. Rather than confining the causes in one perspective, this paper considers both the informational factors and the behavioral factors, and tries to find the dominant factors of stock market crashes.

Although fundamental economic factors may be the ultimate causes for stock market crash,[1] in this study we would like to focus on the move that ignites the crash. Some scholars point out that the existence of noise traders who are uncertain about stock fundamental value is the cause of stock market crash;[2] others suggest that the market crashes as bad news is revealed by informed traders' selling actions(e.g., Romer, 1993). Abreu and Brunnermeier (2003) argue that the degree of heterogeneity among investors decides when market will crash. If profit maximizing rational arbitragers exit the market simultaneously, the market will crash. Boswijk, Hommes, and Manzan (2007) first establish the Heterogeneous Agent Model (HAM) and analyze the relationship between price changes and investor structure. The heterogeneous agent model is an adaptive learning model which captures the heterogeneity of agents and the time varying nature of agents' beliefs. HAM assumes

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[1] For example, Fama and Schwert(1977) found stock market price to be negatively related with lagged inflation rate, Nasseh and Strauss(2000) found European stock prices to be positively related with industrial production and CPI, and negatively related with long term interest rate. Geske and Roll(1983) found stock returns were negatively related with inflation and money supply growth rate, just to name a few.

[2] Garber (2000) , Rosser (2000) and Malkiei (2010) proposed that the price change of assets cannot be explained by the fundamental value, since fundamental deviation exists in long term.

there are two kind of players in the market, fundamentalists and chartists, whose weights are adjusted dynamically based on expected profits. By estimating the weight of fundamental traders and technical traders, they find that during market crashes the weight of technical traders far exceeds the weight of fundamental traders.[3]

In this study we propose three innovative measures of investor behavioral aspect, including the *chartist weight* which captures momentum inclination, the *branching ratio* or degree of endogenous shock in price changes, as well as a stock network topology parameter, specifically the *modularity* of stock network, which captures the extent of diversion of information flow among stocks. Herding is one of the most prevalent behavioral factors. Herding exists mainly because uninformed retail investors, lacking the ability to gather and analyze information, tend to follow the movement of the market, and sometimes even informed traders may ignore their information and follow the decisions made by others if enough critical mass is reached. Klein (2013) discovers that herding behavior changes over time, and it is most significant during stock market crashes. Zouaoui, Nouyrigat, and Beer (2011) examine the influence of investor sentiment on market crises, and they find that the probability of a stock market crisis increases with the level of investor sentiment, especially in countries more prone to herd-like behavior. Among these literatures, herding behavior is usually deemed to be irrational; however, if people possess common information, herding may have some rational component. Rational herding in terms of same direction trading based on homogeneous information may lead to faster responses to new information and increases market efficiency. In contrast, irrational herding or cascading refers to situation where people forgo their own information and blindly follow others' actions, causing overreaction and inciting the risk of market crash. Since the effects of rational herding and irrational herding are different, it is necessary to distinguish the rational component and the irrational component of herding. We will introduce several methods to dissect the herding measure in order to better understand the forces that drive market crashes.

To capture herding, network analysis is used in this study. Network analysis has been recently introduced to financial research to explain stock returns or interbank cash flows from the underlying dynamics of the network structure. Heiberger (2014)

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[3] Huang, Zheng and Chia (2010) applied the idea of HAM and illustrated that when the ratio of technical analysis traders increased, the probability of crash increased. Jong, Verschoor, and Zwinkels (2009) further examined HAM in international study and discovered that the Asia financial crisis was initiated in Thailand due to the increase of technical traders.

and Nobi, Maeng, Ha, and Lee (2014) use the correlation of stock returns to establish stock network, and they discover that during periods of financial crisis, the correlation between the various sectors of stocks significantly increases. Kuzubaş, Ömercikoğlu, and Saltoğlu (2014) and Kyriakopoulo, Thurner, Puhr, and Schmitz (2009) empirically analyze transaction networks of money (in and out) flows of banks to contruct cash flow networks, and they find that the exchange of cash flow decreases before financial crisis starts. Network approach can provide us with a new look at the problem. This study constructs the stock network for each sample market by linking stocks with a relatively high correlation in returns. By measuring the degree of diversion or modularity of the network, we may tell the level of opinion diversion or herding in the market.[4]

In addition to the above herding related behavioral measures, this study also takes investor attention into consideration. Shiller (1984,1987) points out that sentiment and price volatility of speculative assets will be affected by crowd attention, and that investor attention and investor behavior vary over time. Da, Engelberg, and Gao (2011) propose a direct measurement of investor attention using Google search volume index, SVI. They show that the future price of a particular stock will perform better when more investors pay attention to the stock.[5] Peltomäkia & Vähämaa (2015) point out that investor attention using google SVI is able to explain the herding behavior in national bank stock indexes during Eurozone crisis. Yuan (2015) studies headline of newspaper and shows market-wide attention-grabbing events predict the trading behavior of investors and, in turn, market returns. High market-wide attention events lead investors to sell their stock holdings dramatically when the level of the stock market is high. Such aggressive selling has a negative impact on market prices.[6] To measure investor attention we follow Da, Engelberg and Gao (2015) and construct a negative-word-search indicator(FEARS) for twenty national stock markets using google SVI. FEARS captures the kind of investor attention that leads to negative

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[4] Low modularity has dense connections between nodes in different modules, a low modularity estimate may indicate at this moment the traders in this market have dense connections and hence herding behavior.

[5] By using SVI measurement, Da, Engelberg, and Gao (2011) discovers that the amount of retails trade within exchange centers which have less smart investors, are bigger than the amount of retails trade within the exchange centers which have more smart investors (for example, NYSE). This difference means that SVI captures the attention of investors which are less savvy.

[6] Past literatures concerning investor attention are related with the following issues: extreme returns (Barber and Odean, 2008); trading volume (Barber and Odean, 2008; Gervais, Kaniel and Mingelgrin, 2001; Hou、Peng and Xiong, 2008), news headlines (Barber and Odean, 2008；Yuan, 2015), advertisement fee (Chemmanur and Yan, 2009；Grullon, Kanatas and Weston, 2004；Lou, 2014) and price change limit (Seasholes and Wu, 2007).

returns, therefore it is more relevant in explaining stock market crash.

We examine eighteen national stock markets and cover thirty years of time series data. The empirical results show that stock market crash does come in different forms and the main causes vary between crash types. Irrational behavior factor has the highest explanatory power to the magnitude of stock market decline(21.04%)， followed by market microstructure factors (20.35%). In terms of the speed of decline, microstructure factors have the highest explanatory power (25.11%). The duration of the crash is best explained by irrational behavior factor (36.44%). To sum up, behavioral factors are more significant than informational factors in explaining stock market crashes.

2. Data and Methodology

Monthly stock indices from 1985 to 2015 are collected from GFD (Global Financial Database) and TEJ (Taiwan Economic Journal). Macroeconomic data is collected from Federal Reserve Bank of St. Louis, OECD database, and TEJ. We use data from Yahoo Finance and create stock correlation networks for nineteen markets.[7]

Definition of crash

We measure the beginning and end of crash events based on three-month returns calculations. When three-month cumulative return is below the threshold, it is a crash starting signal, and a stock rebound is a signal for end of crash . Details are as follows: First, we calculate 3-month cumulative return $CumD_{i,t}$, from t-3 to t month in i market. The threshold is then set as the mean of $CumD_{i,t}$ minus the standard deviation of $CumD_{i,t}$.[8] Whenever $CumD_{i,t}$ is below the threshold, there is a crash event. Moreover, the day of the highest price of stock in t-3 to t is set to be the starting day of the crash. Finally, when the monthly return $R_{i,t+n}$ at time t+n is greater the variance of return ϵ_i, we set the end of crash time to be the previous month t+n-1.

[7] The period of stock index data varies slighty among different markets. The exact period for each market are available but not shown here to save space.

[8] Mean and standard deviation of $CumD_{i,t}$ are calculated over the study period to obtain the threshold for each market.

The estimated results match the history quite well.

This study posits that a complete depiction of crash has to include three important characteristics: duration of crash, cumulative decline, and speed of decline. The duration of crash is defined as the period between the start of crash and end of crash. Cumulative decline from start to end is calculated for each crash event, and the speed of decline is calculated by dividing cumulative decline by the crash duration period. The three dimensions are normalized for each market and crashes are classified into eight types accordingly.[9]

Fundamental, market and behavioral factors

Macroeconomic factors, market microstructure factors and behavioral factors are the main causes of crash events explored in this study, and they are explained in the following. The macroeconomic or fundamental variables include inflation rate, current account, growth rate of money supply, industrial production, and unemployment rate. Liquidity and volatility are the two key market microstructure variables to capture the market status. Amihud illiquidity measure, high-low range and the standard deviation of return are used. As to the behavioral factors, this study employs modularity (Mod) parameter from network analysis, constructs investors' attention measure from google search volume index (FEARS), estimates chartists weight (Ham_CW) from heterogenous agent model, and measures branching ratio by the Hawkes process. They are explained in the following.

Behavioral factors : network analysis, investor attention, chartist weight, and self-reinforcing process

Network analysis. To capture herding phenomenon from interstock correlation dynamics, we construct the stock network for each market. Each stock is a node in the network, two stocks are connected if return correlation is greater than 0.7. Modularity is a network parameter measuring the strength of division of a network into modules. Networks with low modularity have dense connections between nodes across modules. In other words, stocks return movement or information flow among stocks

[9] Cumulative decline, duration and speed of crash are divided into high and low subgroups based on the median, and there are a total of eight crash types. For example, type1 is the most heavy decline, deep and long crash, while type 8 is the short, small and slow type of crash. The statistics of eight types of crashes are summarized in the following section.

are synchronous or concentrated if modularity is low; conversely, if modularity is high there is dense connection within module but sparse connection between modules, indicating apparent diffusion in return connections . With low modularity all stocks tend to cluster together and herding phenomenon intensifies across stocks, suggesting more irrational sentiment; conversely, high modularity reflects disperse clusters and opinion diversion, suggesting more rational sentiment in the market. Therefore, modularity represents rational behavioral factor in this study. An illustration of modularity is given in Figure 1, the right figure is a low modularity example of Taiwan stock market when stocks cluster together during the peak of 2008 financial crisis, while the left figure is a high modularity example before Lehman went bankrupt.

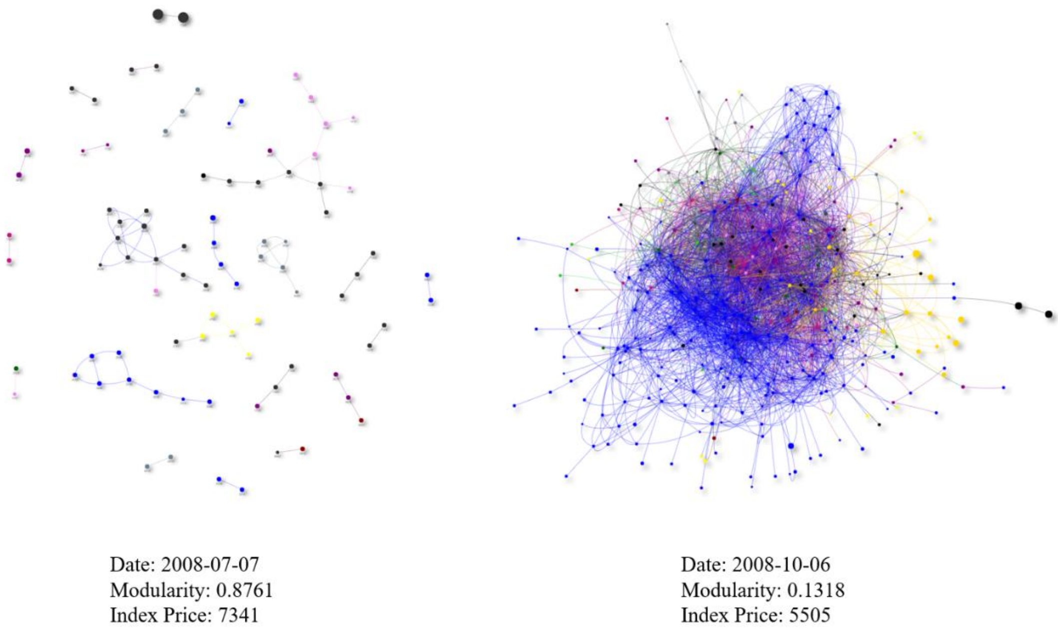

Figure 1 Illustration of Modularity in Stock Network

Modularity (*Mod*) is estimated as follows:

$$Mod = \frac{1}{2x}\sum_{i,j}\left[\alpha_{ij} - \frac{k_i k_j}{2x}\right] f\left(c_i, c_j\right) \quad (1)$$

$x = \sum_{i,j}\alpha_{ij}/2.$

Where α_{ij} is the direct connection of stock i and stock j, k_i is number of neighbors of stocks i, and c_i represents the module which stock i belongs to. If stock i and stock j belong to the same module, then $f\left(c_i, c_j\right) = 1$, otherwise, $f\left(c_i, c_j\right)$ =0.

Negative investor attention. In order to measure investors' attention, we follow Da, Engelberg and Gao (2015) and create the FEARS variable. Da et al. collected Google Search Volume Index (Google SVI) with economic and financial terms in HarvardIV-4 dictionary.[10] In addition, we add other relevant financial and economic terms in news to expand our dictionary. We collect the SVI of these terms in each market, and run a regression on stock returns in each market. Based on regression results, thirty terms that have the most negative influence on subsequent stock returns are chosen for each market. The mean of the SVI of these thirty terms is then used as the negative investor attention index (*Fears*) in each month for each national market.

Chartist's weight. Traders are heterogenous, different in beliefs and behaviors. The constitution of agents has influence on how price behaves. The heterogeneous agent model (HAM) is an adaptive learning model which captures the heterogeneity of agents (fundamentalist and chartist) and the time varying nature of agents' beliefs, thus a more appropriate model to explain the market than the rational representative agent model. Brock and Hommes (1998) develop the heterogeneous agent model and estimate the proportion or weight of fundamentalist and chartist in the market. They point out that high chartist weight may be routes to chaos. Westerhoff and Reitz (2005) also find technical traders increasingly enter the market as booms or slumps enlarge. We estimate the chartist weight for each market and use it to proxy for irrational behavioral factor, explained in the following.

The effective weight chartist model assumes the stock price is the weighted

[10] HarvardIV-4 dictionary is established by the USA National Science Foundation and Research Grant Councils of Great Britainand Australiain 1990. It divides words by three measures, which are positive or negative, strong or weak and vigorous or passive. http://www.wjh.harvard.edu/~inquirer/

average of fundamental and technical traders' beliefs and strategies,

$$P_{t+1} = P_t + \alpha(F_t - P_t) + \frac{\beta(P_t - P_{t-1})}{1+\exp\left(\frac{-\gamma|F_t - P_t|}{\sigma_t}\right)} + \varepsilon_{t+1} \quad \text{.............................} (2)$$

$\varepsilon_{t+1} \sim \mathrm{N}(0, \sigma^2)$

Where P_t is log of stock prices at time t, and F_t is log of fundamental value at time t. γ is a coefficient of the speed of adjustment. α and β are expected to be positive. Chartist's weight increases with the deviation of market price from fundamental price.

Chartist's weight for country c at time t is :

$$\mathrm{Ham\_CW}_t^C = \frac{1}{1+\exp\left(\frac{-\gamma|F_t - P_t|}{\sigma_t}\right)} \quad \text{..} (3)$$

Self-reinforcing process. Lastly, we use Epidemic Type Aftershock Sequence (ETAS) to measure the self-exciting effect or the herding component. The self-exciting effect is broadly applied to different areas. In finance it is also known as market reflexivity, that is, the part of changes in prices that are due to "aftershocks" and not from exogenous reasons. For example, Filimonov and Sornette (2012) use self-excited conditional Poisson Hawkes model to create an indicator, which can measure reflexivity of market price, and called it "branching ratio". Using this indicator, we could measure the endogenous or self-excited component of price changes. The equation for branching ratio is estimated as follows (Francine Gresnigt et al., 2015):

$$\lambda(\mathrm{t}|\theta; H_t) = \mu + \sum_{i:t_i<t} g(t - t_i, m_i) \quad \text{...} (4)$$

$$\text{Branching ratio} = \frac{\sum_{i:t_i<t} g(t-t_i, m_i)}{\lambda(\mathrm{t}|\theta; H_t)} \quad \text{..} (5)$$

λ is arrival rate of price change between time t and t+dt, μ captures the change of price due to exogenous factors, and $g(t - t_i, m_i)$ is the endogenous component. $\mu > 0$,$g(t - t_i, m_i) > 0$, and $H_t = \{(t_i, m_i): t_i < t_g\}$ represents all past event before time t_i; m_i means the size of event. Higher branching ratio indicates more intensive self-excited changes, which is indicative of herding phenomenon.

Besides using modularity to proxy for rational behavior, principal components analysis is employed to combine the negative-word google search FEARS, the proportion of trend chasing chartists Ham_CW, and the self-exciting branching ratio to proxy for irrational behavioral factors.

Principle component

To avoid the multicollinearity problem of macro and market microstructure factors, we also use principal component method to combine macro variables into one factor (Macro), and market microstructure variables into one factor (MM). The irrational component (irrational) are constructed likewise with the three variables mentioned above. Considering the different scale of each market, fixed effect model is employed. Data from eighteen markets are used to run the pooled regression.

3. Empirical Results

3.1 Descriptive statistics of Crash

Based on the definition mentioned in previous section, we identify crash event for 40 national markets. Close examination of these events shows that they can match with historical crises. Table 1 shows that among the 40 sample markets, there are 681 crashes during 1985 ~2015. Comparing the descriptive statistics for the cumulative decline, decline speed and duration of crash, we find that the magnitude and speed of decline in the developing countries such as Turkey, Peru and China are greater than the overall average. The impact of crash in developing countries is more severe than in developed countries. The average return decline of crash event is 25%, and average duration is 4.68 months. Dow Jones has the shortest average duration of 3.77 months while Portugal has the longest average duration of 6.54 months. Argentina has the sharpest speed of decline while Denmark has the lowest speed of decline.

Table 1 · Summary of Crash Events and Crash Characteristics by Market

Country	Number of crash	cumulative decline(average)	decline speed (average)	duration of fall (average in mo)
Total average	17.3	-25%	-0.05494	4.68
Netherlands	18	-21%	-0.05086	4.22

Australia	23	-16%	-0.03963	3.87
Greece	20	-29%	-0.06891	4.80
Austria	18	-23%	-0.04929	4.67
Belgium	13	-18%	-0.04084	4.38
India	25	-21%	-0.04844	4.40
France	18	-20%	-0.04477	4.50
UK	22	-15%	-0.03918	4.14
Singapore	24	-22%	-0.05999	3.96
Germany	17	-22%	-0.05086	4.41
Hong Kong	22	-26%	-0.05601	4.95
Argentina	11	-37%	-0.10554	4.55
Colombia	20	-19%	-0.05035	3.85
Peru	11	-32%	-0.06147	5.36
Ireland	15	-25%	-0.04938	5.20
Indonesia	18	-26%	-0.06270	4.22
Malaysia	18	-28%	-0.06112	4.67
Korea	23	-23%	-0.05282	4.35
Pakistan	14	-25%	-0.05701	4.57
Mexico	13	-25%	-0.06789	3.92
Japan	22	-22%	-0.04719	4.73
Nigeria	13	-23%	-0.03991	6.23
New Zealand	10	-9%	-0.02174	4.50
Norway	13	-22%	-0.05151	4.31
Denmark	20	-17%	-0.03238	5.25
Finland	19	-27%	-0.05431	5.37
Sweden	17	-23%	-0.05771	4.41
NASDAQ	21	-20%	-0.04599	4.29
Ukraine	8	-39%	-0.08930	4.63
Portugal	13	-29%	-0.04618	6.54
Philippines	18	-27%	-0.05565	5.06
Thailand	19	-29%	-0.06334	4.95
Spain	23	-19%	-0.04766	4.43
Dow Jones	22	-13%	-0.03718	3.77
Shanghai	13	-35%	-0.07328	5.08
Switzerland	16	-17%	-0.03882	4.38
Taiwan	18	-32%	-0.06668	5.17
Vietnam	6	-41%	-0.09404	4.50
Poland	12	-28%	-0.06283	5.17

Turkey	15	-35%	-0.07409	5.27

Crash events are classified into eight types based on speed, magnitude and duration. The most common types of crash are type 1 (large magnitude, fast falling speed and long duration), type 2 (large, slow and long) and type 8(small, slow and short). Figure 1 and Table 2 shows the number of crash by types and the statistics of crash type in each market, respectively.

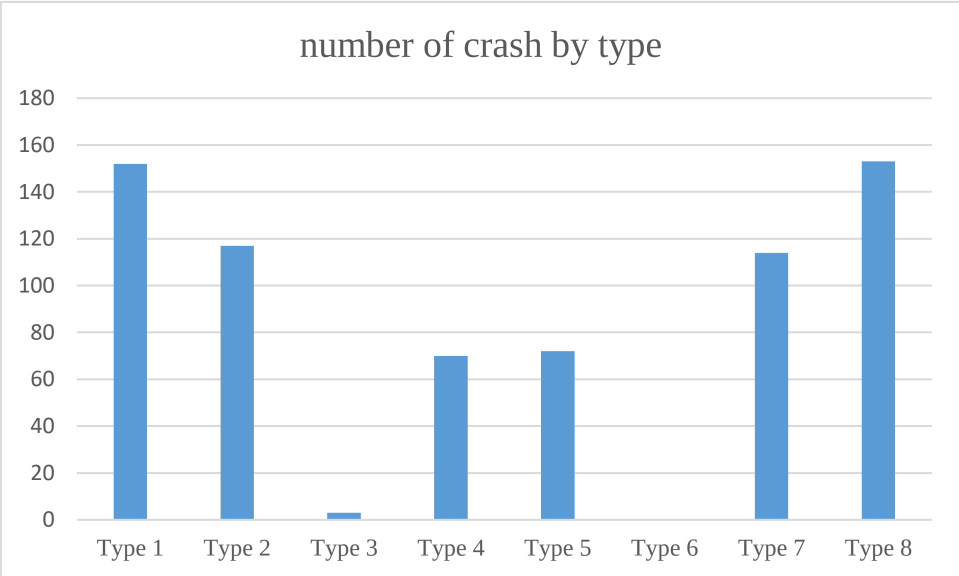

Figure 1 · Frequency by Crash Type

Table 2 · Number of Different Crash Types in Each Market

	An	Au	At	Gr	Be	In	Fr	UK	De	Sg
Type1	5	6	3	2	3	6	2	3	5	7
Type2	4	3	5	4	2	3	4	6	3	2
Type3	0	0	0	0	0	0	0	0	0	0
Type4	0	2	0	2	1	4	0	4	0	5
Type5	1	1	2	4	1	4	3	3	1	0
Type6	0	0	0	0	0	0	0	0	0	0
Type7	3	6	2	3	2	0	3	4	5	5
Type8	5	5	6	5	4	8	6	2	3	5
Total	18	23	18	20	13	25	18	22	22	24
	As	HK	Co	Pe	Ie	Id	My	Kp	Pk	Mx

Type1	1	7	6	3	2	4	3	6	2	4
Type2	4	4	3	2	2	2	3	2	2	2
Type3	0	0	0	0	0	0	0	2	0	0
Type4	0	0	2	2	3	4	0	3	1	2
Type5	1	2	3	2	2	1	3	1	2	1
Type6	0	0	0	0	0	0	0	0	0	0
Type7	2	3	2	2	3	5	3	3	4	1
Type8	3	6	4	0	3	2	6	6	3	3
Total	17	11	20	11	15	18	18	23	14	13

	Jp	Ng	NZ	No	Ph	Dk	Fi	Se	NASD	Ua
Type1	4	3	2	5	3	5	4	5	7	3
Type2	5	2	0	1	3	5	4	3	3	1
Type3	0	0	0	0	0	0	0	1	0	0
Type4	2	1	4	1	3	1	1	3	3	0
Type5	2	1	1	1	2	1	2	1	0	0
Type6	0	0	0	0	0	0	0	0	0	0
Type7	4	4	1	2	4	3	4	2	3	1
Type8	5	2	2	3	3	5	4	2	5	3
Total	22	13	10	13	18	20	19	17	21	8

	Pt	Th	DJ	Cn	Es	Ch	Tw	Vn	Pl	Tr	Total
Type1	3	2	5	2	5	5	3	1	2	3	152
Type2	4	4	2	3	3	1	4	1	3	3	117
Type3	0	0	0	0	0	0	0	0	0	0	3
Type4	0	1	3	1	3	1	3	0	0	4	70
Type5	1	2	5	1	3	3	2	1	2	3	72
Type6	0	0	0	0	0	0	0	0	0	0	0
Type7	3	5	2	2	4	2	2	2	2	1	114
Type8	2	5	5	4	5	4	4	1	3	1	153
Total	13	19	22	13	23	16	18	6	12	15	681

Country code: An = Netherlands, Au = Australia, At = Austria, Gr = Greece, Be = Belgium, In = India, Fr = France, UK = United Kingdom, De = Germany, Sg = Singapore, As = Argentina, HK = Hong Kong, Co = Colombia, Pe = Peru, Ie = Ireland, Id = Indonesia, My = Malaysia, Kp = Korea, Pk = Pakistan, Mx = Mexico, Jp = Japan, Ng = Nigeria, NZ = New Zealand, No = Norway, Ph = Philippines, Dk = Denmark, Fi = Finland, Se = Sweden, NASD = NASDAQ, Ua = Ukraine, Pt = Portugal, Th = Thailand, DJ = Dow Jones, Cn = Shanghai, Es = Spain, Ch = Switzerland, Tw = Taiwan, Vn = Vietnam, Pl = Poland, Tr = Turkey

3.2 General Linear Regression on Crash Characteristics

We use GLS to estimate the pooled regression on crash characteristics:

$$Y_{i,j,t} = \alpha + \beta_1 \cdot Macro_{i,j,t-2} + \beta_2 \cdot MM_{i,j,t-2} + \beta_3 \cdot Rational_{i,j,t-2} + \beta_4 \cdot Irrational_{i,j,t-2} + \varepsilon_{i,j,t-2} \tag{6}$$

Where Y is the three dimensions of crash: cumulative decline, decline speed and duration of crash, i, j, t stands for market i, crash j, and month t, respectively. According to SIC rule, the lag period for the independent variable is 2 months. *Macro*, *MM, Irrational* are the principle component of the macroeconomic variables, market microstructure variables and herding measures(branching ratio, chartist weight and investor attention), respectively, while *Rational* is measured by the modularity of the stock network.

Table 3 shows the regression results of eighteen national markets, Table 4 shows the explanatory power by partial R^2 of the explanatory variables. We can see from Table 3 that liquidity and volatility affect the severity of crash, the greater liquidity and the smaller volatility is, the less severe is the subsequent crash. Higher macroeconomic component (positively related with inflation) is followed by smaller decline and shorter duration of crash. On the other hand, as the irrational factor increases, the cumulative decline will deepen and the speed of decline accelerates, consistent with our expectations. The adjusted R^2 in Table 3 is 39%~64%. In addition, from partial R^2 in Table 4 one can see that the most prominent factor in explaining subsequent crash characteristics is the behavior variable, far more important than macro factor. Macro factor explains a little better only in the duration of fall, while market microstructure factor performs equally well as the irrational factor in explaining the magnitude and speed of crash. Irrational factor beats all in explaining the duration of the crash.

Table 3 · Pooled Regression Result on Crash Characteristics

	Cumulative decline	Decline rate	Duration of fall
Macro	0.045151**	0.001364	-1.660363***
MM	-0.255201***	-0.012370***	3.318075***
Rational /Info.	0.189599***	-0.008337**	1.028695
Irrational /Behv.	-0.018212	-0.002605**	-0.317453
Adjusted R^2	39.18%	64.06%	45.08%

Note: Both cumulative decline and speed of decline are negative. Macro is the principle component of current account, CPI, PPI, M2 and unemployment rate, the most important loading in Macro is CPI. MM is the market microstructure principle component of Amihud illiquidity and Maxmin(volatility), the most important loading in MM is Maxmin. Rational/Info is the modularity of the market, it goes opposite with herding. Irrational/Behv captures irrational sentiment in the market, it is the principle component of Ham_CW(chartist weight), Branching ratio and FEARSs, the most important loading in Irrational/Behv is Ham_CW.

Table 4 · Partial R^2 of Explanatory Factors for Crash Characteristics

	Cumulative decline	Decline speed	Duration of fall
Macro	0.85%	1.59%	10.74%
MM	20.35%	25.11%	15.93%
Rational/Info.	2.64%	0.73%	0.30%
Irrational /Behv.	21.04%	23.70%	36.44%

Overall, the most important variable in influencing crash pattern is behavioral factor. Specifically, cumulative decline is influenced most by behavioral variable (Rational and Irrational), next is market microstructure variable. The most important variable in determining the speed of decline is market microstructure variable, next is behavior variable. The duration of fall is most influenced by the behavior factor (Rational and Irrational), followed by market microstructure variable.

3.3 Threshold Regression on Crash

In previous section we test the significance of the four principle component factors in explaining the various dimensions of crash. From the practical point of view, it may be more interesting to know the threshold value of the individual variables for crash. In this section we use threshold regression to estimate the critical value that signal severity of crash.

$$Y_{i,j,t} = \alpha + \beta_1 \cdot CA_{i,j,t-2}(\boldsymbol{I}\text{>}\mathbf{T}) + \beta_2 \cdot UNE_{i,j,-2}(\boldsymbol{I}\text{>}\mathbf{T}) + \beta_3 \cdot M2_{i,j,t-2}(\boldsymbol{I}\text{>}\mathbf{T}) + \beta_4 \cdot PPI_{i,j,t-2}(\boldsymbol{I}\text{>}\mathbf{T}) + \beta_5 \cdot CPI_{i,j,t-2}(\boldsymbol{I}\text{>}\mathbf{T}) + \beta_6 \cdot Amihud_{i,j,-2}(\boldsymbol{I}\text{>}\mathbf{T}) + \beta_7 \cdot Maxmin_{i,j,t-2}(\boldsymbol{I}\text{>}\mathbf{T}) + \beta_8 \cdot Fears_{i,j,t-2}(\boldsymbol{I}\text{>}\mathbf{T}) + \beta_9 \cdot Modularity_{i,j,t-2}(\boldsymbol{I}\text{>}\mathbf{T}) + \beta_{10} \cdot Ham\_CW_{i,j,t-2}(\boldsymbol{I}\text{>}\mathbf{T}) + \beta_{11} \cdot Branching\_ratio_{i,j,t-2}(\boldsymbol{I}\text{>}\mathbf{T}) + \varepsilon_{i,j,t-2} \quad \text{......................} (7)$$

Where (I>T) indicates threshold, CA is current account, UNE is unemployment rate, $M2$ is money supply growth rate, *PPI* is producer price index, *CPI* is consumer price index, *Amihud* is Amihud illiquidity, *Maxmin* is six month high minus low index return, *Fears* is the negative attention variable, *Ham-CW* and *Branching-ratio* are defined as before. i, j, t stands for market i, crash j, and month t, respectively.

Table 5 gives the estimated thresholds for each variable. For example, if M2 or money supply growth rate is lower than 6.09%, the higher is money supply growth rate, the slower is speed of decline; conversely, if it is higher than the threshold value, higher M2 growth rate accelerates the speed of decline. This is a reasonable outcome as we would expect if money supply is too high the severity of the crash would increase. Unemployment rate higher than 8% increases duration of crash. If Amihud illiquidity is lower than threshold 3.98E-11, the lower the liquidity the slower the speed of decline; however, when illiquidity is greater than the threshold, the lower the liquidity the faster the speed of decline. Likewise, when Maxmin is below the threshold 13%, higher volatility shortens the duration of fall, and when the market fluctuates exceeds the threshold, it will increase the severity of the crash. When Modularity is below the 0.2187 threshold, a more diverse market will slow the speed of decline; when Modularity exceeds the threshold, higher Modularity will accelerate the speed of decline, the results suggest that more sparse stock correlation will slow down decline speed; however when dispersion gets beyond a certain point, market uncertainty increases and crash is more likely to occur. If investor's negative attention (*Fears*) exceeds threshold, both magnitude and duration of crash increases. Similarly, if chartist's weight exceeds threshold, both magnitude and duration of crash increases, but the decline rate reduces. Increase in self-exciting market movement (branching ratio) above threshold also lead to larger magnitude of decline.

Table 5 ·Estimated Threshold Values for Each explanatory Variables in Eighteen Markets

	Cumulative decline	Decline speed	Duration of fall
CA	-	-	-
CPI	102.51(-)	97.11(+)	95.21(-)
M2	10.41 %(-)	6.09 %(▲)	11.12 %(+)
PPI	105.58(-)	99.91(-)	-
UNE	9 (-)	7.19(+)	8.09(+)
Amihud	-	3.98E-11(▲)	-
Maxmin	0.1652 (-)	0.2098(-)	0.1308(▲)
FEARS	35.19 (-)	-	30.58(+)
Modularity	-	0.2187(▲)	-
Ham_CW	0.6607(-)	0.6073(+)	0.5421(+)
Branching ratio	0.4228(-)	-	-

Note : sign in parenthesis indicates significant direction when I > threshold；▲ indicates the regression coefficient reverses above the threshold; - indicates no threshold。Both cumulative decline and decline speed are negative numbers.

3.4 Logistic Regression for the Probability of Crash Occurrence

In addition to the characteristics of crash, we also examine the probability of crash occurrence, the probability of the start month of crash, and the probability of each type of crash.

$$Y_{i,j,t} = \alpha + \beta_1 \cdot Macro_{i,j,t-2} + \beta_2 \cdot MM_{i,j,t-2} + \beta_3 \cdot Rational_{i,j,t-2} + \beta_4 \cdot Irrational_{i,j,t-2} + \varepsilon_{i,j,t-2} \tag{8}$$

Where Y is crash or start month, i, j, t stands for market i, crash j, and month t, respectively. The explanatory variables are the four principle component factors as mentioned in previous section.

Table 6 · Pooled Data Logistic Regression Result of Crash Occurrence (18 markets)

	Crash Occurrence	**The starting month of crash**
Macro	-0.206329**	-0.016867
MM	1.035225 ***	-0.211071
Rational/Info.	-1.083405 ***	-1.156358*
Irrational /Behv.	0.126983 *	0.193199*
McFadden R^2	6.73%	1.49%

Note: Macro is the principle component of current account, CPI, PPI, M2 and unemployment rate, the most important loading in Macro is CPI. MM is the principle component of Amihud illiquidity and Maxmin, the most important loading in MM is Maxmin. Rational is Modularity. Irrational is the principle component of Ham_CW(chartist weight), Branching ratio and FEARS, the most important loading in Irrational is Ham_CW.

Table 6 shows that the probability of crash occurrence is negatively related with liquidity and positively related with volatility(MM is positive); as macroeconomic factor(CPI) increases, the probability of crash occurrence decreases; higher rational factor (modularity) reduces the probability of crash occurrence and higher irrational factor increases the probability of crash. Higher rational behavioral factor reduces the probability of subsequent start of crash while higher irrational factor increases the probability of crash occurrence as well as subsequent start of a crash.

Table 7 gives the result of logistic regression by crash type. As type 3 and type 6 do not have enough samples, they are not included. We can see that market microstructure factor and irrational factor are dominant causes in the most serious crash (type 1), while macroeconomic factor dominates the smaller crash (type8). Categorical analysis reveals there are significant differences in the determining factors across different crash types.

Table 7· Logistic Regression by Crash Type

	Crashtype1	Crashtype2	Crashtype4
Macro	-0.0229	-0.324649***	-0.000648
MM	1.429190***	0.030476	-1.221535
Rational/Info.	-0.622741	-1.790983***	-3.243363**
Irrational /Behv.	0.312275***	0.232146**	-0.093237
McFadden R^2	9.73%	3.96%	5.78%
	Crashtype5	**Crashtype7**	**Crashtype8**
Macro	-0.173546	0.765335**	1.218982***
MM	-0.707854	-0.830435	0.796841*
Rational/Info.	0.442753	-1.408772	0.559797
Irrational /Behv.	0.352824	0.489177 **	0.124501
McFadden R^2	3.97%	5.23%	5.17%

4. Conclusions

In this paper, we define and measure stock market crashes in 40 markets from three dimensions: magnitude, speed and duration of decline. Comprehensive analysis on the factors for different *patterns* of stock market crash was carried out to investigate whether information or behavioral factors dominates stock market crash.

We find irrational and market microstructure factors have the most important role in explaining the three dimensions of crashes. The speed and duration of decline by are best explained by behavioral factors, and the magnitude of fall can be best explained by market microstructure factors. Macroeconomic factor does not do well in forecasting crashes compared with behavioral and microstructure factors.

This paper also performs threshold regression to see if thresholds exist for crash determination, there are differences and agreements compared with other studies. Wang et al. (2009) and Fauzi and Wahyudi (2016) discover that during stock market crash, stocks with higher return volatility face greater falls. This is consistent with the results in this paper that the magnitude of cumulative decline is positively affected by volatility. In addition, our results provide new insight on the issue and point out that when volatility is below the threshold of 0.1308, the *duration* of crash *decreases* with volatility; however, when volatility is above the threshold, the duration of crash *increases* with volatility. Amihud et al. (1990) observes that during the 1987 stock crash period, illiquidity is negatively related with return rate; Wang et al. (2009) and Fauzi and Wahyudi (2016) point out that during crises stock markets with higher liquidity face deeper cumulative price falls. The results of this paper further indicate that when Amihud illiquidity is below the threshold (more liquid), the *speed* of price decline is slower as illiquidity increases; conversely, when Amihud illiquidity is above threshold(less liquid), the speed of price decline accelerates as liquidity worsens.

The result of this paper helps to clarify causes of market crash and provides deeper understanding on the various facets of crashes. Better risk management technology may be generated from the results and further study is needed to explore why the three dimensions of crash are affected by different factors, and detailed cross sectional comparison between the behavioral measures of each markets may be interesting.

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