MODELLING EXTREME RETURNS IN CHINESE STOCK MARKET USING EXTREME VALUE THEORY AND COPULA APPROACH

A thesis submitted in fulfilment of the requirements for the degree of Doctor of Philosophy

Saiful Izzuan Hussain
BSc Actuarial Science (Universiti Kebangsaan Malaysia)
MSc Applied Actuarial Science (University of Kent)

School of Graduate School of Business and Law
College of Business
RMIT University

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DECLARATION

I certify that except where due acknowledgement has been made, the work is that of the author alone; the work has not been submitted previously, in whole or in part, to qualify for any other academic award; the content of the thesis is the result of work which has been carried out since the official commencement date of the approved research program; any editorial work, paid or unpaid, carried out by a third party is acknowledged; and, ethics procedures and guidelines have been followed.

Saiful Izzuan Hussain
14 July 2016
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ABSTRACT

The Chinese stock market has unique features that make it a challenging and interesting research topic. It is one of the biggest stock markets in the world in terms of capitalization yet it is still considered to be an emerging market. This market is very volatile and thus displays some extreme behaviour. Extreme movements in share returns rarely occur. However, they can have devastating consequences. Thus, it is important for investors, speculators and risk managers to comprehend extreme movement events in stock markets. To this end, we employ Extreme Value Theory (EVT) and copulas in this study.

First, we are concerned with the distribution of the extreme daily returns of the Chinese stock market. Generalized Extreme Value (GEV), Generalized Logistic (GL) and Generalized Pareto (GP) distributions are three well-known distributions in extreme value theory. These distributions are used to identify the distribution which is best fitted with the extreme returns. Our results indicate that the GL distribution is a better fit for the minima series and the GEV distribution is a better fit for the maxima series based on daily returns in the Chinese stock market from 1991 to 2013. This is in contrast to the previous studies, such as the one in the US and Singapore stock markets. This finding also considers extreme events that occurred and could potentially impact on the Chinese stock market such as the introduction of stock movement restriction and the Global Financial Crisis (GFC). Our results are robust regardless of these extreme events.

Second, this study explores the dependence structure between the Chinese stock market and other major stock markets. This study reveals that the Chinese stock market seems to be more strongly integrated with stock markets in Australasia than Europe or the United States. It is shown that the dependence between Chinese stock market and those of other stock markets is stronger during the crisis period than a normal period. This study also suggests that not much benefit can be gained during a downturn in portfolio diversification across the pairs of stock markets considered.
Third, this study examines the dependence structure between the stock markets in the Greater China Economic Area (GCEA) including mainland China, Hong Kong and Taiwan. These stock markets have become more and more important in recent years. However, little is known about the dependence structure between these markets. This research reveals that the dependence between all pairs of GCEA stock markets is strong. As expected, the Shanghai-Shenzhen pair has the strongest dependence (overall, lower tail and upper tail) among all pairs considered. This is followed by the Hong Kong-Taiwan pair. This study finds that diversification is effective for two pairs (Shenzhen-Hong Kong and Hong Kong-Taiwan) in the context of negative market extreme events.

Overall, this study reveals some important results regarding the extreme behaviour in the Chinese stock market. This study also demonstrates that combining EVT and copula can provide an effective way to understand extreme behaviour in stock markets. This approach can lead to incremental insights to the conclusions based on the normality assumption. The outcome of this study can have important implications for policy-making and risk management.
CHAPTER 1: INTRODUCTION

1.1. Research Background

Chinese stock market is the largest emerging stock market in the world. It has grown enormously over the past two decades since the 1990s. Continuing economic reforms and liberalization undertaken by the Chinese authorities in recent years have stimulated the development of the Chinese financial markets (Chan et al. 2007; Lien and Chen 2010). The Chinese stock market has surpassed Japan based on market capitalization since 2007 and has become the most influential stock market in the Asian region. It has become the second largest stock market in the world behind the US stock market.

In contrast to developed markets where institutional investors take the leading role, major participants in the Chinese stock market are individual investors. These investors tend to bet on speculative returns rather than viewing the stock market as a long-term investment. Many finance-related studies have been done in this market. However, analyses regarding the extreme return behaviour for this market have been limited.

The information regarding extreme return behaviour in the stock market is still poorly understood. Most studies have examined developed countries such as the US, the UK and Japan. In contrast, this research investigates the extreme returns behaviour in the Chinese stock market. The aim of this research is to understand the distribution of extreme returns in this market. It will also explore how this market is integrated with others using advanced tools in risk management.

Extreme behaviour has become an important consideration for investors, regulators and risk managers. The behaviour of extreme returns can impact on the performance of the stock market significantly, reduce the benefits of risk diversification and affect the stability of the financial system, as can be seen in the Global Finance Crisis (GFC) during 2007 and 2008. The GFC had forced many reputable and large firms to face survival problems.
and bankrupted many of them (e.g. AIG, Lehman Brothers and Merrill Lynch). Most of the stock markets were affected badly during this period. It should be noted that emerging markets have experienced greater volatility and financial instability during the GFC.

The GFC has brought the entire risk management system into question. Following the market crash in late 2008, it has become very critical for financial institutions, regulators and academics to develop models that consider and guard against the extreme behaviour.

Early studies have shown many large financial institutions adopted a conservative model to measure the risk. The most well-known risk measure is Value at Risk (VaR) has been used as an industrial standard risk measure for market risk measurement. This tool has again attracted global attention for its accuracy and therefore, is necessary to have such models that are able to estimate the risk under different market conditions (for example, with or without a financial crisis).

VaR can be defined as the maximum loss which may be incurred by a portfolio, at a given time horizon and a given level of confidence. VaR has been recognized by both official bodies and private sector groups as an important market risk measurement tool. Many official bodies have embraced the concept of VaR. These include the Basel Committee on the Banking Supervision (Supervisions (1998)) and the Bank for International Settlements (Fisher-Report, 1994). The Group of Thirty (1993), a private sector organization which consists of bankers and other derivatives market participants, has advocated the use of VaR for setting risk management standards. Risk Metric that is used for estimation of VaR was first introduced in 1994 by JP Morgan Bank. Since then many methods of estimating VaR have been proposed. For more information on VaR and its estimation, we refer to Jorion (2000).

The important issue for VaR is the distribution function that used to present the returns of the asset. Usually, as allowed by the Basel Committee, a normal distribution is used as the assumption for return distribution. A normal distribution is a popular assumption that has been used to model extreme behaviour. However, research has consistently shown that financial returns tend to have fatter tailed returns than the normal distribution. This
indicates that extreme losses (or gains) have a higher probability of occurring compared to those implied when the normal distribution is employed. This means that the model based on normality assumption can be inaccurate and fail to predict a catastrophic event. Therefore it is important to know the best distribution incorporating the fat tail behaviour.

For this study, one of the objectives is to identify the best distribution that fits with the extreme returns of the Chinese stock market. In the financial market, it is important to quantify extreme losses in current market conditions. This is important for VaR calculation. With growing turbulence in the financial markets worldwide, evaluating the probability of extreme events like the Asian Financial Crisis (AFC) and GFC has become an important issue in financial risk management. This is where Extreme Value Theory (EVT) can play a major role.

EVT provides a comprehensive theory based on statistical models to describe extreme scenarios. EVT techniques are widely used in areas such as weather, hydrology and the environment. EVT is also a well-known technique in many fields of applied sciences including insurance and engineering. It was first applied in finance in the late 1980s by Parkinson (1980).

Second, this thesis is concerned with the dependence structure between Chinese stock market and other major stock markets. The significant increase in market capitalization of the Chinese stock market in recent years has become one of this research motivation to study this behaviour. The Chinese stock market has been increasingly integrated with many markets as pointed out in many previous studies. Therefore a crash or boom in this market is likely to have a contagious effect on another one. This could lead to a huge disaster. In addition, it will be interesting to see the dependence structure between the Chinese stock market with others during the financial crisis periods.

Although extensive studies have been carried out on dependence, there is not much published work regarding fat tail modelling and extreme returns behaviour for the Chinese stock market. Most studies tend to focus on the developed market. The dependence structure between the Chinese stock market and other markets has important implications for risk management, portfolio diversification and international diversification.
The Pearson coefficient is a tool that can be used to compute dependencies of financial asset returns. However, it has several limitations. Several studies showed that asset returns rarely follow a normal distribution. Furthermore, the correlation among financial assets is non-linear. The extreme movements that occur due to economic shocks will also make the modelling of co-movement among asset returns a difficult challenge.

This study uses copula to overcome the shortcomings of simple linear correlation. Recent studies show that copula can serve as an alternative for modelling correlations in terms of the asymptotic dependence and characterization of nonlinearity. Copula is used to model multivariate distribution functions of random variables using flexible marginal distribution functions of each random variable set. Compared to traditional methods for estimating dependence, copula can be a very powerful tool. In this thesis, all returns empirically show non-normal behaviour. Overall dependence and tail dependence are examined in detail. All these features make copula approach a better method to understand the behaviour of each stock market pair than the traditional correlation method.

This research aims to fill the gap in investigating the dependence structure between the Chinese stock market and other major stock markets by focusing specifically on the lower and upper tails. The combination of EVT and time-varying copula has several advantages that help to model the dependence structure between Chinese stock market with others more accurately. In turn this will improve the ability to manage risks in the future and improve our understanding of the behaviour of this emerging market from an international perspective.

Concerning regional dependence, there is evidence showing that local events can cause country-specific stock price reactions. Specifically, most of the volatility in the stock markets can be related to the economic, political and social events that happen in its region. This research will examine the dependence structure in the Greater China Economic Area (GCEA). At the same time, the dependence structure between GCEA has not been treated in much detail. The upper and lower tail dependence between GCEA stock markets are interesting and should be explored further, as they may contribute in
different ways compared to developed countries’ stock markets. The results can provide evidence as to whether the findings from developed stock markets are valid to Chinese stock market.

Overall, this research aims to employ EVT and copula approach to provide a better understanding of extreme behaviour in the Chinese stock market to fill the gap in our knowledge concerning this topic. The contribution of this study is to understand the behaviour of extreme returns of the Chinese stock market regarding the type of distribution and dependence structure. The findings have important implications for both asset pricing and financial risk management in the Chinese stock market.
1.2. Research Questions and Objectives

This research has several objectives to fill the gap in the literature. It aims to:

I. Identify the best distribution for the extreme returns in the Chinese stock market.
II. Understand the dependence structure between the Chinese stock market and other major stock markets around the world.
III. Understand the dependence structure between stock markets in the Greater China Economic Area (GCEA).

The following research questions are developed according to the research objectives above:

I. What is the best fit distribution for the extreme returns in the Chinese stock market?
II. How does Chinese stock market correlate with other major stock markets around the world?
III. How strong is the dependence structure between stock markets in the Greater China Economic Area (GCEA)? Does the dependence structure of GCEA stock markets have strengthen over the years?
1.3. Research Significance

This research contributes to the literature in the following ways. First, the research aims to assess empirically the behaviour of extreme returns in the Chinese stock market by using both EVT and copula. Normality models are often ill-suited to deal with the extreme circumstances that arise in the financial market, especially in emerging markets. Increasing interests in emerging markets have provided the impetus for both adaptations of the current model that considers this behaviour.

Second, this research will explore and analyse the dependence of the Chinese stock market with other major stock markets. The international equity markets have become increasingly volatile and integrated. The dependence that existed between financial markets has always been one of the crucial issues in finance and investment field. For instance, any political tension that happens in the Chinese stock market is likely to affect returns on most stocks in Hong Kong. However, this will not likely wield much influence on the stock market in Ukraine. In contrast, war or political tensions in Russia may have an effect on Ukraine’s stock market (since both of them have strong economic ties and are neighbours) more likely, but have little effect on Hong Kong or Chinese stock market. International portfolio diversification has emerged as one of the key strategies to achieve higher returns compared to domestic market investment alone. This outcome provides useful information for investors in the Chinese stock market who wish to seek another way to diversify their international portfolios and assets. Therefore it is valuable to study the behaviours of the dependence structure empirically.

Third, this study will also contribute to the literature on dependence between GCEA stock markets. So this research contributes to the increasing portfolio diversification and improves active asset allocation of investors interested in this area. Investors can use the results to adjust the asset allocation dynamically to achieve optimal portfolio since the dependence structure between Chinese stock market and others might differ.
Fourth, this research explores the application of EVT and copula models to the risk management process. This study addresses the crucial issues by empirically exploring the effectiveness of EVT and copula in managing portfolios risks in this market for selected areas. It is believed that copula can provide more information on the dependence structure over time compared to the traditional method. The result can improve the confidence of forecasting regarding the volatility persistence and asymmetry of returns.

From a theoretic perspective the results of the extensive empirical study may indicate promising directions for further development of theoretical risk modelling. This method provides new insight on understanding the extreme behaviour of and the dependence structure between stock markets.

Overall, this study will potentially have important implications for risk management. This research will contribute to the topic of VaR estimation and international diversification between the Chinese and other stock markets. Results can be useful for practitioners in portfolio risk management.
1.4. List of Publications

The following are publications arising from this thesis:

**Journal papers**


**Peer reviewed conference paper**

1.3. Structure of the Thesis

The remainder of the thesis consist of six chapters described below.

Chapter 2 reviews the literature on the Chinese stock market, extreme distribution and dependence structure of the stock markets. This chapter reveals several research gaps regarding extreme returns behaviour in the Chinese stock market.

Chapter 3 describes the research methodology used in this thesis. The studies on EVT and copula approaches are discussed in this chapter.

Chapter 4 focuses on modelling the extreme returns in the Chinese stock market. This chapter reproduces in full a scientific paper that has been published in the *Journal of International Financial Markets, Institutions and Money* in January 2015. This particular chapter attempts to identify the best extreme returns distribution for the Chinese stock market.

Chapter 5 provides an empirical analysis and results regarding the dependence structure between Chinese stock market and other major stock markets including US, Canada, UK, Japan, Germany and Australia are studied. This paper is under review by *International Review of Economics & Finance*.

Chapter 6 is an analysis of the dynamic dependence structure between the stock markets in Greater China Economic Area (GCEA). This study describes and discusses the empirical dependence structure between the stock markets of Shanghai, Shenzhen, Hong Kong and Taiwan. This paper is under review by the *Review of Pacific Basin Financial Markets and Policies*.

Chapter 7 provides an overall summary of this thesis and its major findings. Lastly, the limitations of this study, areas for further research, and final concluding remarks are also given.
CHAPTER 2: LITERATURE REVIEW

This chapter begins with a review of the literature on the Chinese stock market in Section 2.1. From this background literature, the review then focuses on extreme return distribution in Section 2.2. In Section 2.3, the literature regarding the dependence structure of the Chinese stock market and others is discussed. Section 2.4 is about the literature on the dependence structure between GCEA stock markets. A summary of the overall literature review is presented in Section 2.5.

2.1. Chinese Stock Market

Since its establishment in the early 1990s, Chinese stock market has experienced tremendous economic growth over the past two decades in terms of capitalisation, the number of listings and turnover. Based on data released by the China Securities Regulatory Commission (CSRC), the number of domestic listed companies on October 2015 is 2800\(^1\).

There are two major stock exchanges that are associated with the Chinese stock market; the Shanghai Stock Exchange (SHSE) and Shenzhen Stock Exchange (SZSE). Both of these stock exchanges started trading in 1990. In 2015 the total market capitalization of the Shanghai Stock Exchange was approximately 18,238 billion RMB while the total capitalization of Shenzhen Stock Exchange 12,22 billion RMB. There are a few differences in the Shanghai and Shenzhen stock exchange systems. Most companies that are listed on SHSE are state-owned and large. In comparison, those companies on the SZSE are joint-ventures, small and export-oriented. The relative size of these markets

has also changed. In 1992, SHSE was relatively small and less active than SZSE but this changed due to a shift in government policy by the end of 1994. This difference could lead to markedly different outcomes (Hilliard and Zhang 2015). Both exchanges operate five days a week except on holidays. SHSE tends to have fewer holidays compared to SZSE.

The Chinese stock market has many interesting features. There are two types of shares on the Chinese stock market: firstly, A Shares (restricted to domestic investors only); and secondly, B Shares (available to both domestic and foreign investors). Another interesting feature is a limit of 10% of the daily movement in share price since 16 December 1996. This limitation was introduced to curb excessive volatility in this market. Indeed, about 70% of shares are non-tradable and this stock is held by the government, state-owned enterprises (SOEs) and Chinese institutions (Mookerjee and Yu 1999). Thus this characteristic enables the Chinese government to wield much influence on the Chinese stock market compared to governments in developed markets. It also means the governments can hugely impact on the stock market price movements.

This stock market is also quite different compared to those in developed countries regarding exchange facilities. Chinese stock market strictly prohibits the practice of short sale trading. Therefore, the supply of shares is limited and affects the stock price formation limit. The behaviour of the Chinese stock market is very different from developed countries’ stock markets. This market has long posed a challenge for finance studies.

Major market participants in this market are individual investors. A-share individual accounts are about 57.59 million and institutional ones number approximately 1.35 million accounts for investors². This indicates there are many unsophisticated individual investors in this market. It also suggests that most investors lack qualified security analysts in the Chinese stock market compared to the developed stock markets (Yao et al. 2014). Individual investors can behave like noise traders as they have low

² Source, the websites of SSE and SZSE: www.sse.com.cn and www.sse.org.cn
transparency and invest more often according to rumour and past trends (Kang et al. 2002).

Many actions have been taken by Chinese authorities to liberalize the Chinese stock market. At an early stage, B-shares were a platform that designed for foreign investors and was denominated in the Chinese local currency, the Renminbi (RMB), which was payable in foreign currency. A-shares have been actively traded by domestic investors. In contrast the trading of B-shares (shares subscribed and traded in foreign currency) is very small. However, a domestic trader could invest in B shares and this is payable in US dollars due to changes in the regulations in 2001. This has contributed to the price of B-shares rising significantly since the regulations were introduced. The removing of the restriction has attracted more foreign investments (Chan et al. 2007).

Another attempt by Chinese authorities to liberalize the Chinese stock market occurred through the Foreign Institutional Investors (QFII) programme in December 2002. This programme allows licensed foreign institutional investors to trade A-shares on the market. After the successful introduction of this programme, trading in A-shares was opened to individual foreign investors on 9 July 2003.

The Chinese authorities also launched the QDII programme in May 2006. This programme permits licensed domestic institutions to invest in overseas stock markets. These changes are expected to increase the dependence between the Chinese stock market and others (Li 2012). All of these liberalization attempts have created greater international links between the Chinese stock market and those of other countries (He et al. 2014).

To conclude, many initiatives have been taken to boost this market by the Chinese government. Since then it has become one of the main markets favoured by international investors. The Chinese stock market is the largest emerging market in the world and is different in various ways from stock markets in developed countries. Chinese stock market is still developing and highly regulated by the government.
2.2. Extreme Return Distribution

A large and growing body of literature on the Chinese stock market has been published in recent years. This research fills several gaps in the literature review regarding extreme returns behaviour. To the best of our knowledge, little is known about Chinese stock market extreme behaviour. Most studies tend to focus on the centralized data and neglect the facts of financial data.

EVT study has renewed interest in analyzing the behaviour of the tails. Extreme returns can be defined as the minimum daily return (the minima) or the maximum daily return (the maxima) of a stock market index over a given period (selection interval) according to Longin (1996).


Longin (1996) found extreme returns in the US can be assigned using (Generalized Extreme Value (GEV)) distribution for both the minima and maxima series. This finding was also reported by Jondeau and Rockinger (2003) and Gençay and Selçuk (2004). However, studies by Gettinby et al. (2004, 2006) found that the Generalized Logistic (GL) distribution is the best distribution that fits the extreme daily stock returns in the US, UK and Japan compared to the GEV distribution. GL distribution also can be used to calculate VaR accurately compared to the GEV or normal distribution. A study by Tolikas and Gettinby (2009) indicates that Singapore’s stock market is fitting best with the GL distribution compared to the GEV and normal distribution. GL distribution is able to describe the extreme returns for the minima and maxima series adequately compared to the GEV distribution for selected intervals of their study.
Since the markets are very volatile, the need for modelling the distribution tails is very apparent. It was concluded that most markets are not characterized by normality and can be described within an extreme value theory frame. Since VaR estimations focus mainly on the tails of a probability distribution, techniques from EVT may be particularly effective for extreme observations. Estimation of VaR using EVT offers major improvements over well-known methods for oil market (Marimoutou et al. 2009).

Furthermore, Bali (2003) and Straetmans et al. (2008) indicated that EVT models provide better estimation than the standard approach, which assumes a normal distribution. More recent application of VaR using EVT has been done by Allen et al. (2013), Karmakar (2013) and others. More studies on estimation of VaR using EVT can be found in Bradley and Taqqu (2003) and Brodin and Kluppelberg (2008). All of this emphasizes the importance of understanding the extreme behaviour returns before they are implemented for the purpose of VaR measurement.

To this end, this study uses EVT to study the tail behaviour of the Chinese stock market. The best distributions that fit well with the minima and maxima series in Chinese stock market are studied in this thesis.
2.3. Dependence Structure with Major Stock Markets around the World

This purpose of this section is to review the literature on the dependence structure of Chinese stock market with those of other countries. China has built a close relationship with the rest of the world regarding international trade and investment. This integration is due to the Chinese government opening its doors to foreign investment and cross-border listings (Sun et al. 2009). Therefore, any change in the Chinese economy or stock market could impact on others.

Over the past decade, there has been a dramatic increase in dependence studies. Chan et al. (2007) have shown that the Chinese stock market is now more integrated with developed markets. A study on inter-Asian-Pacific dependence by Hyde et al. (2007) showed there is a strong correlation between Asian-Pacific countries, Europe, and the US. However, a study by Li (2007) discovered that the Chinese stock market is weakly integrated with regionally developed markets. This is echoed by Lai and Tseng (2010) which show there are no significant dependencies between Chinese stock market and the G7 countries.

The dynamic dependence structures between the Chinese and US financial markets are quite volatile according to Hu (2010). Recent evidence suggests that there is significant mutual feedback of information between domestic (Hong Kong) and offshore (New York) markets in terms of volatility and pricing according to Xu and Fung (2002). The volatility linkages between Chinese stock market, Hong Kong and the US using daily data with a multivariate GARCH framework has been demonstrated by Li (2007). The study showed the spillover effects from Hong Kong to Shanghai but not any between the Chinese stock market with the US stock market. According to Rosch and Schmidbauer (2008) the Chinese stock market appears to be immune to extreme external movements. However, the dependence structure of Chinese stock markets has increased after 2000. The study also shows that a sharp downward movement in the US stock market is more likely to impact the Chinese stock market during a bear period than during a bull period in the US. According to George (2014), the interaction between the Chinese stock market and US stock market has been improved recently. This study also demonstrates US stock market
can forecast Chinese stock market. However, the Chinese stock market has not shown the similar ability to forecast Us stock market.

Next, previous studies also suggest that the tails of return distributions are fatter than normal while the correlations are asymmetric across downside and upside market movements. (e.g. Longin and Solnik 2001; Ang and Chen 2002; Kolari et al. 2008). Therefore, finding a more suitable approach to modelling dependencies between stock returns has become a significant challenge in risk management. One possible solution is to apply the dynamic conditional correlation (DCC) model proposed by Engle (2002) and Engle and Colacito (2006). The family of DCC methods considers the time-variation issue, but does not account for extreme value and departure from normality. Silvennoinen and Terasvirta (2009) and Tsafack (2009) discovered that DCC family models could lead to bias in the estimations used in portfolio management with the presence of asymmetry in a tail correlation. Therefore it would be inappropriate to apply DCC models.

Recent studies show that copula can serve as an alternative method to overcome the limitations of the nonlinearity method. Copula is a risk management tool that models the dependence structure between variables and was first used in finance in the early 2000s (Cherubini et al. 2004). Specifically, copula is a technique used to understand the dependence structure and consideration of nonlinearity without the constraints of normality. It can separate marginal behaviour of variables from the dependence structure through the use of joint distribution function. The assumption of normality used in most of the financial data makes measuring the dependence structure of market returns between two series less accurate. Thus copula can be a better tool for modelling financial data.

There are many types of copula that can be used to fit the different scenarios. Most empirical studies have focused on the equity risk and employ Gaussian copula and $t$ copula. A study by Hsu et al. (2012) focused on Gaussian, Gumbel and Clayton copula on Asian markets while Wang et al. (2010) in their study use Gaussian, $t$ and Clayton copula to describe a portfolio risk structure. In Cherubini and Luciano (2001) an Archimedean copula family is employed and the historical empirical distribution in the estimation of marginal distributions for VaR estimation. Rockinger and Jondeau (2001)
utilized the Plackett copula and proposed a new measure of conditional dependence. De Melo Mendes (2005) investigated the extreme asymmetric dependence in daily returns for seven emerging markets using extreme value copula functions.

This study uses Symmetric Joe Clayton (SJC) copula to model the dependencies between the assets returns. SJC copula is a modification of the “BB7” copula of Joe (1997). This type of copula provides more information regarding tails information. According to Patton (2006a), SJC copula is more efficient at modelling the dependencies between the financial markets. In contrast to Gumbel and Clayton, SJC copula can capture the lower and upper tails at the same time. SJC copula does not impose symmetric dependence on the variables like the Gaussian copula does. This type of copula is able to capture the upper and lower tail dependence of joint distribution at the same time. Bhatti and Nguyen (2012) used SJC copula to examine the dependence structure across financial markets, including Australia, the US, the UK, Hong Kong, Taiwan, and Japan. In another analysis by Nguyen and Bhatti (2012), they investigated the dependence between two stock exchanges, those of China and Vietnam where indices concerning oil prices utilized copula functions.

The recent extension of the unconditional copula theory to the conditional case has been used by Patton (2006a) to model time-varying conditional dependence. This research focuses on time-varying copula based the work over these recent years by Patton(2006a) and Jodeau and Rockinger (2006). This method allows the temporal variation in the conditional dependence in time series, making it more dynamic and time sensitive. For an application, Bartram et al., (2007) have used time-varying conditional copula to study the integration of seventeen European stock market indices.

However, the study might ignore fat-tail phenomena especially for the series. Using EVT with copula is one promising solution in addressing the fat-tailed and nonlinearity issues. The study of copula and EVT has been done by Clemente and Romano (2003), de Melo Mendes and de Souza (2004), Hotta et al. (2006), Hsu et al. (2012) and Wang et al. (2010).
Clemente and Romani (2003) have used copula and EVT approaches to model operational risk using insurance data. De Melo Mendes and Souza (2004) in their study focus on crises scenarios while Hotta et al. (2006) used the copula approach to model market risk for a portfolio consisting of Nasdaq and S&P 500 indices. These are considered to be typical of developed markets. Hsu et al. (2012) incorporate a combination of copula and EVT to access portfolio risk in six Asian markets. Wang et al. (2012) employed copula and EVT to analyse the risk of foreign exchange portfolios.

Our study differs from these studies in several respects. The interest in emerging markets has arisen out of the need to develop a new model and adapt current models to new circumstances. The different economic systems governing these markets allow this research to observe the impact of economic structures on financial dependencies. China is a manufacturing country and now has the largest emerging stock market in the world. The dependence levels of this market are quite interesting to see and compare and results will help investors to identify the opportunities for international portfolio management.

In summary, there are not many details or answers concerning the dependence structure between Chinese and other major stock markets and the results tend to be mixed. It is hard to find any systematic research that has been done on Chinese stock market dependence under extreme setting. The study of extreme returns and integration between EVT and copula has not had much detail. Furthermore, research on the subject has been mostly restricted to the developed stock markets. This research seeks to remedy these problems by using the EVT and copula approach.
2.4. Dependence Structure in the Greater China Economic Area (GCEA)

This section examines the context of dependence in the Greater China Economic Area (GCEA). Chinese stock market is one of the world’s major stock markets. While Taiwan is one of the top ten stock markets in the world. Most companies based on technology originate in Taiwan, for example Asus. Acer Inc, HTC Corporation. Hong Kong is one of the five major stock markets in the world and the main gateway to Chinese stock market for international investors. These markets combined is huge in terms of market capitalization.

The economic exchange within this stock market is strong despite political tensions. Based on trading activities, mainland China is Taiwan's largest import and export destination. Mainland China accounted for 26.8% of Taiwan's exports and 15.8% of its imports in 2013. Mainland China is also the main export and import partner of Hong Kong. Its exports account for 59.9% and imports are 41.5% of Hong Kong's in 2013.

Aggarwal et al. (1999) showed that local events can cause specific stock price reactions. Their study showed that most of the increasing volatility in the emerging market could be linked to economic, social and political events. Nikkinen et al. (2008) found that the impact of extreme events leads to significant increases in volatility across and throughout certain regions. This has implications for the international economy as well. A study by Zhou et al. (2014) showed the volatility of the Chinese stock market has ominously impact on other markets since 2005. However, the volatility interactions among the GCEA stock markets were more prominent than all major stock markets. Thus, it is quite interesting to examine for the dependence between the stock markets in the GCEA as they also share similar cultural, geographical and social ties.

The information regarding dependence structure of GCEA stock markets could have implications on diversification and portfolio management. It is important to understand how these markets relate to each other in terms of the stock market dependence

3 Data sourced from http://www.dfat.gov.au
structure. As dependence structure between GCEA might differ over the time, the results could be used by investors to manage the assets dynamically to achieve optimal asset allocation. At the same time, there is the possibility of diminishing benefit from asset diversification as dependence structure of GCEA stock markets might strengthen over the years.

There are not many studies regarding dependence between GCEA stock markets. Liu and Sinclair (2008) suggested that movements in stock prices in GCEA were determined by economic fundamentals which could be related to the regional area. Johansson and Ljungwall (2009) found that a spill-over effect exists between the GCEA stock markets. There is more integration between the GCEA stock markets (Cheung et al. 2003). This study focused on the macro levels of the economy such as exchange rates, interbank rates, and prices. Cheung et al. (2005) also studied how the GCEA finance market integrates with other economies in their later study. The dependence is more marked after the Asian crisis (Groenewold et al. (2004)). Hong Kong is one of the most influential of the GCEA markets according to Cheng and Glascock (2005). However, this position is threatened by fast-growing of Shanghai Stock Exchange (Wang et al. 2012).

Another interesting study was conducted by Wang and Iorio (2007). They showed that a strong correlation existed between China’s A-share market and Hong Kong’s stock market. According to Yang and Lim (2004), the Hong Kong stock market has become the main gateway between the Chinese stock market and others. This platform has contributed to enhancing the transmission of information and interaction between the Chinese stock market and those of other countries. There are substantial capital flows into the Chinese stock market via the Hong Kong stock market. The results might be different with other; e.g. Taiwan GCEA stock market.

In contrast, Groenewold et al. (2004) found Chinese stock market is relatively isolated from Hong Kong and Taiwan stock market. The evidence demonstrates that Hong Kong has a weak predictive power for returns in the Chinese stock market during the crisis; AFC. This is confirmed by Ho and Zhang (2012) that demonstrated the Chinese stock market is less volatile than the Taiwan and Hong Kong stock markets.
He et al. (2009) demonstrated that the Hong Kong Stock market is more aligned to the Chinese stock market during times of normality but not during turbulent times. Shin and Sohn (2006) concluded there was no significant dependency between Asia countries.

To conclude, there is not much literature discussing the GCEA stock markets on the dependence structure in terms of extreme returns behaviour. This research aims to explore and enrich the literature on this topic.
2.5. Summary of Literature Review

This research fills several gaps in the literature on the Chinese stock market regarding extreme returns behaviour especially on the extreme returns distribution and dependence structure with other stock markets.

This study uses EVT framework to understand the extreme returns distribution in the stock market. From previous studies, most extreme returns tend to fit well with the GEV distribution. However, recent studies by Gettinby et al. (2006) and Tolikas and Gettinby (2009) found that the GL distribution is the best distribution that fits the extreme returns in the US, UK, Japan and Singapore. This study represents a step towards systematically investigating the extreme returns distribution in Chinese stock market.

Drawing upon many mixed results upon dependence structure of the Chinese stock market, this research attempts to understand the dependence structure between Chinese stock market with others by integrating EVT framework with copula. This study will shed some light on the portfolio management and the prospect of economic growth in the Chinese stock market. The main reference regarding this study can be seen in Patton (2006 a), Wang et al. (2010), Bhatti and Nguyen (2012) and Hsu et al. (2012).
CHAPTER 3: EXTREME VALUE THEORY AND COPULA

This chapter discusses the two key techniques employed in the thesis: EVT and copula. The details concerning the research methods used in the empirical chapters (i.e. Chapter 4, Chapter 5 and Chapter 6) are given in the respective chapters.

3.1. Extreme Value Theory

Extreme Value Theory (EVT) is a broad statistical topic that is associated with extreme event modelling. The main purpose of EVT is to model the distribution of sample extremal. This parametric method provides a better estimation since it focuses only on the extreme values, rather than the modelling distribution of all values. The application of EVT can be found in many disciplines such as structural engineering, traffic prediction, earth sciences, geological engineering insurance and finance. It was first introduced by Fisher and Tippett (1928) and followed up by Embrechts et al. (1999, 2005), Poon et al. (2004) and Rachedi and Fantazzini (2009) in finance. In finance, EVT is used to forecast risk and capture the extreme tails of distribution.

EVT can be modelled either by the Block Maxima (Minima) (BMM) or the Peaks Over Threshold (POT). BMM is based on the extreme value distributions of the Gumbel, Fréchet or Weibull distributions which are generalized as the Generalized Extreme Value distribution (GEV). Meanwhile the POT method can be associated with the Generalized Pareto Distribution (GPD).
3.1.1. Block Maxima Method (BMM)

The BMM model is the most traditional and works differently from POT. BMM fits a block of Minima and Maxima (for the extreme events) in a data series of independent and identically distributed observations (i.i.d) to a certain distribution. In finance, the BMM method defines extreme events as the maximum (minimum) value in each sub-period such as weekly, monthly, quarterly and yearly interval.

In BMM, the series of maxima (minima) could be associated with the Fisher-Tippett-Gnedenko theorem. The standardization of this distribution is shown as following the extreme distribution of Frechet, Gumbel or Weibull distributions. The standard form of these three distributions is known as the Generalized Extreme Value distribution (GEV).

The BMM method has its drawbacks. It tends to discard a great amount of data that possibly exists in the same sub-period. However, there are many reasons for applying the BMM method. This method is preferable when the sample is not exactly an i.i.d. For example, this may be due to seasonal periodicity or possibility short range dependence which plays a role in blocks but not between blocks. This method is also easier to be applied since the block of period naturally in many situations. BMM also compares favorably in terms of performance with POT for large sample sizes. More details can be found in Katz et al. (2002), Naveau et al. (2009) and Ferreira and De Haan (2015).

Given the time series of daily index returns $r_1, r_2, r_3...r_n$, the series can be divided into non-overlapping time intervals of length $m$. The time series of the extreme maximum will then be $X_1 = \max(r_1, ..., r_m), X_2 = \max(r_{m+1}, ..., r_{2m}), ..., X_{n/m} = \max(r_{n-m}, ..., r_n)$.

According to Fisher and Tippett (1928), the distribution of the extreme series is best fitted with the GEV, which is assumed to be independent and identical. GEV is known as a three-parameter distribution and is defined as:

$$f(x) = \alpha^{-1}e^{-(1-\xi)y}e^{-e^{-y}}, \text{ where } y = \begin{cases} -\xi^{-1}\log\left(1 - \frac{\xi(x - \beta)}{\alpha}\right), & \xi \neq 0 \\ \frac{(x - \beta)}{\alpha}, & \xi = 0 \end{cases} \quad (3.1)$$
The parameters are referred to as the location ($\beta$), scale ($\alpha$) and shape ($\xi$). The location parameter ($\beta$) is analogous to the mean and the scale ($\alpha$) parameter is analogous to the standard deviation. The shape parameter ($\xi$) determines the fatness of the tail of the distribution. The larger the value of shape parameter ($\xi$), the fatter the tail is.

Regarding the specific type of distribution in GEV, Fréchet distribution is where $\xi > 0$, Weibull distribution is where $\xi < 0$ and $\xi = 0$ is for the Gumbel distribution.

In this research, BMM is used to serve objectives regarding extreme returns distribution for minima and maxima series. This is explained in more detail empirically in Chapter 4.

### 3.1.2. Peaks over Threshold (POT)

On the other hand, the POT approach focuses on sorting clustered observations that are frequently found in data. It models a distribution of excess over a given threshold. This method is found to be more efficient in modelling limited data according to Embrechts et al. (2005). A study on EVT showed that the limiting distribution of exceedance could be modelled via Generalized Pareto distribution (GPD) (see Coles et al. 2001, Gilli 2006). The POT method allows for greater flexibility in many situations much better than BMM since it could be difficult to change the block size in practice. This method does need large data sets such as BMM. Furthermore this method is based on the theorem devised by Pickands (1975), and Balkema and de Haan (1974). This theorem is also known as one of the theorems of extreme values.

Let $(x_1, x_2, ...)$ be a sequence of independent and identically distributed random variables with the distribution function $F$. Then for a large class of underlying distribution $F$ and large $u$, the conditional excess distribution function $F_u$ can be approximated by GPD, that is:

$$F_u(y) \approx G_{\xi, \alpha}(y), u \to \infty$$

where
\[ G_{\xi,\alpha}(y) = \begin{cases} 
1 - \left(1 + \frac{\xi y}{\alpha}\right)^{-1} & \text{if } \xi \neq 0 \\
1 - e^{-\frac{y}{\alpha}} & \text{if } \xi = 0
\end{cases} \]  

(3.2)

For \( y \geq 0 \) when \( \xi \geq 0 \) and \( 0 \leq y \leq \left(-\frac{\alpha}{\xi}\right) \) when \( \xi < 0 \). \( \alpha \) is the scale parameter, \( \xi \) is the shape parameter for the GPD.

The process to determine the threshold value \( u \) is crucial for GPD. According to the Picklands–Balkema–De Haan theorem (Balkema and De Haan 1974; Pickands 1975), a high \( u \) value is important in order to obtain extreme series. However, this result generally leads to a large variance in the estimators due to the probability to discarding the valuable data. Besides, the samples may be too small for data analysis. The data gathered might not belong to the tails and in fact results in a bias in estimators if the value of \( u \) is too low. Thus a trade-off between bias and variance is required to find the optimal threshold.

A study on the dependence structure in the Chinese stock market will consider the POT method. Details on the application could be found in the empirical chapter 5 and chapter 6.
3.2. Copula Models

Copula models have several advantages over other econometric methods concerning dependence measurement. First, the assumption of normality makes multivariate methodology unsuitable for measuring the dependence structure of financial data. The copula model works beyond linear correlation and without the constraint of normality. In recent years copula has emerged as a significant method for managing the relationship between financial markets and risks (Cherubini et al. 2004; Kole et al. 2007). At the same, this method provides a high degree of flexibility better than others.

Second, copula model is able to estimate the joint distribution and marginal distributions without the loss of important information. Third, the latest innovation of copula on time-varying dependence makes this model able to capture the dynamic dependence structures between financial markets which are sensitive over time. This work is based on Patton (2006a).

Based on Sklar’s theorem (1959), formulation of copula is based on the information of the marginal distribution that has been transformed into a uniform distribution.

Mathematically, the joint distribution \( F \) of \( r \) random variables \( x_1, \ldots, x_r \) can be decomposed into \( r \) marginal distributions \( F_1, \ldots, F_r \) and \( C \) known as copula can be used to describe the dependence of the structures among the variables:

\[
F (x_1, \ldots, x_r) = C (F(x_1), \ldots, F(x_r)) \tag{3.3}
\]

This study uses bivariate copula which mathematically can be written as follows:

\[
F (x_1, x_2) = C (F(x_1), F(x_2)) \tag{3.4}
\]
There are many types of copula. This research uses Gaussian and SJC copula to reach the research objective. The Gaussian copula serves to capture the overall dependence and is a benchmark for comparison.

The dependence structure might differ on the upside or downside regimes. This has brought about the need for SJC copula to fill this gap. This type of copula can capture the lower and upper tail dependence simultaneously. This information is useful for assessing the behaviour of the lower and upper tails. On this theme, this study also applies the extended version of copula theory, time-varying conditional copula theory. More details can be found in Patton (2006a, 2006b). This method allows the copula parameters to vary over time and provides a better understanding of the movement of the dependence over time. Informative information can be extracted when employing this approach.

3.2.1. Gaussian Copula

Gaussian copula is also known as multivariate normal distribution. For bivariate definition, Gaussian copula can be denoted as the density of the joint standard uniform variables \((u, v)\), since the random variables are bivariate. Therefore, mathematically the density of Gaussian copula function can be written as:

\[
C(u, v) = \int_{-\infty}^{\Phi^{-1}(u)} \int_{-\infty}^{\Phi^{-1}(v)} \frac{1}{2\pi\sqrt{1-\delta^2}} \exp \left\{ -\frac{x^2 - 2\delta xy + y^2}{2(1-\delta^2)} \right\} dx\, dy
\]

\[
C = \Phi_\delta \Phi^{-1}(u), \Phi^{-1}(v)), -1 \leq \delta \leq 1
\]

where \(\Phi\) and \(\Phi_\delta\) are known as the standard normal CDF’s and \(\delta\) denotes the linear correlation coefficient.

To capture the dynamic path of dependence, parameter in Gaussian copula is assumed to evolve over time based on the Patton equation (2006a):
\[ \delta_t = \lambda \left( \omega + \beta \delta_{t-1} + \alpha \sum_{j=1}^{10} \left[ \Phi^{-1}(u_{t-j})\Phi^{-1}(v_{t-j}) \right] \right) \]  

(3.7)

where \( \lambda = \frac{(1 - e^{-x})/(1 + e^{-x})}{1 + e^{-x}} \) is the modified logistic transformation to ensure \( \delta_t \) within interval (-1,1) at all times. This equation assumes the dependence is determined by past information and to follows an ARMA (1,10) type process where \( \delta_{t-1} \), determined from its previous level, \( \beta \delta_{t-1} \) captures the persistence effect and the mean of the product of the last 10 observations of the transformed variables \( \Phi^{-1}(u_{t-j}) \) and \( \Phi^{-1}(v_{t-j}) \) captures the variation effect in the dependence.

### 3.2.2. Symmetrized Joe Clayton Copula (SJC Copula)

The SJC copula is an innovation of the 1997 Joe-Clayton copula. Previously, Joe-Clayton copula mathematically could be defined as follows:

\[ C_{jc}(u, v|\tau^u, \tau^L) = 1 - \left( [1 - (1 - u)^k]^{-\gamma} + [1 - (v)^k]^{-\gamma} \right) \frac{1}{1 - \gamma} \]  

(3.8)

where

\[ k = \frac{1}{\log_2(2 - \tau^u)} \]  

(3.9)

and

\[ \gamma = -\frac{1}{\log_2(\tau^L)} \]  

(3.10)
\[ \tau^U \in (0, 1), \tau^L \in (0, 1). \quad (3.11) \]

SJC has the characteristic of symmetric when \( \tau^U = \tau^L \) makes it more attractive than the original Joe–Clayton copula. This characteristic makes the SJC copula have the ability to capture the lower and upper tail dependence simultaneously. Therefore, this copula is able to meet the research objectives and help us to understand the tail behaviour of the data.

Based on the extended version of copula theory (Patton 2006a), SJC can be denoted as:

\[
C_{SJC}(u, v|\tau^U, \tau^L) = 0.5[C_{JC}(u, v|\tau^U, \tau^L) + C_{JC}(1 - u, 1 - v|\tau^U, \tau^L) + u + v - 1] \quad (3.12)
\]

where \( C_{JC} \) is the Joe–Clayton copula and \( \tau^U \) and \( \tau^L \) represent upper and lower tail dependence.

Mathematically, the evolution parameters for the SJC copula which be used to capture the dynamic of the upper and lower tail dependences can be denoted in the following way:

\[
\tau^{U/L} = \lambda \left( \omega^{U/L} + \beta^{U/L} \tau_{t-1} + \alpha^{U/L} \frac{1}{10} \sum_{i=1}^{10} |u_{1,t-i} - u_{2,t-i}| \right) \quad (3.13)
\]

where \( \lambda \) is given as the logistic transformation: \( \lambda(x) = (1 + e^{-x})^{-1} \), to ensure the dependence parameter \( \tau^{U/L} \) in interval of (0, 1).
3.3. Summary

We have outlined the fundamental aspects of EVT and copula in this chapter. The BMM method will be used in Chapter 4 to identify the best distributions that fit with minima and maxima series for the Chinese stock market.

The POT and copula method will be used to explain the dependence structure in the Chinese stock market. More details of research methodology regarding this can be found in Chapter 5 and Chapter 6, respectively.
CHAPTER 4: MODELING THE DISTRIBUTION OF EXTREME RETURNS IN THE CHINESE STOCK MARKET*

It is well known that extreme share returns on stock markets can have important implications for financial risk management. In this paper, we are concerned with the distribution of the extreme daily returns of the Shanghai Stock Exchange (SSE) Composite Index. Three well-known distributions in extreme value theory, i.e., Generalized Extreme Value (GEV), Generalized Logistic (GL) and Generalized Pareto distributions, are employed to model the SSE Composite index returns based on the data from 1991 to 2013. The parameters for each distribution are estimated by using the Power Weighted Method (PWM). Our results indicate that the GL distribution is a better fit for the minima series and that the GEV distribution is a better fit for the maxima series of the returns for the Chinese stock market. This is in contrast to the findings for other markets, such as the US and Singapore markets. Our results are robust regardless of the introduction of stock movement restriction and the global financial crisis. Further, the implications of our findings for risk management are discussed.

Keywords: Chinese stock market, extreme value theory, extreme returns, risk management

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4.1. Introduction and Literature Review

Extreme movements in share returns rarely occur. However, they can have devastating consequences when they do occur. Thus, it is important for investors, speculators and risk managers to comprehend extreme market movement events. Modeling the distribution of extreme stock returns has become a hot research topic, and it can contribute to the improvement in risk management.

In the finance literature, it is common to assume that the stock returns follow a Gaussian distribution. For example, Markowitz (1952) and Sharpe (1964) assume normality of the distribution for the stock returns in studying portfolio selection and deriving the capital asset pricing model; Black and Myron (1973) and Merton (1973) assume that the stock price follows the geometric Brownian motion in their option pricing model. More recently, Value at Risk (VaR) models developed and implemented by financial institutions also rely heavily on the Gaussian distribution.

The normality assumption implies that the stock return distribution is symmetric, which may not be true for right-skewed or left-skewed financial data. Previous studies including Longin (1996), Jondeau and Rockinger (2003), Tolikas and Gettinby (2009) have indicated that this assumption may lead to the underestimation of risk. It has been widely accepted that stock returns tend to be fat tailed rather than normally distributed. Thus, the normal distribution assumption is often inadequate in accounting for the catastrophic events and must be dropped for modeling the extreme stock returns.

The extreme value theory (EVT) is appealing for modeling the distribution of extreme stock returns because it focuses only on the extreme returns rather than all returns. EVT is a study on the distribution of extreme values of a random variable, and it has been applied widely in many fields such as hydrology, insurance and finance. It was first introduced by Fisher and Tippett (1928) and applied by Longin (1996), Embrechts et al. (1999) and Poon et al. (2004) in finance.
EVT is used to model the distribution of stock returns by specifically focusing on the tails. Parkinson (1980) reveals that the tail of the empirical distribution contains important information for the variance of returns. The fatness of the tails of the return distribution can be used to calculate the probabilities of a market crash and thus can contribute to the early warning of market risk (Jansen and De Vries, 1991). EVT is also used to the calculation of VaR. Further details can be seen in Cotter (2007), Allen et al. (2013), Marimoutou et al. (2009) and Karmakar (2013). These studies use the Peak Over Threshold (POT) method to model the extreme behavior in financial markets. The POT method considers the sorting of clustered phenomena that are frequently found in data. In contrast, there has been a decline in the number of studies of EVT by using the Block Maxima Minima (BMM) method, which defines extreme events as the maximum (minimum) value in each sub-period.

This research is concerned with the Chinese stock market and aims to identify the best distribution in modeling extreme stock returns by using the BMM method. The main distributions assigned to BMM are the Generalized Extreme Value (GEV), Generalized Logistic (GL) and Generalized Pareto (GP). Studies by Longin (1996), Jondeau and Rockinger (2003) and Gencay and Selcuk (2004) find that extreme stock returns in the US can be characterized by the GEV distribution, which can be used for calculating VaR measures and capital requirements. Gettinby et al. (2004 & 2006) find Generalized Logistic (GL) distribution fits better for extreme daily share return in the US, UK and Japan compared to GEV, in contrast to the previous research. More recently, Tolikas and Gettinby (2009) find that GL distribution is the best fit for the distribution of the extreme daily share returns in Singapore. In sum, the literature confirms that the best distribution for extreme share returns varies across share markets. This may be due to the economic environment and market mechanism of each market. Thus, it is of particular interest to consider the emerging markets such as the Chinese stock market.

This research aims to fill the gap in the literature by modeling the extreme stock returns in the Chinese stock market. Due to the similarity between the Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE), we focus on the SSE Composite Index, which consists of 950 stocks listed on the SSE.
Using the data of Shanghai Stock Exchange Composite Index (SSE Composite) from 1991 to 2013 (23 years), we model the extreme share daily returns of the SSE composite index by employing an EVT approach. Based on the literature review, we focus on the Generalized Pareto (GP), Generalized Extreme Value (GEV) and Generalized Logistic (GL). The parameters of each distribution are estimated by using the Probability Weighted Moments (PWM) method. Our research reveals that the GL distribution fits the empirical data better than the GEV and GP distribution for most intervals in minima series, while GEV distribution fits better for the maxima series of the returns for all intervals.

As a robustness check, we consider two important events during the period: the introduction of the restriction on the stock movement in Chinese stock market and the global financial crisis (GFC) of 2007-2008. For each event, we consider the pre- and post-event periods. It is demonstrated that there is no change in terms of the best distribution due to these events, though the GFC does have an impact with respect to the best distribution of the extreme stock returns during the GFC period.

Our findings have important implications for VaR calculation, risk managers, speculators and risk policies in understanding the distribution of extreme stock returns in the Chinese stock market.

The remainder of this paper is organized as follows. A background on the Chinese stock market is provided in Section 4.2. Section 4.3 describes the data and sample statistics. The research methodology is discussed in Section 4.4. Specifically, we discuss block maxima sampling, L-moment ratio diagram, parameters estimation and the goodness of fit test. Section 4.5 presents the empirical results. Section 4.6 discusses the implications of the findings for the Chinese stock market. A summary and concluding remarks are given in Section 4.7.
4.2. The Chinese Stock Market

The Chinese stock market has grown enormously in the past two decades due to its miraculous economic development, and it has become more and more influential among world stock markets. In terms of capitalization, the Chinese stock market has surpassed Japan and become the second largest stock market behind the US stock market since the end of 2007. There are two main stock exchanges in China, namely, the Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE). Both stock exchanges started trading in 1990. At the end of 2010, the total market capitalization for the Shanghai Stock Exchange was approximately 18,238 billion RMB with 901 listed companies (Chong et al., 2012).

The Chinese stock market is an emerging market with many interesting features. There are two types of shares in the Chinese stock market: A Shares and B Shares. A shares are restricted to domestic investors only, and B shares are available to both domestic and foreign investors. Initially, B Shares were stocks that were designated for foreign investors that were denominated in the Chinese local currency, the Renminbi (RMB), and were payable in foreign currency. However, the regulation changed in 2001; domestic traders can now trade B shares in US dollars as well. When the regulation was introduced, a great deal of B share prices went up significantly (Chen et al., 2007).

It is worth noting that there is a limit of 10 percent in the daily movement in share price since 16 December 1996 to curb excessive volatility. An additional important feature is that 70 percent of shares are non-tradable, held by the government, state-owned enterprises (SOEs) and Chinese institutions (Mookerjee and Yu, 1999). Thus, the Chinese government may have more influence on the Chinese stock market compared to developed markets such as the US and the UK.

Apart from restrictions on the daily movement and ownership, there are two other features in the Chinese stock market that can have a significant impact on the share price movement. First, short-sale trading is strictly prohibited in the Chinese stock market. This characteristic limits the supply of shares and affects the stock price formation. Second,
unlike developed markets, the major market participants in the Chinese stock market are individual investors. The number of A-share individual accounts is 57.59 million, which is in contrast to the 1.35 million accounts owned by institutional investors at the end of 2000. Thus, there are a huge number of unsophisticated individual investors in the market. With the low transparency in the market and the lack of qualified security analysts, individual investors can behave like noise traders, and they often trade on rumors and past price trends (Kang et al., 2002). With the short-sale prohibition, trading volume is likely to indicate the sentiment of these irrational investors.

The above-mentioned features make the study on the Chinese stock market interesting and challenging. The Chinese stock market has thus been extensively studied in the finance literature in recent years. For example, Xu (2000) studies the microstructure of the Chinese stock market; few studies, including Eun and Huang (2007) and Chan et al. (2006), consider the asset pricing in the Chinese stock market; Los and Yu (2008) and Zhu (2006) study the stock price and return properties in the Chinese stock market; the anomalies in the Chinese stock market are considered in Mookerjee and Yu (1999), and Naughton et al. (2008) study the trading strategies based on A- and B-share market segmentation.

Though there are many studies on the Chinese stock market in the literature, there is limited understanding of the behavior of its extreme stock returns. Recent studies in EVT demonstrate the need for understanding the financial market, especially during a financial crisis. Many studies so far focus on the developed stock markets including the United States (US), United Kingdom (UK) and Japan. To the best of our knowledge, no study has been performed in the Chinese market based on EVT. This study aims to fill this gap.

In this research, we also study the effect of the price restriction on the distributions of extreme returns in the Chinese stock market. The price restriction on the Chinese stock market was initially in force when the stock exchange started trading in 1990. The restriction was imposed on daily aggregate price fluctuations of the Shanghai stock

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4 Source, the websites of SSE and SZSE: www.sse.com.cn and www.sse.org.cn
market with the objective to promote share ownership and reduce volatility of the market. However, the restriction was lifted on 20 May 1992 in an attempt to promote trading between investors. On 21 May 1992, the SSE Composite Index jumped by approximately 71.92% as a result of the removal of the existing price limit restriction on shares. There are many positive returns greater than 10% from 1992 to 1996 in the Chinese stock market before the reintroduction of the price restriction.

External factors such as the recent Global Financial Crisis (GFC) can also affect the distributions of extreme returns in the Chinese stock market. GFC began on 9 August 2007 with the BNP Paribas announcement to stop activity in three hedge funds that specialized in the United States. Subsequently, it took a year for the crisis to hit a peak when the US government allowed the financial investment bank Lehman Brothers to go bankrupt on 15 September 2008. This indicated that governments would not always step in to bail out any bank that entered major trouble. Many measures such as fiscal stimulus activities of varying size, interest rate cutting and electronic money through quantitative easing have been taken to avoid a recession by many countries. The GFC has been widely regarded as the most serious crisis to hit the global economy since the Great Depression. In this paper, we thus assess the impact of the GFC by investigating the distribution of extreme stock returns in three sub-periods (pre-GFC, GFC and post-GFC).

4.3. Data and Sample Statistics

In this section, we describe the data and sample statistics. We present the descriptive statistics of extreme daily returns over various intervals including weekly (5 days), monthly (21 days), quarterly (63), half yearly (126 days) and yearly (252 days).

The daily Shanghai Stock Exchange (SSE) Composite Index levels from January 1991 to December 2013 (23 years) are obtained from Yahoo Finance. Daily returns are calculated as $R_t = \ln(P_t/P_{t-1})$, where $R_t$ is the return on the index for period $t$, $P_t$ is the index value at

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the end of period $t$, and $P_{t-1}$ is the index value at the end of the period $t - 1$. Figure 4.1 plots the index levels during the sample period, and Figure 4.2 plots the daily returns during the sample period.

Figure 4.1. Daily SSE Composite Index from 2, January 1991 to 31, December 2013

Figure 4.2. Daily SSE Composite Index from 2, January 1991 to 31, December 2013
Figure 4.1 indicates that the SSE composite index had a huge movement during 2007-2009, in which period the index climbed over 6000 points before it dropped to 2000 as a consequence of the global financial crisis, which led to stock market crashes worldwide.

Figure 4.2 indicates that the daily log returns remain between -10% and 10% after the price movement limit was reintroduced in 1996. The volatility of the SSE Composite Index is much higher during the 1992-1994 period.

It is worth mentioning that Figures 4.1 and 4.2 do not indicate extreme index and index return movements during the Asian financial crisis period (1997-98). This observation is consistent with the fact that the Asian financial crisis did not have a substantial impact on the Chinese economy, as claimed by Mitchell and Ong (2006).

Figure 4.3 displays the QQ plot of the daily log return against the normal distributions. Much of the data depart from the normal line for the lower and upper tails. This pattern indicates the existence of the fat tail phenomenon in the SSE Composite Index data. This justifies the use of the EVT to model the tail distributions.

Figure 4.3. QQ plot of daily log returns against the normal distribution
Table 4.1 reports the descriptive statistics for daily index returns as well as the maximum and minimum series for each interval (weekly, Monthly, Quarterly, Half-Yearly and Yearly).

A few observations can be made regarding the daily index return series. The lowest daily return is −17.9051%, and the highest daily return is 28.8610%. The mean is slightly positive, which indicates an upward movement in the share price. The average standard deviation is 2.1834%. The skewness for the whole period is 1.2065. The value of kurtosis is relatively high at 21.3223. These values indicate the non-normality of the distribution. Further, the Jarque-Bera (JB) test confirms the fat tail and non-normality of the distribution.

Similar observations regarding the distributions for the minima and maxima for each series can be made as follows. The average of the minima series is negative for all intervals. As expected, the value of minima returns decrease as the interval increases. The standard deviation of the minima series is between two to four for all intervals, which indicates the volatility are not too far apart from each other compared to the maxima series. The kurtosis of the minima for the weekly series is much higher compared to the other intervals. This indicates that the non-normality and fat tail of the minima series for the weekly interval are more evident than others. A similar pattern holds for the maxima series for each interval. The average of the maxima series is positive for all intervals. The lowest value for the standard deviation in the maxima series is 2.4137%, while the highest is 7.8544%.
Table 4.1. Descriptive Statistics

<table>
<thead>
<tr>
<th>N</th>
<th>Min (%)</th>
<th>Max (%)</th>
<th>Mean (%)</th>
<th>SD (%)</th>
<th>Skew</th>
<th>Kurt</th>
<th>J-B(p-value)</th>
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</thead>
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<tr>
<td><strong>Daily Returns</strong></td>
<td>5891</td>
<td>-17.9051</td>
<td>28.861</td>
<td>0.0355</td>
<td>2.1834</td>
<td>21.3223</td>
<td>113116.1(0.0000)</td>
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<tr>
<td><strong>Minima</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Weekly</td>
<td>1178</td>
<td>-17.9051</td>
<td>1.4718</td>
<td>-1.9017</td>
<td>2.0512</td>
<td>-2.0512</td>
<td>8.3015</td>
</tr>
<tr>
<td>Monthly</td>
<td>280</td>
<td>-17.9051</td>
<td>0.8639</td>
<td>-3.5369</td>
<td>2.7127</td>
<td>-1.7421</td>
<td>4.0446</td>
</tr>
<tr>
<td>Quarterly</td>
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<td>-17.9051</td>
<td>-0.1506</td>
<td>-4.9926</td>
<td>3.3495</td>
<td>-1.3306</td>
<td>1.7243</td>
</tr>
<tr>
<td>Half-yearly</td>
<td>46</td>
<td>-17.9051</td>
<td>-0.6525</td>
<td>-6.0578</td>
<td>3.6346</td>
<td>-1.1776</td>
<td>1.1031</td>
</tr>
<tr>
<td>Yearly</td>
<td>23</td>
<td>-17.9051</td>
<td>-2.0556</td>
<td>-7.4240</td>
<td>3.7732</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Weekly</td>
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<td>2.0192</td>
<td>2.4137</td>
<td>4.5615</td>
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<tr>
<td>Monthly</td>
<td>280</td>
<td>0.4117</td>
<td>28.8610</td>
<td>3.7870</td>
<td>3.6163</td>
<td>3.6804</td>
<td>18.9305</td>
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<tr>
<td>Quarterly</td>
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<td>28.8610</td>
<td>5.5298</td>
<td>4.9184</td>
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<td>10.0499</td>
</tr>
<tr>
<td>Half-yearly</td>
<td>46</td>
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<td>28.8610</td>
<td>6.8348</td>
<td>6.1655</td>
<td>2.3583</td>
<td>5.2930</td>
</tr>
<tr>
<td>Yearly</td>
<td>23</td>
<td>1.0039</td>
<td>28.8610</td>
<td>9.0727</td>
<td>7.8544</td>
<td>1.5220</td>
<td>1.0414</td>
</tr>
</tbody>
</table>

Notes: The return on 21 May 1992 is treated as an outlier and removed from the sample. N, Min, Max, Mean, SD, Skew and Kurt stand for the number of observations, minimum, maximum, the mean, the standard deviation, skewness and kurtosis for each series, respectively. JB denotes the statistic for the Jarque-Bera normality test with two degrees of freedom.

The skewness and kurtosis values indicate the non-normality of the distribution. Jarque-Bera tests further confirm the fat tail and non-normality of the distribution. Thus, the mean-variance framework applied in portfolio theory as the method of measuring the downside risk is not valid, and the application of EVT can be justified. The value of the JB test decreases as the interval increases. This implies that the tail is fatter for the short intervals. Comparing the two series, the Jarque-Bera test statistic is lower for the minima series than the maxima series. In sum, the SSE Composite Index returns are not normally distributed, as evidenced by the skewness and kurtosis for the entire sample period. Interestingly, the skewness and kurtosis are greater for the maxima returns than
for the minima series. This indicates that the upper tail is likely fatter than the lower tail. This may be due to the existing of many extreme positive returns.

To investigate the impact of the reintroduction of stock movement restriction, we consider two subsamples: May 1992–Dec 1996 without price restriction and Dec 1996–Dec 2001 with price restriction. The results are reported in Section 4.5.2.

Similarly, to consider the impact of GFC on the Chinese stock market, we consider the following three subsamples: Jan. 2002 to Aug. 2007 as the pre-GFC period, Jan. 2007 to Dec. 2010 as the GFC period⁶, and Apr. 2009 to Dec. 2013 as the post-GFC period.

⁶ Due to the fact that we need a sufficient number of observations for the estimates and the follow-on events of the GFC such as the European debt crisis in 2010, the GFC period is taken until Dec. 2010 instead of Apr. 2009.
4.4. Methodology

In this section, we outline the methodology for applying the EVT to model the extreme stock returns in the Chinese stock market. We first describe the GEV and GL distributions, which are commonly used for EVT. Then, we introduce the L-Moment ratio diagram for identifying a suitable extreme distribution. The parameter estimation and the goodness of fit test are also discussed.

4.4.1. GEV and GL Distribution

Extreme events can be modeled either by the BMM method or the POT method. Because we are interested in studying the extreme movement in the selected sub-periods, BMM is suitable for this research.

The intervals in our consideration are the weekly, monthly, quarterly, half-yearly and yearly minima and maxima. These minima and maxima daily returns are collected over non-overlapping successive selection intervals of 5 days (weekly), 21 days (monthly), 63 days (quarterly), 126 days (semester) and 252 days (yearly). Given the time series of daily index returns \( r_1, r_2, r_3...r_n \), the series can be divided into non-overlapping time intervals of length \( m \). The time series of the extreme maximum will then be \( X_1 = \max(r_1, ..., r_m), X_2 = \max(r_{m+1}, ..., r_{2m}), ..., X_{n/m} = \max(r_{n-m}, ..., r_n) \). According to Fisher and Tippett (1928), the distribution of the extreme series is best fitted with the GEV, which is assumed to be independent and identical. GEV is known as a three-parameter distribution defined as:

\[
 f(x) = \alpha^{-1} e^{-\{(1-k)y - e^{-y}\}}, \text{ where } y = \begin{cases} \frac{-K^{-1} \log\{1 - K(x - \beta)/\alpha\}}{K}, & K \neq 0 \\ \frac{(x - \beta)}{\alpha}, & K = 0 \end{cases} \quad (4.1)
\]

The parameters are referred to as the location (\( \beta \)), scale (\( \alpha \)) and shape (\( \kappa \)). The location parameter (\( \beta \)) is analogous to the mean and the scale (\( \alpha \)) parameter is analogous to the
standard deviation. The shape parameter \( \kappa \) determines the fatness of the tail of the distribution. The larger the value of shape parameter \( \kappa \), the fatter the tail is.

According to Peel et al. (2001), this 3-parameter distribution is particularly effective in describing the probability distributions of extreme events in environmental studies. Further, a few special cases of the GEV distribution are worth mentioning. The Frechet distribution is obtained when \( \beta + \alpha / \kappa < x \leq \infty \), where \( \kappa < 0 \). Known as the reverse of GEV, the Weibull distribution is obtained when \( K > 0 \) with \( -\infty < x \leq \beta + \alpha \). The Gumbel distribution is obtained when \( K = 0 \) with \( -\infty < x < \infty \).

There is strong evidence that autocorrelation and heteroskedasticity persist in the financial data. With most stock market index returns, GL distribution appears to be a better fit than GEV distribution for extreme returns (Tolikas, 2008). The GL function is given as:

\[
f(x) = \alpha^{-1} e^{-(1-K)y} / (1 + e^{-y})^2, \text{ where } y = \begin{cases} -K^{-1} \log \left( 1 - \frac{K(x - \beta)}{\alpha} \right), & K \neq 0 \\ \frac{(x - \beta)}{\alpha}, & K = 0 \end{cases}
\]

The logistic distribution is obtained when \( K = 0 \) for \( -\infty < x < \infty \), when \( K < 0 \) for \( \beta + \alpha / \kappa < x \leq \infty \) and when \( K > 0 \) for \( -\infty < x \leq \beta + \alpha \).

### 4.4.2. L-Moment Ratio Diagram

To select a probability distribution for a set of empirical data, we apply the L-moment ratio diagram, which is a graphical test introduced by Hosking (1990). The diagram involves five distributions: Generalized Extreme Value (GEV), Generalized Pareto (GP), Generalized Logistic (GL), Gumbel (G) and Normal (N).

The L-moment, \( \lambda_r \) for a random variable \( X \) is defined as:

\[
\lambda_r = r^{-1} \sum_{k=0}^{r-1} (-1)^k \binom{r-1}{k} EX_{(r-k)} \quad r = 1, 2 \ldots
\]
where $EX_{(r-k):r}$ is the expectation of the $(r-k)^{th}$ extreme order statistic. The first two moments, $\lambda_1$ and $\lambda_2$, are measures of location and scale. The L-moment ratios, $T_3 = \lambda_1/\lambda_2$ and $T_4 = \lambda_2/\lambda_2$, are measures of skewness and kurtosis, respectively.

The values of the L-moment ratios for common continuous probability distributions are normally constant. For example, the value of $T_3$ is 0.1226, while the value of $T_4$ is 0 for a normal distribution. However, for more complex distributions including GEV, GL: and GP, L-moment ratios are not constant.

In the L-moment ratio diagram, L-kurtosis values are plotted against the L-skewness values. The diagram contains the points and curves of the theoretical distributions. The best distribution for the data is identified by plotting the estimated $T_3$ and $T_4$ and choosing the distribution for which the L-skewness and L-kurtosis theoretical curve is closest to the plotted point.

**4.4.3. The Parameter Estimation**

It is common to use the maximum likelihood (ML) method to estimate the parameters of a distribution. However, Tolikas (2008) and Gettinby et al. (2004) suggest the use of probability weighted moments (PWM) to estimate parameters for GEV, GL and GP in modeling the extreme returns of financial series.

PWM is the expectation of certain functions of a random variable $X$ with distribution function $F$, the mean of which exists and its distribution can be written in inverse form. According to Hosking (1986), PWM can be defined as:

$$\alpha_r = E[X \{1 - F(X)\}]^r, \ r = 0,1 ...$$  \hspace{1cm} (4.4)

where $E[X(...)]$ is the expectation of the quartile function of a random variable $X$. The PWM method estimates the parameters of a distribution by equating the sample moments to those of the fitted distribution.
Compared to the ML method in parameter estimation, the PWM method can yield a lower root mean-square error. More specifically, the PWM method is able to obtain less biased parameter and quantile estimates. In addition, this approach has the ability to minimize sampling error for the parameter estimate compare to ML. The estimation of parameters and quantiles by the PWM method are found to be much more efficient for GEV distribution than those estimated by the ML method (Hosking et al. (1985), Hosking and Wallis (1987) and Moharram et al. (1993)).

4.4.4. The Goodness of Fit Measure

After a distribution is fitted to the empirical data, it is important to test the goodness of fit of the chosen distribution. There are many goodness of fit tests. In this paper, we consider Anderson Darling Test (AD), which is described below.

4.4.4.1. Anderson Darling (AD) Test

The Anderson Darling test is the modified version of the Cramer-von Mises (CvM) test. This test yields better results compared to the CvM, test as it gives more weight to the tails of the distribution. According to Arshad et al. (2003), the AD test is the most powerful tool for the empirical distribution function (EDF) test. Much of the time, it performs better than the Kolmogorov Smirnov test in terms of power statistical comparisons. Thus, we choose the AD test for the goodness of the fit test in the paper.

The test statistic for Anderson Darling is defined as:

$$\int_{-\infty}^{\infty} [F_n(x) - F(x)]^2 \phi(x) dF(x)$$  \hspace{1cm} (4.5) $$

where $F_n(x)$ denotes the empirical distribution function (EDF) of a random variable $X$, $F(x)$ is the cumulative distribution function (CDF) of $X$, $n$ denotes the number of observations and $\phi(x)$ is a function that assigns weight to the squared difference $[F_n(x) - F(x)]^2$. 

50
When $\varnothing(x) = [F(x)(1 - F(x))]^{-1}$, the test statistic concentrates on calculating discrepancies in both tails; if either $F(x)$ or $[1 - F(x)]$ is small or $\varnothing(x)$ is large.

According D'Agostino and Stephens (1986), the Anderson-Darling (AD) goodness of fit test can be more effective in a small sample than the Pearson chi-squared test. The lower the value for the AD test statistic, the better is the fit for the empirical data.

**4.5. Empirical Results**

In this section, we present the empirical results. We first discuss the L-moment ratio diagrams and then present and analyse the results on the parameter estimation for the GEV and GL distributions and goodness of fit tests.

Figures 4.4 and 4.5 present the L-moment ratio diagrams for the minima and maxima series, respectively. For each series, the L-skewness and L-kurtosis are calculated and plotted on the graph, with each point representing one of the five intervals of weekly, monthly, quarterly, half-yearly and yearly. In addition, the L-moment ratio curves for Generalized Logistic, Generalized Extreme Value, Generalize Pareto, Gumbel and Normal distributions are also plotted.

For the minima series, Figure 4.4 indicates that the L-moment ratios for the five intervals are between the L-moment ratio curves for the GL and GEV distributions. For the 4.5 maxima, Figure 4.5 indicates that the L-moment ratios for the 5 intervals are very close to the L-moment ratio curves for the GL and GEV distributions. Hence, the Normal, Gumbel and GP distributions can be eliminated from further consideration.
4.5.1. Distributions over the Whole Sample Period

We now turn to the estimate the parameters for the GEV and GL distributions based on the minima and maxima series of the SSE Composites index returns from 1991 to 2013. The results are presented in Tables 4.2 and 4.3 for the GEV and GL distributions, respectively.
Table 4.2. Parameter estimates for GEV distribution

<table>
<thead>
<tr>
<th></th>
<th>Shape</th>
<th>Scale</th>
<th>Location</th>
<th>AD</th>
<th>p-value</th>
</tr>
</thead>
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<td><strong>Minima</strong></td>
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<tr>
<td>Weekly</td>
<td>-0.9318</td>
<td>2.0168</td>
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<tr>
<td>Yearly</td>
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<td>-7.9817</td>
<td>0.1346</td>
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<tr>
<td><strong>Maxima</strong></td>
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<td></td>
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</tr>
<tr>
<td>Weekly*</td>
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<td>Half-yearly</td>
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<td>Yearly*</td>
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<td>3.4686</td>
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</table>

Notes: This table displays the parameter estimates and goodness of fit figures for the GEV distribution for the minima and maxima series of the 5 intervals over the sample period. AD denotes the Anderson-Darling test. p-value denotes the probability of such a fit being obtained in a random sample from a GEV distribution. * means the considered distribution is a better fit than the other one based on the AD test.
Table 4.3. Parameter estimates for GL distribution

<table>
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<th>Location</th>
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<th>p-value</th>
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<td>-0.2842</td>
<td>1.5432</td>
<td>-4.1979</td>
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</tr>
<tr>
<td>Half-yearly*</td>
<td>-0.2614</td>
<td>1.7435</td>
<td>-5.2447</td>
<td>0.3565</td>
<td>0.7401</td>
</tr>
<tr>
<td>Yearly*</td>
<td>-0.2111</td>
<td>2.0166</td>
<td>-6.6861</td>
<td>0.1318</td>
<td>0.9854</td>
</tr>
<tr>
<td><strong>Maxima</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Weekly</td>
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<td>0.9382</td>
<td>1.3445</td>
<td>50.2700</td>
<td>0.0015</td>
</tr>
<tr>
<td>Monthly</td>
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<td>1.1276</td>
<td>2.8065</td>
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</tr>
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<td>Quarterly</td>
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</tr>
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<td>Half-yearly*</td>
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</tr>
<tr>
<td>Yearly</td>
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<td>2.8050</td>
<td>6.6027</td>
<td>0.4563</td>
<td>0.7895</td>
</tr>
</tbody>
</table>

Notes: This table displays the parameter estimates and goodness of fit figures for the GL distribution for the minima and maxima series of the 5 intervals over the sample period. AD denotes the Anderson-Darling test. p-value denotes the probability of such a fit being obtained in a random sample from a GL distribution. * means the considered distribution is a better fit than the other one based on the AD test.

The shape parameter estimates for the Chinese stock market reveal some interesting facts. For example, the shape parameter estimates for the minima series for GEV distribution increases from -0.9318 for Weekly to -0.7055 for the Yearly interval. For the maxima series, the shape parameter estimate increases as the time interval increases. Hence, the tails for both distributions become fatter for larger intervals. Similar observations can be observed for the GL distribution from Table 4.3.

It is known that the scale parameter is related to the volatility. For GEV distribution, the scale parameter estimate increases from 2.0168 to 4.3560 for the minima series and 1.2841 to 3.4686 for the maxima series as the interval increases from Weekly to Yearly. For GL distribution, we can see that the scale parameter estimates increase from 0.8541
to 2.0166 for the minima series and 0.8166 to 2.9719 for the maxima series as the interval increases from Weekly to Yearly. This is consistent with the intuition that extreme daily returns are more volatile for a longer period of the time interval.

Based on the AD statistics in Tables 4.2 and 4.3, we can find the better fit distribution among GEV with the GL for each series. Our results indicate that GL distribution fits better than GEV distribution for the minima series for all five intervals. However, GEV fits better for the maxima series for all intervals except the Half-yearly interval. Overall, we can claim that GEV fits the maxima series better, while GL is a better fit for the minima series.

4.5.2. The Impact of Stock Movement Restriction

As the robustness check of our results, we here consider the impact due to the introduction of the stock movement restriction in 1996. The above analysis for the whole sample period is thus carried out for two sub-periods: May 1992 to Dec 1996 without the 10 percent daily movement restriction and Dec. 1996 to Dec. 2001 with the 10 percent daily movement restriction. The results are reported in Table 4.4 for GEV and in Table 4.5 for GL. Note that due to the limited number of observations for each sub-period, we present the results only for three time intervals, i.e., Weekly, Monthly and Quarterly.
Table 4.4. Parameter estimates for GEV distribution before and after stock movement restriction

<table>
<thead>
<tr>
<th>Period</th>
<th>Interval</th>
<th>Shape</th>
<th>Scale</th>
<th>Location</th>
<th>AD</th>
<th>p-value</th>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>May 1992 - Dec 96</td>
<td>Weekly</td>
<td>-0.9117</td>
<td>2.9796</td>
<td>-3.5022</td>
<td>42.1100</td>
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</tr>
<tr>
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<td>Monthly</td>
<td>-0.9121</td>
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<td>Quarterly*</td>
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<td>4.7584</td>
<td>-9.6864</td>
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<td>0.6892</td>
</tr>
<tr>
<td>Dec 1996 - Dec 2001</td>
<td>Weekly</td>
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<td>-1.5265</td>
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<td>0.9765</td>
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<tr>
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<td></td>
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</tr>
<tr>
<td>May 1992 - Dec 96</td>
<td>Weekly*</td>
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<td>1.7733</td>
<td>0.4216</td>
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<td>7.9172</td>
<td>0.2725</td>
<td>0.9337</td>
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<tr>
<td>Dec 1996 - Dec 2001</td>
<td>Weekly</td>
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<td>0.8679</td>
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<td>Quarterly*</td>
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<td>2.9556</td>
<td>0.2365</td>
<td>0.9451</td>
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</table>

Notes: This table displays the parameter estimates and goodness of fit figures for the GEV distribution for the minima and maxima series of the 3 intervals over the sub-periods. AD denotes the Anderson-Darling test. p-value denotes the probability of such a fit being obtained in a random sample from a GEV distribution. * means the considered distribution is a better fit than the other one based on the AD test.
Table 4.5. Parameter estimates for GL distribution before and after stock movement restriction

<table>
<thead>
<tr>
<th>Period</th>
<th>Interval</th>
<th>Shape</th>
<th>Scale</th>
<th>Location</th>
<th>AD</th>
<th>p-value</th>
</tr>
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<tbody>
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<td></td>
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</tr>
<tr>
<td>Minima</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>May 1992 - Dec 1996</td>
<td>Weekly*</td>
<td>-0.2987</td>
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<td>-2.6954</td>
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<td>0.5731</td>
</tr>
<tr>
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<td>Monthly*</td>
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<td>-5.3450</td>
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<td>0.6933</td>
</tr>
<tr>
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<td>Quarterly</td>
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</tr>
<tr>
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<td>Weekly*</td>
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<td>0.7539</td>
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<tr>
<td>Maxima</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>May 1992 - Dec 1996</td>
<td>Weekly</td>
<td>0.3744</td>
<td>1.4908</td>
<td>2.5652</td>
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<td>0.8873</td>
</tr>
</tbody>
</table>

Notes: This table displays the parameter estimates and goodness of fit figures for the GL distribution for the minima and maxima series of the 3 intervals over the sub-periods. AD denotes the Anderson-Darling test. p-value denotes the probability of such a fit being obtained in a random sample from a GL distribution. * means the considered distribution is a better fit than the other one based on the AD test.

According to Tables 4.4 and 4.5, the scale parameter estimates increase as the interval increases regardless of the sub-periods. This reconfirms the fact that there is a higher volatility in the stock returns for a longer time interval. Similar observations for the shape and location parameter estimates can be said as for the whole sample period. The values of scale parameter are higher before the restriction on the stock market is reintroduced. This indicates that the volatility of the stock index is higher before stock price movement restriction reintroduction.
However, a comparison of Table 4.4 with Table 4.5 reveals that GL distribution is a better fit for the minima series for the Weekly and Monthly intervals. For the maxima series, GEV distribution is a better fit for all intervals except Weekly interval after restriction reintroduction. Overall, the change of the regulation does not affect the types of distribution for extreme returns of the SSE index. This can be explained as follows.

First, the 10% restriction on stock market movement appears to be too high for the index because the average movement for the SSE index is between -1% and 1%. Hence, the impact of the stock movement restriction is limited on the SSE index. Second, the majority of the traders or investors in the Chinese stock market are individuals who have limited resources to swing the market. The selected index consists of for the most part the blue chip stocks that are hard to manipulate. Thus, the stock price movement restriction of 10% rarely comes into effect for the stocks in the SSE composite index.

In sum, the best-fit distribution results for the whole sample periods hold regardless of the stock price movement restriction regulation.

**4.5.3. The Impact of the GFC**

In this section, we investigate the impact of the GFC on the Chinese stock market with respect to the distribution of extreme returns. According to Dungey and Zhumabekova (2001) and Wen et al. (2012), the test of effect can be seriously affected by the size of the “crisis” and “non-crisis” period. For this study, three subsamples are considered: Jan. 2002 to Aug. 2007 as the pre-GFC period, Jan. 2007 to Dec. 2010 as the GFC period, and Apr. 2009 to Dec. 2013 as the post-GFC period. The results are reported in Table 4.6 for GEV and Table 4.7 for GL.
Table 4.6. Parameter estimates for GEV distribution during GFC

<table>
<thead>
<tr>
<th>Period</th>
<th>Interval</th>
<th>Shape</th>
<th>Scale</th>
<th>Location</th>
<th>AD</th>
<th>p-value</th>
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<tbody>
<tr>
<td></td>
<td>Minima</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jan. 2002 – July. 2007</td>
<td>Weekly</td>
<td>-0.4973</td>
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<td>-1.5426</td>
<td>12.3910</td>
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<tr>
<td></td>
<td>Pre-GFC</td>
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<td>-0.7668</td>
<td>1.0485</td>
<td>8.4585</td>
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<td></td>
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<td>-1.3395</td>
<td>1.0835</td>
<td>7.4026</td>
<td>0.8848</td>
</tr>
<tr>
<td>Jan. 2007 – Dec. 2010</td>
<td>Weekly</td>
<td>-0.6779</td>
<td>2.2054</td>
<td>-2.6895</td>
<td>8.2477</td>
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<tr>
<td></td>
<td></td>
<td>Quarterly*</td>
<td>-0.4715</td>
<td>2.2510</td>
<td>0.2322</td>
<td>0.9719</td>
</tr>
<tr>
<td>Apr. 2009 – Dec. 2013</td>
<td>Weekly</td>
<td>-0.7328</td>
<td>1.2615</td>
<td>-1.6892</td>
<td>16.5760</td>
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</tr>
<tr>
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<td>Post-GFC</td>
<td>Monthly*</td>
<td>-0.8139</td>
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<td>0.2322</td>
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<td>Maxima</td>
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</tr>
<tr>
<td>Jan. 2002 – July. 2007</td>
<td>Weekly*</td>
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Notes: This table displays the parameter estimates and goodness of fit figures for the GEV distribution for the minima and maxima series of the 3 intervals over the three sub-periods. AD denotes the Anderson-Darling test. p-value denotes the probability of such a fit being obtained in a random sample from a GEV distribution. * means the considered distribution is a better fit than the other one based on the AD test.
Table 4.7. Parameter estimates for GL distribution during GFC

<table>
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<tr>
<th>Period</th>
<th>Interval</th>
<th>Shape</th>
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<th>Location</th>
<th>AD</th>
<th>p-value</th>
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<td></td>
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</tr>
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<td>Weekly*</td>
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<td>0.4060</td>
<td>0.7536</td>
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<td>0.9414</td>
</tr>
<tr>
<td>Apr. 2009 – Dec. 2013</td>
<td>Weekly</td>
<td>0.0119</td>
<td>0.5233</td>
<td>1.3293</td>
<td>0.6761</td>
<td>0.7656</td>
</tr>
<tr>
<td>Post-GFC</td>
<td>Monthly*</td>
<td>0.1304</td>
<td>0.4942</td>
<td>2.3285</td>
<td>0.1847</td>
<td>0.9916</td>
</tr>
<tr>
<td></td>
<td>Quarterly*</td>
<td>0.0133</td>
<td>0.5187</td>
<td>3.1395</td>
<td>0.1755</td>
<td>0.9947</td>
</tr>
</tbody>
</table>

Notes: This table displays the parameter estimates and goodness of fit figures for the GL distribution for the minima and maxima series of the 3 intervals over the three sub-periods. AD denotes the Anderson-Darling test. p-value denotes the probability of such a fit being obtained in a random sample from a GL distribution. * means the considered distribution is a better fit than the other one based on the AD test.
A few interesting observations can be made from Tables 4.6 and 4.7. First, let us consider the pre- and post-GFC periods. Similar to Tables 4.4 and 4.5, GL distribution is a better fit for the minima series for all intervals, and GEV distribution is a better fit for the maxima series with many of the intervals regardless of the pre- or post-GFC periods. The only exception is that GL distribution appears to be a better fit for the maxima series for the Quarterly interval in the post-GFC period. Further, the values of the shape parameter are negative for the minima series for both pre- and post-GFC periods. This indicates that the minima series has a fatter tail. The values of the shape parameter for the post-GFC period are lower than the ones for the pre-GFC period. This implies that the downside risk is larger before GFC than after GFC. Finally, the values of the scale parameter for the post-GFC period are similar to the ones for the pre-GFC period. This implies that there is no long-term impact of GFC on the volatility of the extreme stock returns.

Next, let us consider the GFC period. The best distributions swing between GL and GEV for different intervals for both the minima series and maxima series during the GFC period. In other words, there is no single distribution that is consistently better for all time intervals for either the maxima or minima series. Thus, GFC had a significant impact on the distribution of extreme stock returns in the Chinese stock market during the GFC period.

Overall, we can claim that there is no long-term change with respect to the best distributions of extreme stock returns in the Chinese stock market due to the GFC, although a significant impact is found during the GFC period.

In summary, our empirical results in this section reveal that both GL and GEV are needed for modeling the extreme stock returns for the Chinese stock market. GL is better at modeling the downside extreme market movements, while GEV is better at modeling the upside extreme market movements. It is worth noting that the results for the Chinese stock market are in stark contrast to the ones for the majority of other markets in the literature, in which only one distribution (either GL or GV) for each market is found to be a better fit for both types of extreme market movements. It is also demonstrated that there is no long-term change with respect to the best distributions of extreme stock returns in
the Chinese stock market due to the GFC, although a significant impact is found during the GFC period.

4.6. Implications for the Chinese Stock Market

The improvement in modeling the distribution of the tails can bring benefits to risk management. VaR is one of the most widely used models for measuring market risk due to its simplicity. In essence, VaR tells us how much we can lose over a certain time horizon with a given probability. According to the Basel Committee on Banking Supervision (1996), banks are required to hold enough capital to cover losses with the 99% time horizon over a 10-day horizon. This has further made the VaR more popular.

The tail distribution is important for VaR calculation. Thus, we examine the percentage of obtaining a daily return within the intervals for the selected distributions. The results are reported in Table 8 for the whole sample period (Jan. 1991 to Dec. 2013) as well as for the two sub-periods\(^7\) (May 1992 to Dec. 1996 and Dec. 1996 to Dec. 2013, representing before and after the stock movement restriction reintroduction, respectively) below.

\(^7\) It should be noted that the sub-period after the stock movement restriction is different from the one used in Section 4.5.2., in which it is a five-year period for the purpose of matching the one before the stock movement restriction.
Table 4.8. Probability (%) of obtaining a daily return within specific intervals for the lower tail

<table>
<thead>
<tr>
<th>Interval (%)</th>
<th>[μ−1σ, μ−2σ]</th>
<th>[μ−2σ, μ−3σ]</th>
<th>[μ−3σ, μ−4σ]</th>
<th>[μ−4σ, μ−5σ]</th>
<th>[μ−5σ, μ−6σ]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Empirical</td>
<td>6.2129</td>
<td>1.7315</td>
<td>0.5602</td>
<td>0.2207</td>
<td>0.1019</td>
</tr>
<tr>
<td>Normal</td>
<td>13.5905</td>
<td>2.1400</td>
<td>0.1318</td>
<td>0.0032</td>
<td>0.0000</td>
</tr>
<tr>
<td>GEV</td>
<td>7.0106</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>GL</td>
<td>9.2347</td>
<td>1.2265</td>
<td>0.1457</td>
<td>0.0176</td>
<td>0.0021</td>
</tr>
<tr>
<td>Empirical</td>
<td>7.3887</td>
<td>1.7632</td>
<td>0.5038</td>
<td>0.0840</td>
<td>0.0000</td>
</tr>
<tr>
<td>Normal</td>
<td>13.5905</td>
<td>2.1400</td>
<td>0.1318</td>
<td>0.0032</td>
<td>0.0000</td>
</tr>
<tr>
<td>GEV</td>
<td>8.9951</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>GL</td>
<td>9.9772</td>
<td>0.9000</td>
<td>0.0447</td>
<td>0.0011</td>
<td>0.0000</td>
</tr>
<tr>
<td>Empirical</td>
<td>8.6227</td>
<td>1.7015</td>
<td>0.6208</td>
<td>0.3219</td>
<td>35.7143</td>
</tr>
<tr>
<td>Normal</td>
<td>13.5909</td>
<td>2.1401</td>
<td>0.1318</td>
<td>0.0032</td>
<td>0.0000</td>
</tr>
<tr>
<td>GEV</td>
<td>9.3153</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>GL</td>
<td>9.9705</td>
<td>1.4001</td>
<td>0.1577</td>
<td>0.0154</td>
<td>0.0014</td>
</tr>
</tbody>
</table>

Note: This table presents the probabilities of obtaining a daily return within specific intervals under certain distributions. The intervals are defined as the numbers of daily standard deviations away from the daily mean return. For each period, μ denotes the overall daily mean, and σ denotes the overall daily standard deviation.

Table 4.8 reports the probability of obtaining a daily return within the specific intervals in a single day according to the distributions under consideration, which are: [μ−1σ, μ−2σ], [μ−2σ, μ−3σ], [μ−3σ, μ−4σ], [μ−4σ, μ−5σ] and [μ−5σ, μ−6σ],
where $\mu$ and $\sigma$ are the mean and standard deviation of the daily returns over the period examined.

According to Table 4.8, the normal distribution appears to yield better estimation than GEV distribution for the downside market movement risk. For most intervals, GEV is unable to capture the existing distribution of risk.

As expected, GL distribution yields better estimation for the majority of intervals than the normal distribution. GL also gives higher probabilities for the majority of intervals than the normal distribution for the downside market risk. For example, in the whole period, the percentage of obtaining the empirical frequency within $[\mu - 4\sigma, \mu - 5\sigma]$ is 0.2207%. GL distribution gives a percentage frequency of 0.0176%, which is closer to the empirical frequency than the one provided by the normal distribution. In contrast, GEV distribution performs the worst, as it gives a 0 probability for this interval.

For the sub-period of May 1992 to Dec. 1996, the normal distribution captures the frequency of returns in the selected intervals better than the GL distribution. However, for the sub-period Dec. 1996 to Dec. 2013, many of the frequency returns can be captured by using GL distribution. Although the value is not too close, the result still gives a better explanation for the daily returns than GEV and the normal distribution. The normal distribution seems to capture the downside market risk better than GEV in many intervals, regardless of the whole sample period or the two sub-periods. GEV only works for interval $[\mu - 1\sigma, \mu - 2\sigma]$.

Overall, the results indicate that GL is a better distribution for the downside market risk for the Chinese stock market. This is consistent with our findings in the previous section.
Figure 4.6 illustrates the difference that the extreme value analysis can make to the VaR calculation. This figure indicates the lower tail of the daily returns of the Shanghai Stock Composite Index from 1991 to 2013. We plot the cumulative density function (CDF) of the GL, GEV and the normal for the comparison purpose. The monthly minima of the daily returns are used to estimate the parameters of each distribution.

According to Figure 4.6, the GL distribution behaves similarly to the SSE Composite Index, whereas the GEV and normal distributions are more apart from the actual observations. As a result, the normality or GEV distribution assumption may lead to severe underestimation of market risk.

4.7. Summary and Concluding Remarks

In this paper, we model the empirical distribution of the extreme daily stock returns in the Chinese stock market over the period 1991 to 2013 by applying the EVT. The Chinese stock market is considered due to its importance and its unique features as an emerging market.
This study is carried out using the BMM method instead of the often used POT method. Our research reveals that the GEV distribution is the best fit for modeling the extreme upward stock market movements, while GL is the best fit for modeling the extreme downward stock market movements. Further, the sub-period analysis indicates that this conclusion holds regardless of the daily share price restriction and the GFC. It is also demonstrated that our findings can improve the VaR calculation for the Chinese stock market, which can have important implications for the stock market risk management.

Our findings for the Chinese stock market are different from the findings for other markets in the literature. GEV and GL distributions are found to be good to model the extreme upside and downside market movements for China, respectively. However, one distribution is normally found to be the best to model both types of extreme movements for other markets in the literature. This may be due to the unique features associated with the Chinese stock market. For example, the effective free-float of the shares in the Chinese market is low. Approximately 70 percent of the shares are non-tradable and held by the government, state-owned enterprise (SOEs) and Chinese institutions. The restricted number of shares available for domestic investors implies a possible artificially strong demand in the Chinese stock market. This is further fuelled by the strong increase in economic wealth (GDP) together with limited alternative investments opportunities and the high savings rate of the Chinese population (Mitchell and Ong, 2006). These empirical findings provide a new understanding of the best distribution to describe extreme behavior for the Chinese stock market.

In addition, our research provides support to the claim that GL distribution does deserve the serious consideration of financial risk analysts in modeling extreme stock market movements (Tolikas and Gettingby, 2009).

It is also demonstrated that there is no long-term change with respect to the best distributions of extreme stock returns in the Chinese stock market due to the stock movement restriction or the GFC, although a significant impact is found during the GFC period. These findings can bring new information for investors or risk managers to understand the current situation in the Chinese stock market and help to improve the measurement of stock market risk.
Finally, we would like to note that this study has a narrow focus and that it is only the first step in modeling the extreme returns in the Chinese stock market. The research presented in this paper can be extended in several aspects. For example, further research can be carried out to compare the EVT approach with the GARCH-based approach in estimating VaR. One can apply the conditional EVT and conditional correlation and copulas (CCC) to investigate the dependency between the Chinese stock market and other major global stock markets. These are left for a future research.
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CHAPTER 5: THE DEPENDENCE STRUCTURE BETWEEN CHINESE AND OTHER MAJOR STOCK MARKETS USING EXTREME VALUES AND COPULAS*

This study employs the extreme value theory (EVT) and stochastic copulas to investigate the dependence structure between the Chinese stock market and other major stock markets including the US, Canada, UK, Germany, Japan and Australia. Our research reveals that the dependence between the Chinese stock market and the developed markets is low. Furthermore, our study indicates Chinese stock market has stronger dependence with Asia and Europe than the US. Among all 6 pairs, the dependence between Chinese and US stock markets is the lowest and that between China and Australia is the highest. It is also found that US and UK do not have significant upper tail dependence with Chinese stock market and the dependence between China and Japan is strong but has weakened since 2012. Overall, diversification across all 6 pairs of stock markets is not effective.

Keywords: Copula, Extreme value theory, Dependence structure, Chinese stock market

* This chapter is reproduced from a paper under review by International Review of Economics & Finance. This chapter has its reference section and style according to this particular journal’s requirements. To accommodate with the thesis flow, figure numbers have been changed and differ from the original submission draft.
In recent years, the dependence structure between stock markets has attracted more and more attention due to the highly volatility and fat tailed distributions associated with the markets. An increase in dependence or correlation can increase the prospect of financial losses. In particular, the existence of asymmetric dependence structure in some periods can have an important impact on international diversification. Therefore, it is important to understand the dependence structure between stock markets for investment and risk management.

Many studies have been done on the dependence structure and most of them tend to focus on the developed markets (Longin and Solnik, 2001; Ang and Chen, 2002; Ane and Labidi 2006; Jondeau and Rockinger 2006; Bartram et al. 2007; Bhatti & Nguyen 2012). However, few studies have been done on the emerging markets including the Chinese stock market.

In this paper, we focus on the Chinese stock market for the following reasons. First, China is the world's second largest economy and it has a close relationship with the rest of the world in terms of international trade and investment. Therefore, any change in the Chinese stock market can have important impact to others. The Chinese stock market has experienced drastic changes since 1990 (He, Wang, & Wu 2013) and is still an emerging market. The Chinese stock market will be more and more influential in the world as the Chinese economy grows.

Second, the Chinese stock market has some unique features which make this study interesting and challenging. There are two main stock exchanges in China: the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE). Most companies listed on the SHSE are state-owned and large while those on the SZSE are mostly small and export-oriented joint-ventures. There are two classes of shares listed and traded on both exchanges and these are known as A- and B-shares. A-shares are restricted to local or domestic investors while B shares are only available to foreign investors. US dollars have been used as the foreign currency for B-shares on SHSE and Hong Kong dollars.
for B-shares on SZSE. Opening up the B-share market to domestic investors in 2001 has been considered a very important government initiative to integrate Chinese stock markets with the rest of the world. In this study, we use the CSI300 Composite Index to represent the overall performance of Chinese stock market. This index was introduced on April 8, 2005 and consists of 300 stocks traded in the Shanghai and Shenzhen stock exchanges.

Third, the Chinese stock market is often very volatile due to excessive speculation. The major force driving Chinese stock market movements is the retail investors who bring the noise to the market although the role of both domestic and foreign institutional investors is growing in recent years. For example, the Shanghai Stock Exchange (SSE) composite index was stagnant between 2010 and 2013, but increased sharply by almost 60% in 2014.

A few studies regarding the dependence between Chinese and other stock markets can be found in the literature. Chan, Fung, and Thapa (2007) illustrated how the financial market in China has emulated and become integrated with developed markets over time. In contrast, Li (2007) demonstrated that the Chinese stock market was weakly integrated with regional or developed markets. Using asymmetric data, Hyde et al. (2007) found a significant correlation between stock markets in Asian-Pacific countries, Europe, and the US according to the dynamic conditional correlation GARCH model (AG-DCC-GARCH). Hu (2010) discovered that the dynamic dependence structure between the Chinese and US financial markets is quite volatile. Lai and Tseng (2010) observed there is no significant dependence between China and the G7 countries. In sum, most studies tend to look at the dependence structure between the Chinese and US stock markets. In contrast, this study aims to consider dependence structure between China and all other major stock markets.

To date, many methods and models have been used to examine the dependence structure between stock markets (Embrechts et al. 2001; Jondeau and Rockinger 2006; Chen and Fan 2006; Longin and Solnik 2001; Patton 2006a &b; Rodriguez 2007). However, these methods all have some drawbacks and limitations. In particular, some
methods neglect the stylised facts of returns and ignore the non-linearity in the financial data. This research aims to model the dependence structure between stock markets using both Extreme Value Theory (EVT) and time-varying copulas.

EVT is a well-known tool that can capture extreme circumstances. As shown in Hussain and Li (2015), EVT can be useful in modelling the extreme returns of stock markets. On the other hand, copula approach is a good choice for modelling the dependence between stock markets as it allows the use of a variety of marginal distributions without the normality limitation and builds more accurate information into joint distribution. Thus combing copula approach with EVT can be an effective way to model the dependence between stock markets.

So far, little is known about the dynamic dependence structure of the Chinese stock market with those of developed countries. This paper aims to enrich the literature. Specifically, this study explores the dependence structure between the CSI300 Index (China) and a set of 6 major stock market indices: S&P500 (US), TSX Composite Index (Canada), FTSE100 (UK), Nikkei 225 (Japan) and ASX200 (Australia) for the period July 1, 2005 to June 30, 2015.

We find that the dependence between the Chinese stock market and the developed markets is still low. Furthermore, our study indicates Chinese stock market seems to have stronger dependence with Asia and Europe than the US. Among all 6 pairs, the dependence between Chinese and US stock markets is the lowest and that between China and Australia is the highest. It is also found that US and UK do not have significant upper tail dependence with Chinese stock market and the dependence between China and Japan is strong but has weakened since 2012. Overall, diversification across all 6 pairs of stock markets is not effective.

The remainder of this paper is organised as follows. The next section explains the theoretical background. The methodology is discussed in Section 5.3. Section 5.4 describes the data and sample descriptive statistics. Section 5.5 presents the empirical results. Finally, Section 5.6 provides some concluding remarks.
5.2. Theoretical Background

This section discusses the details of the theoretical approach used in this research.

5.2.1. Extreme Value Theory

Extreme Value Theory (EVT) is a well-known tool that can capture extreme circumstances. EVT method has been used widely in hydrology, weather, insurance coverage, engineering and ecological analysis. The earliest studies done on EVT include Embrechts et al. (1999) and Poon et al. (2004). Many studies applying EVT in finance can also be found in the literature, e.g. Longin (1996), Danielsson and de Vries (2000), Straetmans (1998), McNeil (1999), Neftci (2000), McNeil (1998), McNeil and Frey (2000), Gencay et al. (2003) and Hussain and Li (2015).

EVT is a technique that focuses on the tail rather than the whole of distribution. In our analysis, we employ the peaks over threshold (POT) method to improve the tail of the distribution for each series. The POT approach works by sorting clustered phenomena that are frequently found in the real world. Identifying a suitable threshold is the crucial process in POT. A trade-off between bias and variance is required to find the optimal threshold. In this research, the observed excesses over the threshold will be fitted to the Generalized Pareto Distribution (GPD) according to the theorem below.

Let \((x_1, x_2, \ldots)\) be a sequence of independent and identically distributed random variables with the distribution function \(F\). Then for a large class of underlying distribution \(F\) and large \(u\), the conditional excess distribution function \(F_u\) can be approximated by GPD, that is:

\[
F_u(y) \approx G_{\xi,\alpha}(y), u \to \infty
\]

where
\[ G_{\xi,\alpha}(y) = \begin{cases} 
 1 - \left( 1 + \frac{\xi y}{\alpha} \right)^{-\frac{1}{\xi}} & \text{if } \xi \neq 0 \\
 1 - e^{-\frac{y}{\alpha}} & \text{if } \xi = 0
\end{cases} \tag{5.1} \]

For \( y \geq 0 \) when \( \xi \geq 0 \) and \( 0 \leq y \leq \left( -\frac{\alpha}{\xi} \right) \) when \( \xi < 0 \). \( \alpha \) is the scale parameter, \( \xi \) is the shape parameter for the GPD.

For details on the above theorem, we refer to Balkema and De Haan (1974) and Pickands (1975).

### 5.2.2. Copula Models

Copula theory was first introduced by Sklar (1959). It was first applied in finance during the early 2000s (Cherubini et al. 2004). Recently, copula models have been widely used to understand the asymmetric dependence structures between stock markets. A key feature of copula models is that there is no normality assumption. Given that the stock returns are often not normal, Copula models can thus be suitable for modelling the dependence between stock markets.

A copula allows us to decompose an \( n \)-dimensional joint distribution into its marginal distributions. The flexibility behind the assumption and the ability to extract information regarding dependence structure from the joint probability distribution function, have enabled it to be widely used in various applications. Mathematically, a bivariate copula that is used in this study can be written as:

\[ F(x_1, x_2) = C(F(x_1), F(x_2)) \tag{5.2} \]

where \( C \) is the copula employed to compose \( F \) with random variables of \( x_1, x_2 \) into marginal distributions.
There are many copulas available. However, given our objectives, we consider only Gaussian and Symmetrised Joe–Clayton (SJC) copulas in this paper. Gaussian copula is used to capture the overall dependence between the markets and (SJC) copula is used to capture the behaviour of the upper and lower tails.

5.3. Methodology

The methodology for this study can be divided into two main parts: marginal distribution and dependence structure. First, we need to specify the functional form of the marginal distributions. Then, the dependence between the variables will be determined with the appropriate copula function.

5.3.1. Marginal Distribution Estimation

In this paper, we use GJR-GARCH model with the mean return modelled as an AR(1) process (Engle and Ng 1993; Glosten et al. 1993). Let \( r_t \) denote the returns and \( h_t^2 \) denote the conditional variance for the period of \( t \). The GJR-GARCH model\(^8\) can be formulated as follows:

\[
\begin{align*}
    r_t &= \mu + \theta r_{t-1} + \varepsilon_t \\
    h_t^2 &= c + \gamma h_{t-1}^2 + \eta_1 \varepsilon_{t-1}^2 + \eta_2 s_{t-1} \varepsilon_{t-1}^2
\end{align*}
\]

(5.3)

(5.4)

where \( s_{t-1} = 1 \) when \( \varepsilon_{t-1} \) is negative and 0 otherwise. Let \( df \) represent the degree of freedom and \( \Omega_{t-1} \) denote the previous information set. The standardize residual of series, \( z_t \) are modelled as a Student t distribution:

\(^8\) Other GARCH models can also be used to compensate for the heteroskedasticity of the returns.
To model the tail behaviour of returns, the residuals that exceed a predefined threshold at level $u$, is modelled via GPD. This combination (empirical distribution of GJR-GARCH for interior part of the marginal distribution and EVT for the tails) is known as conditional EVT. Many methods have been proposed to determine the suitable threshold value $u$ (Neftci 2000; McNeil and Frey 2000; Longin and Solnik 2001). We use $10^{th}$ and $90^{th}$ percentile of the whole sample as suggested by Du Monchel (1983).

In sum, the cumulative function of GARCH-EVT can be written as:

\[
F(z) = \begin{cases} 
\frac{k^L}{n}(1 + \xi \frac{u^L - z}{\alpha})^{-1/\xi} & \text{for } z < u^L, \\
\emptyset(z) & \text{for } u^L < z < u^U \\
1 - \frac{k^U}{n}(1 + \xi \frac{z - u^U}{\alpha})^{-1/\xi} & \text{for } z > u^U,
\end{cases}
\]  

(5.6)

where $\alpha$ is the scale parameter, $\xi$ is the shape parameter, $u^L$ ($u^U$) is the lower (upper) threshold, $n$ is the number of observations, $\emptyset$ is the empirical distribution function and $k^L(k^U)$ is the number of observations below(exceeding) the threshold $u^L$ ($u^U$).

5.3.2. Copula Estimation

In this study, we use both constant and time-varying copulas (Gaussian and SJC) to examine the dependence structure between the China-related pairs of stock market return series.
5.3.2.1. Gaussian Copula

Gaussian copula is a well-known copula used in finance and it is associated with multivariate normal distribution. In the bivariate case, the random vector of random variables \( u \) and \( v \) can be considered bivariate normal if both \( u \) and \( v \) are normal. Therefore the dependence structure based on Gaussian copula can be written as:

\[
C(u, v) = \int_{-\infty}^{\Phi^{-1}(u)} \int_{-\infty}^{\Phi^{-1}(v)} \frac{1}{2\pi\sqrt{1-\delta^2}} \exp\left\{ -\frac{x^2 - 2\delta xy + y^2}{2(1-\delta^2)} \right\} dx dy
\]

\[\text{where } C = \Phi_\delta(\Phi^{-1}(u), \Phi^{-1}(v)), -1 \leq \delta \leq 1 \]

\[
(5.7)
\]

\[
(5.8)
\]

where \( \Phi \) and \( \Phi_\delta \) are the standard normal CDF's and \( \delta \) is the linear correlation coefficient between \( u \) and \( v \).

For the time-varying copula, the Gaussian dependence parameter is assumed to evolve over time according to Patton’s (2006a):

\[
\delta_t = \lambda \left( \omega + \beta \delta_{t-1} + \alpha \sum_{j=1}^{10} \Phi^{-1}(u_{t-j})\Phi^{-1}(v_{t-j}) \right)
\]

\[\text{where } \lambda = (1 - e^{-x})/(1 + e^{-x}) \text{ is the modified logistic transformation to ensure } \delta_t \text{ in the interval } (-1, 1). \text{ Note that in Equation (8), an ARMA (1,10) type process is assumed and } \beta \delta_{t-1} \text{ captures the persistence effect and the mean of the product of the last 10 observations of the transformed variables } \Phi^{-1}(u_{t-j}) \text{ and } \Phi^{-1}(v_{t-j}) \text{ captures the variation effect in the dependence.}\]

\[\text{(5.9)}\]
5.3.2.2. Symmetrised Joe–Clayton Copula (SJC Copula)

The SJC copula is a modified version of the 1997 Joe–Clayton copula. In general, the Joe-Clayton copula can be defined as:

\[ C_{JC}(u, v|\tau^U, \tau^L) = 1 - \left( [1 - (1 - u)^k]^{-\gamma} + [1 - (v)^k]^{-\gamma} \right) 1/\gamma \]  \hspace{1cm} (5.10)

where

\[ k = \frac{1}{\log_2(2 - \tau^U)} \] \hspace{1cm} (5.11)

\[ \gamma = -\frac{1}{\log_2(\tau^L)} \] \hspace{1cm} (5.12)

and

\[ \tau^U \in (0, 1), \tau^L \in (0, 1). \] \hspace{1cm} (5.13)

The original Joe–Clayton copula is not as attractive as the SJC copula because the SJC copula can be used to explore the lower and upper tail dependence simultaneously. Consequently the SJC copula is the ideal choice for understanding the tail behaviour and the SJC copula can be written in the following form:

\[ C_{SJC}(u, v|\tau^U, \tau^L) = 0.5[C_{JC}(u, v|\tau^U, \tau^L) + C_{JC}(1 - u, 1 - v|\tau^U, \tau^L) + u + v - 1] \] \hspace{1cm} (5.14)

where \( C_{JC} \) is the Joe–Clayton copula and \( \tau^U \) and \( \tau^L \) represent the upper and lower tail dependence, respectively.

For the time-varying copula, the evolution parameters for the SJC copula can be defined according to Patton (2006a):
\[ \tau^{U/L} = \tilde{\lambda} \left( \omega^{U/L} + \beta^{U/L}\tau_{t-1} + \alpha^{U/L} \frac{1}{10} \sum_{i=1}^{10} |u_{1,t-i} - u_{2,t-i}| \right) \]  

(5.15)

where \( \tilde{\lambda} \) is given as the logistic transformation: \( \tilde{\lambda}(x) = (1 + e^{-x})^{-1} \), which ensures the dependence parameter \( \tau^{U/L} \) in (0,1).

**5.3.3. Estimation Method**

**5.3.3.1. Marginal Estimation**

The Maximum Likelihood Estimation (MLE) is used to estimate the parameters for the marginal distributions. Based on (6), the full estimation of the combination of the parametric and GPD distributions can be written as:

\[ \hat{F}(z) = \begin{cases} 
\frac{k_L}{n} \left( 1 + \frac{\hat{\xi} u^L - z}{\hat{\alpha}} \right)^{-1/\hat{\xi}} & \text{for } z < u^L, \\
\Phi(z) & \text{for } u^L < z < u^U, \\
1 - \frac{k_U}{n} \left( 1 + \frac{\hat{\xi} z - u^U}{\hat{\alpha}} \right)^{-1/\hat{\xi}} & \text{for } z > u^U, 
\end{cases} \]  

(5.16)

where \( \hat{\alpha} \) and \( \hat{\xi} \) denote the MLE of \( \alpha \) and \( \xi \), respectively.

**5.3.3.2. The Inference Functions of Margins (IFM) for Copula**

IFM method is used to estimate copula parameters due to several reasons. This method is more flexible compared to MLE method. It also brings the advantage of assessing the fit of the margin distribution separately. By contrast, MLE method needs extensive computation which requires the parameters of the marginal distributions and the copula functions to be estimated simultaneously.

There are two main steps with IFM method:

**Step 1:** The parameters of the marginal distribution are estimated by using MLE:
\[ \hat{\theta}_i = \arg \max_l^c (\theta_i) = \arg \max \sum_{t=1}^{T} \log f_i(x_t, \theta_i) \]  

where \( l^c \) is the log-likelihood function of the marginal distribution \( F_i \)

Step 2: The copula parameters \( \delta \) are estimated in the next step based on the \( \hat{\theta}_i \):

\[ \hat{\delta} = \arg \max_l^c (\delta) = \arg \max \sum_{t=1}^{T} \log (c(F_1(x_1, \theta_1), ..., F_n(x_n, \theta_n); \delta)) \]  

where \( l^c \) is the likelihood function of the copula. The estimators are consistent under standard regularity conditions.

### 5.3.4. Model Selection

In this research, we use Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) to select the best model for the copula.

AIC can be defined as:

\[ AIC = -2 \log(\text{likelihood}) + 2k \]  

where \( k \) is the number of parameters used in the model. AIC works based on the trade-off between complexities and information lost when a given model is utilised to represent the process that generates the data. The lower value of AIC, the closer is the fit of a model to the empirical data.

BIC can be defined as:
where \( n \) is the number of data and \( k \) is the number of parameters used in the model. BIC penalises model complexity more heavily compared to the AIC. The lowest value of BIC indicates the best fit model.

\[
\text{BIC} = -2 \log(\text{likelihood}) + k \cdot \log(n) \tag{5.20}
\]

5.4. Data and Descriptive Statistics

China Securities Index 300 stock index (CSI300) was officially launched on April 8, 2005. This index consists of 300 stocks that represent approximately 70% of the total market capitalisation of both the Shanghai and Shenzhen stock markets. Most shares in this index are A-shares. This index reflects the performance of the Chinese A-share markets. This study thus uses the CSI300 Composite Index as a representation of the Chinese stock market.

The selection of other major stock markets is based on the consideration of demographic location and market capitalization. The US and Canada stock markets are selected to represent North America; the UK and Germany are selected to represent Europe; and Japan and Australia are selected to represent Australasia. These stock markets are among the major stock markets in the world. Consequently, the following stock indexes are used for this study: S&P500 (US), TSX Composite Index (Canada), FTSE100 (UK), DAX30 (Germany), Nikkei225 (Japan) and ASX200 (Australia). The daily closing index levels from 1 July 2005 to 31 June 2015 are obtained from Datastream. The returns of series can be calculated as \( r_t = \ln P_t - \ln P_{t-1} \) where \( P_t \) is the closing level of the index at time \( t \) in our study. To compare the performance of all indices, we need to use the relative daily index which is defined as the index normalised by using the initial index level for each market index. Figure 5.1 illustrates the relative daily index series of the selected stock markets for the whole sample period.
The data consists of 2607 daily observations over 10 years for each stock market. It is worth noting that the sample period covers a few extreme volatile events in the financial market including the Global Financial Crisis (GFC) and European Debt Crisis. As can be seen from Figure 5.1, the volatility of the Chinese stock market is very high compared to the others. Chinese stock market experienced an upward trend from 2006 to 2008 as the other stock markets did. All the markets dropped dramatically between 2008 and 2009 due to the GFC.

A drastic upward trend began in early 2014 for the Chinese stock market. Two triggers are behind this sharp rise\(^9\). First, the People's Bank of China unexpectedly cut interest

rates for the first time in two years. The government’s monetary policy made the Chinese stock market very attractive for investors who wanted to take advantage of this opportunity. At the same time, the retail investors who make up about 80% of stock trading volume in China have been moving money out of the main asset classes and property into stocks. The second catalyst was the launch of Shanghai-Hong Kong Stock Connect. This platform has enabled foreign investors to access and invest in the mainland market. This trading scheme permits mainland investors to trade in Hong Kong stocks while foreign investors can trade in the Shanghai market for the first time via the Hong Kong stock exchange.

Table 5.1. Descriptive statistics of daily returns

<table>
<thead>
<tr>
<th></th>
<th>China</th>
<th>US</th>
<th>Canada</th>
<th>UK</th>
<th>Germany</th>
<th>Japan</th>
<th>Australia</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.0633</td>
<td>0.0210</td>
<td>0.0148</td>
<td>0.0090</td>
<td>0.0331</td>
<td>0.0212</td>
<td>0.0094</td>
</tr>
<tr>
<td>Med</td>
<td>0.0250</td>
<td>0.0448</td>
<td>0.0544</td>
<td>0.0062</td>
<td>0.0745</td>
<td>0.0000</td>
<td>0.0093</td>
</tr>
<tr>
<td>Std</td>
<td>1.7790</td>
<td>1.2684</td>
<td>1.1712</td>
<td>1.2059</td>
<td>1.3943</td>
<td>1.5365</td>
<td>1.1247</td>
</tr>
<tr>
<td>Skew</td>
<td>-0.4690</td>
<td>-0.3365</td>
<td>-0.7137</td>
<td>-0.1427</td>
<td>0.0341</td>
<td>-0.5782</td>
<td>-0.4251</td>
</tr>
<tr>
<td>JB Stat</td>
<td>1.363E+03</td>
<td>1.42E+04</td>
<td>1.34E+04</td>
<td>8.00E+03</td>
<td>4.80E+03</td>
<td>8.55E+03</td>
<td>2.76E+03</td>
</tr>
<tr>
<td>Count</td>
<td>2607</td>
<td>2607</td>
<td>2607</td>
<td>2607</td>
<td>2607</td>
<td>2607</td>
<td>2607</td>
</tr>
</tbody>
</table>

Mean, Med, Min, Max, Std, Skew and Kurt stand for the mean, median, minimum, maximum, the standard deviation, skewness and kurtosis for each series, respectively. JB Stat denotes the statistics for the Jarque-Bera normality test with two degrees of freedom.

Table 5.1 presents the descriptive statistics of daily returns for the Chinese stock market and those of the developed markets. The data are taken for the period from July 1, 2005 to June 31, 2015. The mean values for all stock markets are positive. Chinese stock market has the highest value of mean with 0.0633% followed by Germany with 0.0331%. The lowest mean belongs to the UK with 0.0090%. The standard deviation figures show
that Chinese stock market is very volatile compared to the others. The standard deviation for Chinese stock market is 1.7790, followed by that of Japan, which is 1.5365. The lowest value for the standard deviation belongs to Australia with 1.1247%. The US has the highest value of kurtosis with 11.4350. This indicates the US market has highest frequencies of the extreme returns. Referring to skewness, Australia has the highest with 0.0341 and Japan has the lowest with -0.5782. Positive skewness means the data has a long tail to the right while negative skewness means the data has a long tail to the left. The Jarque-Bera test results confirm that the return series are not normal for all markets. In particular, the highest Jarque-Bera test statistic is reported for Japan.

In sum, Table 5.1 indicates that all return series exhibit some non-linear phenomenon and extreme behaviour. The model that works on the normality assumption is thus not appropriate.

<table>
<thead>
<tr>
<th></th>
<th>China</th>
<th>US</th>
<th>Canada</th>
<th>UK</th>
<th>Germany</th>
<th>Japan</th>
<th>Australia</th>
</tr>
</thead>
<tbody>
<tr>
<td>China</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>US</td>
<td>0.0693</td>
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<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Canada</td>
<td>0.1142</td>
<td>0.7412</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>UK</td>
<td>0.1499</td>
<td>0.5857</td>
<td>0.5784</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Germany</td>
<td>0.1356</td>
<td>0.6256</td>
<td>0.5468</td>
<td>0.8586</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Japan</td>
<td>0.2538</td>
<td>0.1143</td>
<td>0.2265</td>
<td>0.3254</td>
<td>0.2930</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Australia</td>
<td>0.2684</td>
<td>0.1455</td>
<td>0.2347</td>
<td>0.3690</td>
<td>0.3173</td>
<td>0.6241</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 5.2 reports the correlation coefficients between the return series. The linear correlation values for the Chinese stock market related pair range between 0.0693 and 0.2684. Among the Chinese stock market related pairs, it is evident that the strongest correlation is between China and Australia, followed by that between China and Japan. Table 5.2 also shows that China appears to have a stronger correlation with Asia and Europe than North America.
The weakest correlation is the one between China and US. Lower correlation is normally associated effective diversification across the pair. This means that for investors in Chinese Stock market, the US stock market may be a good choice for portfolio diversification. However, this can be misleading and we need a better understanding of the dependence between these markets which can be achieved by using copula modelling. Upper and lower tail information used in copula modelling will enable us to better comprehend the dependence structure between Chinese stock market and other major stock markets.

5.5. Empirical Results

The empirical results are presented in this section.

5.5.1. Estimating Marginal Models

In this study, the marginal distributions are estimated by using a semi-parametric approach. This method is an innovation derived from GARCH methodology. First, the estimated residuals are obtained as described in Section 5.3.1 and then we employ EVT approach for the tail modelling. The values of the parameters obtained using GPD for the upper and lower tails are presented in Table 5.3 below.
Table 5.3. The estimated parameters for the tails based on GPD

<table>
<thead>
<tr>
<th></th>
<th>China</th>
<th>US</th>
<th>Canada</th>
<th>UK</th>
<th>Germany</th>
<th>Japan</th>
<th>Australia</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Lower tail</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\xi$</td>
<td>-0.0941</td>
<td>-0.0208</td>
<td>-0.0441</td>
<td>-0.0695</td>
<td>0.0294</td>
<td>0.0599</td>
<td>-0.0630</td>
</tr>
<tr>
<td></td>
<td>(0.0908)</td>
<td>(0.0600)</td>
<td>(0.0554)</td>
<td>(0.0782)</td>
<td>(0.0926)</td>
<td>(0.0697)</td>
<td>(0.0750)</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>0.7911</td>
<td>0.6686</td>
<td>0.6701</td>
<td>0.6138</td>
<td>0.5744</td>
<td>0.5846</td>
<td>0.5966</td>
</tr>
<tr>
<td></td>
<td>(0.0996)</td>
<td>(0.0710)</td>
<td>(0.0556)</td>
<td>(0.0720)</td>
<td>(0.0732)</td>
<td>(0.0654)</td>
<td>(0.0688)</td>
</tr>
<tr>
<td><strong>Upper tail</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\xi$</td>
<td>-0.0905</td>
<td>-0.1373</td>
<td>-0.1816</td>
<td>-0.1279</td>
<td>-0.1266</td>
<td>0.0393</td>
<td>-0.1534</td>
</tr>
<tr>
<td></td>
<td>(0.0865)</td>
<td>(0.0820)</td>
<td>(0.0483)</td>
<td>(0.0626)</td>
<td>(0.0930)</td>
<td>(0.0857)</td>
<td>(0.0641)</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>0.5519</td>
<td>0.5016</td>
<td>0.5331</td>
<td>0.5046</td>
<td>0.4658</td>
<td>0.3297</td>
<td>0.4654</td>
</tr>
<tr>
<td></td>
<td>(0.0678)</td>
<td>(0.0599)</td>
<td>(0.0414)</td>
<td>(0.0541)</td>
<td>(0.0593)</td>
<td>(0.0404)</td>
<td>(0.0502)</td>
</tr>
</tbody>
</table>

Notes: This table represents estimated parameters for selected stock markets using Generalised Pareto Distribution (GPD). $\xi$ represents the shape and $\alpha$ is the value of the scale parameter of the fitted GPD. Standard errors are in parentheses.

Table 5.3 summarises the parameter estimates for the lower and upper tails based on GPD. A positive value for the shape parameter indicates the tail decreases as a polynomial. A negative value for the shape parameter indicates the distribution has a finite tail. Referring to the lower tails, Table 5.3 shows Japan has the highest value $\xi = 0.0599$. This is followed by Germany with $\xi = 0.0294$. These values indicate Japan and Germany’s stock markets demonstrate long tail behaviour compared to all others for the lower tail. The remaining stock markets demonstrate the returns exhibit short tail behaviour. Chinese stock market has the lowest value of $\xi$ (-0.0941). For the upper tails, Table 5.3 shows most of the return series exhibit short tail behaviour. Only Japan has a positive value of $\xi = 0.0393$ which means long tail behaviour.

In terms of heaviness, there is heavy tail behaviour exhibited by the Chinese stock market. This is evident with the highest absolute value of $\xi$ for the Chinese stock market compared to others. The UK has the second highest absolute value of $\xi$ (-0.0695) while the US has the lowest absolute value of $\xi$ (-0.0208). Regarding the upper tails, Australia has the
highest absolute value of $\xi$ (-0.1534). Japan has the lowest absolute value of $\xi$ (0.0393). Based on these values, we can conclude that Chinese stock market is most likely to have negative extreme returns while Australia is most likely to have positive extreme returns among all seven stock markets considered. In other words, Chinese stock market has the highest frequency for extreme negative returns while Australia stock market has the highest frequency for extreme positive returns.

In general, the findings indicate that Chinese stock market has both heavy upper and lower tails. This means that the Chinese stock market is volatile with both upside and downside extreme returns. In contrast to the US and the UK, the upper tail is significantly heavier than the lower tail for Chinese stock market.

Figure 5.2 plots the empirical Cumulative Distribution Function (CDF) of the exceedance of the residuals for the upper tail along with the CDF from GPD for each selected stock market. The fitted distributions closely follow the exceedance of the residuals although only 10% of the standardised residuals are employed. Thus GPD appears to be a good choice to model the upper tails. This is also valid for the lower tails\(^1\).

The overall CDF semi-parametric marginal distributions used in this study are shown in Figure 5.3. As mentioned above, the tails are fitted by using EVT while the interior part is estimated via a GARCH model. GARCH model is well suited for the interior body of the distribution. However, this method seems to perform poorly in terms of tail modelling. Combining it with EVT for the tails can overcome this problem.

In summary, Table 5.3 and Figures 5.2 and 5.3 demonstrate that our approach can adequately model the marginal distributions of the return series for the stock markets under consideration.

\(^{10}\) The results for the lower tails are similar and available upon request.
Figure 5.2. Upper tail distributions
5.5.2. Estimating the Copula Models

In this research, we are interested in the dependence structure between the Chinese stock market and other major stock markets with a focus on the behaviour of extreme returns. To this end, both Gaussian copula and SJC copula as well as their dynamic versions are employed.
Gaussian copula assesses the overall dependence structure while SJC copula helps us to explore the behaviour of the lower and upper tails. In this research, Equation (9) is used for the path of parameters (for Gaussian and SJC) (Patton, 2006a).

Table 5.4 provides an overview of parameter estimates for the Gaussian and SJC copulas. \( \delta \) (Gaussian), \( \tau^U \) and \( \tau^L \) (SJC) are the keys parameters for the constant copula. For the time-varying copulas, the keys parameters are \( \omega \) (Gaussian), \( \omega^U \) and \( \omega^L \) (SJC), \( \alpha \) (Gaussian), \( \alpha^U \) and \( \alpha^L \) (SJC) and \( \beta \) (Gaussian), \( \beta^U \) and \( \beta^L \) (SJC).\( \omega \) (Gaussian), \( \omega^U \) and \( \omega^L \) (SJC) are used to describe the dependence level of each pair. The adjustment in the dependence is captured by \( \alpha \) (Gaussian), \( \alpha^U \) and \( \alpha^L \) (SJC). Lastly, parameter \( \beta \) (Gaussian), \( \beta^U \) and \( \beta^L \) (SJC) are used to represent the degree of persistence of dependence. The values for the AIC and BIC serve to identify the best model. A lower value of AIC or BIC indicates a better fit. To assess the parameters path for every pair, Figure 5.4 is used as well.
Table 5.4. Parameter estimates for constant and time-varying copulas

<table>
<thead>
<tr>
<th></th>
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<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td><strong>Gaussian Copula</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\delta)</td>
<td>0.0747***</td>
<td>0.1273***</td>
<td>0.1438***</td>
<td>0.1282***</td>
<td>0.2333***</td>
<td>0.2442***</td>
</tr>
<tr>
<td>AIC</td>
<td>-14.6010</td>
<td>-42.5774</td>
<td>-54.4557</td>
<td>-43.2116</td>
<td>-145.8945</td>
<td>-160.3129</td>
</tr>
<tr>
<td>BIC</td>
<td>-14.5987</td>
<td>-42.5752</td>
<td>-54.4535</td>
<td>-43.2093</td>
<td>-145.8923</td>
<td>-160.3106</td>
</tr>
<tr>
<td><strong>SJC Copula</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\tau^U)</td>
<td>0.0000</td>
<td>0.0059</td>
<td>0.0000</td>
<td>0.0038</td>
<td>0.0035</td>
<td>0.0171</td>
</tr>
<tr>
<td>(\tau^L)</td>
<td>0.0068</td>
<td>0.0265*</td>
<td>0.0718***</td>
<td>0.0320**</td>
<td>0.1442***</td>
<td>0.1566***</td>
</tr>
<tr>
<td>AIC</td>
<td>-14.5170</td>
<td>-46.8231</td>
<td>-66.0327</td>
<td>-47.4981</td>
<td>-137.4972</td>
<td>-171.7967</td>
</tr>
<tr>
<td>BIC</td>
<td>-2.7851</td>
<td>-35.0912</td>
<td>-54.3008</td>
<td>-35.7662</td>
<td>-125.7653</td>
<td>-160.0648</td>
</tr>
<tr>
<td><strong>Dynamic Gaussian Copula</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\omega)</td>
<td>0.3264***</td>
<td>0.5343***</td>
<td>0.3264</td>
<td>0.6046***</td>
<td>0.8257***</td>
<td>0.5073***</td>
</tr>
<tr>
<td>(\alpha)</td>
<td>0.1699</td>
<td>0.0659</td>
<td>0.1699</td>
<td>-0.1811</td>
<td>0.3672**</td>
<td>0.1115</td>
</tr>
<tr>
<td>(\beta)</td>
<td>-2.0200</td>
<td>-2.017***</td>
<td>-2.0200</td>
<td>-2.0472</td>
<td>-1.7263</td>
<td>-0.0805</td>
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<tr>
<td>AIC</td>
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<td>-59.8190</td>
<td>-50.6548</td>
<td>-149.5580</td>
<td>-161.3507</td>
</tr>
<tr>
<td>BIC</td>
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<td>-42.8739</td>
<td>-59.8122</td>
<td>-50.6480</td>
<td>-149.5513</td>
<td>-161.3440</td>
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<td><strong>Dynamic SJC Copula</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\omega^U)</td>
<td>-7.9552***</td>
<td>-6.8484*</td>
<td>-8.3489</td>
<td>-8.0512***</td>
<td>-7.5142***</td>
<td>-1.5913</td>
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<td>(\alpha^U)</td>
<td>-1.7770</td>
<td>-3.4312</td>
<td>-3.5720</td>
<td>-0.9450</td>
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<tr>
<td>(\beta^L)</td>
<td>2.5755*</td>
<td>-0.5830</td>
<td>9.8635**</td>
<td>9.1835***</td>
<td>8.3881***</td>
<td>0.8185***</td>
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<tr>
<td>(\omega^L)</td>
<td>-5.2912*</td>
<td>-1.7071</td>
<td>0.2669</td>
<td>-1.3312</td>
<td>0.1124***</td>
<td>-0.3619</td>
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<tr>
<td>(\alpha^L)</td>
<td>-0.8187</td>
<td>-9.9996***</td>
<td>-3.2891*</td>
<td>-2.5490</td>
<td>-0.5200***</td>
<td>-1.4514</td>
</tr>
<tr>
<td>(\alpha^L)</td>
<td>0.6378***</td>
<td>-0.4096</td>
<td>0.7114***</td>
<td>0.3139</td>
<td>0.9777***</td>
<td>0.4223</td>
</tr>
<tr>
<td>(\beta^L)</td>
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<td>-41.6007</td>
<td>-62.1295</td>
<td>-40.2667</td>
<td>-140.6450</td>
<td>-164.7622</td>
</tr>
<tr>
<td>BIC</td>
<td>30.4822</td>
<td>-6.4050</td>
<td>-26.9337</td>
<td>-5.0710</td>
<td>-105.4493</td>
<td>-129.5665</td>
</tr>
</tbody>
</table>

Notes: \(\delta\) is the parameter of Gaussian copula. \(\tau^U\) and \(\tau^L\) are the upper and lower tails of the SJC copula; \(\omega\) is constant; \(\alpha\) and \(\beta\) are the coefficients of the time-varying process proposed. AIC and BIC are Akaike and Bayesian Information Criteria. * = P<0.1, ** = P<0.05 and *** = P<0.01. CAN, GERM, JAP and AUS stand for Canada, Germany, Japan and Australia, respectively.
Figure 5.4 represents the evolution of the dependence parameters for each pair of selected stock markets.
China-Japan

China-Germany
5.5.2.1. Constant copula models

A few interesting observations can be made from Table 5.4 and Figure 5.4:

1. The overall dependence for the six pairs of stock markets can be ranked in decreasing order as: China-Australia > China-Japan > China-UK > China-Germany > China-Canada > China-US;
II. The upper tail dependence for the six pairs can be ranked in decreasing order as:
China-Australia > China-Canada > China-Germany > China-Japan > China-US and China-UK;

III. The lower tail dependence for the six pairs can be ranked in decreasing order as follows: China-Australia > China-Japan > China-UK > China-Germany > China-Canada > China-US.

The above rankings imply: i) China-Australia pair has the strongest overall and tail dependence; ii) China-Japan pair has the second highest overall and lower tail dependence and iii) The weakest dependence (overall or tail) is found between China and the US.

Furthermore, this study reveals more insight regarding the dependence among the 6 pairs of stock markets. China-Australia pair has the greater dependence compared to China-Japan pair. From Table 5.4, the dependence of the Chinese stock market with the UK or Germany is much stronger than that between China and US. This indicates Chinese stock market is more dependent on the European stock markets compared to the US. Canada stock market seems to have more dependence with the Chinese stock market compared to the US stock market.

China-Australia pair has the greatest upper tail dependence. In contrast, the dependence for the upper tails is low for China-US and China-UK. This indicates that the US and the UK are not significantly affected by China or vice versa in the case of extreme positive market movements. At the same time, it is apparent that $\tau^L$ is larger than $\tau^U$ for each pair. This result demonstrates all 6 pairs have stronger lower tail dependence than upper tail dependence.

A possible explanation for these results may come from the economic factors. China is the largest exporter of goods in the world. It has created a huge demand for commodity products and consequently has generated huge export booms in many markets. Australian stock market is affected by China since its economy traditionally is driven by resources and China has been the largest importer from Australia. In fact, 36% of
Australia’s exports went to China\textsuperscript{11}. As a result, Chian-Australia pair has the strongest dependence.

The lowest dependence structure between China and the US can be explained by their trading relationship. It is evident that the US seems to have a cushion saving it from the impact of Chinese economic volatility. The US is not greatly affected by declines in the Chinese stock market. The US economic structure has a bilateral trade deficit with China and the relationship is mostly one-way. The US imports three times as much from China as it exports to China.

5.5.2.2. Time-varying copula models

In this section, the dynamic dependence structure of the six pairs of stock markets is discussed. Figure 5.4 demonstrates the time paths for the overall, lower and upper tail dependence by using both Gaussian and SJC copulas. In this study, the time variations of dependence measures between return series are captured by the coefficients, $\alpha$ ($\alpha^L$ or $\alpha^U$) and $\beta$ ($\beta^L$ or $\beta^U$) as in Equation (15). Based on the results for the time-varying Gaussian copula model in Table 5.4, it can be seen that most of the time paths are close to white noise as the values for the variation coefficient $\alpha$ are relatively higher than the persistence coefficient $\beta$. However, for the SJC copula, all the persistence coefficient $\beta$ is larger than the variation coefficient $\alpha$ for all pairs. This outcome provides insights regarding the changes of dependence structure for the upper and lower tails over the time period.

For China-US pair, we can see the dependence parameter $\delta_t$ for the time-varying Gaussian copula ranges between 0.05 and 0.15. These values are quite low compared to the other pairs. The values of parameters for the time-varying SJC copula, $\tau^U$ and $\tau^L$ are almost zero. This indicates a low dependence for the upper and lower tail dependence between these two markets. In sum, these results indicate that Chinese stock market has low dependence with the US stock market (overall or tails).

For the China-Canada pair, the values of dependence parameter \( \delta_t \) in the time-varying Gaussian copula model are between 0.1 and 0.2. This path of \( \delta_t \) is more stable compared to the one for the China-US pair. In contrast, the lower dependence \( \tau^L \) for this pair seems to be more volatile. There are a few spikes as shown in Figure 5.4 which range between 0.02 and 0.05. The values for \( \tau^U \) are close to zero. Overall, Chinese stock market seems to have a stronger dependence with the Canada stock market in terms of lower tail dependence compared to the US.

For the China-UK pair, the values of dependence parameter \( \delta_t \) in the time-varying Gaussian copula are very volatile with \( \delta_t \) moving between 0.1 and 0.2. These values are slightly higher than those for the China-US pair. The path for \( \tau^L \) in the time-varying SJC copula model ranges between 0.03 and 0.07. In contrast, the value for the upper tail is almost zero.

For the China-Germany pair, Figure 5.4 reveals that the values of dependence parameter \( \delta_t \) before 2007 are quite volatile and range between 0.05 and 0.2. The lower tail dependence parameter for this pair ranges between 0.03 and 0.05. Similar to China-Japan pair, the parameter \( \tau^U \) for this pair is almost zero which indicates there is hardly any dependence between these two markets in the case of positive extreme events. In sum, these results provide important insight into the dependence of Chinese stock market with the European stock markets.

Figure 5.4 also demonstrates the values for the parameter \( \delta_t \) range between 0.3 and 0.4 for the China-Japan pair. These values are quite high compared to the ones for other pairs. There is a significant dependence between Chinese stock market and Japanese stock market in terms of lower dependence. We can see the values of \( \tau^L \) range between 0.1 and 0.4. In contrast to the values of \( \tau^L \), the values for the \( \tau^U \) are almost zero. The most striking result to emerge from these findings is regarding the behaviour of \( \tau^L \). The lower dependence for the China-Japan pair has become weaker starting in 2014. Investors might become more aware with the drastic upward trend in Chinese stock market in early 2014. To the best of our knowledge, this outcome has not been previously documented.
Finally, China-Australia pair has the strongest dependence among all 6 pairs. The parameter values for $\delta_t$ in the time-varying Gaussian copula are stable and fluctuating around 0.25. The lower tail dependence parameter, $\tau^L$ for this pair also exhibits the same characteristic and ranges between 0.1 and 0.2. The upper tail dependence parameter $\tau^U$ has a few peaks. These results are likely due to the strong Australia-China economic and trade relationship during the sample period. China was Australia’s largest two-way trading partner in goods and services in 2014. The amount of Chinese investment in Australia in 2015 was more than fourteen times the level it was in 2005. The Australian federal government has also been promoting its open investment regime and Foreign Investment Review Board process$^{12}$.

In this research, we are also interested in comprehending the opportunity to diversify among the selected stock markets. To this end, the values of $\omega$ in the SJC copula model need to be examined in detail. These values are useful for providing better insights into active risk management practices for portfolio diversification (Wang et al. 2011). Based on Table 5.4, all values of $\omega^L$ are relatively higher than $\omega^U$ for all 6 pairs of stock markets. This can also be confirmed by observing the paths for the lower and the upper tail dependence in Figure 5.4. Thus the dependence is stronger during a crisis for all 6 pairs than during booming period. Risk diversification is thus not effective during a crisis. This does have further implications for the financial risk management tools like VaR, expected shortfall or other downside risk measures.

### 5.6. Concluding Remarks

Over the past few years, dependence structure between financial markets has been actively studied. However, some methods employed are subject the normality assumption. Most financial data tend to be non-linear, non-stationary and heavy-tailed. Hence, suitable models that can incorporate these features are needed.

This study attempts to assess the dependence structure between the Chinese and other major developed stock markets by using EVT and copula model. These methods can provide more information compared to the linear correlation regarding understanding the potential of risk diversification and risk management strategy.

Our results show that the Chinese stock market has higher levels of dependence with the Asian and European markets than the US market. This outcome implies that the probability of a downward extreme movement is high in these stock markets if there is a downward extreme movement in the Chinese stock market and vice versa. This finding might be attributed to the trading relationships and their geographical proximity.

This study also reveals that China-Australia pair has the strongest dependence and China-Japan pair has the second highest dependence. However, the dependence between China and Japan became weaker since the beginning of 2012.

This study enhances our understanding of Chinese stock market and its link to the developed stock markets by exploring the tail behaviour. The research also makes a contribution in terms of the diversification benefits. It is found that the dependence for these pairs is much stronger during a crisis than during a booming period. Portfolio diversification across these pairs during a downturn will not lead to many benefits. The outcomes of this study thus have implications for policy-makers and risk management practitioners. For example, this information can help investors to build confidence and seek risk diversification opportunities in other asset classes.

Overall, this study makes a significant contribution to the literature. Further research can be done by investigating the factors behind these relationships and the methodology employed in this paper can be applied to computing Value at Risk (VaR) and optimal portfolio weights.
5.7. References


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CHAPTER 6: THE DYNAMIC DEPENDENCE BETWEEN STOCK MARKETS IN THE GREATER CHINA ECONOMIC AREA*

Greater China Economic Area (GCEA) has become very important in the world economy. This study employs the dynamic copula method and extreme value theory (EVT) to investigate the dependence structure between pairs of GCEA stock markets consisting of Shanghai (SHSE), Shenzhen (SZSE), Hong Kong (HKSE) and Taiwan (TWSE) stock exchanges. Overall, this paper reveals the dependence between all pairs of GCEA stock markets is strong. We also find the risk diversification is effective for only two pairs (SZSE-HKSE and HKSE-TWSE) in the case of negative market extreme events and there is a significant GFC effect on the dependence structure between the GCEA stock markets.

Keywords: Copula, extreme value theory, Dependence structure, Chinese stock markets, Global financial crisis (GFC)

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6.1. Introduction

The dependence structure between international financial markets has become a research topic in recent years. The boom and bust of one financial market can affect other ones. Diversification via international asset allocation is important for investors, especially during an economic crisis period. Thus, it is important to monitor and measure the dependence between stock markets. Many studies (e.g. Ane & Labidi 2006; Jondeau & Rockinger 2006; Longin & Solnik 2001; Forbes & Rigobon 2002) have been done on the dependence between developed stock markets. However, there are hardly any such studies on emerging markets including the Greater China Economic Area (GCEA) stock markets.

China is now the second largest economy in the world and Greater China Economic Area (GCEA) has become very important in the economic landscape. Thus it is important to understand the dependence between the stock markets in GCEA consisting of Shanghai (SHSE), Shenzhen (SZSE), Hong Kong (HKSE) and Taiwan (TWSE) stock exchanges. These markets are relatively large although they are regarded as emerging markets. The economic exchanges in these areas are active despite some political tensions. Mainland China is Taiwan’s largest import partner and its main export partner. In fact in 2013, Mainland China accounted for 26.8% of Taiwan’s exports and 15.8% of its imports. Similarly, Mainland China has become Hong Kong’s main principal export and import partner, accounts for 59.9% and 41.5% of Hong Kong’s total exports and imports in 2013, respectively.\footnote{Data sourced from http://www.dfat.gov.au}

Cheng and Glascock (2005) found that Hong Kong is the most influential among the GCEA markets. There is also evidence of an increasing trend in the financial integration of the GCEA, especially between China and Hong Kong by focusing on the macro variables such as interbank rates, exchange rates, and prices (Cheung et al., 2003). Later, Cheung et al. (2005) analysed financial integration in GCEA and how its economies
are integrated with the rest of the world. Wang and Di Iorio (2007) showed that there is a strong correlation between China’s A-share market and Hong Kong’s stock market. However, these findings are conflicting with other studies. For example, Shin and Sohn (2006) found there is not much integration between Asia countries.

A few studies have shown that there is a strong relationship between Chinese stocks that were dual-listed on the Hong Kong and New York stock exchanges (Xu and Fung, 2002). Hyde et al. (2007) applied the asymmetric dynamic conditional correlation GARCH model (AG-DCC-GARCH) and found a significant correlation and strong dependence between US, Europe and Asian countries. In contrast, results by Li (2007) reveal that the dependence between Chinese stock market and the more developed markets is weak.

The GCEA stock markets share some strong historic, geographic and economic ties, thus it is expected that these markets have a close relationship. However, understanding the delicate differences in the dependence structure between GECA stock markets require a closer look at the tail behaviour. It is well known that stock returns rarely follow the normal distribution. Instead, they often follow distributions with fatter tails, especially during an economic crisis. Thus copula and EVT can serve as a good alternative to model the correlations in such financial data (e.g., Embrechts et al. 2001; Jondeau and Rockinger 2006; Chen and Fan 2006; Longin and Solnik 2001; Patton 2006a,b; Rodriguez 2007). Thus this research applies the Extreme Value Theory (EVT) and dynamic copula to investigate the dependence between pairs of GECA stock markets. Moreover, this study also explores the diversification benefits across GECA stock markets.

The literature shows major stock markets tend to form a strong dependence during a crisis. Diversification benefit across the stock markets can thus diminish as the dependence increases. To our best knowledge, little is known about the dependence between GCEA stock markets and the potential of diversification benefits across them. This paper aims to fill this gap.

Our results reveal that the dependence between all pairs of the GCEA stock markets is strong. SHSE-SZSE pair has the strongest dependence (lower tail, upper tail or overall) among all the six pairs. It is followed by the HKSE-TWSE. Interestingly, we find that
SHSE-TWSE pair and the SZSE-TWSE pair do not have significant upper tail dependence.

We also find the risk diversification is effective for only two pairs (SZSE-HKSE and HKSE-TWSE) in the case of negative market extreme events. This finding can help investors make better decisions regarding their diversification strategy. This paper also reveals the existence of the GFC effect on the dependence structure. The depended structure has become stronger after the GFC for most pairs except for SHSE-SZSE and HKSE-TWSE.

Finally, it is worth noting that the dynamic copula models outperform their constant counterparts. We are also able to gain more information about dependence structure using an asymmetric copula. The use of SJC copula allows us to understand better the impact of upper and lower tail dependence among the GCEA stock markets.

The remainder of this paper is organised as follows. Section 6.2 explains the theoretical background. The methodology is discussed in Section 6.3. Data and sample statistics are described in Section 6.4. Section 6.5 presents the empirical results. Finally, concluding remarks are provided in Section 6.6.

6.2. Theoretical Background

This section discusses in detail the Extreme Value Theory (EVT) and copula theory.

6.2.1. Extreme Value Theory

Extreme Value Theory (EVT) is a statistical tool that works with extreme event modelling. EVT is widely used in many disciplines such as structural engineering, finance, earth sciences, traffic prediction, and geological engineering. EVT was first introduced by Fisher and Tippett (1928).

EVT can provide a better estimation for risk modelling since it focuses only on extreme values, rather than the distribution of all values. Financial market disasters such as the
Asian Financial Crisis (AFC, 1997-98) and Global Financial Crisis (GFC, 2008-2010) have taught us to be more prudent in assessing the extreme behaviour in the financial markets. Therefore, the study of extreme scenarios is one of the key aspects of risk management for which EVT is a suitable modelling tool. Extensive studies on EVT in finance include Longin (1996), Embrechts et al. (1999), Danielsson and de Vries (2000), Straetmans (1998), McNeil (1999), Neftci (2000), McNeil (1998), McNeil and Frey (2000), Gencay et al. (2003), Poon et al. (2004) and Hussain and Li (2015).

EVT has two approaches: block maxima method (BMM) and peaks over threshold (POT). The block maxima method defines extreme events as the maximum (minimum) value in each sub-period such as weekly, monthly, quarterly and yearly interval. This method has its drawback. It tends to discard a great amount of data that possibly exist in the same sub-period. On the other hand, POT approach focuses on sorting clustered observations that are frequently found in data. This study will use the POT approach to model the extreme returns as we are primarily concerned with the tails of the stock market returns. The POT approach is employed by fitting Generalized Pareto Distribution (GPD) to the observed excesses over the threshold based on the theorem below.

Theorem 1. Let \((x_1, x_2, \ldots)\) be a sequence of independent and identically distributed random variables with the distribution function \(F\). Then for a large class of underlying distribution \(F\) and large \(u\), the conditional excess distribution function \(F_u\) can be approximated by GPD, that is,

\[
F_u(y) \approx G_{\xi, \alpha}(y), \quad \text{as} \quad u \to \infty
\]

where

\[
G_{\xi, \alpha}(y) = \begin{cases} 
1 - \left(1 + \frac{\xi y}{\alpha}\right)^{-1/\xi} & \text{if } \xi \neq 0 \\
1 - e^{-y/\alpha} & \text{if } \xi = 0
\end{cases}
\]

(6.1)
for \( y \geq 0 \) when \( \xi \geq 0 \) and \( 0 \leq y \leq \left( \frac{\alpha}{\xi} \right) \) when \( \xi < 0 \). \( \alpha \) is the scale parameter, \( \xi \) is the shape parameter for the GPD parameters.

For the proof of this theorem, we refer to Balkema and De Haan (1974) and Pickands (1975).

### 6.2.2. Copula Models

Copula is a risk management tool that models the dependence structure between variables and it was first used in finance in the early 2000s (Cherubini et al. 2004). Specifically, copula is a technique for modelling the dependence structure without the assumption of normality. It can separate the marginal behaviour of variables from the dependence structure through the use of joint distribution function.

The traditional linear correlation method does suffer from a few limitations. Zero correlation does not necessarily mean independence. It also does not work well for distributions with strong kurtosis. Besides, linear dependent data do not often appear in finance. Many studies have demonstrated financial dependency are typically nonlinear. Further, linear correlation only works well if the joint distribution of the variables is elliptical such as multivariate normal distribution and Student \( t \) distribution (Meissner, 2013).

On the other hand, copula does not require the assumption of joint normality and it allows us to decompose any \( n \)-dimensional joint distribution into its \( n \) marginal distributions. The flexibility behind the assumption and the ability to extract information regarding dependence structure from the joint probability distribution function enable the copula method to be widely used in various applications. The innovations in copula theory introduced by Patton (2006a) allow a temporal variation to occur in the conditional dependence in a time series. This makes copula method more dynamic and time sensitive. More applications of this method can be found in Bartram et al. (2007), Nguyen and Bhatti (2012), Wang et al. (2011) among others.
Based on Sklar’s theorem (1959), copula values are based on the information of the marginal distribution that has been transformed into a uniform distribution. The joint distribution \( F \) of \( r \) random variables \( x_1, \ldots, x_r \) can be decomposed into \( r \) marginal distributions \( F_1, \ldots, F_r \) and \( C \) which is known as copula and can be used to describe the dependence of the structures among the variables:

\[
F(x_1, \ldots, x_r) = C(F(x_1), \ldots, F(x_r))
\] (6.2)

This study uses bivariate copula for which the above equation for dependence can be written as:

\[
F(x_1, x_2) = C(F(x_1), F(x_2))
\] (6.3)

In this paper, we use both Gaussian and Symmetrized Joe–Clayton (SJC) copula to examine their effectiveness in modelling the dependence between GCEA stock markets. Gaussian copula is used as a benchmark for the overall dependence, whereas SJC copula is used to capture the upper and lower tail dependence simultaneously.

6.3. Methodology

There are two main steps to model the dependence structure between a pair of stock markets. The first step is to estimate the marginal distribution. The second step is to use copula model this joint distribution. These twos steps are described below.

6.3.1. Marginal Distribution Estimation

A generalized autoregressive conditional heteroscedastic (GARCH) framework is often applied to model the volatility of a stock market. In this paper, we apply the GJR-GARCH model with the assumption of \( t \) distribution in the process to discard any serial correlation and conditional heteroskedasticity process (Engle and Ng, 1993 and Glosten et al., 1993).
The \( t \) distribution is selected instead of normal distribution because of the strong empirical evidence in rejecting the concept of normality distribution in financial data.

Let \( r_{i,t} \) denote returns and \( h_{i,t}^2 \) denote the conditional variance for the period of \( t \). The GJR-GARCH model\(^{14}\) can be formulated as

\[
\begin{align*}
    r_t &= \mu + \vartheta r_{t-1} + \varepsilon_t \\
    h_t^2 &= c + \gamma h_{t-1}^2 + \eta_1 \varepsilon_{t-1}^2 + \eta_2 s_{t-1} \varepsilon_{t-1}^2
\end{align*}
\]

where \( s_{t-1} = 1 \) when \( \varepsilon_{t-1} \) is negative and 0 otherwise. The standardize residual of series, \( z_t \) are modelled as a Student \( t \) distribution with \( df \) represents the degree of freedom and \( \Omega_{t-1} \) denotes the previous information set:

\[
z_t | \Omega_{t-1} = \sqrt{\frac{df}{\sigma_t^2 (df - 2)}} \varepsilon_t z_t \sim iid\ t_{df}
\]

With regard to modelling the (upper and lower) tails of these residuals, the POT method is applied with a predefined threshold value \( u \) and the GPD is then used to model the tails. The process to determine the threshold value \( u \) is crucial for the GPD modelling. According to the Picklands–Balkema–De Haan theorem (Balkema and De Haan 1974; Pickands 1975), a high \( u \) value is important in order to obtain extreme series. However, this result generally leads to a large variance in the estimators due to the probability to discarding the valuable data. Besides, the samples may be too small for data analysis. The data gathered might not belong to the tails and results in a bias in estimators if the value of \( u \) is too low. Thus a trade-off between bias and variance is required to find the

\(^{14}\) Other GARCH models may also be suitable for treating the heteroskedasticity of the returns. GJR-GARCH is commonly used and thus selected for this study.
optimal threshold. Similar to Du and Mouche (1983), $u$ is selected as the 90th percentile for the upper tail the 10th percentile for the lower tail in this study.

The cumulative function for this combination (GPD for the tails and the empirical distribution for the remaining part) can be written as:

$$F(z) = \begin{cases} 
\frac{k^L}{n} \left(1 + \xi \frac{u^L - z}{\alpha} \right)^{-1/\xi} & \text{for } z < u^L, \\
\emptyset(z) & \text{for } u^L < z < u^U \\
1 - \frac{k^U}{n} \left(1 + \xi \frac{z - u^U}{\alpha} \right)^{-1/\xi} & \text{for } z > u^U,
\end{cases} \quad (6.7)$$

where $\alpha$ is the scale parameter, $\xi$ is the shape parameter, $u^L$ ($u^U$) is the lower (upper) threshold, $n$ is the number of observations, $\emptyset$ is the empirical distribution function and $k^L$ ($k^U$) is the number of observations below (exceeding) the threshold $u^L$ ($u^U$).

6.3.2. Copula Estimation

6.3.2.1. Gaussian Copula

A Gaussian copula is based on a multivariate normal distribution. In the bivariate case, the random vector $X = (X_1, X_2)$ is bivariate normal if $X_1$ and $X_2$ are normal. Therefore the dependence structure between the margins can be described by the following copula function:

$$C(u, v) = \int_{-\infty}^{\Phi^{-1}(u)} \int_{-\infty}^{\Phi^{-1}(v)} \frac{1}{2\pi\sqrt{1-\delta^2}} \exp \left\{ -\frac{x^2 - 2\delta xy + y^2}{2(1-\delta^2)} \right\} dx dy \quad (6.8)$$

$$= \Phi_\delta(\Phi^{-1}(u), \Phi^{-1}(v)), -1 \leq \delta \leq 1 \quad (6.9)$$
where $\Phi$ and $\Phi_\delta$ are the standard normal CDF’s and $\delta$ is the linear correlation coefficient.

6.3.2.2. Symmetrized Joe–Clayton Copula (SJC Copula)

SJC copula is a modified version of the 1997 Joe–Clayton copula. In general, the Joe–Clayton copula can be defined as:

$$C_{JC}(u, v|\tau^U, \tau^L) = 1 - ([1 - (1 - u)^k]^{-\gamma} + [1 - (v)^k]^{-\gamma})^{1/k}$$ (6.10)

where

$$k = \frac{1}{\log_2(2 - \tau^U)}$$ (6.11)

$$\gamma = -\frac{1}{\log_2(\tau^L)}$$ (6.12)

and

$$\tau^U \in (0, 1), \tau^L \in (0, 1).$$ (6.13)

However, the original Joe–Clayton copula is not as attractive as SJC copula because SJC can be symmetric when $\tau^U = \tau^L$. Further, SJC copula enables us to capture the lower and upper tail dependence simultaneously. Thus, SJC copula is the ideal choice for understanding the tail behaviour of the data (Patton, 2006a) and it can be defined as:

$$C_{SJC}(u, v|\tau^U, \tau^L) = 0.5[C_{JC}(u, v|\tau^U, \tau^L) + C_{JC}(1 - u, 1 - v|\tau^U, \tau^L) + u + v - 1]$$ (6.14)
where $C_{JC}$ is the Joe–Clayton copula and $\tau^U$ and $\tau^L$ represent upper and lower tail dependence, respectively.

### 6.3.3. Dependence Parameters of Dynamic Copula

In this study, Gaussian dependence parameter is assumed to evolve over time according to the Patton (2006a):

$$
\delta_t = \lambda \left( \omega + \beta \delta_{t-1} + \alpha \frac{1}{10} \sum_{j=1}^{10} \Phi^{-1}(u_{t-j}) \Phi^{-1}(v_{t-j}) \right) \quad (6.15)
$$

where $\lambda = (1 - e^{-x})/(1 + e^{-x})$ is the modified logistic transformation which ensures $\delta_t$ in the interval (-1,1) at all times. Note that in Equation (15), an ARMA (1,10) type process is assumed and $\beta \delta_{t-1}$ captures the persistence effect and the mean of the product of the last 10 observations of the transformed variables $\Phi^{-1}(u_{t-j})$ and $\Phi^{-1}(v_{t-j})$ captures the variation effect in the dependence.

While according to Patton (2006a), the evolution parameters for the SJC copula can be defined as:

$$
\tau^{U/L} = \lambda \left( \omega^{U/L} + \beta^{U/L} \tau_{t-1} + \alpha^{U/L} \frac{1}{10} \sum_{i=1}^{10} |u_{1,t-i} - u_{2,t-i}| \right) \quad (6.16)
$$

where $\lambda$ is given as the logistic transformation: $\lambda(x) = (1 + e^{-x})^{-1}$, which ensures the dependence parameter $\tau^{U/L}$ in (0,1).
6.3.4. Estimation Method

6.3.4.1. Marginal Estimation

The Maximum Likelihood Estimation (MLE) method is used for estimating the parameters. Based on (7), the full estimation of the combination parametric and GPD distribution can be written as:

\[
\hat{F}(z) = \begin{cases} 
\frac{k^L}{n} \left(1 + \frac{\xi u^L - z}{\hat{\alpha}} \right)^{-1/\xi} & \text{for } z < u^L, \\
1 - \frac{k^U}{n} \left(1 + \frac{\xi z - u^U}{\hat{\alpha}} \right)^{-1/\xi} & \text{for } z > u^U,
\end{cases}
\]  

(6.17)

where \(\hat{\alpha}\) and \(\hat{\xi}\) denote the MLE of \(\alpha\) and \(\xi\), respectively.

6.3.4.2. The Inference Functions of Margins (IFM) for Copula

Copula parameters are estimated by using IFM method rather than MLE method mainly due to the consideration of computation time and complexity. Moreover, it has advantage of assessing the goodness of fit of the margin separately. IFM method has two main steps as follows.

Step 1: MLE is used to estimate the parameters of marginal distribution according to:

\[
\hat{\theta}_i = \arg \max_{\theta_i} l^c(\theta_i) = \arg \max_{\theta_i} \sum_{t=1}^{T} \log f_i(x_i, \theta_i)
\]

(6.18)

where \(l^c\) is the log-likelihood function of the marginal distribution \(f_i\).

Step 2: Based on the \(\hat{\theta}_i\), the copula parameters \(\delta\) are estimated:
\[ \delta = \arg \max l^C(\delta) = \arg \max \sum_{t=1}^{T} \log(c(F_1(x_1, \theta_1), \ldots, F_n(x_n, \theta_n); \delta)) \tag{6.19} \]

where \( l^C \) is the likelihood function of the copula. The estimators are consistent under standard regularity conditions.

### 6.3.5. Model Selection Criteria

There are many goodness of fit tests which can be used to identify a suitable model (Fermanian 2005; Chen and Fan 2006; Hans 2007). In this study, we use Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) which are derived from information theory. They are widely used to determine the best type of copula.

AIC works based on the trade-off between complexities and information lost when a given model is used to represent the process that generates data. AIC can be defined as

\[ AIC = -2 \log(\text{likelihood}) + 2k \tag{6.20} \]

where \( k \) is the number of parameters used in the model. The value is a measure based on the relative distance between the unknown true likelihood function of the data and the fitted likelihood function of the model. Therefore, a lower AIC means a model is closer to the truth.

Bayesian Information Criterion (BIC) is defined as

\[ BIC = -2 \log(\text{likelihood}) + k \cdot \log(n) \tag{6.21} \]

where \( n \) is the number of data and \( k \) is the number of parameters used in the model. BIC works similarly as AIC test, but it penalizes model complexity more heavily. The best one that fits the model is the one with the lowest BIC.
6.4. Data and Descriptive Statistics

In this study, we use Shanghai Composite Index for SHSE and Shenzhen Composite Index for SZSE, Hang Seng Index for HKSE and Taiwan Stock Exchange Weighted Index for TWSE. The daily closing prices from 1 January 2000 to 31 December 2013 were obtained from Datastream. Daily logarithmic returns can be defined as \( r_t = \ln P_t - \ln P_{t-1} \), where \( P_t \) is the closing price of the index at time \( t \) in our study.

![Relative Daily Index Closings](image)

Figure 6.1. Relative daily index level

The sample consists of 13 years of daily data with 3651 observations. This period has witnessed a few of financial crises such as the Global Financial Crisis (GFC) and European Debt Crisis. The GFC that erupted in 2008 is considered by many as the worst financial crisis in history and it has an enormous impact on the GCEA. However, the European Debt Crisis had limited impact on the GCEA. Thus we will consider the GFC effect on dependence structure among the GCEA stock markets.

Figure 6.1 presents the relative index level series of GCEA stock markets for the whole sample period. It is clear that the series of SHSE and SZSE have an upward trend from 2006 to 2008. The same trend is also evident for the HKSE and TWSE. Both show an
upward trend between 2006 and 2008. There is and downward trend between 2008 and 2009 which reflects the impact of the Global Financial Crisis (GFC) that began in August 2008. The indices started to rebound and gain a positive momentum in 2009.
Figure 6.2 depict the daily logarithmic returns for the GCEA stock markets. It clearly shows that all the stock markets under consideration are more volatile during the GFC period. Moreover, as expected, the figure also shows that SHSE and SZSE are more closely related in terms of volatility.
Table 6.1. Descriptive statistics of daily returns

<table>
<thead>
<tr>
<th></th>
<th>SHSE</th>
<th>SZSE</th>
<th>HKSE</th>
<th>TWSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. Obs.</td>
<td>3651</td>
<td>3651</td>
<td>3651</td>
<td>3651</td>
</tr>
<tr>
<td>Mean</td>
<td>0.0120</td>
<td>0.0265</td>
<td>0.0081</td>
<td>0.0005</td>
</tr>
<tr>
<td>Median</td>
<td>0.0000</td>
<td>0.0118</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>Std</td>
<td>0.0256</td>
<td>1.6915</td>
<td>0.0256</td>
<td>0.0242</td>
</tr>
<tr>
<td>Skew</td>
<td>-0.0896</td>
<td>-0.3725</td>
<td>-0.0675</td>
<td>-0.2295</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>4.7693</td>
<td>3.5930</td>
<td>8.2963</td>
<td>3.0351</td>
</tr>
<tr>
<td>JB Sta (p-value)</td>
<td>3453.3530(0.0000)</td>
<td>2041.1310(0.0000)</td>
<td>10440.4200(0.0000)</td>
<td>1428.025(0.0000)</td>
</tr>
</tbody>
</table>

Mean, Med, Min, Max, Std, Skew and Kurt stand for the mean, median, minimum, maximum, the standard deviation, skewness and kurtosis for each series, respectively. JB sta denotes the statistic for the Jarque-Bera normality test with two degrees of freedom.

Table 6.1 reports the descriptive statistics of daily returns for the GCEA stock market. A few observations can be made. All the series have positive means. SZSE has the highest mean with 0.0265% followed by SHSE with 0.0120%. TWSE has the lowest mean (0.0005%). The median for all series is 0.0000% except for SZSE. HKSE has the lowest minimum (-13.5820%). HKSE also has the highest maximum return (13.4068%). The standard deviation measure shows that SZSE has the highest volatility (1.6915) while TWSE has the lowest volatility. This indicates SZSE is most volatile among the four markets. All the series are skewed to the left. HKSE has the highest value of skewness and SZSE has the lowest skewness. Finally, HKSE has the highest Kurtosis value (8.2963) and TWSE has the lowest Kurtosis value (3.0351). Thus the return distributions of the four markets are all leptokurtic.

Looking at Jarque Bera statistics, HKSE has the highest value and TWSE has the lowest value. The Jarque Bera test results strongly reject the normal distribution for all return
series. All series exhibit a nonlinear phenomenon and extreme behaviour. The normality assumption is not valid for all series. Thus the EVT approach seems to be a valid choice.

Table 6.2. Linear correlations between markets

<table>
<thead>
<tr>
<th></th>
<th>SHSE</th>
<th>SZSE</th>
<th>HKSE</th>
<th>TWSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>SHSE</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SZSE</td>
<td>0.9324</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>HKSE</td>
<td>0.3516</td>
<td>0.3013</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>TWSE</td>
<td>0.1861</td>
<td>0.1583</td>
<td>0.4751</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 6.2 reports the returns correlation among the series. The strongest correlation is exhibited between SHSE and SZSE. This is an expected outcome because both are located in mainland China. The second highest correlation is between HKSE and TWSE. The weakest correlation is between SZSE and TWSE. These figures show the strength of overall dependence among the GCEA stock markets. However, there is no information content regarding the tail dependence.

### 6.5. Empirical Results

In this section, we present the empirical results of this study. First, we consider the estimation of the marginal models. Second, we discuss the estimation of the copula models; Third, the GFC effect is analysed.

#### 6.5.1. Estimating Marginal Models

In this paper, EVT approach is employed to model the tail distributions for every index series. The top and bottom 10% of the residuals are used for modelling the upper and
lower tails, respectively. These residuals are obtained as described in Section 6.3.1. GPD is used to fit these residuals. The values of the parameters obtained using GPD for the upper and lower tails are presented in Table 6.3.

Table 6.3. The parameter tails fitted by GPD

<table>
<thead>
<tr>
<th></th>
<th>SHSE</th>
<th>SZSE</th>
<th>HKSE</th>
<th>TWSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lower tail</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\xi$</td>
<td>-0.0101</td>
<td>-0.0189</td>
<td>0.0093</td>
<td>0.0282</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>0.6599</td>
<td>0.7132</td>
<td>0.5805</td>
<td>0.6128</td>
</tr>
<tr>
<td>Upper tail</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\xi$</td>
<td>0.1026</td>
<td>0.0903</td>
<td>-0.1719</td>
<td>-0.1179</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>0.5217</td>
<td>0.4602</td>
<td>0.6182</td>
<td>0.5514</td>
</tr>
</tbody>
</table>

Notes: This table represents estimated parameters between selected stock markets using Generalized Pareto Distribution (GPD). $\xi$ represents the shape and $\alpha$ is the value of the scale parameter of the fitted GPD.

Table 6.3 summarizes the parameter estimates for the lower and upper tails based GPD. First look at the lower tails. Clearly, TWSE exhibits the strongest heavy tail as it has the highest absolute value of $\xi$. It is followed by SZSE with $\xi$ =0.0189. HKSE has the lowest absolute value for the $\xi$, thus its lower tail is not so heavy.

Now turn to the upper tails. The values of $\xi$ are positive for SHSE and SZSE, and negative for both HKSE and TWSE. The estimates indicate that HKSE and TWSE have heavy upper tails ($\xi$ =0.1719, 0.1179 for HKSE and TWSE, respectively). In contrast, the upper tails for SHSE and SZSE are not so heavy. In summary, TWSE has heavy tails on both sides. This means that the TWSE is more volatile than other ones in terms of upside and downside risks. Further, let us compare SHSE with SZSE. The $\xi$ estimates indicate SZSE has a stronger heavy lower tail than SHSE, whereas SHSE has a stronger heavy upper tail than SZSE.
To visually assess the GPD fit, we plot the empirical CDF of the upper (lower) tail exceedances of the residuals along with CDF by the GPD in Figure 6.3 (6.4). Although only 10% of the standardized residuals is used, the fitted distribution closely follows the exceedance data. Thus GPD model seems to be a good choice for both tails.

The overall marginal distributions used in this study are shown in Figures 6.5. The tails are fitted by using EVT while the central part is estimated by a Gaussian kernel. This smooths the CDF estimates, eliminating the staircase pattern of unsmoothed sample CDFs. The non-parametric method kernel CDF is well suited for the interior of the distribution where most of the data is found. However, this method tends to perform poorly when applied to the upper and lower tails. The combination with EVT for the tails can overcome this problem.

In summary, Figures 6.3, 6.4 and 6.5 demonstrate that our approach can adequately model the marginal distributions of all data series.
Figure 6.3. Upper tail of GCEA markets’ residuals
Figure 6.4. Lower tail of GCEA markets’ residuals

Figure 6.5. Fitting residuals for the GCEA stock markets
6.5.2. Estimating the Copula Models

In this paper, we are interested in the behaviour of extreme returns. Thus we use copula functions which specifically focus on the tails. To this end, Gaussian and SJC copula are considered. The SJC copula has the advantage of allowing different parameters for the lower and upper tails and thus takes the difference in the behaviour of the upper and lower tails into account. In this paper, the dependence parameters (for Gaussian and SJC) are assumed to follow Patton equation (Patton 2006a).

Table 6.4 presents the parameter estimates for the Gaussian and SJC copulas. For the constant copulas, the key parameters are $\delta$ (Gaussian), $\tau^U$ and $\tau^L$ (SJC). For the dynamic copulas, we focus on $\omega$ (Gaussian), $\omega^U$ and $\omega^L$ (SJC) which are used as a measure of the dependence level of each pair of stock markets. The adjustment in the dependence is captured by $\alpha^U$ (Gaussian), $\alpha^U$ and $\alpha^L$ (SJC). The degree of persistence of dependence is represented by parameter $\beta$ (Gaussian), $\beta^U$ and $\beta^L$ (SJC). The values for the AIC and BIC are used as goodness of fit measure. A lower AIC or BIC value indicate a better fit.

Figure 6.6 represents the time evolution of the dependence parameters of each pair of GCEA stock markets.
Table 6.4. Parameter estimates for constant and dynamic copulas

<table>
<thead>
<tr>
<th>Parameter</th>
<th>SHSE-SZSE</th>
<th>SHSE-HKSE</th>
<th>SHSE-TWSE</th>
<th>SZSE-HKSE</th>
<th>SZSE-TWSE</th>
<th>HKSE-TWSE</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Gaussian Copula</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\delta$</td>
<td>0.9276***</td>
<td>0.3094***</td>
<td>0.1898***</td>
<td>0.261***</td>
<td>0.1635***</td>
<td>0.4901***</td>
</tr>
<tr>
<td>$AIC$</td>
<td>-7188.7</td>
<td>-367.279</td>
<td>-133.9235</td>
<td>-257.6178</td>
<td>-98.869</td>
<td>-1002.7202</td>
</tr>
<tr>
<td>$BIC$</td>
<td>-7188.7</td>
<td>-367.2773</td>
<td>-133.9218</td>
<td>-257.6161</td>
<td>-98.8673</td>
<td>-1002.7185</td>
</tr>
<tr>
<td><strong>SJC Copula</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\tau^U$</td>
<td>0.7920***</td>
<td>0.0976***</td>
<td>0.0012</td>
<td>0.0706***</td>
<td>0.0037</td>
<td>0.2773***</td>
</tr>
<tr>
<td>$\tau^L$</td>
<td>0.8337***</td>
<td>0.1789***</td>
<td>0.1216***</td>
<td>0.1295***</td>
<td>0.0772***</td>
<td>0.3220***</td>
</tr>
<tr>
<td>$AIC$</td>
<td>7504.2526</td>
<td>-385.0091</td>
<td>-158.8489</td>
<td>-271.1503</td>
<td>-111.1265</td>
<td>-1026.5926</td>
</tr>
<tr>
<td>$BIC$</td>
<td>7491.8471</td>
<td>-372.6036</td>
<td>-146.4433</td>
<td>-258.7448</td>
<td>-98.721</td>
<td>-1014.1871</td>
</tr>
<tr>
<td><strong>Dynamic Copula</strong></td>
<td><strong>Gaussian</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\omega$</td>
<td>-8.1017***</td>
<td>0.0136</td>
<td>0.0034</td>
<td>0.0083</td>
<td>0.0003</td>
<td>0.1197</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>0.0231***</td>
<td>0.125***</td>
<td>0.0527***</td>
<td>0.0794***</td>
<td>0.0196***</td>
<td>0.1843***</td>
</tr>
<tr>
<td>$\beta$</td>
<td>12.2696***</td>
<td>1.9505***</td>
<td>1.9785***</td>
<td>1.9709***</td>
<td>2.0066***</td>
<td>1.8057***</td>
</tr>
<tr>
<td>$AIC$</td>
<td>-7194</td>
<td>-474.0517</td>
<td>-188.7604</td>
<td>-314.8249</td>
<td>-129.1187</td>
<td>-1054.7051</td>
</tr>
<tr>
<td>$BIC$</td>
<td>-7194</td>
<td>-474.0466</td>
<td>-188.7553</td>
<td>-314.8198</td>
<td>-129.1136</td>
<td>-1054.7</td>
</tr>
</tbody>
</table>

Matlab is used in the calculations of copula parameters. The authors would like to thank Manthos Vogiatzoglou from the and Osvaldo Silva for their help.
### Table 1

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Value</th>
<th>Value</th>
<th>Value</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\omega_U^*)</td>
<td>1.2891**</td>
<td>0.076*</td>
<td>-9.5043***</td>
<td>0.0931***</td>
<td>-4.8826</td>
</tr>
<tr>
<td>(\alpha_U^*)</td>
<td>-0.3347</td>
<td>-0.3766*</td>
<td>-9.9942***</td>
<td>-0.4012***</td>
<td>-1.1221</td>
</tr>
<tr>
<td>(\beta_U^*)</td>
<td>-4.0354***</td>
<td>0.99***</td>
<td>10.0000***</td>
<td>0.9932***</td>
<td>3.2603</td>
</tr>
<tr>
<td>(\omega_L^*)</td>
<td>1.3821**</td>
<td>0.1141**</td>
<td>0.0985***</td>
<td>0.0591</td>
<td>0.1527</td>
</tr>
<tr>
<td>(\alpha_L^*)</td>
<td>-0.3202***</td>
<td>-0.5343**</td>
<td>-0.4372***</td>
<td>-5.4625*</td>
<td>-0.8053</td>
</tr>
<tr>
<td>(\beta_L^*)</td>
<td>-4.2186**</td>
<td>0.9812***</td>
<td>0.9865***</td>
<td>0.1500</td>
<td>0.9654***</td>
</tr>
</tbody>
</table>

### AIC and BIC

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Value</th>
<th>Value</th>
<th>Value</th>
<th>Value</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>AIC</td>
<td>3910.2329</td>
<td>-501.7875</td>
<td>-190.5665</td>
<td>-302.789</td>
<td>-123.5252</td>
</tr>
<tr>
<td>BIC</td>
<td>3873.0164</td>
<td>-464.571</td>
<td>-153.3499</td>
<td>-265.5728</td>
<td>-86.3086</td>
</tr>
</tbody>
</table>

### Notes:

- \(\delta\) is the parameter of Gaussian copula. \(t^U\) and \(t^L\) are the upper and lower tails of the SJC copula; \(\omega\) is constant; \(\alpha\) and \(\beta\) are the coefficients of the dynamic process proposed. AIC and BIC are Akaike and Bayesian Information Criteria.* = \(P<0.1\), ** = \(P<0.05\) and *** = \(P<0.01\).

---

### SHSE-SZSE

![Gaussian Copula](image)

![SJC Copula - Lower tail](image)

![SJC Copula - Upper tail](image)
Gaussian Copula

SJC Copula - Lower tail

SJC Copula - Upper tail

SZSE-HKSE

Gaussian Copula

SJC Copula - Lower tail

SJC Copula - Upper tail

SZSE-TWSE
6.5.2.1. Constant Copula Models

A few observations can be made from Table 6.4 and Figure 6.6. According to results for the constant Gaussian copula model, the overall dependence among the 6 pairs of stock markets can be ranked in a decreasing order as: SHSE-SZSE > HKSE-TWSE > SHSE-HKSE > SZSE-HKSE > SHSE-TWSE > SZSE-TWSE. According to the results for the SJC copula, the upper tail dependence among the 6 pairs of stock markets can be ranked in a decreasing order as: SHSE-SZSE > HKSE-TWSE > SHSE-HKSE > SZSE-HKSE > SZSE-TWSE > SHSE-TWSE; the lower tail dependence among the 6 pairs of stock markets can be ranked in a decreasing order as: SHSE-SZSE > HKSE-TWSE > SHSE-HKSE > SZSE-HKSE > SZSE-TWSE > SHSE-TWSE. These facts clearly indicate that
I. SHSE-SZSE pair has the strongest overall or tail dependence;
II. HKSE-TWSE pair has the second highest overall or tail dependence;
III. The weakest dependence (overall or tail) is found between TWSE and either SHSE or SZSE.

Our study focuses on the dependence of stock markets which come from the GCEA region of the same cultural background. Due to the strong economic ties in the GCEA, the dependence among these markets is expected to be strong. This is confirmed by the \( \delta \) values of all pairs in Table 6.4 which range from 0.1635 for SZSE-TWSE to 0.9276 for SHSE-SZSE. In contrast, the range of \( \delta \) values are between 0.0479 and 0.4265 in Bhatti and Nguyen (2012) which examines the dependence between Australia, United Kingdom, Japan, United State, Taiwan and Hong Kong stock markets.

Consider the tail dependence for the constant SJC copula. Table 6.4 reveals that \( \tau^L \) is larger than \( \tau^U \) for each pair. This indicates that all the pairs have stronger lower tail dependence than upper tail dependence. Further, the values of \( \tau^L \) for SHSE-TWSE and SZSE-TWSE pairs are below than 0.01 which indicates very low upper tail dependence. This implies that TWSE are not dependent on the mainland China stock markets or vice versa in case of good extreme events. In contrast, they are dependent on each other in case of the negative extreme events.

6.5.2.2. Dynamic Copula Models

Let us look at the results for dynamic copulas. The dynamics of dependence measures between return series are captured by the coefficients, \( \alpha \) (\( \alpha^L \ or \ \alpha^U \)) and \( \beta \) (\( \beta^L \ or \ \beta^U \)) in the evaluation equations. Based on Table 6.4, the persistent coefficient \( \beta \) is larger than the variation coefficient \( \alpha \) for all the pairs except for SHSE-SZSE (\( \alpha^L \) and \( \beta^L \)). This indicates the evolution parameters plot in Figures 6.6 could provide insights on the changes of dependence structure over the time period.

From Figure 6.6, we can see that the dependence between SHSE-SZSE is more stable compared to the other pairs. The dependence parameter \( \delta_t \) for the dynamic Gaussian copula ranges between 0.9 and 0.95 which indicates a very strong relationship between
the two stock markets. Further, with the dynamic SJC copula, $\tau^U$ and $\tau^L$ are around 0.8 and 0.7, respectively. This indicates strong upper and lower tail dependence between these two markets. In sum, SHSE-SZSE pair has the strongest dependence as confirmed above.

For the SHSE-HKSE, the values of dependence parameter $\delta_t$ in the dynamic Gaussian copula are between 0 and 0.3 before 2007, and it is between 0.3 and 0.5 after 2007. A similar change around 2007 can be observed for the parameters $\tau^U$ and $\tau^L$ in the dynamic SJC copula.

For the SHSE-TWSE pair, Figure 6.6 reveals that the values of the dependence parameter $\delta_t$ before 2007 are quite volatile ranging between 0 and 0.3, whereas the values after 2007 are more stable fluctuating around 0.4. The lower tail dependence parameter $\tau^L$ for this pair has an upward trend since 2007. The parameter $\tau^U$ for this pair is almost zero which indicates there is hardly any dependence between these two markets in the case of positive extreme events.

For the SZSE-HKSE pair, the dependence structure is quite revealing in several ways. Similarly to the SHSE-TWSE pair, Figure 6.6 reveals that the values of the dependence parameter $\delta_t$ before 2007 are quite volatile ranging between 0 and 0.3, whereas the values after 2007 are more stable fluctuating around 0.4. However, the lower tail dependence parameter $\tau^L$ for this pair is stable and ranging between 0.1 and 0.2. The upper tail dependence parameter $\tau^U$ has an upward trend since 2009.

For the SZSE-TWSE pair, Figure 6.6 reveals that the values of the dependence parameter $\delta_t$ before 2007 are quite volatile ranging between 0 and 0.25, whereas the values after 2007 are more stable fluctuating around 0.25. However, the lower tail dependence parameter $\tau^L$ for this pair is stable except a peak around 2010. The parameter $\tau^U$ for this pair is almost zero which indicates there is hardly any dependence between these two markets in the case of positive extreme events.

Finally, let us consider the HKSE-TWSE pair. Figure 6.6 reveals that the values of the dependence parameter $\delta_t$ are quite stable ranging between 0.4 and 0.55. The tail
dependence parameters $\tau^L$ and $\tau^U$ for this pair are also stable between 2002 and 2010. Thus the dependence structure between this pair was not affected by the GFC.

Next, we explore the information regarding the relative strength of upper and lower tail dependence. These values could be used to identify the diversification opportunity that might exist. Table 6.4 shows that $\omega^L$ is bigger than $\omega^U$ for most pairs except two pairs (SZSE and HKSE, HKSE and TWSE). Thus the lower tail dependence is relatively higher for these pairs. When market is down, the risk diversification is less effective because of this greater dependence for these pairs. Similarly, when market is down, the risk diversification is more effective for the two pairs: SZSE and HKSE, HKSE and TWSE.

Investors who invest in HKSE might consider SZSE or TWSE to be their preferred choice for managing the downside risk. These results are not in line with the linear correlation reported in Table 6.2 which implies that SZSE-TWSE pair is the best choice for diversification purpose in the mean-variance setting. This may be due to the normality assumption associated with the linear correlation approach. Thus the copula method provides more information compared to the linear correlation. It can provide better insight to portfolios diversification (Wang et al., 2011). This significantly demonstrates the advantages of using copula compared to linear correlation.

Finally, it is worth noting the goodness of fit results. According to Table 6.4, dynamic copulas (Gaussian or SJC) generally fit the data better than the constant copulas. One exception is a SHSE-SZSE pair for which the constant SJC copula yields the best fit due to the high correlation between them. For other pairs, dynamic Gaussian copula is the best fit for two pairs (SZSE-HKSE and SZSE-TWSE) while the dynamic SJC is the best fit for three pairs (SHSE-HKSE, SHSE-TWSE, and HKSE-TWSE). The results are summarised in Table 6.5 below.
Table 6.5. Model comparison: constant vs. dynamic copulas

<table>
<thead>
<tr>
<th>Model Comparison</th>
<th>SHSE-SZSE</th>
<th>SHSE-HKSE</th>
<th>SHSE-TWSE</th>
<th>SZSE-HKSE</th>
<th>SZSE-TWSE</th>
<th>HKSE-TWSE</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Gaussian Copula</strong></td>
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<td></td>
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<td></td>
<td></td>
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<tr>
<td>Constant</td>
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<tr>
<td>Dynamic</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X'</td>
<td>X'</td>
<td>X</td>
</tr>
<tr>
<td><strong>SJC Copula</strong></td>
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<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
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<td>X'</td>
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<td>Dynamic</td>
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<td></td>
<td>X'</td>
<td>X'</td>
<td>X'</td>
</tr>
</tbody>
</table>

X indicates the better fit model among the constant and dynamic copula for each type of copula. X' indicates the best fit model among all 4 constant and dynamic copula models.

In summary, the empirical findings on dynamic copula models can improve our understanding of the dependence among GCEA markets and help in considering portfolio allocation and risk management strategy.

6.5.2.3. GFC effect

Based on the literature, the dependence structure between markets tends to be greater during a financial crisis. GFC is a major event in the sample period and it is natural that we consider GFC effect on the GCEA stock markets. Figure 6 shows that the dependence structure for most of the pairs of stock markets started to increase during 2007 when the GFC started. Thus the dynamic copula models appear to have some prediction power on the GFC.

There is no evident GFC effect on the dependence (overall, lower tail or upper tail) between two pairs, namely, SHSE-SZSE and HKSE-TWSE. SHSE-SZSE are highly dependent on each other with values of $\delta_t$ fluctuating between 0.9 and 0.95. The dependence between HKSE-TWSE is highly stable with $\delta_t$ fluctuating around 0.5. Thus the dependence structure is strong and mature for these two pairs and thus not affected by GFC.
Next, consider the dependence structure for the other 4 remaining pairs. Figure 6.6 shows the overall dependence structure changes and the overall dependence becomes stronger after 2007 for the remaining four pairs. With respect to the lower tail dependence, it becomes stronger for the SHSE related pairs and there is no evident GFC effect for the SZSE related pairs. With respect to the upper tail dependence, it becomes stronger for the HKSE related pairs and there is no evident GFC effect for the TWSE related pairs.

It can also be observed that the lower tail dependence is stronger than the upper tail dependence during GFC for all pairs of stock markets considered. This observation is in the same vein as the findings in the literature with other markets.

Finally, it should be notated that the dependence between most of the pairs of stock markets remains strong in the post-GFC period. Thus, the regime for the dynamic dependence structure between most pairs of stock markets appears to have changed as a result of the GFC.

6.6. Concluding remarks

Over the past few years, there have been a lot of interests in the research on the dependence between financial markets by using the copula approach. Until now, little is known about the dependence structure between GCEA markets despite their importance. This study examines the dynamic dependence of the GCEA markets using dynamic copula and EVT.

EVT is good for modelling tail behaviour. We thus use EVT to estimate all the marginal distributions. We then use Gaussian and SJC copula models to assess the dependence structure between each pair of the stock markets. In this study, copula parameters are allowed to vary over time and follow ARMA-type evolution equations. Gaussian copula is used as a benchmark for comparison. SJC copula is used to capture the upper and lower tail dependence of the return series.
This study reveals that the SHSE-SZSE pair, followed by HKSE-TWSE, has the strongest overall or tail dependence among all pairs. The weakest dependence (overall or tail) is found between TWSE and either SHSE or SZSE. Further, we note that the upper tail dependence between two TWSE related pairs (SHSE-TWSE and SZSE-TWSE) is very low. This implies that at booming times, TWSE does not have much dependence with the stock markets in mainland China. In contrast, HKSE does have significant dependence with the stock markets in mainland China at booming times. Thus it appears that HKSE is more closely related to the stock markets in mainland China at booming times than TWSE. This may be due to the dual listing of many mainland stocks in the HKSE rather than the TWSE.

The risk diversification is more effective for SZSE-HKSE pair as well as HKSE-TWSE pair than other pairs when the market is down. To the best of our knowledge, this outcome has not been previously documented in the literature.

Overall, we obtain more information regarding the dependence structure by using the SJC copula than using the linear correlation. This study thus provides evidence supporting that the combination of Copula and EVT can be a promising method to understand the dependence structure.

Finally, we note that further research can be pursued in the vein of this paper. For example, the combination of the dynamic copula model and EVT used in this paper can be useful in computing Value at Risk (VaR). Moreover, the reasons for the dependence results obtained in the paper can be further investigated.
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CHAPTER 7: SUMMARY AND CONCLUDING REMARKS

7.1. Main Findings

A study on the Chinese stock market by using EVT and copula is carried out in this thesis. Some major conclusions can be summarised as follows.

In Chapter 4, we investigate the distribution of the extreme returns in the Chinese stock market. Specifically, the best distributions that fit with the extreme returns of the Chinese stock market for the minima and maxima series are explored in depth. This approach is expected to yield better results for computing VaR or the expected shortfall than the traditional methods based on normal assumption.

Traditionally, normal distribution has been used to model the extreme returns. The misuse of distribution can lead to underestimating the financial risk based on measures such as VaR.

There are three main distributions often used in EVT: GEV, GL and GP distribution. Most literature concerning EVT tends to focus on the GEV distribution. In contrast to what has been published, this study shows that the GL distribution is the best fit for the Minima series while the GEV distributes the best fit for the maxima series for the Chinese stock market.

A robust test is carried out by considering the price restriction and GFC. It is found that the result remains the same regardless of the events. This finding can have an impact on the application and measurement of risk management.

Chapter 5 reveals that China-Australia stock market pair has the strongest overall dependence, followed by the China-Japan pair. The Chinese stock market seems to have
a greater dependence on Australian stock market compared to Japanese stock market. It is also found that the dependence for the upper tails is low for the China-US and China-UK pairs. This indicates that the Chinese stock market is not much affected by the UK or US or vice versa in the case of positive extreme events. In contrast, these pairs seem to have more dependence in the case of negative extreme events. This implies that the Chinese stock market will have more impact on these stock markets in a burst than a boom.

As we compared between continents, the dependence of the Chinese stock market with the UK or Germany is almost double that of the US. This indicates the Chinese stock market has greater dependence on the European stock markets than the US stock market. The Canadian stock market seems to have more dependence on the Chinese stock market compared to the US stock market. There are many reasons for these empirical results. From the economic perspective, China is the largest exporter of goods in the world. It has created a huge demand for commodity products and consequently has generated huge export booms in many markets and especially Australia.

This study also demonstrated that the dependence for these pairs is much stronger during a crisis compared to a normal period. Therefore, portfolio diversification across these pairs will not lead to many benefits during a crisis. Furthermore the empirical results show the time-varying copula perform better than constant copula. The evidence of this study suggests that the information gathering from time-varying copula also is more useful than constant copula. This method provides us important information regarding the time path of dependence. As we can see, there is a stable and volatile time path. These findings indicate the regimes of time path might change during a certain period. This cannot be captured accurately by the constant copula.

The outcomes of this study have implications for policy-makers and risk management practitioners for the international diversification between major stock markets.

In Chapter 6, the dependence structure between stock markets in the Greater China Economic Area (GCEA) is studied. The dependence between these markets is expected to be strong as they have a similar economic and cultural background. The behaviour of
upper and lower tail dependence between GCEA stock markets should be explored separately as they may contribute in different ways compared to what happens in developed stock markets.

The findings regarding the GCEA make several contributions to the current literature. First, this study demonstrated that the SHSE-SZSE pair had the strongest overall or tail dependence and is followed by HKSE-TWSE which has the second highest overall or tail dependence. It is interesting to note that of all five pairs in this study, the weakest dependence (overall or tail) is found between TWSE and either SHSE or SZSE.

Next, there are two pairs that exhibit only the lower tail behaviour; SHSE-TWSE and SZSE-TWSE. This indicates that Taiwan’s stock market seems not to be affected by the booming mainland Chinese stock market or vice versa. However, the negative extreme events in mainland Chinese stock market could affect Taiwan’s stock market or vice versa. Thus based on the literature, this study has shown that there is asymmetry in tail dependence over the period. Most of the time, the lower tail dependence tends to be greater than the upper tail dependence.

Regarding the GFC, we can see that dynamic copula seems to have some prediction power to the GFC. As we can see, the dependence structure for most of the pairs started to increase during 2007 which could be associated with the GFC. The dynamic dependence movement for most pairs has moved into new regimes after the crisis. Interestingly, the dependence on the markets remains strong despite the GFC coming to an end.

Chapter 6 also shows that the lower tail dependence is stronger than upper tail dependence during the GFC. This observation is the same as observed in other studies on the financial crisis. However there is no GFC impact on the SHSE-SZSE and HKSE-TWSE. The dependence for these pairs is stable and mature.
7.2. Limitations and Future Research Directions

This research has done a thorough investigation on the extreme returns distribution and dependence structure between Chinese stock market with others, but it is worthwhile to point out some restrictions and shed light on some future research directions.

(i) Modeling the distribution of the extreme returns in Chinese stock market

For the first objective, this research suggested further research could be extended to SZSE data. The daily returns of the SZSE index are different compared to the daily returns of the SHSE index. The types of companies listed on each exchange differ. Most companies that are listed on the SHSE are large and state-owned whereas SZSE data tend to consist more of micro-sized companies. Therefore their extreme distribution could differ. These markets also differ in terms of capitalization. The size of the SHSE market is almost double that of the SZSE and thus lead to different outcomes. The SZSE is expected to be more volatile and generates a few extreme cases regarding this type of company or business.

Next, this paper's data are restricted to 2013 (1991 to 2013). There is an excessive movement in the Chinese stock market during 2015. The SHSE composite index has increased almost 60% in the first half of 2015. This movement could be associated with an action by China’s central bank which has unexpectedly decided to cut interest rates for the first time in two years. It could also be due to the launch of Shanghai-Hong Kong Stock Connect. This platform has allowed the mainland investors to trade in Hong Kong stocks from Shanghai while foreign investors can trade in the Shanghai market for the first time via the Hong Kong stock exchange. The study of the SHSE during this behaviour might be quite interesting.

(ii) Dependence structure between the Chinese stock market and other major stock markets

In Chapter 5, two stock markets in each continent are selected to represent US, Europe and Australasia continent. Future potential research might extend it to the other stock
markets. The research could take more than two stock markets to represent each continent. More information and concrete conclusion could be made from there.

With reference to the dynamic dependence, the Dynamic Conditional Correlation (DCC) method proposed by Eagle (2002) is one alternative that can model the multivariate correlation. In this study, the comparison has not been made as our aim is to understand the extreme returns behaviour and extract more information from it. An extended comparison between DCC method with EVT and copula method could be done and provide a better picture regarding the dependence structure in this stock market. The information regarding this can help to understand the effectiveness of EVT and copula method.

Regarding the actual application, we believe that integrating the time-varying copula model with EVT will be very helpful in computing the Value at Risk (VaR) for those selected stock markets. Back-testing analysis about this method and how they react to the real world could be studied. At the same time, a comparison between another method (Wavelets and vine copulas) should be considered (Brechmann and Schepsmeier 2013; Aloui and Jammazi 2015; Cooke et al 2015).

iii) Dependence Structure in the Greater China Economic Area (GCEA)

This study only focuses on the dependence structure between the GCEA stock markets. Studies in the future could be extended to see how these regional stock markets are related to others. More exploration on this dependence could include the major stock markets in the US, UK, Germany and other developed economies. Regarding application in risk measurement, the recommendation is the same as the above. EVT and copula can be implemented in the context of VaR measurement. The results could be compared to several other approaches.

In this study, we found that there is possibility diversification for the SZSE-HKSE pair as well as for the HKSE-TWSE pair. However, the study does not look into details about this matter and how it respond during the crisis personally. The trial of the portfolio could be made to see how this suggestion works.
Last but not least, the study might consider the impact of certain economic events. For this case, certain regional events that happen in GCEA could be considered. These stock market behaviour and how they related to economic events are interesting to be considered, e.g. the introduction of Shanghai-Hong Kong Stock Connect which is a cross-boundary platform that connects the Shanghai Stock Exchange and the Hong Kong Stock Exchange. This platform has allowed investors in these markets to trade stocks on the other market using their local brokers and clearing houses. This event could potential impact the relation between GCEA stock markets.

7.3. Conclusions

The Chinese stock market has grown rapidly since 1990s due to stunning economic development. This stock market has become one of the most influential in the world. There are many reasons to focus on the Chinese stock market as it has many interesting features.

This market endures frequent government intervention and it was closed to foreign investors compared to others before. However, this market has experienced significant changes over the recent decades. Many liberalisation actions have been taken by the Chinese government regarding this via investment and international trade, e.g. B-shares platform is a platform that designed for foreign investors, Foreign Institutional Investors (QFII) programme, QDII programme. No doubt any changes in the Chinese stock market will have an impact on others. Next, most participants in this stock market are individual investors. Most of the time, these traders engage more in speculation rather than long-term investment.

This stock market is more volatile compared to others. There are several extreme movements for these two decades in the Chinese stock market. This study explores the extreme behaviour of the Chinese stock market. One of the issues is to identify the best distribution that suits the extreme returns of the Chinese stock market.
In this research, the best distribution of the extreme returns for minima and maxima in the Chinese stock market over the period 1990 to 2013 is investigated. Three main distribution related to extreme values are considered. In this study, popular GEV or GL is not the best model for both minima and maxima series. This study has shown that GL distribution is a better fit for the Minima series while the GEV distribution is a better fit for the maxima series of the Chinese stock market’s returns.

This is in contrast to the findings for other stock markets such as those in the US and Singapore. This brings an important finding since most of the time, EVT application in finance tend to focus on the GEV or current popular distribution, GL. The miss use of a distribution may underestimate the extreme events that happen in Chinese stock market. Thus this result can improve VaR calculation and other market risk tools.

Dependence on markets and information regarding asymmetric dependence have been considered by risk managers, investors when selecting portfolios, asset pricing and risk management. Recent developments in risk management have led to a renewed interest in this topic. This study uses EVT and time-varying copula to model the dependence structure between stock markets. To date, many models and methods have been employed to understand the behaviour of the dependence between stock markets. However, these methods tend to have certain limitations. Many methods tend to work under the normality assumption which is often not valid. Investment managers and risk managers should be careful when using models that are based on normality assumption and linear correlation when it comes to asset allocation for portfolio diversification.

In this study, the EVT and copula models are used to study the dependence between Chinese stock market and other ones in the world. Before copula is employed, we construct a model marginal distribution that is derived from GARCH and EVT. The study confirms that EVT helps improve the empirical distribution of the extreme returns. Two types of copula are considered. Gaussian copula is used to capture the general dependence and SJC copula with upper and lower tail dependence. The dependence of these parameters follows the ARMA type evolution. These time paths of the pairs have been examined.
Taking asymmetry characteristics in financial data into account can provide a better understanding of dependence structure between stock markets. This study has demonstrated the usefulness of EVT and time-varying copula in understanding the dependence between Chinese stock market and others.

Overall, the research results reported in this thesis enhance our understanding on the Chinese stock market as well as its dependence with other stock markets. The results from this study can be useful for international diversification and portfolio management.
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