SCHOOL OF ECONOMICS AND MANAGEMENT

Research on Herding Effect in Emergencies

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Abstract

In this paper, herding effect among pandemic emergencies, natural disaster emergencies and terrorist attacks emergencies is studied. This paper uses quantile regression with the approach proposed by Chiang and Zheng (2010) to detect herding during the time period 2001-2020. In terms of event types, herding is captured in every event group. More specifically, the pandemic group shows the most significant evidence of herding, the next is natural disaster group, and the last is the terrorist attack group. No evidence shows industries related to events are more likely to lead to herding, comparing with unrelated industries.

Keywords: *Behavioral finance, Herding effect, Cross-sectional absolute deviation, quantile regression*

Table of contents

1. Introduction

This section introduces traditional finance and behavioral finance briefly. In addition, the purpose and outline of this paper are mentioned.

Traditional economics assumes that people's economic behavior is rational at any time, under this assumption, efficient market hypothesis (EMH) has been the central proposition of finance since the 1970s (Shleifer, 2000). Under the efficient market condition, all assets available information can be accurately reflected (Fama, 1970). However, since Paul Slovic developed the research on risk perception in 1976, this hypothesis was argued by a growing number of scholars. This research documented behavioral risk characteristics from psychology that can be applied within a financial and investment decision-making context (Ricciardi, 2008). After that, some “market anomalies” were discovered by researchers. For example, in 1980, Grossman and Joseph Stiglitz argued that market agents cannot acquire accurate asset prices as all relevant information about the asset is not fully reflected in the price (Nikolai, 2001). “Monday effect” was reported by Gibbons and Hess in 1981; Bondt and Thaler (1985) concluded that the stock market tends to overreact to long series of bad news. A new field known as behavioral finance began to emerge in many academic journals since 1990s. Behavioral finance assumes that investors have cognitive biases when making investment decisions and these biases may lead to quasi-rational investors. More specifically, news, culture, emergencies and other factors can affect investor’s cognitive process then have an impact on investment activities in stock markets.

A large number of literatures show that abnormal fluctuations in financial markets, such as financial crisis, will lead to herding, such as the research about the European financial crisis (Galariotis et al.2016). Moreover, other external factors, such as earthquakes and terrorist attacks, will have an impact on the financial market is also a popular issue in academia. Luo (2012) takes the Japanese 2011 earthquake and nuclear leakage as an example and concludes that the earthquake has a very small impact on the Japanese stock market, but has a relatively large impact on some specific industries. Chesney, Reshetar and Karaman (2011) studied the impact of natural catastrophes, financial crashes and terrorist events on financial markets. They documented about two-thirds of the terrorist attacks showed a significant negative impact on at least one stock market under consideration. Wu (2003) used the event analysis method and concluded that the impact of SARS on the investment field was limited and transient. Zhang et al. (2009) investigate large-scale wars related to major oil-producing countries and conclude that wars have a significant impact on oil prices.

At the end of 2019, the new coronavirus first appeared in Wuhan, China, and spread throughout the world in the ensuing time. BBC mentions that in the last week of February 2020, several major global stock markets show the worst performance since the 2008 financial crisis. The large but possibly heterogeneous impact of the pandemic begs questions such as whether large-scale emergencies besides pandemic event can generally trigger herd behavior in stock markets? Are directly related industries in emergencies more likely to show evidence of herd behavior than unrelated industries? To reduce limitations due to samples selection and improve the universality of conclusions, this paper selects three major markets and three categories of emergency: public health incidents, natural disasters, and terrorist attacks, which are sudden events and have an impact on many economic sectors. The paper then tests if these emergencies trigger herd behavior in stock markets, examining both related and unrelated industries.

The approach used in this paper is a cross-sectional absolute deviation (CSAD), proposed by Chang et al. (2000). From the results of regressions, we find that the group of pandemic events is the most likely to cause herding among the three-event groups, the next is the group of natural disasters then terrorist attacks. However, we do not find evidence of direct related industries being more likely to show evidence of herding than unrelated industries. The innovation of this paper is previous researchers mainly focus on detecting herding in some markets without limitation of events (Hwang and Salmon, 2004) or investigating certain events within the original market. This paper provides a comprehensive research of several types of events in several markets. It adds to evidence of herding in a more complex condition. Additionally, quantile regression is applied in this paper, providing more robust results comparing with OLS regression.

The remainder of this thesis is structured as follows: section 2 introduces reviews of some theories about behavioral finance and herd behavior and introduces some empirical methodologies of detecting herd behavior. The third section presents data and approach used to test herd behavior. In section four and five empirical results and related conclusions will be discussed respectively.

2. Theory and Literature Review

This section reviews previous theories of behavioral finance and herding effect, including definition of herding, reasons for herding etc.

2.1. Traditional finance and Behavioral finance

Traditional finance is based on the assumption that individuals, or economic agents, conduct rational and utility-maximizing decisions in financial market. In 1952, Harry Markowitz created modern portfolio theory that associated the modern portfolio theory with the efficient market (Ricciard and Simon, 2000). The term efficient market (EMH) was systematically introduced by Fama's doctor thesis in 1965. According to this hypothesis, some main theories were derived, such as the Capital asset pricing model (CAPM) and the Arbitrage pricing theory (APT). After the EMH was introduced, many researchers try to test the efficient stock market by various approaches and more and more evidence argued that the stock market is efficient especially since the 1980s. For instance, Shefrin and Statman (1984) analyzed the dividend puzzle with a consideration of prospect theory.

These abnormal volatilities or extreme returns which cannot be explained by standard finance are considered as financial anomalies. The evidence of these financial anomalies implies that at least some of these abnormal changes in stock prices occur because of such things as: "sunspots" or "animal spirits" or just mass psychology. Since then, behavioral finance came into being and attracted wide attention of the academia. The first question is how to define the term “behavioral finance”? Scholars have given their own views of defining the term of behavioral finance. From Ricciardi and Simon’s (2000) belief, they define behavioral finance is consists of finance, psychology and sociology. Behavioral finance attempts to explain the investors’ behaviors from the perspective of incomplete rationality or existing some cognitive biases and studies financial markets to provide explanations to many stock market anomalies. Ritter (2003) stated that cognition refers to people own thoughts. People are overconfident and pay too much attention to the systematic mistakes made in this way of thinking in recent experiences. Many literatures predict under what circumstances arbitrage forces are effective and under which circumstances it is impossible to determine the meaning of arbitrage restrictions. Barber and Odean (1999, p.41) state that people systematically deviate from optimal judgment and decision-making. Behavioral finance enriches the understanding of economy by bringing these aspects of human nature into financial model. Shefrin (2000) defines behavior finance as the interaction between the psychological factors of financial market participants and financial behavior and performance. In addition, he suggested that investors should be aware of their investment mistakes and peer judgment errors

2.2 Theories of Behavioral finance

From previous literature, there are three main theories about behavior finance: the theory of regret, cognitive dissonance and prospect theory. Herding is one of the specific manifestations of financial cognitive dissonance.

Regret theory is a model in theoretical economics proposed by Loomes and Robert (1982), In Ricciardi and Simon (2000), the theory can be explained that a investor evaluates his or her expected reactions to a future event or situation. More specifically, investors prefer to buy popular stocks, so that regret feeling result from potential losses in the future would be decreased because they think the rest of investors also suffered losses, which can reduce the investor's emotional reaction. Moreover, investors may avoid selling stocks that have declined in value in order to avoid the regret of making a bad investment choice and the discomfort of admitting the loss.

Kahneman and Tversky (1979) developed the theory of Prospect to explain decision-making under uncertainty. The main idea of this theory is most people become risk-averse when they confront with the expectation of a financial gain. It explains that if investors face the possibility of losing, they tend to select riskier decisions which are loss aversion (though they may sometimes refrain from investing altogether).

Financial cognitive dissonance theory demonstrates that investors in the stock market trying to rationalize contradictory behaviors. In this case, it seems that they follow naturally from personal values or viewpoints. One of the well-known manifestations of cognitive dissonance is herding. For example, people ignore the objective economic law and buy or sell stocks blindly, such as the initial economic crisis of selling of tulips in Holland and the Internet bubble in 2000. Apart from herding behavior, there are other biases reported. For example, disposition effect investigates investors tend to sell the winning stock and are prone to hold on to the loss-making asset (Satish and Nisha, 2014). Home bias is another common bias which refers to investors including institutions would hold on to domestic securities rather than to foreign assets in their portfolio.

Apart from these systematic theories, other scholars also developed opinions and ideas about behavioral theory. For instance, Hirshleifer (2015) described some financial theories based on feelings. Saunders (1993); Hirshleifer and Shumway (2003); Edmans, Garcia and Norli (2007) mentioned a basic theme that mood swings affect optimism, risk tolerance, and market prices. Owing to misattribution of transient moods to long-term prospects, mood swings associated with weather or sports events can affect prices. Kamstra, Kramer and Levi (2000) argued seasonal changes in length of time can cause seasonal emotional disorders and are related to market returns. Goel and Thakor (2010) argued envy sentiment also helps explain the attractiveness of investments related to lottery earnings. In the model of Goel and Thakor (2010), managers' takeover decisions are influenced by feelings of envy toward other managers, resulting in merger waves.

2.2.1 Herd behavior

The notion of herding is met in very different settings from neurology and zoology, to sociology, psychology, economics and finance (Spyros, 2013). Researchers have not given an identical definition of herding behavior in finance and economics field. Lakonishok, Shleifer and Vishny (1992) gave the definition of herding which refers to buying (selling) the same stocks as other investors buy (sell) at the same time. Ricciardi and Simon (2000) defined that herding or herd behavior is a large number of investors making investment decisions depending on limited information while ignoring other relevant information such as news or financial reports. While Christian (2009) thought if the decisions of a player are positively influenced by the decisions of the other players, this is referred to as herding behavior. Spyros (2013) defined herding as a process in which economic entities imitate each other and (or) make decisions based on the behavior of others. In this thesis, we follow Spyros's definition of herding behavior since it is one of the most common definitions of herding effect among literatures.

Researchers tend to divide the herd behavior into rational and irrational (or near-rational) herd behavior. Cristian (2012) demonstrated rational herd behavior (profit-seeker) may lead to economic and financial prosperity, but it will eventually lead to financial instability. An irrational herd behavior is based on the psychological factors that determine the behavior process of financial participants (therefore, there is no objective behavior factor). There are three main causes of rational herd behavior (Devenow and Welch, 1996): compensation-based herding, reputation-based herding and imperfect information (cascade).

The intuition behind the compensation-based herding is that if an investment manager's (i.e., an agent's) compensation is decided by how his performance after comparing with other similar professionals, then this distorts the agent's incentives mechanism of the agent, and he may finally get an inefficient portfolio to be consistent with other investment managers. This can also lead to herd behavior. Reputation-based herding arises from uncertainty about a manager's abilities or skills. The basic idea of this kind of herd behavior is that if the investment manager and his employer are uncertain about the manager's ability to select the right stocks, the consistency with other investment professionals will keep the fog, that is, the uncertainty of the manager's ability to manage the portfolio. This is beneficial for managers, and if other investment professionals are in a similar situation, there will be herding. There are a large amount of literatures (i.e. Sharma and Bikhchandani, 2000; Hott, 2009) interpreting how imperfect information (or cascade) leads to herding. The main content of cascade can be summarized as three aspects: first, the actions (and assessments) of early determined investors may be the key to determining how the majority will decide. Second, the decision that investors flock to is likely to be wrong. Third, if investors make a wrong decision, they are likely to eventually reverse their decision and start a herd in the opposite direction based on their experience and / or knowledge of new information. This in turn increases the volatility of the market.

Near-rational herd behavior is associated with investor psychology. Many scholars (i.e. Lee, Shleifer, and Thaler, 1991; Baker and Wurgler, 2006; Schmeling, 2009; Zouaoui, Nouyrigat and Beer, 2011) use the term “investor sentiment” to represent the psychological factors of investors and consider that investor sentiment has a significant impact on the stock market crisis. (Zouaoui, Nouyrigat and Beer, 2011).

It is plausible to assume that in periods of increased anxiety and fear regarding economic conditions investors would be more inclined to follow the market consensus rather than their subjective beliefs, contributing to the development of a herd. Philippas, et al. (2013) used volatility index (VIX) as the sentiment indicator to test whether investors' sentiment is actually related to the herding effects in the REIT market under financial crisis background and concluded that as investors' sentiment deteriorates, herding behavior becomes more intense. In addition to the financial crisis, other major emergencies are also likely to cause panic among investors, thereby leading to herding. Therefore, we plan to examine whether herd behavior becomes more intense on days with emergencies, and which sectors are more likely to be affected.

2.3 Review of empirical research on herding

Previous studies on herding effect mainly focus on two aspects: one is to detect whether there is herding effect in a market; the other is to improve the approach of detecting herding.

Considering the asymmetrical characteristics of asset returns, previous empirical researches usually divide the market into the up and down markets and test the herding effect of the stock market. For example, McQueen, Pinegar and Thorley (1996) examined monthly nominal returns from January 1963 to December 1994 for common stocks trading on the New York Stock Exchange and found that small companies lagged behind big companies when the market was greatly affected by positive news, while there was no time difference between small companies and big companies when they were affected by negative news. This is consistent with the research results of Lo and Mackinley (1990). Chang et al. (2000) used CSAD model to detect the herding effect of developed and developing markets, where they used dummy variables to express extreme upward or downward price. They concluded that there was no herding effect in developed markets such as the U.S market and Japanese market while emerging markets like Taiwan and South Korea exist herding. Dai and Lu (2016) constructed the deviation indicator based on CSAD model between individual stock return and market return to investigate if the herding effect occurred in China's stocks composite CSI 300 Index market. Their research suggested that the rising market was more significant than in the falling market regarding herd behavior.

In addition to considering the situation of the asymmetry market condition, i.e. dividing the market into upward and downward conditions, some exogenous variables such as company size and financial crash that tend to cause herding are also considered into models.

Chiang and Zheng (2010) used both CSSD (cross-sectional standard deviation) and CSAD model testing herding in 18 major global stock markets and documented that herding was more significant in the countries of origin of financial crisis, and had contagion effect in neighboring countries. Additionally, an important contribution to previous research is they tested if the U.S stock market has significant impact on other economies by adding U.S stock market return as a proxy on the right-hand side of the equation. The empirical results suggested most of the countries in the sample were affected by the US market. Philippas et al. (2013) investigated the herding effect of the REIT market in 2004-2011 in the United States and added the index of VIX to measure investor's sentiment. They found that investor's sentiment not only affects the herding effect in the current market but also has a relationship with the herding effect in the future market. Besides, Philippas et al. (2013) also pointed out that the funding conditions have an impact on herding. Xiao, Zhou and Zhou (2019) built three network emotion indexes through text mining technology then used the quantile regression model to analyze the influence of network emotion on the herding effect of the stock market. It was found that the interaction of network information affected the rational degree of investors, thus increasing or reducing the herding effect of the stock market. Henker et al. (2006) selected 200 largest ASX stocks by market capitalization for the year 2001 to 2002 on Australian equity to study whether market-wide herding occurred intraday and concluded that neither market-wide nor industry sector herding occurred intraday.

Two approached widely used to measure the herding in the financial market are CSSD and CSAD proposed by Christie and Huang (1995) and Chang et al. (2000). In Christie and Huang (1995), they examined whether herding was an attribute to market stress during the extreme market decline and the result showed there was no herding in financial crises while Hwang and Salmon (2004) gave the inconsistent result. They proposed a new method based on the CSSD and analyzed US and South Korean stock markets. The empirical result indicated that herding existed in both bull and bear markets. Chang et al. (2000) modified the CSSD approach by transferring the standard deviation to absolute deviation. They found the evidence of significant herding in South Korea and Taiwan and partial evidence of herding in Japan. Notably, they argued that CSSD model only can detect very significant herding as CSSD required a far greater magnitude of non-linearity in the return dispersion and mean return relationship. Therefore, the two approaches may provide conflicting results regarding the presence of herd behavior. This argument is consistent with the empirical result of Al-Shboul's research (2012), who combined quantile regression and CSAD model to investigate the herding behavior in Jordanian equity market before and after the 2008 global financial crisis. The result indicated that by making use of the CSSD approach, evidence of the absence of herding tendency was reported in extreme and normal market conditions, while CSAD approach detects herding in extreme up market condition. Due to the stricter requirement of CSSD approach, more scholars tend to use CSAD approach when capturing herding. For example, Lindhe (2012) applied to CSAD approach to investment herd behavior among market participants in four Nordic countries. Evidence of herding was found in Finland and all Nordic countries were found to herd around the European market. Chen (2013) evaluated whether investors herd for 69 countries and documented evidence of the presence of herding in almost all markets. Also, the paper reported the herding effect was more apparent in the developed markets comparing with emerging markets. Another major finding is investors tend to herd in response to bad news instead of good news. Klein (2013) tested herd behavior in stock markets during times of market turmoil and tranquil trading periods by using CSAD approach and Markov switching SUR model. The findings of this paper showed that during periods of crisis, stock prices were much more driven by behavioral effects compared to tranquil times. In addition, there was a contagion effect between the US market and the Eurozone market.

Apart from several mainstream methods like CSSD and CSAD (the two models are introduced in the next section) to capture the herding effect, there are other methods used in both the measuring model and the robustness test part. For instance, Lin (2013) used ARMA model to test if emergencies affected financial markets; Zhan et al. (2019) used GRACH model to test herd behavior in China A-share real estate market, Saumitra and Siddharth (2013) used symmetric properties of the cross-sectional return distribution to identify herding in Indian stock market. This paper found evidence of herding during the sample period and the 2007 crash.

3. Methodology and data

This section offers some recent researches on herding effect on financial market and *introduces several mainstream methods of detecting herding. Also, descriptive statistics part is presented.*

3. 1 Approaches of measuring herding

Previous literatures are based on dispersions among a group of securities to measure the herding effect. There are three mainstream approaches to test herding behavior.

3.1.1 LVS approach

Lakonishok Vishny and Shleifer (1992) explored whether money managers tend to end up on the same side (buying or selling) of the market in a given stock in a given quarter. They used the below equation to measure herding H:

$$H_{i,t} = \left|p_{i,t} - E(p_{i,t})\right| - E\left|p_{i,t} - E(p_{i,t})\right| \qquad (1)$$

Where t is defined as an independent variable. p_{it} means the net purchase amount of all traders of stock i in period t. and $E(p_{i,t})$ is the expected value of the amount of random net buyers buying in period t, and measures the probability of buying the stock. When the trading volume of a stock increases, the proportion of investors' net purchase of the stock, $p_{i,t}$, tends to move closer to the expected value of $E(p_{i,t})$. i.e. If the value of H is significantly not 0, and the adjustment parameter $E\left|p_{i,t} - E(p_{i,t})\right|$ tends to 0, it shows evidence of herding. The intuition behind this method is it used the trading volume of the buyer and the seller in the stock market to measure herding, that is, it investigated whether the trading direction of the market traders is consistent by calculating the proportion of the buying volume in the investment market.

3.1.2 Cross-section Standard Deviation

The second method was developed by Christie and Huang (1995) using the cross-section standard deviation (CSSD) to capture herd behavior. The regression model is as follows:

$$CSSD_t = \alpha_0 + \beta_1 D_{Lt} + \beta_2 D_{Ut} + \varepsilon_t \qquad (2)$$

With

$$CSSD_t=\sqrt{\frac{\sum_{i=1}^{n}(R_{it}-R_{mt})^2}{N-1}} \quad (3)$$

Where R_{it} is the stock return of firm i and R_{mt} is market return. D is the dummy variable equals to 1 when the return at time t falls in the up or down tails, otherwise equals to 0. The intuition behind this model is to investigate if return dispersions of individual stock and market show decrease significantly in the tails of the distribution, which would indicate that individual stocks increasingly move with the market. More specifically, if the market return falls on the upper (lower) tail, dummy variables controlling extremely high or low return would equal to 1 otherwise equal to 0. The coefficients of dummy variables should be negative if herding behavior is examined.

3.1.3 Cross-sectional Absolute Deviation

Chang et al. (2000) argue that linear and increasing relation between dispersion and market return may not hold under irrational markets. Therefore they modify the model based on CAPM intuition and Efficient Market Hypothesis (EMH). If the market is efficient and rational, the return of stock i should be as follows:

$$E(R_i)=R_f+\beta_i * E(R_m-R_f) \quad (4)$$

Where R_f refers to the risk-free return of interest rate, β_i is the time-invariant systematic risk measure of the stock i at time t,

The absolute value (AVD_{it}) of the deviation degree between stock i and market return is as follows:

$$AVD_{it}=|E(R_{it})-E(R_{mt})|=|\beta_{it}-\beta_{mt}| * E_t(R_{mt}-R_{ft}) \quad (5)$$

Where β_m is the systematic risk of stock market index which is generated by the average of betas of all firms. N is the number of firms.

Chang et al. (2000) define the expected cross-sectional absolute deviation of stock returns (ECSAD) in period t as follows:

$$ECSAD_t = \frac{1}{N}\sum_{I=1}^{N} AVD_{it} = \frac{1}{N}\sum_{I=1}^{N}|\beta_{it} - \beta_{mt}| * E_t(R_{mt} - R_{ft}) \quad (6)$$

The relationship between dispersion of market return and individual stock and market return (CSAD) should be increasing linear function, which can be proofed by below equations (7) and (8).

$$\frac{\partial \text{ECSADt}}{\partial ER_{mt}} = \frac{1}{N}\sum_{I=1}^{N}|\beta_{it} - \beta_{mt}| > 0 \quad (7)$$

$$\frac{\partial^2 \text{ECSADt}}{\partial^2 ER_{mt}} = 0 \quad (8)$$

If herd behavior exists, the linear relationship tends to be nonlinear and the non-linearity would be captured by a negative and statistically significant coefficient β_3 in equation (9). The explanation is with the increase of market return, herding effect will make investors chase the development trend of the market, which will reduce the deviation between stock return and market return or at least increase at a decreasing rate with the market return (Al-Shboul, 2012).

$$CSAD_t^{up(down)} = \propto + \beta_1(R_{m,t}^{up(down)}) + \beta_2\left|R_{m,t}^{up(down)}\right| + \beta_3(R_{m,t}^{up(down)})^2 + \varepsilon_t \quad (9)$$

Besides, Nicolaos et al. (2013) add single dummy variable to present the financial crisis when testing herd behavior in REITs industry (eq. (10)). Furthermore, in Thomas, Chang and Dazhi's paper (2010), dummy variables are introduced to define certain market conditions like tranquil and turbulent periods to test herd behavior in asymmetrical condition and the model is expressed as the equation (11).

$$CSAD_t = \propto_0 + \beta_1 * |R_{mt}| + \beta_2 * (R_{mt})^2 + \beta_3 D^{crisis}(R_{mt})^2 + \varepsilon_t \quad (10)$$

$$CSAD_t = \propto_0 + \beta_1 * |R_{mt}| + \beta_2 * (R_{mt}) + \beta_3 (1-D_t) * (R_{mt})^2 + \beta_4 D_t * (R_{mt})^2 + \varepsilon_t \quad (11)$$

It is worth mentioning another novel method which is pointed out by Soosung and Mark (2004) who argue that even if there is a negative relationship between the cross-sectional standard deviation of individual stock returns and the dummy variables, but whether this relationship is originated from herding is still unsure. Therefore, instead of testing the global stock markets, they use a new approach combining the Fama and French factors model to detect and measure herding based on the CSSD but adding the factor sensitivity of assets within a given market. Due to the space limited, we don't introduce the specific derivation process.

These three methods can obtain the same empirical results at most of time but the CSSD approach requires a far greater magnitude of non-linearity in the return dispersion (Chang et al. 2000). In this case, it may obtain the opposite conclusions with other two methods. The third approach is more detailed and common used, so in this paper, we use the CSAD method to test regressions.

Due to heteroscedasticity and autocorrelation of financial data, the use of OLS sometimes leads to biased statistical results. In this case, many scholars (i.e. Xiao, Zhou, and Zhou, 2019; Ouyang, 2015) tend to employ quantile regression when detecting herding effect on stock market, as it takes extreme values falling into two tails into consideration. Since herding often occurs under market turmoil period, when more extreme values emerge which can be hard to be captured by the OLS. Comparing with OLS, quantile regression is more effective to interpret the conditional probability distribution of the dependent variable as the quantile regression estimation parameter adopts the method of minimizing the sum of the absolute value of the weighted residuals. It does not need to make any hypothesis for the random disturbance term, and it is regression for all quantiles. The model has strong robustness and resistance to abnormal points, so it can effectively overcome the main shortcomings of OLS model. Quantile points, τ=0.1, 0.5 and 0.9 are common points used in quantile regression. In this paper, we not only consider these common points but add other two new points τ=0.05 andτ=0.95 to make empirical results more general. Besides, previous literaures show major emergencies will have a severe impact on the stock market, so that stock returns tend to extreme value. Therefore, it is reasonable to consider some quantiles at the end of distribution.

From above introduction, CSAD is a common herding indicator, which is used to measure the degree of market dispersion of a trading day. Suppose the number of stocks in the market is n, R_{it} represents the return rate of the stock i on the trading day t, R_{mt} represents corresponding market return rate on the trading day, so the regression model for trading day t at quantile point τ is expressed as eq. (12).

$$CSAD_{t,\tau} = \alpha_\tau + \beta_{1,\tau}(R_{mt}) + \beta_{2,,\tau} \mid R_{m,t} \mid + \beta_{3,\tau} R_{m,t}^2 + \varepsilon_{t,\tau} \quad (12)$$

In this paper, we combine eq. (11) and eq. (12) also considers different quntile point condition. Therefore, the model we use in this paper can be expressed as eq. (13)

$$CSAD_{t,\tau} = \propto_{0,\tau} + \beta_{1,\tau}(R_{mt}) + \beta_{2,\tau} * |R_{mt}| + \beta_{3,\tau} D_t * (R_{mt})^2 + \beta_{4,\tau}(1-D_t) * (R_{mt})^2 + \varepsilon_t \quad (13)$$

Where D=1 when the trading day falls into the window period and 0 otherwise. If coefficients of $(R_{mt})^2$ of the above quintile model is significant, it indicates there is a herding effect at this quantile.

3.2 Data

The data employed in this paper include daily stock price, which are collected from Warthon database. We search all companies in each industry within corresponding window period. After excluding companies with invalid data (such as large missing historical data), the remaining companies consist of our effective samples. As mentioned in the Introduction part, there are three events groups, which cover 25 industries. All related information is summarized in table 1.

Table 1 Events and related & unrelated industries

Type	Event	Related industries	Unrelated industries
Pandemic	COVID-19	Casino,Airline, Auto parts&Equipment, Recreation activity	Property&Casualty insurance, Health care REITs,Life insurance, Insurance miscellaneous
	SARS		
	H1N1		
Terrorist attacks	9/11	Restaurant,Hotel, Airline,Insurance	Advertising,Apparel, Broadicasting
	KunMIing		
	Paris		
Natural disaster	Earthquake in WenChuan,China	Restaurant,Hotel, Airline,Insurance	Advertising,Apparel, Broadicasting, Software,Computer hardware
	Australian forest fire		
	Indonesian tsunami		

First, look at details of pandemic group, covering COVID-19, SARS and H1N1 event. Related and unrelated industries are selected following the research report of S&P 500 global (2020), which lists five most and least impacted industries by COVID-19 from the perspective of probability of default. For comparison, another two similar events, SARS and H1N1, have the same related and unrelated industries. As no research has determined how long the window period needs to be to test the herding effect, and the COVID-19 has not been over in the worldwide, this paper chooses a uniform date as the end date, 2020.05.01(the date of collecting data), while the starting dates are based on the date when the first case was reported in various countries. It is worth mentioning that the sample of Europe consists of Germany, Italy, France and Spain. The selection of these countries is based on the number of people infected in each country until 1 May, 2020. Since this paper selects four countries to form the European sample, and the time for reporting the first case varies from country to country, we choose the country with the latest case among these four countries as the starting point of the time window (January 31, 2020). For SARS and H1N1, we follow the same industries and window period of the same length of time in the COVID-19 test, i.e. from one month before the first case was reported to the next five months. Window period of each event is presented in table 2 and table 3

Table 2 Window period and Non-window period of terrorist attacks and natural disaster events

Event	Window time	Non-window time
9/11	2001.09.17-2001-12.11	2001.08.13-2001.09.16
KunMIing	2014.3.1-2014.6.1	2014.1.22-2014.2.28
Paris	2014. 11.13-2014.12.13	2014.10.13-2015.11.12
Earthquake in WenChuang,China	2008.05.12-2008.08.12	2008.04.12-2008.05.11
Australian forest fire	2009.02.07-2009.05.07	2009.01.07-2009.02.06
Indonesian tsunami	2004.12.26-2005.03.26	2004.11.26-2004.12.25

Table 3 Window and non-window period of pandemic events

Event	U.S	CHINA	EUROPE
COVID-19	2020.01.22-2020.05.01	2019.12.26-2020.05.01	2020.01.31-2020.04.29
SARS	2003.02.21-2003.07.13	2002.11.16-2003.7.13	2003.03.22-2003.07.11
H1N1	2009.04.12-2009.09.12	2009.05.11-2009.10.11	2009.05.04-2009.10.02
Non-window period of pandemic events			
COVID-19	2019.12.22-2020.01.21	2019.11.26-2019.12.25	2019.12.27-2020.01.30
SARS	2003.01.21-2003.02.20	2002.10.16-2002.11.15	2003.02.12-2003.03.21
H1N1	2009.03.12-2009.04.11	2009.04.11-2009.05.10	2009.04.06-2009.05.01

For the natural disaster group, this paper selects three natural disaster events with greater impact: the Wenchuan earthquake in China, the forest fire in Australia, and the tsunami in Indonesia. Some scholars believe that natural disaster events have a limited impact on the whole stock market, but have a greater impact on specific industries (Luo, 2012). However, common view is that natural disasters will have a greater impact on the tourism industry and the insurance industry. Specifically, we decompose the tourism industry into the restaurant industry, hotel industry, and airline industry. In addition, there is no document which industries will not be affected by natural disasters. Therefore, we apply literature review method to determine the unrelated industries by excluding the affected industries mentioned in the previous articles and the upstream and downstream industries of these industries. Among the remaining industries, broadcasting or media industry, advertising industry, clothing industry, and software programming industry are selected. Regarding window periods of these events, we define one month before and three months after the event as the window period not only to avoid window periods overlapped but also natural disasters will not have a large impact on the stock market as a whole.

The last one is the terrorist attack group. The situation of this group is similar to that of the natural disaster group. We select three terrorist attacks with greater influence in since 2000 as samples: the 9/11 terrorist attack, terrorist attack in Kunming, China, and the terrorist attack in Paris, France. Terrorist attacks will also have an impact on the insurance and tourism industries, but the long-term impact on the stock market is not large, so we follow the same rule to define window period and industry as the natural disaster group.

3.3 Descriptive statistics of CSAD

The following table soley extracts mentioned data of descriptive statistics of $CSAD_t$ for industries in each event respectively, remaining statistics are presented in Appendix A. The data range is from 11/08/2001 to 01/05/2020. CSAD is calculated by equation:

$$\text{CSAD}= \frac{1}{N}\sum_{I=1}^{N}|R_{mt} - R_{it}| \tag{14}$$

Where R_{it} is calculated as $R_{it} = \log (P_{i,t}/P_{i,t-1})$, P_{it} denotes the daily close price of indivisual stock i. Missing information for holidays is carefully inspected or interpolated.

Table 4: Extracted descriptive statistics of CSAD in pandemic events gruop

Statistics	leisure,SARS,China	leisure,SARS,U.S	life insurance, COVID,China
Mean	0.005	0.056	0.007
Median	0.003	0.001	0.006
Maximum	0.026	4.488	0.018
Minimum	0.000	-0.151	0.001
Std. Dev.	0.005	0.438	0.003
Skewness	2.024	9.232	0.908
Kurtosis	8.002	91.596	3.473
Jarque-Bera	331.237	40267.990	15.420
Probability	0.000	0.000	0.000
Sum	0.874	6.586	0.703
Sum Sq. Dev.	0.005	22.443	0.001
Observations	192	118	105

This table presents descriptive statistics used to analyze in this paper, including leisure industry in Chinese market of SARS, leisure industry in U.S market of,SARS and life insurance industry in Chinese market of COVID-19.

Complete descriptive statistics of CSAD in stock returns for the U.S, China and Europe market of the pandemic group is presented in appendix A. The number of observations in the sample range from 86 to 192. The leisure industry of SARS in the Chinese market has the highest number of dates. The mean values of the sample differ across the different industries and the highest mean value is found in the data for leisure industry of SARS in the U.S while the lowest mean value is found in the data for leisure industry of SARS in China. Furthermore, the standard deviation should also be mentioned. The higher standard deviation value indicates a higher variation in the market across industrial returns. As in the situation with mean values, the standard deviation for leisure industry of SARS in the U.S is also the highest whereas life insurance industry of COVID-19 in China has the lowest standard deviation. A higher standard deviation indicates that the market had unusual cross-sectional variations. The null hypothesis of Jarque-Bera test is sample data have the skewness and kurtosis matching a normal distribution. From appendix A, we can know that all CSAD except Chinese leisure industry in H1N1 in the pandemic group do not match the normal distribution. This can also be confirmed from the skewness and kurtosis. Most of CSAD's skewness is positive and has excess kurtosis, which is above three. In this case, quantile regression is more effective than the OLS.

Table 5: Extracted descriptive statistics of CSAD in terrorist attack events gruop

CSAD	apparel, 9/11, U.S	hotel, 9/11,U.S	airline,Kunming,China	hotel,Kunming,China
Mean	0.027	0.051	0.006	0.010
Median	0.024	0.043	0.005	0.009
Maximum	0.072	0.188	0.032	0.021
Minimum	0.011	0.010	0.001	0.003
Std. Dev.	0.012	0.034	0.004	0.004
Skewness	1.379	1.831	3.228	0.738
Kurtosis	5.151	6.945	18.680	2.980
Jarque-Bera	40.783	98.970	1018.441	7.726
Probability	0.000	0.000	0.000	0.021
Sum	2.122	4.174	0.506	0.867
Sum Sq. Dev.	0.011	0.094	0.002	0.002
Observations	80	82	85	85

This table presents descriptive statistics used to analyze in this paper, including insurance industry of ,Kunming terrorist attack in Chinse market, hotel industry of 9/11 in U.S market, airline industry of Kunming terrorist attact in Chinese market and hotel industry of Kunming,terrorist attact in Chinese market.

Table 5 presents extracted descriptive statistics of terrorist attacks group. The number of dates in the sample ranged from 80 to 85. The event of market with the lowest number of dates is apparel industry in the 9/11, and all industries in the terrorist attack in Paris have the highest number of dates. On the other hand，the highest mean value is found in the data of hotel industry in the 9/11， the lowest mean value is found in the data for airline industry in terrorist attacks of Kunming terrorist attack. The standard deviation should also be mentioned. As in this situation with mean values the standard deviation for hotel industry in 9/11 event is the highest, whereas hotel industry in the terrorist of Kunming has the lowest standard deviation. Jarque-Bera test indicates the null hypothesis solely cannot be rejected in the China broadcasting industry and France apparel industry.

Table 6: Extracted descriptive statistics of CSAD in natural disaster events gruop

CSAD	Airline industry,forest fire	Insurance industry,forest fire	Hotel industry,tsunami	Apparel,earthquake
Mean	0.050	0.002	0.006	0.022
Median	0.041	0.000	0.004	0.020
Maximum	0.188	0.023	0.028	0.066
Minimum	0.000	0.000	0.000	0.009
Std. Dev.	0.042	0.004	0.006	0.010
Skewness	0.911	3.305	1.425	2.273
Kurtosis	3.514	15.023	4.961	10.404
Jarque-Bera	12.550	658.861	37.382	270.524
Probability	0.002	0.000	0.000	0.000
Sum	4.242	0.177	0.450	1.850
Sum Sq. Dev.	0.146	0.001	0.002	0.008
Observations	84	84	75	86

This table presents descriptive statistics used to analyze in this paper, including airline industry of Australian forest fire in Australian market, insurance industry of Australian forest fire in Australian market, hotel industry of Indonesian tsunami in Indonesian market and apparel industry of 5/12 earthquake in Chinese market.

The descriptive statistics of CSAD of natural disaster is shown in table 6. The number of dates in the sample range from 75 to 86. The event of market with the lowest number of dates is the hotel industry in the Indonesian tsunami and apparel industry in the earthquake of China is the highest number of dates. Besides, the highest mean value is found for the data of airline and the lowest mean value is found in the data for insurance industry in Australia forest fire. Furthermore, the standard deviation for airline industry in Australia forest fire is the highest while insurance industry in Australia forest fire has the lowest standard deviation. Only the sofware and programming industry in Indonesia cannot reject the Jarque-bera test, which means other CSAD do not match the normal distribution.

4. Empirical Results

This section porvides the empirical results of this paper, coveing regression results and related analysis.

According to Luo (2012) and Sun (2012) 's studies, whether major emergencies and natural disasters will have an impact on the overall market, and whether they will have spillover or contagion effects depends on the severity of the event. In addition, Luo (2012) also showed evidence that Japanese 2011 earthquake has only an impact on some industries and limited impact on the overall market, which is consistent with Wu (2003), who reported that the impact of SARS on China's financial market is limited and not significant in the statistical results. Shelor et al.(1992) reported that the San Francisco earthquake in 1989 has a significant impact on the local real estate industry. According to previous scholars' research, it can be concluded that the events of exogenous variables in the financial market do not have a significant impact on the whole market unlike the events such as the economic crisis. Therefore, we believe that herding effect is not easy to be observed in the whole market. In this case, this paper first tests the industry directly related to the event as a representative to explore the two questions proposed above.

To investigate the first question, i.e. whether some events are more likely to cause herding effect than other events. We estimate eq. (13) in three events group and the results are shown in appendix B.

From the results of table 16 to table 19 in appendix B, three related industries occur herding effect in SARS event within window period. It is worth noting that the herding effect of casino industry and auto industry only appears in some specific quantiles, while leisure industry shows negative coefficients in all quantiles. One possible explanation for this difference is investors only show overconfidence in a certain range of security. Once the degree of individual stock yield deviates from the market exceeds a certain threshold, investors' confidence in private information will be significantly reduced and they will be more willing to trust the market consensus, so their investment behavior will change from decentralized decision-making to following the flow, and their investment style will change from radical to conservative. Another noteworthy point is the change of coefficient. We can see that the coefficient of β_4 in the regression equation of casino industry is more significant than that of β_3, which indicates that there is herding effect in this industry before the event. Therefore, we can't think that herding effect is caused by the event of SARS. The opposite is auto industry of Chinese market. The β_3 values of this industry are negative when $\tau = 0.5$ and 0.9, while the corresponding β_4 values are positive, which means that the herding effect of this industry is caused by SARS. This is consistent with the view of Chiang (2010), who documented the evidence of herding in Chinese stock market. There is a significant herding effect in both window period and non-window period in the leisure industry, and the absolute value of R_{mt}^2 coefficients in window period is smaller than that in non-window period, suggesting that herding effect has appeared in the leisure industry before SARS, and SARS intensifies the herd mentality of investors.

The results of H1N1 indicate similar evidence of herding with SARS. Only leisure and airline industry in US market show herding. Noticeably, coefficients are only significant at extreme point 0.95 and 0.90 in airline industry, indicating that investors would hide their own information and follow the market consensus in some extreme conditions, which also can be shown in leisure industry with only significant β_3 value at τ=0.95 point. Although the coefficient of leisure industry is significant, it cannot be concluded that there is herding effect, as the coefficient of non-window period is also significant and the value is larger than herding coefficient. In contrast to the leisure industry, the airline industry can be considered herding, although β_4 is significant at τ = 0. 95, its value is smaller than that of β_3. Therefore, the herding effect is caused by H1N1.

Unlike the first two pandemics, in the recent event of COVID-19, all markets show herding. First, for auto industry, there's only one positive and significant coefficient of β_3 for the US market. However, as mentioned above, many previous scholars have not detected herding in the US market. One possible explanation is that they test the whole stock market so herding in some industries may be hidden by other large-weighted sectors. This opinion is supported by Philippas el at. (2013) and Humayun Kabir (2018). They report herding effect in certain industries of US market. In contrast to the situation in the United States, all tested industries in China have no herding effect except for airline industry. Although the airline industry has shown herding effect in the non-window period, this phenomenon is more significant after COVID-19, which can be found from large absolute coefficient values of β_3 comparing with the β_4. European market has herding effect in COVID-19, and this is contrast to the first two events, and the values are concentrated between 0.5 and 0.95 quantiles. In this case, the overall response of European market to the pandemic is not strong, only in the extreme situation of the most serious pandemic where investors have panic and overreaction, which is in line with Economou et al. (2011), who study stress that inheriting comes stronger during periods of abnormal information flow and volatility.

In general, these three markets do not show excessive panic or overconfidence for the pandemic events, thereby leading to herding. Among the three markets, the most notable is the United States, and the calmest is the European market, while this result is rejected by Mobarek et al. (2014) and Galariotis et al. (2016). They found significant herding in almost European countries during turmoil period. In addition, we notice that industries with herding effect in non-window period are more likely to intensify in the period of market turbulence, which is not reported by previous papers

Table 24 to table 27 in appendix B Appendix reflect regression results of the natural disaster group. As one of the natural disaster events, no finding of herding is present in related industries of Indonesian market during 2004 tsunami, but herding is found in the media and software industries, which is contrary to our hypothesis. However, due to the coefficient of non-window period is also significant, we are not sure that tsunami is the cause of herding.

Generally speaking, the herding coefficient in this event is not significant, whether it is related or not. Therefore, it is reasonable to think that this event has no spillover effect, so it is not necessary to detect neighboring countries. This is contrary to the conclusion of Hsien-Yi Lee et al.(2007), who examined the impact of Indonesian tsunami on the market and find that the Indonesian tsunami not only affect the domestic stock market, but also affects Taiwan, the Philippines and other markets.

Worthington and Valadkhani (2004) proposed that forest fires, hurricanes and other natural disasters have an impact on the Australian market, but we find no evidence to support herding by exploring the most serious fire events in Australia in 2009. The only significant coefficient presents in broadcasting industry non-window period, but in the three months after the disaster, this herding effect turns to insignificant.

We can see that China's market has a strong response to the May 12 earthquake, and airline industry, restaurant industry, broadcasting industry and apparel industry show herding effect, of which the airline industry has the strongest response, while the apparel and broadcasting industry are not related to the earthquake disaster. One potential explanation is that the impact of the earthquake on China's stock market is significant, and the overreaction of investors leads to sharp fluctuations in the whole market, which can be seen from the negative herding coefficients of other industries in the table. Although these coefficients are not significant, compared with the non-window period, their values show a downward trend, indicating that investors tend to hide their own information and follow the market industry, which is presented by β_3.

Generally speaking, not every disaster causes herding. This view is also supported by Charles et al. (2008), who analyzed Japanese stock market using event study and could not found any supportive evidence of herding.

Terrorist attacks lead to a significant and negative impact on at least one stock market (Chesney et al., 2011). Evidence of heridng of terrorist attacks is shown in table 33 to table 36 in appendix B. After 9 /11, the U.S. stock market stopped trading for a week in order to avoid a severe impact on the stock market, so we think this may affect the result of herding effect. From the results, only the airline industry that is most related to terrorist attacks has herding effect, and from the significant coefficients of $\tau = 0.9$ and $\tau = 0.95$, it is reasonable to think that part of the herding effect after 9/11 event is affected by the herding effect before the window period, so we think that 9/11 event only has a partial impact on the airline industry. In other industries, we do not detect herding. However, Chesney et al. (2011) concluded the airline industry and insurance sector exhibit the highest susceptibility to terrorism after investigating the terrorist events that took place in 25 countries over an 11-year time period.

The herding effect in the airline industry is also caused by the terrorist attacks in Kunming, China. From table 35, we can see that only the airline industry has herding effect, but only the β_3 coefficient which is below the 0.5 quantile point is greater than the corresponding β_4 coefficient. This indicates that herding effect only occurs at this time. From the overall data, herding effect cannot be completely summed up as the result of this event. A similar situation also appears in the 2014 terrorist attacks in France, which is the most sever terrorist attacks in Europe since 2000. Surprisingly, no industry has herding effect in this event, only the apparel industry's herding coefficient is significant, but it is obvious that we have no reason to obtain a conclusion since β_4 is also significant.

In order to explore the second question, i.e.whether some industries directly related to events are more likely to cause herding than unrelated industries, we compare the tables of related industries with those of unrelated industries. Results of unrelated industries are in table 20 to table 23; table 28 to table 32 and table 37 to table 39 in Appendix B.

According to above introduction, leisure industry, auto industry and airline industry are the three most significant industries among the affected industries. Contrary to the research report of S&P, herding effect in unrelated industries is also obvious. This is mainly reflected in the U.S. market, which shows that the impact of the pandemic on the U.S. market is extensive, so we cannot conclude that some directly related industries are more likely to cause herding. It is worth noting that the recent occurrence of COVID-19 shows the most significant herding effect, no matter in related or unrelated industries. The possible reason is this event contains more data than another two similar events. This may affect the regression results.

The most relevant industries to terrorist attacks are insurance and tourism industries, in particular, the airline, hotel, restaurant and insurance industries. However, comparing table 33-36 with table 37-39 in Appendix B, we can see that except the airline industry, which is significant in the 9 /11 and Kunming terrorist attacks, the other related industries do not reflect significant herding. Therefore, it cannot be concluded that related industries are more likely to cause herding than unrelated industries in terrorist attacks.

For natural disaster events, we chose the same related and unrelated industries as terrorist attacks. From the results, we can see that the impact of natural disasters on the market is larger than terrorist attacks this can be reflected by the herd effect in more industries directly related to natural disasters. Generally speaking, the response to natural disasters is not strong in related or unrelated industries, only a few directly related industries such as airline industry have an obvious herding effect. It is worth noting that some industries, such as software industry, which are not considered to be related to events, also have a significant herding effect.

Through the analysis of these three kinds of events directly related industries and non-related industries, we can get that the industries directly related to the events are not more likely to cause herding than the non-related industries.

5. Conclusion

This section sums up the main conclusions based on empirical results. Moreover, the contribution and limitaion of this paper as well as prospects for future research are mentioned.

In this paper, herding effect in large emergences is investigated, more specifically, pandemic events, natural disaster event and terrorist events among the US, China, Australia, Indonesia and the EU market. Two questions are explored in this paper: whether some events are more likely to cause herding; whether some directly related industries are more likely to occur herding comparing with unrelated indusries. The approach is applied to the CSAD proposed by Chiang and Zheng (2010).

Regarding the first question, the significant result is only found in airline industry in the terrorist event among three selected event samples, covering three stock markets and eight industries. For other two event groups, empirical results differ with markets and events. Although industries to be tested are identical with the terrorist event, natural disaster events are more likely to lead to herding comparing with terrorist events. This is reflected by Indonesian market and Chinese market. No herding evidence support Australian forest fire event and this result is inconsistent with Worthington and Valadkhani's (2004) view, who report natural disaster has an impact on the Australian stock market. For the pandemic events, fewer industries are found herding effect in SARS and H1N1 events, only leisure and airline industry being detected herding effect.

Herding is more common in COVID-19, since most related industries have significant and negative herding coefficients. In particular, significant results in American related and unrelated industries offer opposite evidence of absence of herding in US market (Chang et al. 2000).

As mentioned in the previous section, many researchers reckon such emergencies solely affect certain industries rather than the whole market. In this case, it is plausible to suppose these certain industries are more likely to capture herding. However, this argument is rejected in this paper. We compare related and unrelated industries in the same event and find herding is reflected in both related and unrelated industries in particular in the US. This finding is supported by Chen's (2014) research, who argues that herding is prevailing in almost all markets after studying the herding effect in 69 countries. In addition, Chen (2014) also reports herding effect is more apparent in the developed markets in that a better environment to process and disseminate information. This argument is reflected by US stock market in this paper.

This paper contributes in providing additional research on herding in the global market. Previous research mainly focuses on herding effect in a single type of emergency or financial crisis. But this paper combines several types of emergencies and several markets at the same time. Moreover, the conflicting results comparing with Worthington and Valadkhani (2004) provides more studies of herding in the financial market may lead to conflicting evidence.

One of the deficiencies of this paper is this paper solely selects limited number of events in each group resepctively. This may lead to biased conclusions. In addition, robustness test is not included although quantile regression shows more robust than OLS as mentioned above. Researchers usually use two methods to capture herding, but this paper only uses one method so that it is impossible to compare which method is more effective. Last but not least, spillover and contagion are very common topics discussed in herding papers, which are not examined in our paper.

For the further research, the range of events can be expanded so that a more general conclusion can be drawn. In addition, since the outbreak of COVID-19 is not over, the conclusions regarding this event is very limited. If the future research could include a complete window period, it will be able to draw more convincing conclusions. Furthermore, the approach of detecting herding can be further developed to precisely distinguish whether herding is caused by emergencies.

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APPENDIX:

Appendix A: descriptive statistics of CSAD

Table 1：CSAD of SARS in U.S:

CSAD	Airline	casino	healthcare	Life.in	p&c	ins.m	leisure	auto
Mean	0.030	0.025	0.035	0.024	0.014	0.009	0.056	0.015
Median	0.024	0.023	0.030	0.020	0.014	0.008	0.001	0.014
Maximum	0.153	0.055	0.285	0.085	0.029	0.035	4.488	0.032
Minimum	0.008	0.006	0.009	0.007	0.008	0.002	-0.151	0.007
Std. Dev.	0.022	0.010	0.028	0.018	0.004	0.005	0.438	0.005
Skewness	2.702	0.937	6.934	1.571	1.032	2.165	9.232	1.169
Kurtosis	12.951	3.768	60.850	4.976	4.685	10.712	91.596	4.153
Jarque-Bera	635.801	20.323	14745.490	50.499	35.482	387.821	40267.990	33.954
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Sum	3.535	2.963	3.486	2.146	1.721	1.080	6.586	1.776
Sum Sq. Dev.	0.057	0.012	0.080	0.027	0.002	0.003	22.443	0.003
Observations	119.000	119.000	100.000	88.000	120.000	119.000	118.000	120.000

Table 2: CSAD of SARS in CHINA:

CSAD	Airline	healthcare	leisure	auto
Mean	0.009	0.012	0.005	0.011
Median	0.007	0.011	0.003	0.010
Maximum	0.034	0.042	0.026	0.030
Minimum	0.001	0.001	0.000	0.004
Std. Dev.	0.006	0.008	0.005	0.004
Skewness	1.404	1.112	2.024	1.058
Kurtosis	5.104	4.162	8.002	4.864
Jarque-Bera	91.313	46.713	331.237	58.950
Probability	0.000	0.000	0.000	0.000
Sum	1.551	2.206	0.874	1.936
Sum Sq. Dev.	0.006	0.012	0.005	0.003
Observations	178.000	178.000	192.000	178.000

Table 3: CSAD of SARS in EU

CSAD	Airline	casino	healthcare	Life.in	p&c	leisure	auto
Mean	0.026	0.017	0.015	0.021	0.019	0.021	0.019
Median	0.023	0.012	0.014	0.019	0.019	0.016	0.016
Maximum	0.083	0.383	0.061	0.055	0.047	0.099	0.191
Minimum	0.006	0.003	0.002	0.004	0.005	0.003	0.006
Std. Dev.	0.013	0.037	0.009	0.009	0.008	0.016	0.019
Skewness	1.360	9.642	1.772	0.958	0.625	2.240	7.533
Kurtosis	5.896	96.567	9.959	4.139	3.275	9.815	68.893
Jarque-Bera	68.383	39548.760	264.315	21.947	7.228	288.221	19798.140
Probability	0.000	0.000	0.000	0.000	0.027	0.000	0.000
Sum	2.696	1.732	1.515	2.214	2.048	2.163	1.947
Sum Sq. Dev.	0.019	0.139	0.007	0.009	0.007	0.025	0.036
Observations	104.000	104.000	104.000	106.000	106.000	104.000	104.000

Table 4: CSAD of COVID in U.S:

CSAD	Airline	casino	healthcare	Life.in	p&c	ins.m	leisure	auto
Mean	0.027	0.024	0.032	0.024	0.020	0.014	0.034	0.025
Median	0.019	0.023	0.026	0.020	0.016	0.011	0.026	0.020
Maximum	0.121	0.523	0.104	0.085	0.080	0.053	0.107	0.090
Minimum	0.005	0.099	0.011	0.007	0.006	0.002	0.007	0.006
Std. Dev.	0.022	0.011	0.019	0.018	0.015	0.010	0.023	0.016
Skewness	2.109	0.181	1.467	1.571	1.732	1.367	1.113	1.562
Kurtosis	8.230	3.193	5.228	4.976	6.142	4.614	3.469	5.565
Jarque-Bera	169.276	10.693	49.185	50.499	82.021	37.795	19.419	61.248
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Sum	2.423	2.353	2.757	2.146	1.825	1.281	3.079	2.215
Sum Sq. Dev.	0.043	0.026	0.030	0.027	0.020	0.009	0.049	0.023
Observations	90.000	99.000	87.000	88.000	90.000	90.000	90.000	90.000

Table 5: CSAD of COVID in U.S:

CSAD	Airline	healthcare	Life.ins	leisure	auto
Mean	0.017	0.017	0.007	0.016	0.023
Median	0.014	0.016	0.006	0.014	0.019
Maximum	0.094	0.040	0.018	0.067	0.113
Minimum	0.003	0.005	0.001	0.002	0.012
Std. Dev.	0.012	0.007	0.003	0.011	0.013
Skewness	2.879	0.745	0.908	1.720	3.891
Kurtosis	17.284	3.411	3.473	7.886	23.410
Jarque-Bera	1037.699	10.439	15.420	156.239	2087.401
Probability	0.000	0.005	0.000	0.000	0.000
Sum	1.787	1.792	0.703	1.725	2.363
Sum Sq. Dev.	0.015	0.006	0.001	0.012	0.019
Observations	105.000	105.000	105.000	105.000	105.000

Table 6: CSAD of COVID in EU:

CSAD	Airline	casino	healthcare	Life.ins	p&c	ins.m	auto
Mean	0.038	0.031	0.021	0.021	0.029	0.026	0.032
Median	0.034	0.023	0.016	0.014	0.022	0.021	0.028
Maximum	0.117	0.113	0.083	0.067	0.101	0.089	0.086
Minimum	0.000	0.001	0.004	0.002	0.003	0.003	0.001
Std. Dev.	0.023	0.022	0.016	0.015	0.020	0.018	0.018
Skewness	0.963	1.706	1.686	1.001	1.406	1.361	0.999
Kurtosis	3.826	5.517	5.910	3.073	4.636	4.590	3.368
Jarque-Bera	15.743	64.402	71.067	14.542	38.350	35.606	14.799
Probability	0.000	0.000	0.000	0.001	0.000	0.000	0.001
Sum	3.294	2.665	1.821	1.811	2.529	2.198	2.794
Sum Sq. Dev.	0.044	0.041	0.021	0.019	0.034	0.028	0.027
Observations	86.000	86.000	86.000	87.000	87.000	86.000	86.000

Table 7: CSAD of H1N1 in U.S

CSAD	Airline	casino	healthcare	Life ins.	P&C	ins.m	leisure	auto
Mean	0.021	0.035	0.025	0.025	0.024	0.014	0.037	0.036
Median	0.019	0.031	0.024	0.024	0.022	0.012	0.031	0.031
Maximum	0.064	0.109	0.044	0.053	0.097	0.044	0.197	0.119
Minimum	0.007	0.011	0.011	0.010	0.012	0.003	0.012	0.014
Std. Dev.	0.010	0.016	0.008	0.009	0.011	0.008	0.024	0.018
Skewness	1.626	1.620	0.501	0.713	2.719	1.264	3.298	1.970
Kurtosis	6.671	6.870	2.366	3.021	15.230	4.840	19.195	8.255
Jarque-Bera	128.311	135.856	7.436	10.838	955.472	52.118	1630.940	230.056
Probability	0.000	0.000	0.024	0.004	0.000	0.000	0.000	0.000
Sum	2.655	4.481	3.176	3.229	3.126	1.762	4.780	4.551
Sum Sq. Dev.	0.012	0.031	0.008	0.009	0.017	0.007	0.073	0.040
Observations	128.000	128.000	127.000	128.000	128.000	128.000	128.000	128.000

Table 8: CSAD of H1N1 in China:

CSAD	Airline	healthcare	leisure	auto
Mean	0.020	0.019	0.216	0.019
Median	0.016	0.018	0.166	0.018
Maximum	0.057	0.098	0.689	0.032
Minimum	0.000	0.004	0.004	0.009
Std. Dev.	0.013	0.013	0.183	0.005
Skewness	1.096	2.425	0.822	0.755
Kurtosis	3.476	14.112	2.574	3.108
Jarque-Bera	25.372	741.057	14.410	11.472
Probability	0.000	0.000	0.001	0.003
Sum	2.421	2.359	/	2.230
Sum Sq. Dev.	0.022	0.019	4.007	0.003
Observations	121.000	121.000	120.000	120.000

Table 9: CSAD of H1N1 in EU:

CSAD	Airline	casino	healthcare	Life ins.	P&C	leisure	auto
Mean	0.025	0.024	0.011	0.022	0.028	0.021	0.027
Median	0.020	0.020	0.010	0.018	0.019	0.019	0.020
Maximum	0.112	0.104	0.026	0.064	0.670	0.071	0.122
Minimum	0.002	0.004	0.003	0.005	0.005	0.003	0.002
Std. Dev.	0.019	0.017	0.005	0.011	0.059	0.010	0.023
Skewness	1.913	2.427	0.827	1.434	10.061	1.469	1.809
Kurtosis	7.468	10.957	3.404	5.110	108.806	6.876	6.427
Jarque-Bera	180.235	452.544	14.484	67.104	61381.930	125.217	129.354
Probability	0.000	0.000	0.001	0.000	0.000	0.000	0.000
Sum	3.186	3.050	1.343	2.755	3.569	2.640	3.393
Sum Sq. Dev.	0.046	0.037	0.003	0.015	0.445	0.013	0.066
Observations	125.000	125.000	120.000	127.000	127.000	127.000	125.000

Table 10: CSAD of terrorist attack in China:

CSAD	Hotel	Airline	Insurance	Advertising	Apparel	Broadcasting
Mean	0.010	0.006	0.007	0.022	0.015	0.014
Median	0.009	0.005	0.006	0.021	0.013	0.013
Maximum	0.021	0.032	0.029	0.105	0.045	0.031
Minimum	0.003	0.001	0.001	0.005	0.007	0.005
Std. Dev.	0.004	0.004	0.005	0.014	0.006	0.006
Skewness	0.738	3.228	1.948	3.618	2.320	0.617
Kurtosis	2.980	18.680	8.035	21.386	11.663	2.557
Jarque-Bera	7.726	1018.441	141.854	1382.615	342.022	6.096
Probability	0.021	0.000	0.000	0.000	0.000	0.047
Sum	0.867	0.506	0.623	1.889	1.236	1.199
Sum Sq. Dev.	0.002	0.002	0.002	0.015	0.003	0.003
Observations	85.000	85.000	84.000	85.000	85.000	85.000

Table 11: CSAD of terrorist attack in France:

CSAD	Restaurant	Insurance	Advertising	Apparel	Broadcasting
Mean	0.012	0.011	0.016	0.011	0.008
Median	0.010	0.010	0.014	0.010	0.006
Maximum	0.049	0.034	0.050	0.025	0.037
Minimum	0.001	0.001	0.006	0.001	0.001
Std. Dev.	0.009	0.006	0.006	0.005	0.006
Skewness	1.911	0.942	2.226	0.531	2.484
Kurtosis	7.372	3.814	12.381	2.853	11.369
Jarque-Bera	120.870	15.083	386.355	4.115	339.409
Probability	0.000	0.001	0.000	0.128	0.000
Sum	1.060	0.938	1.342	0.912	0.652
Sum Sq. Dev.	0.007	0.004	0.003	0.002	0.003
Observations	86.000	86.000	86.000	86.000	86.000

Table 12: CSAD of terrorist attack in U.S:

CSAD	Hotel	Airline	Insurance	Advertising	Apparel	Broadcasting
Mean	0.040	0.051	0.024	0.018	0.032	0.027
Median	0.034	0.043	0.019	0.016	0.023	0.024
Maximum	0.194	0.188	0.130	0.040	0.174	0.072
Minimum	0.014	0.010	0.007	0.006	0.009	0.011
Std. Dev.	0.025	0.034	0.018	0.007	0.029	0.012
Skewness	3.358	1.831	3.727	1.056	3.087	1.379
Kurtosis	20.043	6.945	19.717	4.334	14.119	5.151
Jarque-Bera	1132.485	98.970	1130.680	21.051	545.894	40.783
Probability	0.000	0.000	0.000	0.000	0.000	0.000
Sum	3.278	4.174	1.919	1.452	2.628	2.122
Sum Sq. Dev.	0.048	0.094	0.027	0.004	0.066	0.011
Observations	81.000	82.000	81.000	81.000	81.000	80.000

Table 13: CSAD of natural disaster in Australia:

CSAD	Airline	Insurance	Hotel	Bro.	Adv.	s&p
Mean	0.050	0.002	0.022	0.034	0.026	0.032
Median	0.041	0.000	0.022	0.024	0.023	0.030
Maximum	0.188	0.023	0.070	0.239	0.091	0.057
Minimum	0.000	0.000	0.003	0.003	0.002	0.014
Std. Dev.	0.042	0.004	0.011	0.032	0.015	0.009
Skewness	0.911	3.305	1.296	3.703	1.642	0.537
Kurtosis	3.514	15.023	5.774	22.173	7.156	2.796
Jarque-Bera	12.550	658.861	50.445	1478.541	98.226	4.189
Probability	0.002	0.000	0.000	0.000	0.000	0.123
Sum	4.242	0.177	1.873	2.862	2.186	2.682
Sum Sq. Dev.	0.146	0.001	0.011	0.085	0.020	0.007
Observations	84.000	84.000	84.000	84.000	84.000	84.000

Table 14: CSAD of natural disaster in China:

CSAD	Airline	restaurant	insurance	hotel	apparel	adv	s&p
Mean	0.011	0.013	0.014	0.016	0.022	0.021	0.022
Median	0.010	0.010	0.011	0.014	0.020	0.021	0.019
Maximum	0.030	0.074	0.042	0.034	0.066	0.048	0.082
Minimum	0.000	0.000	0.000	0.006	0.009	0.003	0.006
Std. Dev.	0.006	0.012	0.008	0.007	0.010	0.009	0.013
Skewness	0.805	2.351	1.385	0.745	2.273	0.561	2.980
Kurtosis	3.933	11.156	4.993	3.033	10.404	3.216	13.173
Jarque-Bera	12.127	310.175	40.743	7.770	270.524	4.567	486.520
Probability	0.002	0.000	0.000	0.021	0.000	0.102	0.000
Sum	0.904	1.056	1.135	1.309	1.850	1.725	1.841
Sum Sq. Dev.	0.003	0.012	0.006	0.004	0.008	0.007	0.015
Observations	84.000	84.000	84.000	84.000	86.000	84.000	84.000

Table 15: CSAD of natural disaster in Indonesia:

CSAD	restaurant	insurance	hotel	apparel	broadcasting
Mean	0.011484	0.01039	0.005995	0.020103	0.021055
Median	0.009104	0.007911	0.004393	0.019667	0.017966
Maximum	0.038106	0.03724	0.027507	0.040034	0.073906
Minimum	0.001189	0.001346	8.95E-05	0.006647	0
Std. Dev.	0.008068	0.007087	0.005603	0.006509	0.014136
Skewness	1.599497	1.444225	1.424647	0.641055	0.921011
Kurtosis	5.377408	5.495912	4.960557	3.750803	4.22765
Jarque-Bera	54.27591	49.79011	37.38208	7.542334	16.12972
Probability	0	0	0	0.023025	0.000314
Sum	0.941728	0.851975	0.449591	1.648483	1.663315
Sum Sq. Dev.	0.005273	0.004069	0.002323	0.003432	0.015587
Observations	82	82	75	82	79

Appendix B: Quantile regression results

Table 16: The coefficients of the quantile estimation of herding behavior for airline in pandemic											
Event	**Market**	τ=0.95		τ=0.90		τ=0.50		τ=0.10		τ=0.05	
		β3	β4	β3	β4	β3	β4	β3	β4	β3	β4
COVID	U.S	-0.705559**	60.33829**	-0.606835***	47.9161***	-0.018101	0.678976	0.095875	-13.6349	0.103104	-14.27824
		(-2.123144)	(-2.131466)	(-3.29417)	(-3.131602)	(-0.127472)	(-0.038888)	(-1.073776)	(-1.386971)	(-0.975791)	(-1.210414)
	CHINA	-3.289962***	-24.37475***	-3.207198***	-15.91544***	-3.018054***	-6.289845*	-1.623625**	-0.07728	-1.748307***	3.794865
		(-3.233011)	(-3.08337)	(-4.644687)	(-4.139982)	(-3.915771)	(-1.684415)	(-2.318043)	(-0.032551)	(-3.098746)	(1.077658)
	EU	3.692342	-9.747276	-2.079308	-16.64205	-4.994416**	-5.929665	0.463784	-0.006602	0.063532	1.069865
		(-0.396193)	(-0.674991)	(-0.241796)	(-1.168181)	(-2.421882)	(-0.727393)	(-0.301364)	(-0.00053)	(-0.046818)	(0.160897)
SARS	U.S	-3.466478	-4.452442	-1.867586	-3.63797	2.744751	3.016393	4.884208***	5.807054***	6.405152***	3.595439
		(-0.89947)	(0.0429)	(0.6739)	(0.1072)	(0.6775)	(0.2969)	(3.52616)	(4.109366)	(4.172409)	(0.509486)
	CHINA	3.055859	-2.645761	-0.472834	-3.775388	-0.432626	-3.312577	1.625521*	-3.451248	3.045479***	-0.468453
		(0.668781)	(-0.38758)	(-0.099435)	(-0.492349)	(-0.453201)	(-1.046996)	(1.657448)	(-0.621813)	(3.203802)	(-0.086805)
	EU	24.72136**	13.43951	22.77831***	14.69093***	13.77655**	8.767608*	7.644795	7.912794	4.297713	7.361196
		(2.43417)	(1.404132)	(3.282365)	(2.866234)	(2.031476)	(1.788031)	(1.010831)	(1.0027)	(0.618463)	(1.057293)
H1N1	U.S	-18.37489***	-27.23121***	-8.006813**	-5.359825	-4.099827	0.026977	5.8778**	6.293347***	6.059567***	4.553339
		(-3.674678)	(-3.149808)	(-2.515369)	(-0.949803)	(-0.422354)	(0.004397)	(2.390776)	(3.040254)	(3.104149)	(1.26284)
	CHINA	-1.654452	-2.581973	14.49225	63.63463	29.13153	126.8953*	69.63328*	84.47978***	59.06995	92.5474***
		(-0.040813)	(-0.044702)	(0.303714)	(1.34223)	(0.458991)	(1.725481)	(1.711955)	(2.781477)	(1.592628)	(3.102142)
	EU	3.69721	0.267754	7.87903***	16.77111***	14.33839***	13.75632**	6.108811	9.395428	5.819085	10.13296
		(0.660063)	(0.010236)	(2.617601)	(4.502351)	(4.327948)	(2.03127)	(0.840597)	(1.132513)	(0.967779)	(1.56856)

Table 17: The coefficients of the quantile estimation of herding behavior for Auto parts&Equipment in pandemic											
EVENT	**MARKET**	τ=0.95		τ=0.90		τ=0.50		τ=0.10		τ=0.05	
		β3	β4	β3	β4	β3	β4	β3	β4	β3	β4
COVID	U.S	-1.410522	-76.56393***	0.835349	-43.27013***	-0.032793	-27.02014*	-0.626854	-12.53586	-0.95501	-12.65516
		(-0.612416)	(-4.466714)	(0.652487)	(-2.886013)	(-0.046219)	(-1.939816)	(-0.403968)	(-1.435115)	(-0.656656)	(-1.590967)
	CHINA	1.940067	-16.37808**	2.579302**	-5.073702	3.452652	1.955018	4.176214***	-17.80146	4.120903***	-14.98096
		(1.166181)	(-2.277598)	(2.212657)	(-0.756636)	(0.801904)	(0.182765)	(5.754882)	(-0.80074)	(6.962612)	(-0.758058)
	EU	-18.27342***	-28.68275***	-19.08348***	-28.81226***	-1.457488	8.167275	3.433909	14.14255	1.013183	12.57887
		(-4.915531)	(-3.186438)	(-4.719151)	(-2.619314)	(-0.464082)	(0.908034)	(1.206988)	(1.227611)	(0.169826)	(1.204443)
SARS	U.S	-4.476748	-2.270859	8.679781	22.68709	5.646897	3.882701	5.0353	6.706003	5.664736	7.462299*
		(-0.353266)	(-0.096211)	(1.296186)	(1.26558)	(1.20511)	(0.680619)	(1.057469)	(1.260388)	(1.553173)	(1.857411)
	CHINA	-2.215638	-2.321649	-10.21095	-3.218881	-7.113201**	-4.713888	-2.598626	-3.682206	0.738762	0.746236
		(-0.031592)	(-0.048003)	(-1.702481)	(-0.528171)	(-2.057208)	(-0.740753)	(-1.074538)	(-0.922865)	(0.283376)	(0.182049)
	EU	9.338607***	-8.645793	12.16422**	5.24942	13.53111***	19.34725**	14.74814***	15.85925	/	
		(2.709097)	(-0.520352)	(2.475091)	(0.218005)	(8.04297)	(2.038789)	(7.860018)	(0.940441)		
H1N1	U.S	0.452463	2.057693	6.406226	5.513391	5.140861	4.882243	5.117152	2.009482	5.87589	3.137268
		(0.087446)	(0.174092)	(0.92792)	(0.64397)	(0.745425)	(0.871758)	(1.089946)	(0.884309)	(1.417119)	(1.604906)
	CHINA	-0.053724	-1.400596	3.038887	4.332338	-2.638346	-2.004055	1.907755	2.703007	0.937566	4.985477
		(-0.791573)	(-0.263834)	(1.140606)	(0.169784)	(-0.619933)	(-0.479943)	(0.593977)	(0.752604)	(0.175709)	(1.066804)
	EU	-3.583655	-2.214815	-2.87272	-1.130337	5.337434	0.263033	6.892517***	5.279478***	6.708807***	5.879397***
		(-0.453609)	(-0.214915)	(-0.396002)	(-0.106989)	(1.394619)	(0.06103)	(4.13453)	(2.817515)	(4.725421)	(3.592906)

Table 18. Coefficients of the quantile estimation of herding behavior for casino in pandemic											
EVENT	MARKET	τ=0.95		τ=0.90		τ=0.50		τ=0.10		τ=0.05	
		β3	β4	β3	β4	β3	β4	β3	β4	β3	β4
COVID	U.S	-0.90332	-16.30847	4.08863	-2.080761	18.16405**	16.14717	-10.46007	-7.421583	12.97523	20.76507
		(-0.06977)	(-1.135322)	(0.334168)	(-0.11999)	(2.02876)	(1.290662)	(-0.42919)	(-0.313739)	(0.468019)	(0.687912)
	CHINA	/		/		/		/		/	
	EU	0.986097	-72.58733***	-2.709426	-63.46517***	3.419605	-25.21982	0.871377	1.080331	1.636619	6.475553
		(0.159071)	(-4.105422)	(-0.561135)	(-3.915558)	(1.340119)	(-1.636532)	(0.263437)	(0.099681)	(1.077021)	(0.645156)
SARS	U.S	-24.52691*	-49.33184***	-11.2575	-25.7414	11.82445	6.442045	16.37966	7.248338	3.031418	1.713645
		(-1.947729)	(-2.840438)	(-0.525186)	(-0.944123)	(1.213407)	(0.443547)	(1.113112)	(0.40649)	(0.149479)	(0.091477)
	CHINA	/		/		/		/		/	
	EU	5.698192	5.361778***	6.106082	4.828156***	5.820676***	1.551752	5.571427***	-0.257572	5.49983***	-0.378435
		(0.459646)	7.174621	(0.466537)	(6.508946)	(8.511218)	(0.207919)	(11.21494)	(-0.060516)	(12.97318)	(-0.107708)
H1N1	U.S	2.838673	6.598665*	6.55803**	12.60902***	4.200878**	6.943682***	2.081219	4.565833	0.062733	2.828426
		(0.889371)	(1.824552)	(2.519366)	(2.660661)	(2.446584)	(4.09119)	(0.357513)	(1.279344)	(0.011242)	(0.780254)
	CHINA	/		/		/		/		/	
	EU	4.172577***	4.812315***	3.189393***	3.657754**	3.677479***	4.387343***	0.853328	2.427938**	2.269488	3.614554***
		(2.740763)	(2.677011)	(2.67152)	(2.536822)	(5.202639)	(5.194601)	(0.491669)	(2.126745)	(1.417895)	(3.470614)

Table 19. The coefficients of the quantile estimation of herding behavior for recreation activities industry in pandemic											
EVENT	**MARKET**	τ=0.95		τ=0.90		τ=0.50		τ=0.10		τ=0.05	
		β3	β4	β3	β4	β3	β4	β3	β4	β3	β4
COVID	U.S	-0.555752	-25.1081	-0.935838	12.41034	-1.173496**	-13.57194	0.308348	12.31706	0.718558*	-0.436774
		(-0.787295)	(-0.876391)	(-1.63919)	(0.465386)	(-2.540498)	(-1.055146)	(0.878271)	(1.099308)	(1.789468)	(-0.030867)
	CHINA	3.951682	-19.40126**	11.43019**	-6.457141	6.799131	4.687714	2.667593	-2.05668	2.032237	-0.613392
		(0.844856)	(-2.281688)	(2.361935)	(-0.673583)	(1.350682)	(0.618552)	(0.600941)	(-0.102469)	(0.599678)	(-0.041222)
	EU	/		/		/		/		/	
SARS	U.S	-0.143295***	-103.1125***	-0.141043***	-98.49551***	-0.135594***	-65.20346	-0.12433***	-81.12794*	-0.12466***	6.783044
		(-51.92786)	(-2.806845)	(-40.70326)	(-2.609458)	(-37.32213)	(-1.416309)	(-49.14709)	(-1.81955)	(-60.76493)	(0.185453)
	CHINA	-3.437668	-11.44842	1.521739	-4.686632	2.222304	-2.11186	-1.481707	-1.636856	-0.667954	-0.432647
		(-0.986748)	(-0.944098)	(0.20778)	(-0.343282)	(0.26302)	(-0.219568)	(-0.499373)	(-0.468641)	(-0.288823)	(-0.15789)
	EU	12.49473	-2.588695	6.430203	-5.144495	13.58011**	12.89464	10.17231	12.91117	14.06562**	17.76047**
		(0.863392)	(-0.243734)	(0.506234)	(-0.497568)	(2.200352)	(1.609495)	(0.680106)	(1.411102)	(2.434808)	(2.544364)
H1N1	U.S	-0.895048**	-13.89536***	-0.277859	-12.45636***	1.338527***	-3.135103	1.686818***	-3.135195*	1.519773***	-2.984715*
		(-2.198232)	(-4.450981)	(-0.861408)	(-4.177166)	(2.928611)	(-1.122898)	(6.647035)	(-1.756592)	(6.516232)	(-1.875587)
	CHINA	-0.007277	-0.003317	-0.005278	0.000885	0.001778	0.013621	0.007474	-0.012402	0.002023	-0.004777
		(-0.378555)	(-0.544566)	(-0.242273)	(0.131497)	(0.203329)	(1.589208)	(0.531823)	(-1.315862)	(0.12289)	(-0.550255)
	EU	-0.758213	80.13214	-3.133877	-7.788885	-2.319895	4.549164	7.251112	19.53773**	10.20449	25.09337***
		-0.021891	(0.949966)	(-0.093871)	(-0.119231)	(-0.196585)	(0.48714)	(0.670773)	(2.465024)	(0.943908)	(3.137616)

Table 20. The coefficients of the quantile estimation of herding behavior for Property&Casualty insurance in pandemic											
EVENT	MARKET	τ=0.95		τ=0.90		τ=0.50		τ=0.10		τ=0.05	
		β3	β4	β3	β4	β3	β4	β3	β4	β3	β4
COVID	U.S	-3.735423	-21.01186***	-4.543073	-18.89601***	0.41457	-3.959318	1.213657	-1.225108	1.175445	-2.411123
		(-1.225519)	(-3.948841)	(-1.196274)	(-3.928906)	(0.490603)	(-1.033111)	(0.425974)	(-0.369693)	(0.476395)	(-0.734967)
	CHINA	/		/		/		/		/	
	EU	-1.963806	-101.2399***	-3.831313	-46.70826	-1.206757***	-0.702628	0.78934	-3.453136	1.24896	3.158792
		(-0.408139)	(-3.654065)	(-0.585228)	(-0.878493)	(-34.34314)	(-1.588578)	(0.674942)	(-0.225417)	(1.164823)	(0.215164)
SARS	U.S	4.127034	9.745678	9.410109	17.93959	13.74098**	23.61642*	20.52446***	31.30704**	16.07849	19.21808
		(0.299755)	(1.188503)	(0.566016)	(1.65188)	(2.39606)	(1.878662)	(2.789403)	(2.427013)	(0.058)	(0.505)
	CHINA	/		/		/		/		/	
	EU	-8.025268	-2.512443	2.560514	2.36937	6.335259	5.975354	2.408128	-2.170928	-10.15256	-2.158799
		(-0.924707)	(-0.193486)	(0.379776)	(0.297091)	(0.737764)	(0.353595)	(0.32161)	(-0.324497)	(-0.518519)	(-0.220214)
H1N1	U.S	1.237398	2.221103	13.29585**	7.5889	4.813914	7.856064	3.823085	4.508904**	4.04998*	3.913098**
		(0.210551)	(0.200641)	(2.36755)	(0.835147)	(1.237341)	(1.449983)	(1.583286)	(2.469025)	(1.866241)	(2.447411)
	CHINA	/		/		/		/		/	
	EU	0.192886	-11.68051***	0.505075	-7.040902	2.446545***	1.184775	3.74105***	11.39117***	3.86501***	12.95294***
		(0.207796)	(-2.881892)	(0.72481)	(-1.480663)	(6.442564)	(0.411017)	(8.732084)	(3.715868)	(9.958722)	(4.356115)

Table 21. The coefficients of the quantile estimation of herding behavior for Health care REITs in pandemic											
EVENT	MARKET	τ=0.95		τ=0.90		τ=0.50		τ=0.10		τ=0.05	
		β3	β4	β3	β4	β3	β4	β3	β4	β3	β4
COVID	U.S	2.1	-190.9862***	-1.491687	-138.8832***	0.199085	-15.98739	1.650106	-6.385389	0.97611	-3.822123
		(0.145981)	(-4.655231)	(-0.687724)	(-3.576363)	(0.042476)	(-0.549762)	(1.260475)	(-0.340666)	(0.858106)	(-0.232813)
	CHINA	-1.765895	-22.12375	-4.603568	-20.12652	0.193421	-40.23328*	-0.376984	-8.631248	2.391849	6.977716
		(-0.263816)	(-1.726786)	(-0.94538)	(-1.570675)	(0.068143)	(-1.777327)	(-0.06018)	(-0.470108)	(0.397824)	(0.396302)
	EU	-24.66995	-218.8587*	-12.65649	-142.0474**	-8.070216**	-56.51717*	-7.837933	-19.36939	-7.188483	-14.31961
		(-0.379043)	(-1.958716)	(-0.329119)	(-2.017658)	(-2.248967)	(-1.880066)	(-0.389296)	(-0.354192)	(-0.393463)	(-0.313911)
SARS	U.S	6.004679**	0.251419	9.815839***	0.761215**	9.872854***	0.248725	14.08017***	0.349458	13.44975***	0.325332*
		(2.030251)	(0.134595)	(11.54835)	(2.251895)	(9.968906)	(1.19572)	(5.789868)	(1.503257)	(6.554867)	(1.809311)
	CHINA	-52.26763	-95.40517	0.504799	-18.11191	-2.348751	11.53048	10.24102	13.63588	-0.309635	-20.53523
		(-0.286546)	(-0.441639)	(0.00779)	(-0.244434)	(-0.047044)	(0.22979)	(0.274331)	(0.296843)	(-0.008471)	(-0.32124)
	EU	-3.709217	-21.90461	-2.100407	-7.019475	-11.10603	-20.04109	-2.983662	7.569884	0.996107	15.56268*
		(-0.174419)	(-1.353525)	(-0.084769)	(-0.455873)	(-1.470897)	(-1.378977)	(-0.591143)	(0.839503)	(0.195088)	(1.742562)
H1N1	U.S	-2.053118	-2.38249	-11.42365**	-10.55011***	-5.904312	-5.150853	-7.586728	-3.251182	-7.019484	-3.047016
		(-0.320515)	(-0.445878)	(-2.172324)	(-2.6933)	(-1.087941)	(-1.463257)	(-0.852429)	(-0.969992)	(-0.97463)	(-1.08111)
	CHINA	-4.81682	-0.496073	-11.01624***	-2.49229	-6.045051***	-0.501473	-5.364747**	-6.667083	-1.693784	-1.025811
		(-1.358056)	(-0.058816)	(-3.945078)	(-0.320693)	(-2.876723)	(-0.199635)	(-2.316389)	(-1.681874)	(-0.565083)	(-0.203692)
	EU	-12.80307	-49.50321***	-16.49558	-51.07314***	1.677344	-16.46611	5.64487	-3.616257	10.03509	-7.631982
		(-1.224913)	(-2.780412)	(-1.556733)	(-3.040512)	(0.125339)	(-1.195118)	(0.653328)	(-0.374566)	(1.211776)	(-0.518819)

Table 22. The coefficients of the quantile estimation of herding behavior for Insurance miscellaneous in pandemic											
EVENT	MARKET	τ=0.95		τ=0.90		τ=0.50		τ=0.10		τ=0.05	
		β3	β4	β3	β4	β3	β4	β3	β4	β3	β4
COVID	U.S	-14.37929***	-162.1431***	-6.257919***	-123.0833***	-1.975613	-32.57969	-0.688876	-2.50909	-0.055851	2.708223
		(-2.659972)	(-3.710546)	(-3.993781)	(-5.455477)	(-1.562764)	(-1.363099)	(-0.787334)	(-0.16536)	(-0.065297)	(0.173221)
	CHINA	/		/		/		/		/	
	EU	-8.22428	8.83321	-9.832522	7.34988	0.994973	13.09016	3.862728	23.32711**	5.574349	25.33494***
		(-0.526326)	(0.536427)	(-1.571232)	(1.047267)	(0.167388)	(1.528133)	(0.262601)	(2.012918)	(0.576343)	(3.125418)
SARS	U.S	31.99533*	25.3898***	30.24727*	23.18503**	5.269494	1.521354	8.528936**	4.2854	3.246467	4.350936
		(1.977368)	(2.697075)	(1.685864)	(2.133802)	(1.35718)	(0.366069)	(2.313709)	(1.189792)	(0.22908)	(1.087833)
	CHINA	/		/		/		/		/	
	EU	/		/		/		/		/	
H1N1	U.S	13.35127	1.913919	-8.103338**	-14.86247**	6.388532**	2.826123	10.74594***	9.500404**	11.91385***	8.731293**
		(0.148699)	(0.030041)	(-2.161746)	(-2.110978)	(2.442582)	(0.725008)	(3.530657)	(2.35994)	(4.931646)	(2.272651)
	CHINA	/		/		/		/		/	
	EU	/		/		/		/		/	

Table 23. The coefficients of the quantile estimation of herding behavior for Life insurance in pandemic											
EVENT	MARKET	τ=0.95		τ=0.90		τ=0.50		τ=0.10		τ=0.05	
		β3	β4	β3	β4	β3	β4	β3	β4	β3	β4
COVID	U.S	-1.785697	-85.13302***	-1.275141	-65.05923***	-0.442655	-28.22676	0.605834	2.473227	0.453181	9.768103
		(-0.78853)	(-4.272548)	(-0.551946)	(-3.635548)	(-0.692475)	(-1.5213)	(1.61849)	(0.21161)	(1.260949)	(0.897563)
	CHINA	-0.299301	10.3228	-0.610908	-5.138873***	0.746508	0.391903	1.216767	2.726878	2.09692**	3.351754***
		(-0.309104)	(0.156177)	(-0.479758)	(-2.825571)	(0.925)	(0.210807)	(1.751057)	(1.968059)	(2.419752)	(2.715062)
	EU	-8.828783	-630.7266***	-7.031558	-509.5014***	-7.162678*	-154.3934**	1.702116	2.707802	2.782782	32.75314
		(-0.848281)	(-5.147828)	(-0.9052)	(-4.006605)	(-1.958029)	(-2.41348)	(0.659603)	(0.062135)	(0.966219)	(0.783617)
SARS	U.S	-1.785697	-85.13302***	-1.275141	-65.05923***	-0.442655	-28.22676	0.605834	2.473227	0.453181	9.768103*
		(-0.78853)	(-4.272548)	(-0.551946)	(-3.635548)	(-0.692475)	(-1.5213)	(1.61849)	(0.21161)	(0.897563)	(1.739532)
	CHINA	/		/		/		/		/	
	EU	32.858	41.12633	4.292742	7.222186	6.844888	7.275813	1.477976	2.494746	8.736706	7.384239
		(1.360315)	(1.222266)	(0.496571)	(1.115188)	(0.894193)	(1.087212)	(0.190104)	(0.272776)	(1.08524)	(0.746958)
H1N1	U.S	-14.35345**	-11.23791	-18.51745***	-15.38847***	-15.27558	-9.747317*	-6.44696	-3.548358	-10.53005	-3.914287
		(-2.037578)	(-1.647926)	(-3.511165)	(-3.011384)	(-1.561583)	(-1.880068)	(-0.498833)	(-0.745852)	(-1.447441)	(-1.195521)
	CHINA	/		/		/		/		/	
	EU	31.9961**	8.948472	15.33861	6.737153	3.443006	5.859016**	2.922006	5.472233***	0.706277	3.795108*
		(2.074226)	(1.427284)	(1.347404)	(1.284039)	(0.707443)	(2.008665)	(0.76822)	(2.605527)	(0.213533)	(1.916631)

Table 24. The coefficients of the quantile estimation of herding behavior for insurance industry of natural disaster

EVENT	MARKET	τ=0.95		τ=0.90		τ=0.50		τ=0.10		τ=0.05	
		β3	β4	β3	β4	β3	β4	β3	β4	β3	β4
EARTHQUAKE	CHINA	-9.816328	-9.398143**	-3.564813	-4.584664**	-2.738994*	-2.52391**	0.418269	-0.405625	1.884987	0.515029
		(-1.526452)	(-2.10184)	(-1.569795)	(-1.980652)	(-1.92329)	(-2.080672)	(0.191747)	(-0.362062)	(1.130837)	(0.524029)
FOREST FIRE	AUSTRALIAN	6.806572***	3.918920	7.440306***	7.005983	5.788614**	8.880620***	0.016882	6.534367***	0.010168	0.904462
		(4.711808)	(1.622701)	(3.664998)	(1.589278)	(2.13925)	(3.211177)	(0.006026)	(3.99235)	(0.002299)	(0.041651)
TSUNAMI	INDONESIAN	20.12027	125.3334	10.20139	63.21478	43.39449**	81.24074	25.92683	0.968264	24.69948	-0.149822
		(0.881837)	(1.312401)	(0.408481)	(0.5428)	(2.199806)	(1.247397)	(1.057714)	(0.013756)	(1.380894)	(-0.002136)

Table 25. The coefficients of the quantile estimation of herding behavior for restaurant industry of natural disaster

EVENT	MARKET	τ=0.95		τ=0.90		τ=0.50		τ=0.10		τ=0.05	
		β3	β4	β3	β4	β3	β4	β3	β4	β3	β4
EARTHQUAKE	CHINA	-13.7055***	-14.98358***	-9.024144***	-9.260821***	-1.462835	-0.420687	-0.179363	-0.026562	-0.049415	0.224668
		(4.62635)	(4.765804)	(3.158174)	(3.253961)	(-0.980461)	(-0.213489)	(-0.165617)	(-0.024399)	(-0.053331)	(0.21629)
FOREST FIRE	AUSTRALIAN	-2.435063	11.18071	-2.145585	6.36692	-0.421866	1.309774	-0.199775	3.194715*	-0.484371	2.813959*
		(-0.985137)	(1.13647)	(-0.804444)	(0.40993)	(-0.183293)	(0.459641)	(-0.123356)	(1.729638)	(-0.351239)	(1.686747)
TSUNAMI	INDONESIAN	18.72286	42.01951	6.05931	26.17062	-2.936865	23.57133	9.123013	32.09277	21.25712**	38.88915***
		(0.541128)	(0.696419)	(0.148177)	(0.392599)	(-0.239622)	(1.339283)	(0.303118)	(1.4733)	(2.112176)	(3.24414)

Table 26. The coefficients of the quantile estimation of herding behavior for airline industry od natural disaster

EVENT	MARKET	τ=0.95		τ=0.90		τ=0.50		τ=0.10		τ=0.05	
		β3	β4	β3	β4	β3	β4	β3	β4	β3	β4
EARTHQUAKE	CHINA	-3.549739***	-3.080981**	-2.466055	-1.703082	-2.195474***	-1.39484	-1.977053***	-1.742312***	-0.986737*	-0.471858
		(-3.144272)	(-2.390688)	(-1.614494)	(-1.003409)	(-2.93554)	(-1.537721)	(-3.392858)	(-2.821431)	(-1.657759)	(-0.763869)
FOREST FIRE	AUSTRALIAN	7.601284***	0.017421	7.392833***	0.031302	7.305576***	0.112186	8.263325***	0.038374	8.411152***	0.043392
		(10.15945)	(0.389106)	(6.149781)	(0.609085)	(10.36519)	(1.595222)	(18.73094)	(0.570806)	(19.14161)	(0.692595)
TSUNAMI	INDONESIAN	/		/		/		/		/	

Table 27: The coefficients of the quantile estimation of herding behavior for hotel industry of natural disaster

EVENT	MARKET	τ=0.95		τ=0.90		τ=0.50		τ=0.10		τ=0.05	
		β3	β4	β3	β4	β3	β4	β3	β4	β3	β4
EARTHQUAKE	CHINA	0.973687	5.604849	1.704138	0.797103	1.246504	1.437608	5.057819**	2.834232*	1.436737	-0.832676
		(0.10597)	(0.212312)	(0.547846)	(0.260544)	(0.625479)	(0.839085)	(2.478878)	(1.768574)	(0.40308)	(-0.12584)
FOREST FIRE	AUSTRALIAN	6.648256**	3.599574	4.828791	1.516846	1.17195	-0.391173	2.136402**	1.013765	2.716754***	2.090286
		(2.128202)	(1.064385)	(1.431374)	(0.335754)	(0.733595)	(-0.196562)	(2.236962)	(0.822706)	(2.928321)	(1.566346)
TSUNAMI	INDONESIAN	/		-16.54296	27.62223*	38.19294	-28.63087	0.604555	22.95548	/	
				(-1.429344)	(1.700715)	(1.295513)	(-0.791468)	(0.02944)	(0.862694)		

Table 28: The coefficients of the quantile estimation of herding behavior for software and programming industry of natural disaster

EVENT	MARKET	τ=0.95		τ=0.90		τ=0.50		τ=0.10		τ=0.05	
		β3	β4	β3	β4	β3	β4	β3	β4	β3	β4
EARTHQUAKE	CHINA	-8.579439	-4.403714	-12.75705	-5.281252	-0.31102	4.544689***	-2.512447	0.714345	-1.023901	0.688877
		(-0.971574)	(-0.620885)	(-1.046834)	(-0.555219)	(-0.20439)	(3.677369)	(-1.176463)	(0.242481)	(-0.512908)	(0.317891)
FOREST FIRE	AUSTRALIAN	-2.232706	0.38608	0.386605	5.918724	-0.652342	1.715948	-4.980362	-5.795024	-3.69286	-4.277214
		(-0.509316)	(0.093854)	(0.033231)	(0.212785)	(-0.223452)	(0.658835)	(-0.453828)	(-0.3354)	(-0.378654)	(-0.266193)
TSUNAMI	INDONESIAN	/		/		/		/		/	

Table 29: The coefficients of the quantile estimation of herding behavior for advertising industry of natural disaster

EVENT	MARKET	τ=0.95		τ=0.90		τ=0.50		τ=0.10		τ=0.05	
		β3	β4	β3	β4	β3	β4	β3	β4	β3	β4
EARTHQUAKE	CHINA	0.474762	6.782228**	3.153883	7.881835	1.474051	5.289315*	-0.546036	-2.462068	-0.066235	-1.647001
		(0.089937)	(2.024255)	(0.210689)	(0.976158)	(0.527755)	(1.819907)	(-0.144835)	(-0.296616)	(-0.019491)	(-0.207314)
FOREST FIRE	AUSTRALIAN	11.69492	35.01188*	7.754751	12.90212	5.66713	-6.040547	14.44241	8.713281	12.2615	5.450323
		(1.269218)	(1.813526)	(1.299513)	(0.675453)	(0.331017)	(-0.365159)	(1.002243)	(0.633044)	(1.002661)	(0.45923)
TSUNAMI	INDONESIAN	/		/		/		/		/	

Table 30: The coefficients of the quantile estimation of herding behavior for apparel industry of natural disaster

EVENT	MARKET	τ=0.95		τ=0.90		τ=0.50		τ=0.10		τ=0.05	
		β3	β4	β3	β4	β3	β4	β3	β4	β3	β4
EARTHQUAKE	CHINA	10.29541***	13.3066***	7.786381***	10.55454***	-1.334603	-1.113685	-3.042591***	-1.877423**	-2.122823**	-0.686575
		(2.67553)	(2.901841)	(2.974423)	(3.007745)	(-0.597671)	(-0.646327)	(-3.333305)	(-2.07927)	(-2.403478)	(-0.757339)
FOREST FIRE	AUSTRALIAN	/		/		/		/		/	
TSUNAMI	INDONESIAN	-5.115669	-18.47244	6.60882	3.154796	0.00000939**	13.02094***	-0.460607	-0.261183	25.38058**	44.04442***
		(-0.472045)	(-1.296041)	(0.806873)	(0.374145)	(0.00000228)	(5.373601)	(-0.042245)	(-0.008328)	(3.068225)	(6.373048)

Table 31: The coefficients of the quantile estimation of herding behavior for hardware industry of natural disaster

EVENT	MARKET	τ=0.95		τ=0.90		τ=0.50		τ=0.10		τ=0.05	
		β3	β4	β3	β4	β3	β4	β3	β4	β3	β4
EARTHQUAKE	CHINA	/		/		/		/		/	
FOREST FIRE	AUSTRALIAN	/		/		/		/		/	
TSUNAMI	INDONESIAN	-9.709142***	-12.72217**	-8.822419**	-11.42941*	-1.048347***	-0.095566	-14.45197	-9.151246	-13.54833	-8.709183
		(-3.111129)	(-2.526543)	(-2.160236)	(-1.822957)	(-3.209044)	(-0.182013)	(-0.536507)	(-0.947718)	(-0.869701)	(-0.965761)

Table 32: The coefficients of the quantile estimation of herding behavior for broadcasting industry of natural disaster

EVENT	MARKET	τ=0.95		τ=0.90		τ=0.50		τ=0.10		τ=0.05	
		β3	β4	β3	β4	β3	β4	β3	β4	β3	β4
EARTHQUAKE	CHINA	-4.577075	-1.302992	-2.731447	1.755069	-1.213731	6.754808*	-2.408728*	7.623179***	-1.490873	8.360234***
		(-0.213013)	(-0.048302)	(-0.792871)	(0.317316)	(-0.39763)	(1.649652)	(-1.788903)	(3.510165)	(-1.127631)	(3.719876)
FOREST FIRE	AUSTRALIAN	0.300791	-12.27228***	-0.396618	-10.42069***	6.691528***	4.746511	7.447056	11.12641**	12.998***	16.49271***
		(0.20978)	(-2.906891)	(-0.254917)	(-2.713316)	(4.333837)	(1.355011)	(1.409085)	(2.269747)	(8.743691)	(6.78966)
TSUNAMI	INDONESIAN	7.651177	0.313949	13.52719	14.66565	-15.93420***	-15.23411***	-10.19426	-6.190317	-23.53307	-15.51051
		5.462892	0.221187	0.702436	0.722613	-2.665000	-3.321213	-0.619036	-0.883901	-1.400849	-1.348755

Table 33: The coefficients of the quantile estimation of herding behavior for restaurant industry of terrorist attack

EVENT	MARKET	τ=0.95		τ=0.90		τ=0.50		τ=0.10		τ=0.05	
		β3	β4	β3	β4	β3	β4	β3	β4	β3	β4
PARIS	FRANCE	80.81609	130.7485	77.42159*	144.3315***	19.72072	52.00663***	1.094914	7.600924	-17.38609	-13.26136
		(0.55016)	(0.975966)	(1.759553)	(2.852378)	(1.557151)	(2.986139)	(0.107762)	(0.292687)	(-0.228999)	(-0.140902)
KUNMING	CHINA	/		/		/		/		/	
911	U.S	21.95469**	-19.52849	15.02263	-30.21718	17.51882**	-6.099657	22.04442***	9.111704	19.03237***	-22.8398
		(2.126639)	(-0.940584)	(1.175481)	(-1.203776)	(2.370571)	(-0.344848)	(4.356289)	(0.769137)	(3.580173)	(-0.371397)

Table 34: The coefficients of the quantile estimation of herding behavior for hotel industry of terrorist attack

EVENT	MARKET	τ=0.95		τ=0.90		τ=0.50		τ=0.10		τ=0.05	
		β3	β4	β3	β4	β3	β4	β3	β4	β3	β4
PARIS	FRANCE	/		/		/		/		/	
KUNMING	CHINA	23.68345	15.11139	16.60643	10.56508	2.449433	6.08591	7.670311	9.719303	4.501295	5.065986
		(0.748606)	(0.867713)	(0.558676)	(0.606417)	(0.248441)	(0.648983)	(0.642393)	(0.362409)	(0.369325)	(0.183036)
911	U.S	4.525781	4.381973	0.51688	0.920787	0.978851	1.927683	2.168016	1.929998**	1.387926	1.39117
		(1.19792)	(1.508194)	(0.185403)	(0.413812)	(0.419668)	(1.425911)	(1.397305)	(2.086652)	(0.84834)	(1.430209)

Table 35: The coefficients of the quantile estimation of herding behavior for airline industry of terrorist attack

EVENT	MARKET	τ=0.95		τ=0.90		τ=0.50		τ=0.10		τ=0.05	
		β3	β4	β3	β4	β3	β4	β3	β4	β3	β4
PARIS	FRANCE	/		/		/		/		/	
KUNMING	CHINA	-0.869105**	-19.76135**	-0.701246*	-15.4103*	-0.589416***	-11.28183**	-0.521852***	-8.805844***	-0.640243***	-9.317301***
		(-2.002178)	(-2.105283)	(-1.774396)	(-1.812541)	(-3.075864)	(-2.377524)	(-4.139734)	(-2.626179)	(-5.340065)	(-3.089324)
911	U.S	-7.81111**	-54.43305**	-1.778938	-36.82944***	-0.253558	-28.21498	0.30261	-22.36686	0.379686	-16.93887
		(-2.173018)	(-2.15915)	(-1.044726)	(-2.695631)	(-1.323511)	(-1.397912)	(0.323548)	(-0.868435)	(0.462734)	(-0.825244)

Table 36. The coefficients of the quantile estimation of herding behavior for insurance industry of terrorist attack

EVENT	MARKET	τ=0.95		τ=0.90		τ=0.50		τ=0.10		τ=0.05	
		β3	β4	β3	β4	β3	β4	β3	β4	β3	β4
PARIS	FRANCE	-27.95817	-52.07414	-10.06532	-28.05536	-2.509678	-12.34592	-1.577409	5.808884	/	
		(-0.906357)	(-1.328416)	(-0.926386)	(-0.614204)	(-0.474585)	(-0.670541)	(-0.356711)	(0.413858)		
KUNMING	CHINA	0.913744	22.34327	4.0396	31.47323	1.182553	10.64237***	5.381871	13.69873*	1.508251	9.753996*
		(0.102908)	(0.887814)	(0.543416)	(1.357558)	(0.284031)	(2.776527)	(1.283809)	(1.880387)	(0.424687)	(1.764606)
911	U.S	-1.424321	-20.0692***	-2.844247	-21.26352***	0.129842	-8.573421	-0.238517	-5.146396	1.565555	-0.051973
		(-0.674419)	(-3.521695)	(-1.482716)	(-4.046174)	(0.047541)	(-1.085431)	(-0.12123)	(-1.016099)	(0.703477)	(-0.008464)

Table 37: The coefficients of the quantile estimation of herding behavior for advertising industry of terrorist attack

EVENT	MARKET	τ=0.95		τ=0.90		τ=0.50		τ=0.10		τ=0.05	
		β3	β4	β3	β4	β3	β4	β3	β4	β3	β4
PARIS	FRANCE	24.72896	-25.52623	37.53429	-12.69812	-2.171355	-21.24976	-0.171725	-1.465222	0.844179	3.139927
		(0.423544)	(-0.34566)	(0.517584)	(-0.145973)	(-0.389902)	(-1.311952)	(-0.039689)	(-0.143346)	(0.205175)	(0.311965)
KUNMING	CHINA	35.91566*	26.98241	15.58552**	7.44872	26.09336***	20.84046***	-0.116061	-2.851429	5.871435	3.605324
		(1.85092)	(1.3765)	(2.309832)	(0.642549)	(6.093419)	(2.967871)	(-0.010425)	(-0.279178)	(0.549103)	(0.385018)
911	U.S	/		/		/		/		/	

Table 38: The coefficients of the quantile estimation of herding behavior for apparel industry of terrorist attack

EVENT	MARKET	τ=0.95		τ=0.90		τ=0.50		τ=0.10		τ=0.05	
		β3	β4	β3	β4	β3	β4	β3	β4	β3	β4
PARIS	FRANCE	-39.1307***	-37.02715***	-30.66587***	-29.88461***	-0.891532	-1.984095	-3.244873	-1.035106	-2.291407	-13.73397
		(-3.704856)	(-3.880678)	(-2.946769)	(-3.083235)	(-0.092527)	(-0.21496)	(-0.520551)	(-0.178771)	(-0.180939)	(-0.242787)
KUNMING	CHINA	2.598382	-19.60287	0.252497	-22.1349	-10.66341**	-11.49395**	-3.282564	-3.846795	0.172505	-6.785261
		(0.024742)	(-0.388135)	(0.002759)	(-0.421417)	(-2.123142)	(-2.298756)	(-0.71855)	(-0.851684)	(0.025853)	(-0.185963)
911	U.S	59.39568	20.56704	27.29519	-10.93256	2.307962	-6.657287	0.159218	-27.91066	1.151148	-34.60731
		(0.741305)	(0.236377)	(0.460595)	(-0.164748)	(0.567721)	(-0.440634)	(0.04589)	(-0.615755)	(0.332159)	(-0.926266)

Table 39: The coefficients of the quantile estimation of herding behavior for broadcasting industry of terrorist attack

EVENT	MARKET	τ=0.95		τ=0.90		τ=0.50		τ=0.10		τ=0.05	
		β3	β4	β3	β4	β3	β4	β3	β4	β3	β4
PARIS	FRANCE	/		/		/		/		/	
KUNMING	CHINA	-2.480525	-19.81749	13.05665	-18.88423	4.589303	-0.749467	3.738798	-0.045567	4.496947	-3.659078
		(-0.032665)	(-0.437812)	(0.160477)	(-0.503769)	(0.869239)	(-0.09876)	(0.75313)	(-0.003723)	(1.107541)	(-0.497503)
911	U.S	10.4591***	177.0481***	8.775269**	175.3444**	4.682522	3.771244	6.862337	3.924053	14.19181**	35.81252
		(2.634212)	(14.13348)	(2.445282)	(10.66546)	(1.006805)	(0.156915)	(1.619847)	(0.140089)	(2.25673)	(1.377206)

The numbers in the parentheses are t-statistics.

*Statistical signifiance at the 10 % level

**Statistical signifiance at the 5 % level

***Statistical signifiance at the 1 % level

Appendix C: Symbol of companies

Table 40: Companies of U.S

CCL	ITW	AAIGF	MMC	BRKa	HUM	LUV	OXBR	WINR	SGRY	KENS	VMD	EXETF	ITCC
LYV	ORLY	LFC	AON	BRKb	CNC	DAL	MCD	BDL	MAR	OMC	LVMUY	NFLX	DOGZ
MTN	AZO	PUK	WLTW	CB	HCA	RYAAY	CMG	COFE	HLT	WPP	HESAF	SIRI	CTRC
PLNT	APTV	MET	VRSK	ZURVY	FMS	CEA	YUM	BBQ	IHG	PUBGY	CHDRF	LBRDK	ICON
MSGS	PCRFF	PRU	AJG	PGR	LH	ZNH	YUMC	LUB	HTHT	IPG	VFC	LBRDA	FORD
NCLH	PCRFY	MFC	FOSUF	ZFSVF	DGX	UAL	DPZ	FRHHF	H	DNTUF	RL	FOX	EVK
MANU	MGA	MET_pa	BRO	TKOMY	MOH	SINGF	SDXAY	GTIM	CHH	WTM	LEVI	FOXA	HPMM
TRIP	GPC	SLF	EHTH	ALL	DVA	BABWF	DRI	RAVE	WH	MATW	COLM	DISH	UNIR
SIX	LKQ	GL	GSHD	TKOMF	SKHHY	DLAKY	SDXOF	FCCG	VAC	CRTO	UA	ROKU	KBSF
ISCA	WBC	LNC	FANH	TRV	UHS	CPCAF	ARMK	NROM	WYND	CCO	TPR	LBTYB	NAKD
FUN	GNTX	AIZ	BRP	AIG	CHE	AAL	DNKN	BABB	STAY	GSMG	UAA	LBTYA	JLMC
SEAS	LEA	RGA	HUIZ	MSADY	EHC	ALK	WEN	DBUB	HGV	ICLK	HBI	VIAC	EXLA
ACEL	BWA	PNXGF	CRDa	HIG	AMED	JBLU	TXRH	IPICQ	GHG	NCMI	PVH	LBTYK	BMXC
TRK	DCI	AEG	CRDb	MKL	LHCG	AFLYY	WING	GIGL	DLTTF	YLWDF	GIL	LSXMB	NICH
OSW	ALV	ATH	MVRK	ACGL	LVGO	CPA	CBRL	GCFB	BXG	OPRX	CPRI	LSXMK	OMVE
ECXJ	ALSN	PRI	AZIL	WRB	ONEM	LTM	CNNE	GTEH	PLYA	VERI	LFUGF	LSXMA	ICBT
SKIS	CW	ESGR	LVS	CINF	NEO	ALGT	PZZA	GRLT	INTG	THRV	WACLY	FWONA	WDLF
LIVX	FOXF	UNM	GXYEF	ERIE	IRTC	SKYW	SHAK	STRZ	RLH	SRAX	KTB	FWONK	OPTI
DS	DORM	BHF	WYNN	L	ACHC	AZUL	SSPPF	KONAQ	FPFI	MOBQ	OXM	NXST	TBACQ
BWLa	DAN	FG	WYNMF	RE	OPCH	GOL	JACK	PAPA	KYNC	CNET	GIII	SBGI	GFTX
CPHC	ADNT	CNO	MGM	CNA	THC	SAVE	GGRUF	WCVC	IDVV	HHS	DELTY	BATRA	DMHI
DVD	MTOR	AEL	CZR	RNR	GHDX	HA	EAT	HVCW	RUTH	SGRP	VRA	BATRK	CGAC
CLUB	THRM	GNW	MLCO	FNF	ENSG	VLRS	CAKE	RIBS	CHUY	NWCN	SGC	CETV	HYLT

TIXC	SMP	AHL_pc	SJMHF	Y	SEM	MESA	ARCO	EURI	DFRG	AUTO	LAKE	SSP	RJDG
WODI	DLPH	FFG	MSC	FAF	PGNY	AVH	BHa	SWRL	FRGI	ANTE	CSS	IHRT	YYYH
YOGA	AXL	SG	CHDN	AFG	MGLN	JETMF	DIN	MHGU	NDLS	ISIG	DLA	HMTV	TSMI
MXMG	INDHF	NWLI	PENN	SCRYY	BEAT	EVCC	DENN	STKS	NATH	UCPA	JRSH	SGA	LKST
SMCE	TOWR	IHC	BYD	EUHMF	ADUS	OMTK	LOCO	ARKR	TAST	CNFN	BSHI	GAIA	DCLT
USBL	SRI	AXAHY	IGT	AGO_pb	MD	CDTI	BJRI	PBPB	TACO	INND	UONEK	CMLS	MEDT
BLIAQ	TEN	AXAHF	ERI	ORI	VCYT	JBZY	PLAY	FAT	RRGB	YDRMF	SALM	BBGI	TTSI
MLFB	GTX	CIA	SGMS	KMPR	NFH	MTG	HABT	SONN	KRUS	DBMM	RICK	UONE	ATAR
CGLD	MPAA	WTRE	RRR	THG	CDNA	KNSL	SYPR	CAAS	MHLD	FLL	AFSIM	AMEH	LCSHF
BLIBQ	MOD	GWGH	MCRI	RLI	CRVL	PRE_pf	ZXAIY	STRT	EMGC	UWN	ESNT	DHC	PLMR
PRXIQ	CPS	KCLI	TRWH	AXS	NHC	AGO	CRGS	HZN	AAME	EVGEF	NGHCP	HNGR	HMN
UGHL	MEC	TIPT	NYNY	AFSIA	USPH	MCY	YDVL	GLXZ	EVH	DHCC	CO	GTS	TVTY
SUP	SORL	VERY	GDEN	SIGI	RDNT	ANAT	FLFG	FCNE	BKD	VCBD	HEMA	CYH	NTEK
GTEC	CVGI	AZSEY	CNTY	RDN	GWHP	NGHC	YZCM	SAUC	BH	MLMN	JAX		

Table 41: Companies of China

300015	601111	300144	603121	2406	2708	796	300237	300733	603768	600148	603758	603809	600177
300347	600115	600593	600081	603035	600960	2186	603586	760	2765	600178	2536	2265	600398
2044	600029	2033	2590	2448	300707	2306	2406	900946	2715	300745	2725	300100	601233
600763	601021	888	2703	300816	300507	721	603035	603085	600148	603335	2593	603701	300526
300244	600221	2858	300237	2708	300681	600754	2448	603161	600178	300742	603809	300585	2563
300143	603885	2159	603586	600960	300694	600054	300816	603926	300745	300742	2265	603037	601718
300404	2928	2863	603701	300707	757	524	603037	300652	603335	2863	300100	2865	600120
600896	200152	603085	300585	300507	603023	428	2865	603917	603178	2921	2027	600637	300180
150	900945	603161	603009	300681	300473	601007	2763	2269	603557	603665	600556	300770	2091
2173	603037	603926	603767	300694	600698	603199	603477	601339	2029	600287	300058	156	600400
603121	2865	300652	603319	757	603758	613	600630	603839	850	601599	300805	600037	603587
600081	603917	603009	603768	603023	2536	900934	2485	2699	2154	603196	2400	839	726
2590	603178	603767	2765	300473	2725	200613	971	603055	603558	2098	603825	917	2832
2703	2921	603319	2715	600698	2593	900942	600107	600278	2486	603555	2181	600996	982
2634	200726	2612	2687	38	601929	2341	603500	600626	600128	603157	603598	2622	2072
603889	420	2404	300591	300280	2238	300577	600493	600826	2569	600156	300242	300392	600241
600448	600220	300005	2494	607	665	601566	600137	2656	2070	2071	2143	603729	2951
2674	2003	603518	600250	2712	600831								

Table 42: Companies of EU

BRKa	RABA	LVS	CCL	HUM	2318	ITW	TQ71	SIAR	EMHn	RGBG	PQIA	HVXA	LNR
BRKb	MSAG	599A	CCLC	QEN	2628	ORLY	RDN	A1G	AIRF	CBS	TNHA	PRI	JOHB
ACEL	1188	27	MTN	HCA	1299	6902	AGO	293	CPAU	1C0	9792	VIGR	8NX
ZURN	TINCk	ALLT	M59	FREG	2601	AZO	H2X3	LHAG	S64	3DC	2LS	UNIQ	QA4A
ALL	HTPGa	PPB	GVC	FMEG	PRU	MCa	MTG	ALK	1HW	1P4	CYH	CNO	SHA_p
TRVN	ZM7	WYNN	3PL	LH	1JP	DLPA	UIPN	QAN	FINN	SHLTN	6CB	GNW	CUVG
AIG	BKTG_p	1128	CHDN	DGX	MUVGn	2338	OCZA	WI2	THAI	V3VGn	MEDG	WUWGn	INHG
2328	MMC	MGM	1NC	RHC	PUFCX	MGA	LRE	EJT1	VBA	MAKG	CBAV	XCW	18B
HNRGn	VA7A	880	MUF	DVA	GASI	GPC	VAHN	JBLU	32A	FEEL	ENZ	65C	TEN
PIRG	WTY	1WE	T6A	UHS	SR9	5802	FGPN	FFHC	GIAA	GTG	FREG	NLVGn	03M
HIG	AJGH	M04	JUVE	SHLT	MET	LKQX	MBI	ALVG	NWC	EIFG	FMEG	AXAF	AXL
MKL	656	CWN	W2L	AMED	8750	WB0	FBD	95S	AB1	1C81	GHC	0CKA	AN9
CINF	FO4N	6460	TIMAn	NG9	SLHN	GNTX	GAME	LHAG	AGES	MUV2	HIA	US	JUVE
LTR	M5V	OPAR	9681	KORI	POW	LEA	BRBI	AF	ASSI	GASI	EUKE	UNPI	ASR
GJFS	APRL	200	BVB	MM6A	2NN	BWA	CIRI	AIRF	ORP	AEGN	AXAF	ALV	LAZI
IAG	DEL	7IG	CDAF	MO4G	TLXGn	LIV	CARRA	FDJ	KORI	CASS	APRL	NETI	CDAF
ADML	LUV	WMH	AJAX	GHDX	SLC	EPED	SGFI	FCMC	GDSF	AXA	COFA	EPED	OLG
T2V1n	753	TTE	ASR	GDSF	8729	1A7	LR	RARP	LNA	CNPP	MRSP	PLOF	TLVB
SUNC	RYAy	RNK	OLG	THC1	0CI	HLE	MARPZ	SFCA	PQR	SCOR	LGT	BLUE	MUSE
QBE	CIAH	V72G	CCP	BEAT	4JP	6471	CBAV	TCNP	CDRE	ATRY	GCO	AKW	EESP
CNPP	1055	163	YB2P	L53	LNC	5334	EXHO	ACCP	EDEN	LVMH	MMTP	LAFU	ALDP
SOAN	UAL1	JUM	LAZI	RHKG	BALN	RHMG	ELIOR	BAIN	PUBP	HRMS	TFFP	ALDAR	ALANT
7PZ	9202	LO24n	LOUDG	MD	AV	PLOF	GFLO	PVAC	JCDX	DIOR	SONO	ALTAN	ALWEB
MAP	PWTN	ARTG	SPSO	G5LN	SLMJ	425	ALPOU	ALLHB	ALMIL	SMCP	FINM	BBUI	MED6

ORPI	JALG	PZ21	BROCb	NTCJ	966	BRCA1	ALDBL	LZTL	CAPLI	DLTA	ALCES	MLSML	ALINV
SUA2	ADH2	CNTY	FCPP	PGZG	AEGN	CIEA	GIRO	ADUX	ALPRI	ALTBG	NWZI	MLONE	HOP
D1LN	ICAG	LIL3	CLUB	SNFG	C53G	TU0	ALMAK	ALACT					

Table 43: Companies of Australia

AQZ	QBE	EBG	HT1	WPP	SWM	XTD	QAN	IAG	RDC	NEC	OML	GLB	NCL
REX	GMA	TCO	MRN	IGL	GTN	R3D	VAH	SUN	APZ	SXL	QMS	GLE	AAU
PNW	PRT	LTN	SW1										

Table 44: Companies of Indonesia

FAST	CASA	ASMI	INPP	BELL	EMTK	VINS	ICON	JMAS	ASRM	HOME	MYTX	ARGO	ESTI
MAPB	LIFE	TUGU	KPIG	PBRX	IPTV	AHAP	INDR	MTWI	ASDM	JIHD	TRIS	ERTX	RICY
PZZA	PNLF	ABDA	SHID	SSTM	SCMA	POOL	BHIT	VIVA	INDO	MABA	ESTA	PSKT	HOTL
PTSP	MREI	AMAG	JSPT	POLU	MSKY	ASBI	BMTR	MARI	SOTS	MAMI	FITT	PNSE	EAST
DUCK	PNIN	GSMF	HRME	STAR	MNCN	ASJT	MDIA	PGLI	ARTA	SINI	BUVA		