UNIVERSITY COLLEGE LONDON

School of Slavonic and East European Studies

Charles University

Faculty of Social Sciences

Qihao Su

Testing CAPM, Three Factor Model and Volatility in Emerging Market: Evidence from China and Poland

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Supervisors: Jiří Novák (PhD), Eugene Nivorozhkin (PhD)

Prague, Czech Republic

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Abstract

Capital Asset Pricing Model (CAPM) is an equilibrium model to test relationship between expected return and market risk (Sharpe, 1964). The model research on pricing and return when the securities market reaches equilibrium and investors are rational and investing by diversification based on Markovitz portfolio theory (Markovitz, 1952). Fama and MacBeth (1973) proposed a cross-sectional testing methodology on CAPM and this regression method has been widely used in testing CAPM in developed markets since then. While CAPM is hard to explain more and more market anomalies (excessive return in smaller market value company) in cross section regression, Fama and French (1992) added two more factors (SMB and HML) and proposed three factor model. The empirical results show that three factor model is superior to CAPM in developed markets. Relevant studies have been conducted by Manjuunatha (2006) and Trimech et al. (2015) but show different results. This dissertation will use Fama-MacBeth cross section approach to test CAPM and Fama-French's three factor model in Chinese and Polish stock market respectively. Following Fama and MacBeth (1972) and Shweta and Anil (2015), three sub periods of Polish and Chinese stock market returns ranging from 2007 to 2018 are examined. The empirical results in this thesis covering different time periods aim to support CAPM and three factor model by providing emerging markets evidence but the empirical results in Chinese and Polish stock markets do not unambiguously support Capital Asset Pricing model and Fama-French's conclusion. The thesis also refers to GARCH model and Maximum Likelihood estimation to test volatility in Chinese and Polish stock market. As supplement of volatility test, this thesis follows Phillips, Wu and Yu (2011) and Deng (2013) to run newly-proposed supADF and supKSS, namely bubble tests. The results show that over-volatility and bubbles exist in both Chinese and Polish stock markets, especially during crisis period.

Key words: Capital Asset Pricing Model; Portfolio theory; Fama-French Three-factor model; Fama-MacBeth cross-sectional approach; GARCH model; SupADF; Over-volatility

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1. Introduction

Capital Asset Pricing Model (CAPM) is an equilibrium model to test relationship between expected return and risk (Sharpe, 1964). Since one of assumption of classical CAPM is that investment and consumption are within one period, this situation does not fit real capital market. Lintner (1965) and Black (1972) developed CAPM and assume that market is Mean-Variance efficient in the sense of Markowitz (1959). The relationship between systematic risk (known as beta) can explain cross sectional expected return. This is also described as Security Market Line (SML). Merton (1973) proposed Intertemporal CAPM (ICAPM) and Rubinstein (1974) constructed single-period Linear Risk Tolerance Model (LRT). Then scholar combined the asset pricing question with consumption utility function and proposed Consumption Capital Asset Pricing Model (CCAPM) (Hansen and Singleton, 1984).

Early work of CAPM theory starts from assuming the existence of the perfect competition in stock market (Sharpe, 1964; Lintner, 1965; Mossin, 1966). They describe the pricing model for a single period and return follows normal distributions. Theoretically, classical CAPM assumes stock market follows competitive trading equilibrium and there are no arbitrage opportunities. The assumptions of Capital Asset Pricing Model also include: Investors prefers higher returns; investors are risk aversion; the information within capital market is free and available to all investors in same; the risk-free return exists in capital market that can be lent and borrowed; investments are infinitely divisible and all assets are available to investors. The Fama and MacBeth (1972) believes the price of stock is depended on expected return and risk. Investors have homogeneous expectations on expected return, risk of assets and covariance of securities.

In order to adapt to complex data in real world, further research lessen up the assumptions of CAPM. Since CAPM was proposed, the scholar have produced several empirical researches on this topic in the last four decades. Black and Scholes (1972) argued that market risk can explain returns of datasets before 1969 but lost explanatory power on the data after that time. Fama and MacBeth (1972) pointed out that market risk could not fully explain average return of stock market and other factors that can contribute investment on stocks should be considered.

Fama and French (1992) considered beta, market size, book-to-market equity, leverage and E/P ratio into regression and conducted chi-square tests for the effects of each factor on stock return. All of these four factors show significant strong impact on investment return. Further research results on multiple variables regression show the explanatory power of financial leverage and P/E ratio is completely absorbed by market value factors and book-to-market ratio factors. Therefore, market value and book-to-market ratio has been the determining factors on market return in this research. However, Fama and French (1996) pointed out that book-to-market value and market capitalization simultaneously generating earnings are still unknown, confirming the needs for future pricing procedures (CCAPM and ICAPM).

After three-factor model being proposed, Chui and Wei (1998) selected five typical stock markets (South Korea, Taiwan, Malaysia, Hong Kong and Thailand) in Asia and the both two factors can perfectly explain the return in whole markets though the market risk premium has weaker impact. Daniel, Titman and John (2001) chose Tokyo stocks as their research samples over the period of 1975 to 1997 and got similar results. Connor and Sehgal (2001) selected Indian stock markets and acquired ideal investment portfolios. Haward and Robert (2005) derive new factor models by adding stock exchange rate using samples in Australian stock market between 1990 and 1998. Bundoo (2006) researches on Mauritius markets between 1997 and 2003 and employs GARCH model and multiple regression to conclude that three factor model is supported by empirical evidence during this period in Mauritius while time dummies can improve the goodness of fit in three-factor model. On the other hand, Alan, Richard and Harris (2001) conduct empirical research on UK stock markets and suggest that three-factor model can’t explain the UK stock market return. Denis (2013) firstly chose emerging European stock markets, Croatia as examples, and selected 145 stocks over the period of 2007 to 2013. The empirical results present that Fama-French three-factor model can describe Croatia stock market in some perspective but further factors should be added to increase explanatory power.

Compared with developed markets, emerging stock markets are characterised by higher volatilities and returns while the research on emerging markets are still limited (Fama and French, 1996). This dissertation will focus on China and Poland, two large transition economies in East Asia and Eastern Europe respectively to test CAPM in their own stock markets to fulfil the research in emerging markets.

In Chinese stock market, research on asset pricing start later than developed market because of the political environment and national economy began to become steady in 1995. Fan and Yu (2002) selected Chinese stocks between 1995 and 2000 and conducted Fama-MacBeth cross-sectional test and conclude that three-factor model favours Chinese stock market over this period. The size and value effect are corresponding with results in developed markets. Zhou and Jiao (2011) selected samples over period of financial crisis (2007-2009) and post-financial crisis. The empirical results show that Fama-French three factor model can't explain the Chinese stock market but it can be explanatory when the test period is extended. In summary, the conclusions are different based on various datasets and different periods. However, most of research ignores the irrational behaviour in stock markets, resulting in speculation and over-volatility.

As one of the emerging markets in Central and Eastern Europe, Poland has high trading volumes and adequate public listed stocks for our research. Extensive examples in Polish Stock market have presented significant relationship between three factors and future returns (Rosenberg, Reid and Lanstein, 1985; Lakonishok and Shapiro, 1986). Borys (2011) applies cross-section approach to test CAPM and combines so-called macroeconomic factor model in transition European countries:

Czech Republic, Hungary, Poland and the Slovak Republic over the period of 1993-2003 and the empirical results show that excess market risk, production, inflation and economic structure can explain the return of stocks in Central and Eastern European stock markets. Another research in 2013 harnesses Fama-French three factor model to explain cross section returns of new public listed companies in European Union's areas (Foye, Mramor, and Pahor, 2013). The majority (over 65%) of them are on Warsaw Stock Exchange (WSE). The results show poor explanatory power of 'Small minus big' (SMB) variable but it can be increased by replacing it with net income/cash flow from operating activities, a proxy of earning management ability. The previous research on Polish stock market show poor explanatory power of CAPM on cross section return but this dissertation will conduct new empirical tests using data from new periods and consider the effects of financial crisis. Since emerging markets are more volatile considering descriptions and conclusions from historical research (Rouwenhorst, 1998; Martin, 2003). Therefore, this dissertation will investigate over-volatility problems in Chinese and Polish stock markets as a supplementary of asset pricing research in emerging markets and further information will be discussed in section 2.

This dissertation is developed by following structures. To begin with, Chapter 2 (literature review) will start with a brief introduction to portfolio theory. Following by this, this dissertation summarizes the previous findings about testing the CAPM and Fama-French three factor model in developed and emerging markets for comparative analysis, which is helpful to interpret the empirical results and explain the results of testing CAPM and Fama-French three factor model in emerging markets in different sub sample periods. Then, section 2.2 reviews over-volatility theory and present previous research on volatility in stock markets. The thesis also introduces models (approaches) to test volatility in this section and will harness it in empirical part. Section 2.2.4 introduces the definition of bubbles in stock price and approaches to test bubbles as supplement of testing volatility for our research. Section 2.3 reviews CAPM and Fama-French three factor model. This part compares the research results of testing two models in different stock markets and sample periods. Section 2.4 will present relevant testing CAPM researches on emerging markets. Finally, this thesis summarizes contributions to current literatures and further improvement suggestions of this research.

Secondly, section 3 is structured with theoretical methodology of framework. Section 3.1 firstly introduces background theory of Capital Asset Pricing Model and presents testing model of CAPM. The testing procedures are illustrated in this section. Followed by descriptions of Fama-French three factor model, section 3.2 presents process from portfolios formation to factors (SMB and HML) calculation. The chapter 3.3 describes theoretical model of testing volatility and bubble tests. The data, variables and descriptions are presented in section 4.2 following with the estimation structure. This dissertation divides samples periods into three sub periods for its research propositions.

Finally, Chapter 5 presents the results and discusses performance of models in three sub periods in Polish and Chinese stock markets. This thesis tests volatility as supplement to explain asset pricing in emerging stock markets. Based on results and comparative analysis obtained in section 5, chapter 6 will give conclusions on testing CAPM and Fama-French three factor model in Chinese and Polish stock market respectively. Explanations of empirical evidence and alternative suggestions for further research are given at the end of this dissertation.

2. Literature Review

This chapter first presents the theories of capital asset pricing model based on portfolio theory claimed by Markovitz (1952). The section 2.1.2 continues with an introduction to CAPM and Fama-French factor model. Section 2.2 will further discuss excessive volatility as a supplement of asset pricing research in emerging stock markets. Finally, the chapter summarizes previous research findings on testing CAPM and Fama-French three factor model and volatility of Stock market in emerging stock markets (especially our samples, Chinese and Polish stock markets). In addition, this thesis claims the contributions to current literature at the end of this section.

2.1 Theory for CAPM and Fama-French Three Factor Model

Sharpe (1964) first introduced CAPM and argued that increasing the amount of risk with investments taken by investors is the only way to increase the excessive return. The model and explanations were developed and modified by relaxing initial conditions or adding other hypothesis in the last four decades. The aim of Capital Asset Pricing Model is to quantify systematic risk and reveal the relationship between risk and expected returns (Cai, Ren and Yang, 2015).

2.1.1 Portfolio Theory

Investment opportunities consist of risky and non-risky assets. According to the Separation Theorem, efficient portfolios are combination of both risky and non-risky investments, which means rational investors favour different exposure to risk in a portfolio (Fama and French, 2004). According to their visual description of investment opportunities, it is possible for investors to minimize their variance on the central level of expected return and reach a optimal investment in a portfolio with their own willingness and strategy. Markovitz (1952) proposed investment portfolio theory, which includes mean variance analysis methods and portfolio boundary efficient model. This model harnesses variance of stock price to measure relevant risk and quantify return and risk. This theory is derived and developed by Sharpe (1964), Lintner (1965) and Black (1972) and used as a tool in Capital Asset Pricing Model. They believe non-systematic risk can be eliminated by diversified investment. The stock returns measured by this pricing model can't be eliminated by diversified investment, namely systematic risk premium.

2.1.2 CAPM and Fama-French Three-Factor Model

Later, Fama and French (1993) develop a new pricing model by introducing two additional factors and they are firm size and book-to-market ratio. In CAPM, they point out the key is how the true covariance of market can be efficiently explained by Capital Asset Pricing Model but this model will test the explanatory power of three variables on cross section return. Before the development of this model, Sharpe (1964) argues that the average return premium in Three-Factor Model can be misleading with pricing. Empirical researches propose that explanation power of CAPM is weak (Sharpe, 1964; Lintner, 1965). In 1980s, pricing-ratios and firm size variables were empirically proved to explain the portfolio returns (Cheng and Grauer, 1980; Van and James, 1980). They corrected the CAPM and point out that new three-factor model can predict the expected excess return of investment portfolios more accurately than CAPM (Fama and French, 2004). The Fama-French Three-Factor Model has encouraged a debate in academia since its publication. Fama and French contribute a significant work in the field of CAPM and Three-Factor model with investment portfolios. Their research methodology has an influence on the global research of CAPM and three-factor model because the three-factor model is better than CAPM in estimating average returns on investment portfolios. In majorities of market regression results, three-factor model presents a favourable applicability, especially in emerging markets (Davis, Fama and French, 2000; Drew, 2003; Gaunt, 2004). Stock market data used in the research of Fama and French are during 1963 to 1990 while it is not comparable to current USA stock market. Thus, some research believe that empirical results of emerging markets can support Fama-French three factor model, which is corresponding to USA development stage in the late 20th century (Drew, 2003).

Some research test three-factor model by different time slots and countries but the results suggest that some selected factors can’t explain cross section returns.

Bartholdy and Peare (2005) employ CAPM and Three-Factor Model to compare the performance of estimating expected return in the U.S. stock market. The figures show that the difference of CAPM explained is approximately 3% and on average of 5% for Three-Factor Model. The different interval and indexes of regression results suggest that the best fit were monthly observations over five years period. Although the results show both CAPM and Three-Factor Model are imperfect for expected return estimating, it reveals different datasets and periods can produce different outcomes. However, after correction of three-factor model, some empirical results show a favourable explanatory power. Trimech, Kortas and Benammou (2009) combines wavelet analysis in stock market and find Three-Factor model has stronger explanatory power with increasing wavelet. They note that the link of expected return and three factors is determined by time period. A time-series test is conducted on the performance of CAPM and Three-Factor Model by estimating equity capital in the field of company investment (Suh, Song and Lee, 2014). Suh creates the dataset by monthly stocks over a 5-year period in global stock market. The empirical results show a significant figure in regression results. The interaction results reveal that two model can work as counterparts. For investment portfolios with less value, the estimation of Three-Factor Model is more efficient. CAPM, on the contrary, is more appropriate for investment portfolios with large-growth portfolios. This research keeps consistence with the conclusion and methodology of Bartholdy and Peare (2005). Grauer and Janmaat (2010) conducted a cross-sectional testing and note that increasing significance sees in beta when replacing the portfolios from low-beta to high-beta. As mentioned in Bartholdy and Peare (2005), results of two models’ performance are affected by the selected datasets.

2.1.3 Continued Development for CAPM

In an effort to provide a more appropriate model for investment outcome enhancement, examining models explanatory power on cross section returns, improvements and alternatives for CAPM is continuing (Kahn and Lemmon, 2016). The Three-Factor Model enlarges the research of CAPM and contributes to mainstream asset pricing theory. More criticizations arise mainly because factor model does not have micro-foundation. Breeden (1979) proposed Consumption-based Capital Asset Pricing Model (CCAPM). It explained whether investors choose current buy in or delay equal assets investment.

Hansen and Singleton (1982, 1984) employs data from New York stock market and Generalized Method of Moments (GMM) Estimation to design its empirical research. The results are corresponding with the research of Breeden (1979) and show that investors have preference in risk aversion and pay more attention to current utility where buying into stocks is a rational expectation. However, GMM model still does not explain the abnormal phenomena. Including risk-free rate, equity premium and excessive volatility (Lettau and Ludvigson, 2010).

To find explanations on the phenomena, research has been conducted by adding more factors to construct new models to explain cross section return. Campbell and Cochrane (1999) explain abnormal variances on dynamic asset prices by CCAPM with formation and change of consumption habits factor. CCAPM with Expected Utility equation suggest that consumption growth can explain equity premium (Campbell, 2003; Bansal and Yaron, 2004). Eiling (2013) argues that heterogeneity of human capital plays an essential role in asset pricing. The heterogenous risk premium produced by the covariance on stock and human capital reveals that cross-sectional gain of stock is affected by industrial level instead of total labour income.

2.2 Theory for Excessive Volatility

The excessive volatility in stock market is observed in emerging markets (Borys, 2011). The behaviour bias, market frictions, incorrect pricing and other irrational behaviour will cause stock price excessive volatility (Shiller, 1981). As mentioned by Shiller, the excessive volatility cannot be explained by rational expectation theory but reveals the irrational behaviour in stock markets. There are three approaches for previous scholars to investigate the measure of excessive volatility.

2.2.1 Theory for Measuring Excessive Volatility

Schiller (1981) conducted variance-ratio methodology to test excessive volatility of capital market. It assumes the variance of dividends is the main factor of the variance of stock price. Theoretically, Schiller (1981) believes the variance of actual stock price should be less than the variance of basic stock price. The empirical results reject the hypothesis of rational expectation and reveals the existence of excessive volatility. Although this test is appropriate for both stationary and non-stationary series, the dividends system in emerging markets is not developed and the discounting factor is difficult to obtain.

Patel and Sakar (1998) developed a Relative Value of stock price index approach and definite relative Value of stock price (*CMAXt)*. This index is the stock price in time *t* divided by the historical highest (or lowest) stock price index. The determination of excessive volatility is this figure higher than 20% in developed markets or 35% in emerging markets. Since there may exist outlier in historical market, the calculated figure can be large.

Probability Density Approach is developed by probability theory. Under probability density assumption, all indexes follow a certain probability distribution. Excessive Volatility is observed as a small probability event. Feng (2011) ever tested excessive volatility in Chinese capital market using this method. She assumes a group of samples subject to standard distribution and all data is expected to lie within (μ-3σ,

$\mu+3\sigma$). Any samples beyond this interval are regarded as excessive volatility time. This method makes it easy to obtain when excessive volatility happens in the stock market in statistical approach.

2.2.2 Theory for Wave in Capital Market

Traditional CAPM assumes that market participants have same active expectation on investment return while empirical results show that the average figure and variance of return on assets will change with time and this phenomenon is called Volatility Aggregation. The aggregation can't be explained by traditional CAPM so Engel et al. (1982) propose an autoregressive conditional heteroscedasticity model (ARCH). It is a random variable when expected return changes with time but will transform to ARCH when adding conditional expectation. To improve the model, Bollerslev (1986) proposed a generalized autoregressive conditional heteroscedasticity model (GARCH), from which the conditional variance is an equation of previous errors and variances. The research of Engel and Bollerslev (1988) supports conditional CAPM. In real capital market, the variance of expected return is time-varying. Jorion (1988) conducted research on Poisson Jump of the price indexes in stock and exchange market. Daal (2007) improves the CARCH model through the variance of volatility, interest rate and autoregressive structure.

2.2.3 Theory for Over-Volatility and Behavioural Finance

In 1980s, academia believes the variance on dividends determines the variance of stock price. However, Shiller (1981) designed an excessive volatility test and the empirical results of Dow Jones Industrial Average Index and dividends reject the agreement of dividends determination. Campbell and Shiller (1987) reject Present Value Pricing Model and raise a debate between rational and irrational expectations in effective or ineffective market.

Shiller (1987, 1988, 1989) started his behaviour finance research in over-volatility in stock market and noted that psychosocial factors play a vital role in excessive volatility.

Shefrin and Statman (1994, 2000) proposed Behaviour Asset Pricing Model (BAPM) and the permanent traders and their strategies reflect on the fundamentals of behaviour finance theory. The expected return of stocks is always determined by behaviour exposure. The core of behaviour finance theory is that pricing is a production of interaction between rational and irrational traders.

Based on behaviour capital pricing theory, many results against CAPM got their explanations. Lakonishok et al. (1994) explain value premium in irrational perspective and, that is, irrational traders are lack of full understanding of relevant information resulting in deviation of investment decisions and value premium. Barberis (2001) explain difference of return on individual stock. The irrational factors are various and debate arise during the development of BAPM. In the research of Barberis et al. (1998), investors will hold the view of risk aversion and lack response to stock price, promoting short-term inertial effect. Otherwise, Hong et al. (1999) believes the reason why inertial effects arise is that private information slowly diffuses in economy accelerating lack of response to stock price. In all, BAPM concentrates on behaviour of investors. The stock price of a central period is the interaction between irrational and rational traders. This explain paradox of mainstream CAPM. However, behaviour finance theory cannot be supported by data and empirical results. Behaviour finance is only a complement of mainstream CAPM.

Over-volatility in stock market is identified by volatility rate and figures. Relevant methods include ARCH, GARCH model and model derived from GARCH model (i.e. MRS-GARCH, SV model). Engle (1982) proposed Autoregressive conditional heteroscedasticity model for those time series data with characteristics including volatility clustering, spike and thick tail, which starts the ARCH model. Bollerslev (1986) modified and developed ARCH model and introduced infinite error items into conditional variance equation, namely GARCH model. Glosten (1991) introduce risk factor and proposed TGARCH model, which is more accurate in observing stock return time series data. Toshiaki (2000) believe that EGARCH model can fit Japanese daily market return data perfectly and the empirical results is corresponding with its proposition. Blair (2001) suggests American daily stock return data is full of characteristics of cumulative information content and uses ARCH model together with maximum likelihood estimation to describe daily return time series data in New York Stock Exchange. Ser Huang and Granger (2003) compared the predictable ability of GARCH, HISVOL and ISD model in different stock markets. They find GARCH model is the most powerful in emerging markets. Mala and Reddy (2007) harness GARCH model in Fiji Stock Exchange for 16 stocks over the period of 2001 to 2005. They observed that seven stocks were over-volatile. Joshi (2008) selects daily return data of Indian BSE Senses Index between 1990 and 2006 and constructs ARCH and GARCH model. The results show that GARCH (1,1) model can perfectly fit Indian stock markets and over-volatility phenomenon exist in Indian stock market. Chiadmi (2012) applies GARCH model for SP sharia Index and S & P 500 Index. The results show that continuous over-volatility exist in both stock markets but the volatility rate of S & P 500 Index is lower, indicating lower risk in this stock market. Li and Zhu (2010) harnesses GARCH-M model to test market return in 30 stock markets over the period between 1997 and 2007. They suggest that Chinese stock market is seventh volatile markets and Polish stock market is the 9th.

In Chinese stock market, Wen (2002) harnesses GARCH model, ARCH M model, TGARCH model and EGARCH to test over-volatility in Shenzhen Stock Exchange over the period of 1994 to 2001. The figures of DW, AIC, Log L. present the perfect fitness of GARCH model and forecast-period mean squared error indicate that GARCH model is the best choice of Chinese stock market. Mo (2004) compares time series return of London, Tokyo, Shanghai and New York. The results show the highest volatile stock market is Shanghai Stock Exchange. Wei (2008) chose GARCH, EGARCH, TGARCH model to test the over-volatility. The results conclude that ARCH effect exists in Shanghai Stock Index series data and both GARCH and EGARCH have better fitness on Chinese stock market.

2.2.4 Bubble Test of Stock Price

Volatility is defined as bubbles in a new perspective (Mankiw, 1985). The other side of excessive volatility can be regarded bubble, which reflects the long-term high nature of price and fundamental value. Bubble of asset price usually refers to exorbitant basic value in stock market. Testing the bubbles is beneficial to understanding asset pricing variance, adjusting macroeconomics policy and protecting economic stability.

Since financial data of stock price is easy to obtain, most research aim at whether bubbles exist in stock price. Although excessive volatility is not designed for bubble test, it can indirectly provide methodology for testing assets with bubbles. However, excessive volatility is different from bubbles in stock price tests. Mankiw (1985) theoretically point that the existence of bubbles may not reject excessive volatility in stock market. Therefore, no bubbles can be observed under this situation. Bubble test can be regarded as development of excessive volatility of stock market, even making the results and analysis more accurate.

Traditional bubble test, including West (1987), Diba and Grossman (1988), ever employed bubble test in emerging market by calculating value of basic stock price. Phillips and Wu (2011) find a more accurate way to test bubbles. The finding is that stock price with bubbles is a divergent process while no bubbles existence is unit-root process. Therefore, the null hypothesis is unit-root and divergent process is alternative hypothesis. The combination of Augmented Dickey–Fuller test and supremum test can be harnessed to estimate when the bubbles exist and disappear. Evans (1991) note periodically burst bubbles with complex change characters.

The typical limitation of Supremum ADF test is that it tends to over-reject null hypothesis with heteroscedasticity errors. Based on exponential smoothing model, Deng (2013) proposed supremum KSS test. Unlike supremum ADF test, supremum KSS test relaxes exogenous restrictions on foam expansion rate and it reaches the expectation that supremum KSS is robust to heteroscedasticity characteristics in disturbance terms. However, few tests consider the effect of financial crisis eras using this bubble tests to analyse irrational behaviour in emerging stock markets.

2.3 Review of Model

Capital Asset Pricing Model and Three-Factor Model introduced by Fama and French (1992) have become the most popular models in the analysis of the relationship between expected return and risk. However, mainstream asset pricing model experienced development by adding or replacing some factors in the models.

2.3.1 Capital Asset Pricing Model

Capital Asset Pricing Model is an OLS estimation model and it reveals that the return on any stock depends on its risk relative to the market. Fama and MacBeth (1973) proposed a cross-sectional regression approach to test CAPM using individual stock to avoid the strong relationship among each stock.

The Capital Asset Pricing Model (CAPM) regression equation can be written as follows:

$$R_{it} - R_{ft} = \alpha_i + \beta_i\left(R_{mt} - R_{ft}\right) + \varepsilon_{it} \tag{2.1}$$

R_{it} represents the return of stock i in month t and R_{ft} is the return (interest rate) of risk-free rate in month t. R_{mt} is the monthly return of market portfolios in month t. The β_i is the risk coefficient that estimated by this model. To form the portfolios, most research employ portfolio grouping approach proposed by Fama and French (1992) to replace single return of stocks. Compared with single assets, portfolios as samples can promote the accuracy of estimation between required return and systematic risk. The thesis selects first 24 months as periods of portfolios. When obtaining estimated beta (risk coefficient) of each stock, all beta samples are arranged from small to large and divided into 10 groups. The samples that lie in each group have the same number. In the next 12 months, we calculate the estimated beta as initial portfolio beta. The cross-sectional method is applied for next 48 months. This dissertation selects 7 years as one sub period to run a cross-sectional regression.

Basic Fama and MacBeth cross section regression methods are widely used in testing CAPM in emerging markets. The research of Sharpe (1964), Lintner (1964), Treynor (1964) and Mossin (1964) prove that expected return can be explained by market risk factor. After Capital Asset Pricing Model was proposed, research on different stock markets varied from person to person. However, Campbell et al. (1997) test Capital Asset Pricing Model in American stock market over the period of 1965 to 1994 and the results show that CAPM model can't explain market return variance in New York Exchange Stock. Manjuunatha (2006) applies classical capital asset pricing model in daily data of Indian stock markets over the period of 2000 to 2003. The empirical evidence of Indian stock market is against CAPM during this period. Therefore, obtaining support of theory of Capital Asset Pricing Model still needs further research datasets to test.

In Chinese stock market, testing CAPM starts from 1990s. Chen and Qu (2000) test Chinese stock market and the results present that systematic risk in stock market can be measured by beta. Xu and Wu (2001) applies Hurst Exponent Algorithm to calculate daily return of Chinese stock markets but obtain the data that does not follow normal distribution. Therefore, the periods of stock return will affect the distribution of return and our calculated beta coefficients. Wang (2010) applies Fama-MacBeth cross section method to test relationship between expected return of stocks and market return. The article investigates stationarity of beta time-series data and conducts time-series regression. The empirical results show that Capital Asset Pricing Model can explain Chinese stock market over the period before financial crisis period and whole sample periods. Qian (2010) uses samples from Shanghai Stock Exchange and find that size premium and value premium exist in Chinese stock markets and the difference between groups can be explained perfectly. Tian and Wang (2014) select stock data from Shanghai Stock Exchange over the period of 1995 to 2012. They employ Fama-MacBeth cross section method to continue their empirical test and obtain that turnover is negatively correlated with stock expected return. The further discussion reveals that size effect do exist in Chinese stock market.

2.3.2 Review of Factor Model

Factor Model aims at factors explaining variance on asset returns in capital market or macroeconomy. Fama and French (1993) employs excess return, firm size, market-to-book value, interest risk and default risk to construct factor-model. Likewise, Pan and Xu (2011) construct factor model using Pricing Earning ratios replacing market-to-book ratio to construct a new three-factor model. The results of Hu (2013) 's empirical research suggest improved four-factor model brings negative effect on estimation and applicability may varies in different periods and market. The specific application of three-factor model will be computed in next section.

Fama and French (1992) consolidate market risk (beta), size, book-to-market ratio and leverage to test these variables' explanations on market return and market interactions. The results present a higher explanation when more factors are added into the model instead of single Capital Asset Pricing Model. More accurate results can be obtained from the empirical results. The three-factor model is derived by Fama and French (1993) and the efficient factors are B/M ratio, market return and size.

However, Fama and French three factor model is continued to be altered by other research. Although this model explains various anomalies of stock markets but the empirical results can't explain the momentum effect (Jegadessh and Titman, 1993). Later in 2001, Jegadesh and Titman (2001) suggest that the momentum effect still exist and continues in 1990s. Rouwenhorst (1998) conducted profitability test on momentum effect of factor models and it is profitable in 13 European stock markets. Griffin, Ji and Martin (2003) conducted worldwide momentum factor test and conclude this phenomenon arises all over the world while Chui, Titman and Wei (2000) summarize that this effect does not exist on Japan and South Korea. Carhart (1997) derives a four-factor model from Fama and French by adding factor 'winners minus loser' (WML), a proxy of difference between one-year winners who earn highest return within one year and one-year losers who earn lowest return within one year. Fama and French (2010, 2012) has applied this factor and conducted in developed markets as three factor model. The empirical results show that four factor-model can better explain the variance of market return than three factor model.

Chae and Wang (2008) summarize that most asset pricing models ignore the factor of transaction costs and probability of investors' irrationality. Most scholars have considered new factors to alter the model. Zhang and Chen (2008) derive a new model by investment to asset factor and productivity of assets factors to replace size and book to market ratio factors. The empirical results show that their new model can better explain the average returns of portfolios constructed by momentum, investment profitability and accruals and earning potentials in Chinese and developed markets. New models are modified by other research use Tobin's Q (Chen, Marx and Zhang, 2010). This factor considers market risk, gaps between return on portfolio of low investment or return and high investment or return stocks. Chen, Marx and Zhang (2010) claim that new three factor model can capture many anomalies in stock markets while Fama and French three factor can't explain. Foye, Mramor and Pahor (2013) suggest that market factor should be replaced by proxy to measure the degree of accounting manipulation and assert that results can be better than standard one in emerging markets according to their datasets.

Most of discussed papers aim to add or replace a factor and harness it into Fama and French standard three factor model. The dominant portions of research prefer momentum variable, risk factor WML as we discussed before. This factor is proved efficient in Hon and Tonks (2003), Bello (2008), Lan, Li and So (2010) and Fama and French (2012) by further adding this factor and get better explanation of average return. Although momentum factor is considered and tested in developed markets, Fama and French (2012) still claim that the results of international comparison of this model can only be applicable to minority of stocks. The global model can't explain the portfolio return by region and local model performs poorly in emerging markets and European stock markets. On the contrary, Al Mwalla (2012) claim that Fama and French three factor model is superior to momentum four factor model in Amman Stock market. More research points out that momentum factor is strong at short horizon (maximize 1 years) and it is not appropriate for long term prediction and forecast long term returns in stock markets (Arnott, 2018).

Apart from factor momentum, liquidity is another factor considered by most research (Amihud and Mendelson, 1986). Datar, Naik and Radcliffe (1998) harnesses asset turnover rate and empirical results present that liquidity is effective on explaining cross section return variation. Liu (2006) applies two factor model (market and liquidity factors) in Chinese stock market and obtain better explanation results. Gharghori, Chan and Faff (2007) test Fama French three factor model and suggest liquidity risk can't be a proxy of three factor model. Piesse (2008) focus more on emerging markets in Southern Frican markets and the results show that small markets do not respond significantly to liquidity along with size. Minovic and Zivkociv (2012) select samples from Serbian stock market and the results support the findings of Liu's (2006) in Chinese stock market. However, compared with Chinese stock market, the liquidity risk factor can't explain Polish stock market when testing CAPM (Lischewski and Voronkova, 2012). Lee and Swaminathan (2000) use averge daily turnover as a proxy of liquidity risk during portfolio formation. Other empirical results including Sehgal et al. (2012) support that liquidity -augmented factor model is better than classic and three factor models for Bombay stock market. They also argue that it is necessary to incorporate other risk factors into returns to improve explanations. Yuksel, Yuksel and Doganay (2010) uses Istanbul stock market and support that liquidity risk factor is significant and better explains average return.

More and more research of CAPM applicability on developing countries arose after the research of Fama and French three factor model. Chordia (2006) employs Nasdaq and AMEX over the period of 1965 to 2000 by using size, market value and momentum factors. They conclude that beta can't be allowed to vary with changes in size, none of tested anomalies will be captured by model we designate. However, if it is allowed to vary, historical returns are dominant factors of cross section stock returns though it is adjusted by liquidity factor and momentum factor. Shaker and Elgiziry (2013) test five factor model by adding liquidity and momentum factors based on Fama and French three factor model. The results support that Fama French Factor model is superior to Capital Asset Pricing Model in Egypt stock market. Gharghori et al. (2007) assert that whether the risk that Fama French factor models can capture or not is still a problem. Zhao, Yan and Zhang (2016) select stocks from Chinese stock market and firstly apply five factor model in Chinese stock market. The empirical results do not support Fama and French (2015) and they suggest that profitability factor and investment size factor have no explanatory power on excessive return of portfolios in Chinese stock markets. They believe three factor model is superior to five factor model.

2.4 Relevant Studies in Emerging Market

Emerging stock markets are equipped with some characteristics of developed markets but did not fully meet the standards of developed markets. Therefore, research of Capital Asset Pricing Model and Fama French Factor Models' applicability in emerging markets may have further research values for scholars. Renzende et al. (2019) suggest that emerging economies are new ideal subjects for research on testing CAPM as it is more volatile and growing in capital market. The information of emerging stock markets is relevant to investors' benefits so it is of practical significance to test CAPM in transition economies.

In central and eastern European stock market, Mariola (2006) employs datasets from Greek stock market and refuses the conclusion from Fama and French (1993). They find that greater market risk does not bring higher market return. Trifan (2009) tested the applicability of Capital Asset Pricing Model in Romanian stock market and suggested that financial crisis period affects the results of applicability of model. Fruk and Huljak (2004) tested factor model on Zagreb stock market and empirical results show that positive relationship exist between returns and coefficients of market risk but whether beta can be used for investment decision still needs more practice to prove. Perković (2011) did research of same topic and obtained similar results.

Particularly, this dissertation selects Polish stocks in Warsaw Stock Exchange as our research samples. However, the comprehensive data used for testing Fama and French three-factor model for Polish stock market is not easy to access. Developed empirical literature of Capital Asset Pricing Model applicability in Polish stock market is also limited. The empirical results of Asness, Moskowitz, and Pedersen (2013) and Cakici, Fabozzi and Tan (2013) in Polish stock market suggest that market value and momentum factors are negatively correlated. The previous research in Polish stock market have confirmed market value factors (Lischewski and Voronkova, 2012 ; Zaremba and Konieczka, 2014) , market size (Lischewski and Voronkova, 2012; Sekuła, 2013; Zaremba and Konieczka, 2014) and momentum effects (Witkowska, 2008; Zaremba and Konieczka, 2014) are significant factors that can explain market return variance in Polish stock market. Some literature tried to test applicability of Fama and French three or four factors model (Czapkiewicz and Skalna, 2010; Olbryś, 2010; Urbański, 2012; Waszczuk, 2013) and most results in Polish stock markets support Fama-French three factor model considering datasets financial crisis but some research identifies that size effect is not observed in Polish stock market (Czapkievicz and Skalna, 2010). However, this dissertation is not aware of papers that test both CAPM and Fama's French Three-factor model in emerging markets. Most comparative research focus on Central and Eastern European countries but few of them will consider comparative analysis between emerging markets in Central European and Asian-Specific emerging markets.

In fact, most literature studies aim at testing CAPM using crossing-sectional and different factor models. The testing of CAPM has been a new mainstream in asset pricing field of emerging markets. Drew and Veeraraghavan (2002) observe that the market risk factor has weak explanatory power in Malaysia stock market. Weng and Xu (2004) summarize the applicability of the three-factor model in different countries and suggest that this model perfectly apply to stock market in China before 2004. Lin et al. (2012) investigate the stock market in China by replacing explanatory factors. For Russia and Central-eastern European countries, Bruner et al. (2008) conducted a research and argue that CAPM shows an empirical failure in explaining Russia and China cross section stock returns.

Some literature analyse the applicability considering time effects. The selected sample periods may affect the evidence of testing CAPM while more volatility may damage this balance with irrational expectations. Data has a significant impact on the research results, which are empirically tested and mentioned in Bartholdy and Peare (2005), Kilsgard and Wittorf (2010). They suggest that both CAPM and three-factor model are weak to explain return premium. Zhang and Wihlborg (2010) selected 6 European transition economies characterized by excessive volatility. More conclusions from Manhoor (2017) show that stock on transition economies react more inconsistent to produce efficient results and changing samples will have a negative impact on final results.

There are few literatures revealing the bubbles of emerging markets supporting the testing of CAPM. The research of Phillips, Wu and Yu (2011) analyse bubbles of global markets and proposed an innovative way of testing, a combination of supremum and ADF test. This method is empirically tested efficient in developed markets and central-eastern European countries. The post financial-crisis era is a new period in most research. Testing whether bubbles still exist and have an impact on transition economies.

In Chinese stock markets, there are klimited research on stock markets to test Fama French factor models. Liu, Lu and Huang (2000) select size, P/E ratio, net asset per share, earning per share and total risk of companies to run cross section regression and the empirical results show that only market size and P/E ratio can significantly explain expected return of stocks. Yang and Chen (2003) applied classical Fama and French three factor model and select samples over the period between 1990 and 2002 and find that Fama and French three factor model is supported by Chinese stock market while capital asset pricing model lack enough explanatory power on market return variance. Wu and Xu (2004) employ public listed companies over the period of 1995 to 2002 and compared CAPM and three factor model and find that size effect is significant during whole sample periods but B/M ratio effect is weak and only significant during 2000 to 2002. Fan and Shan (2004) analyze monthly return, trading volumes, total market capitalization and financial data and the empirical results are corresponding with Fama and French (1992) . The size effect is significant but B/M ratio effect does not exist during sample periods. Fan and Shan (2004) suggest that Fama and French three factor model is applicable to Chinese stock market and can explain market return perfectly.

Novy-Mark (2013) assert that profitability indicators have significant explanatory power on stock return. They suggest gross profitability factor has same power as book to market ratio factor. While in emerging markets like China, research results on the explanatory power of profitability factor is different as their datasets vary from different sub market. The results show different trend and explanations. Relevant research of t is still limited in five factor model in Chinese stock markets.

2.5 Contribution to Literature

The reviews summarize previous research findings on testing Capital Asset Pricing Model and the Three-Factor Model and investigating volatility of stock market in emerging markets. The notable work from Fama and MacBeth (1973), Fama and French (1991, 1993, 2011), Bruner et al. (2008), Dzaja and Aljinovic (2013), Saji (2014), Neslihanoglu et al. (2017) are still as comparing performance of testing CAPM and three-factor model and assert that three factor model in emerging markets can provide more accurate information to investors in emerging markets. The stock market size has seen rapid development and growing trading volumes in Polish and Chinese stock markets. The characteristics of higher return and volatility in emerging markets indicate that more attention should be paid in the currency and applicability of CAPM.

This dissertation firstly investigates the Polish and Chinese stock market. The two markets are both emerging markets although the size of them are different. The thesis hopes to find evidence in emerging markets that support the theory to compare their market characteristics during Capital Asset Pricing Model and three factor model testing. Unlike other research in developing stock markets, this dissertation divides sample periods into three parts because irrational expectations are part of our research points and global financial crisis period is full irrational investment behaviour. This dissertation also employs Probability Density Approach to test excessive volatility in emerging markets and supremum ADF and KSS with mathematical explanations to test bubbles in the emerging stock markets.

Finally, the dissertation applies Three-Factor Model applicability test in emerging market considering the effect of global financial-crisis as emerging markets on previous research are volatile. To measure the volatility of the emerging stock market, supremum ADF and KSS tests are employed to make empirical results more convincing.

In an effort to provide more accurate information for investors interested in emerging markets, this dissertation aims at promoting mainstream applicability of capital asset pricing model in emerging markets. Most of research methodologies are proved sufficient in developed market and innovative empirical methodology has been employed to explain asset pricing

In emerging stock markets. This research aims to contribute to current research in emerging stock markets. The conclusions based on modern financial theories hope to present empirical evidence on testing CAPM and Fama French three-factor model in Chinese and Polish stock market. To fulfil the research on investigating stock markets in emerging markets, the thesis also present volatility test results for further investigation.

3. Theoretical Framework

This dissertation adopts methodology of Fama and MacBeth (1972) cross section regression approach to test Capital Asset Pricing Model and Fama and French (1992) three factor model for testing capital asset pricing model in Chinese and Polish market, established by portfolio theory. Section 3.1 presents the background theory of Capital Asset Pricing Model and its testing procedures, followed by empirical theoretical framework of Fama-French three factor model in section 3.2. Then this thesis introduces volatility testing procedures and theoretical framework in section 3.3, together with an introduction to bubble test in stock market. Section 3.4 proposes the questions based on the models and previous research.

3.1 Capital Asset Pricing Model

The simplified CAPM model starts from the assumption that capital market is under perfect competition. All investors plan to invest in the same period of time and accept the same risk-free interest rate. Investors estimate the expected return, variance and covariance of assets at the same level. It also assumes that investors only care about higher expected return and lower risk. Before conducting the tests, investment portfolio should be established based on our test contents.

In Fama-MacBeth cross-sectional regression, the beta of each stock time-series data is obtained from regression and used to form different investment portfolios according to the figure of beta from small to large.

To measure the stock returns, constructing investment portfolio to estimate is widely used to effectively reduce non-systemic risk and increase estimation accuracy between portfolios return and systemic risk (Fama and MacBeth, 1972). The formula 2.1 can be transformed into equation in abnormal returns form like 3.1.

$$r_{it} = \alpha_i + \beta_i r_{mt} + \varepsilon_{it} \tag{3.1}$$

r_{it} is the excess expected return of stock i in month t while r_{mt} is the return of market portfolios in month t. The standard deviation s($\widehat{\varepsilon_{it}}$) of ε_{it} can be regarded as the systemic risk. This dissertation will follow the approaching based on Fama and MacBeth (1973) to conduct time-series regression on equation 3.1 and obtain each estimated $\widehat{\beta_i}$ as the substitution variables of β_i.

This dissertation will divide our sample into three sub periods in each panel. For each sub period, the first 24 months will be the portfolio formation period. The beta of each stock obtained from regression results based on equation (3.1) will be divided into 10 groups by its figure from small to large. The number of stocks in each group is the same. In the next 12 month (initial estimation period), this dissertation will recalculate the beta for each portfolio (30 groups) and its non-systemic risk level (ε).

$$\beta_p = \frac{\widehat{cov}(r_p, r_m)}{\delta^2(r_m)} = \sum_{i=1}^{n} w_{ip} \frac{\widehat{cov}(r_i, r_m)}{\delta^2(r_m)}$$

After initial estimation, cross-section approach will be applied in the last 48 months. In order to minimize the estimated errors, FM method extends the length of the initial estimation period month by month. Based on extended periods, $\hat{\beta}_i$ of each stock and $\hat{\beta}_p$ as well as $s_p(\widehat{\varepsilon_i})$ of each investment portfolio should be updated as new portfolio return R_p. The above variables obtained can be used in cross-section regression using following model:

$$R_{pt} - R_{ft} = \hat{\gamma}_{ot} + \hat{\gamma}_{1t}\hat{\beta}_{p,t-1} + \hat{\gamma}_{2t}s_{p,t-1}(\widehat{\varepsilon_i}) + \hat{\eta}_{pt} \tag{3.2}$$

Especially, p=1,2,3…m (final test period length, m=48). $\hat{\beta}_{p,t-1}$ is the weighted average figure of all single asset's $\hat{\beta}_i$ in portfolio p in period t-1. $s_{p,t-1}(\widehat{\varepsilon_i})$ is the weighted average figure of all single asset's $s(\widehat{\varepsilon_i})$, non-systemic risk. $s(\widehat{\varepsilon_i})$ is obtained in monthly updated data.

For each portfolio, the error items ε_{it} obtained from 3.1 is continuous and independent from market return rate. The standard deviation of β_i is as followed:

$$\sigma(\beta_i) = \frac{\sigma(\varepsilon_i)}{\sqrt{n}\sigma(R_m)} \tag{3.3}$$

N is the month for calculating β_i. The standard deviation of portfolio β_p is:

$$\sigma\left(\beta_{p,t-1}\right) = \frac{\sigma(\varepsilon_p)}{\sqrt{n}\sigma(R_m)} \tag{3.4}$$

Fama and French (1993, 1996) derives three-factor model by suggesting new factors: M/B and size. In the three-factor model, there are two portfolio formations. The size is the multiple of stock price and the number of shares in capital market. The first step is to divide all stocks into two groups (BIG and SMALL) by their size from lowest to highest. In each group, the new group will be divided into 3 groups by its M/B from lowest to highest. The largest 30% B/M is called Valuable Group. The 40% in the middle is the Middle Group. The smallest 30% is the Growing Group. The new 2*3 cross-reorganization Size-B/M will be used for constructing SML (Small minus large) and HML (High minus low).

Table 1 Three-Factor Portfolio formation

VALUE / SIZE	50% (SMALL)	50% (BIG)
30%（VALUABLE）	S/H	B/H
40%（MIDDLE）	S/M	B/M
30%（GROWING）	S/L	B/L

Then we obtain six portfolios and SMB as well as HML as chart shown:

$$SMB = \frac{1}{3\left(R_{\frac{S}{L}}+R_{\frac{S}{M}}+R_{\frac{S}{B}}\right)} - \frac{1}{3\left(R_{\frac{B}{L}}+R_{\frac{B}{M}}+R_{\frac{B}{H}}\right)} \tag{3.5}$$

$$HML = \frac{1}{2\left(R_{\frac{S}{H}}+R_{\frac{B}{N}}\right)} - \frac{1}{2\left(R_{\frac{S}{L}}+R_{\frac{B}{L}}\right)} \tag{3.6}$$

Where S and B represent small-size and big-size portfolio respectively. L, M and H are low, medium and high M/B portfolio. The meaning of SMB is the return difference between small and big size portfolio after deducting the influence of B/M. The meaning of HML is the return difference between high and low B/M portfolio after deducting the influence of size. Then this dissertation will reorganize investment portfolio by dividing all stocks into 25 portfolios by size and B/M from smallest to biggest and lowest to highest. The portfolio is written as P_{ij} (where i=group size number and j=group M/B number) and the return of portfolio is R_{ij} weighted averaged by market value.

$$R_{ij} = \sum_{k-1}^{n} W_k R_k \tag{3.7}$$

$$W_k = \frac{ME_k}{\sum_{k-1}^{n} ME_k}$$

Where R_k is monthly return of single asset. ME is the total market capitalization of stock k, n is the number of stocks in portfolio P_{ij}. Before time-series regression of these 25 portfolios, it is necessary to run stationary test and correlation test for SMB, HML, *Rm-Rf* and *Ri-Rf*. Then, this dissertation will run regression in different periods to see whether financial crisis significantly affect our applicability of CAPM in China and Poland's stock market.

Table 2 5*5 Portfolio Formation

VALUE/SIZE	1	2	3	4	5
1	P_{11}	P_{21}	P_{31}	P_{41}	P_{51}
2	P_{12}	P_{22}	P_{32}	P_{42}	P_{52}
3	P_{13}	P_{23}	P_{33}	P_{43}	P_{53}
4	P_{14}	P_{24}	P_{34}	P_{44}	P_{54}

5	P_{15}	P_{25}	P_{35}	P_{45}	P_{55}

3.2 Volatility of Stock Market

Last section summarizes measurements in asset pricing in the assumption of rational expectations. However, Shiller (1981) believes that behaviour like market frictions can result in over-volatility in stock price and this can't be explained by our models as they assume investors are rational. To test volatility of stock price in market, the appropriate method is ARCH model (Engle, 1982) and GARCH model (Bollerslev, 1986). This dissertation employs GARCH model to do research on volatility of stock price in Polish and Chinese stock markets.

Bollerslev (1986) suggests GARCH model to test the volatility of stock return in developed market. GARCH model assumes conditional volatility in current period as an equation contain historical information and it perfectly presents asset return characteristics including wave aggregation and spiked thick tail. GARCH (1,1) model (Engle, 1982; Bolerslev, 1986) can be described as followed:

$$r_t = \mu + \epsilon_t, \epsilon_t = \sigma_t z_t, z_t - i.i.d.N(0,1) \tag{3.8}$$

$$\sigma_t{}^2 = w + \alpha_1 \epsilon_{t-1}{}^2 + \beta_1 \sigma_{t-1}{}^2$$

To model a time series data using GARCH method, let ϵ_t be return residuals. w, α_1 and β_1 are all positive figures and $\alpha_1 + \beta_1 > 1$. These restrictions promise that condition variance is positive and the stationarity of conditional variance trend.

Unlike previous literature, this dissertation will combine both GARCH model and supreme ADF test mentioned in previous emerging markets (China and Malaysia) to identify the bubbles in Chinese and Polish markets.

Following Phillips, Wu and Yu (2011)'s empirical methodology, they harness ADF model (3.9) and derives supADF statistics. According to Phillips and Yu (2011) and

Deng (2013), bubbles in stock price can be described as data explosion process. This can be tested using unit root test on the right side of ADF to distinguish the unit-root and moderately high explosive unit-root. They employ ADF model (3.7) by testing whether $\rho\ is\ higher\ than$ 1.

$$p_t = \mu + \rho p_{t-1} + \sum_{j=1}^{j} \varphi_j \Delta p_{t-1} + \epsilon_t, \epsilon_t - iid(0, \sigma^2) \tag{3.9}$$

For a given sample sequence pt (t=1,…,T). Firstly, this Phillips and Yu (2011) use part of samples pt (t=1,…,[Tr0], 0<r0<1) to run OLS regressions to obtain t-statistics of ρ. Then they gradually increase the volumes of samples and use first [Tr0] number of samples to run recursive regression and obtain a series of t-statistics of ρ (so-called ADF_γ^t).

$$ADF_\gamma^t = \frac{\hat{\rho}_r - 1}{se(\hat{\rho}_r)}, t = 1, \dots, [rT], r \in [r_0, 1] \tag{3.10}$$

Where $\hat{\rho}_r$ and se($\hat{\rho}_r$) are OLS statistics. The alternative Hypothesis H1 is ρ>1. Then Phllips and Yu (2011) run supremacy right side of ADF unit-root test for equation 3.8. When statistics is higher than critical value, the null hypothesis will be rejected.

$$sup\text{ADF}(r_0) = sup_{r \in (r0,1)} \frac{\hat{\rho}_r - 1}{se(\hat{\rho}_r)} \tag{3.11}$$

3.3 Questions

From equation (3.2), the test method is to calculate average figure of monthly data and obtain the average figure ($\overline{\hat{\gamma}_j}, j = 0{,}1{,}2$) of $\hat{\gamma}_{ot}, \hat{\gamma}_{1t}\ and\ \hat{\gamma}_{2t}$. Since returns of all portfolios follows multivariate normal distribution, $\hat{\eta}_{it}$, $\hat{\gamma}_{ot}$, $\hat{\gamma}_{1t}$ and $\hat{\gamma}_{2t}$ must follow multivariate normal distribution as well. If $\hat{\gamma}_{jt} \sim N(\mu, \sigma^2)$, $\hat{\gamma}_{1t} \sim N(\mu, \frac{\sigma^2}{n})$, $\frac{\hat{\gamma}_{1t} - \mu}{\sigma/\sqrt{n}} \sim N(0,1)$, $\frac{(n-1)s^2(\hat{\gamma}_j)}{\sigma^2} \sim \chi^2(n)$. Therefore,

$$\frac{\hat{\gamma}_j - \mu}{s(\hat{\gamma}_j)/\sqrt{n}} \sim t(n) \qquad \text{(n=month)}$$

$$t(\hat{\gamma}_j) = \frac{\hat{\gamma}_j - \mu}{s(\hat{\gamma}_j)/\sqrt{m}} \tag{3.12}$$

The m is the month of regression period and the month used for estimation of $\hat{\gamma}_j$and s($\hat{\gamma}_j$). If the market data in Poland and China is corresponding with the description of CAPM, the following model (3.5) holds:

$$E(R_{pt} - R_{ft}) = \beta_i E(R_{mt} - R_{ft}) \tag{3.13}$$

Thus. in testing model (3.2) in section 1, the estimated coefficient of γ_{0t}=0, $\gamma_{1t} = R_{mt} - R_{ft}$ and $\gamma_{2t} = 0$. This dissertation will construct t-statistics for our H0 hypothesis: $\gamma_j = 0$ and calculate t-statistics using equation 3.4 to test whether there is significant difference between estimated and theoretical figure and applicability of CAPM in the selected period. Based on this distinguished method, the sample periods are divided into three periods to explore the applicability of CAPM in different periods. A three-stage test will be used in FM cross-section method.

To enhance our research on asset pricing models and improve its accuracy of explanation power on emerging stock market. This dissertation follows Fama and French (1993) discussed in section 3.2 and introduce book-to-market value and size to the CAPM. Thus, we add size premium (SMB) and B/M premium (HML) variables to test the three-factor model as we mentioned in section 3.1.2. In this section, time periods will be also considered into CAPM applicability in emerging markets.

Equation (3.6) indicates the relationship between volatility and historical return. According to Phillips and Yu (2011), the emerging markets tend to be more volatile than developed markets. Their findings suggest that over-volatility exists in Chinese stock market during Asian financial crisis and global financial crisis in 2018. Deng and Tang (2013) conducted supreme ADF test as we discussed in section 3.2 and obtained bubbles in stock price in East Asian stock markets. This dissertation will follow their methodology to conduct GARCH model test and bubbles in stock price test, namely supADF test, in Polish and Chinese stock markets.

Therefore, the thesis aims to address following questions:

Question (1)

Whether the testing results of Chinese and Polish stock market support CAPM?

Question (2)

Whether the testing results of Chinese and Polish stock markets support Fama and French Factor Model?

Question (3)

Whether over-volatility phenomenon exists in Chinese and Polish stock market?

4 Empirical methodology

This section starts from an introduction to our empirical testing methods to test CAPM and Fama-French three factor model in Chinese and Polish stock market. The testing procedures will follow the method of Fama-MacBeth cross section regression, which are widely used in asset pricing and business economics literature. Section 4.1 specifies the Capital Asset Pricing equation and Fama-French three factor model equation. Section 4.2 explains the data and variables used in testing Capital Asset Pricing model and Fama-French three factor model, together with principles of samples selection. Since the thesis investigates the changes in sample periods perspective, the description statistics of sub periods are computed. Section 4.3 will discuss estimation strategies and logic of testing procedures in ths thesis.

4.1 Econometric Model

Capital Asset Pricing Model (CAPM) is one of the most popular models widely used in asset pricing field. It not only fit the data of most developed markets well in previous literature but also can be derived from theoretical model by adding factors (Fama and French, 1992). This dissertation harnesses both Fama-MacBeth cross section regression (Fama and MacBeth, 1973) for CAPM testing in Chinese and Polish stock markets and Fama-French three factor model (Fama and French, 1992, 1993 and 2011). Finally, the thesis will test over-volatility and bubbles in asset price for both stock markets. The two-stage testing has several strengthens. It divides our testing CAPM into rational and irrational expectations. Moreover, the thesis combines two methodologies that tested efficiently in developed markets.

Section 4.1.1 specifies the classic one-factor CAPM equation based on different periods. Then, section 4.1.2 introduced the specification that estimates the effect of size premium and M/B premium. Section 4.1.3 introduces the model used for testing irrational expectation CAPM.

4.1.1 CAPM Equation

Fama and MacBeth (1972) derived a theory consistent selection equation given as follows:

$$R_{pt} - R_{ft} = \hat{\gamma}_{ot} + \hat{\gamma}_{1t}\hat{\beta}_{p,t-1} + \hat{\gamma}_{2t}s_{p,t-1}(\hat{\varepsilon}_i) + \hat{\eta}_{pt} \tag{4.1}$$

From this cross section regression equation, p=1,2,3,..,m (m is the length of test period and m is 36 in this dissertation). The variable $\hat{\beta}_{p,t-1}$ is the weighted average figure of all single asset i in portfolio p in the period of t-1.

4.1.2 Three-Factor Model Equation

Since this dissertation is exploring the stock market, the primary testing model of Three-Factor CAPM test model is as followed:

$$R_{it} - R_{ft} = a_i + b_i(R_{mt} - R_{ft}) + s_i SMB + h_i HML + \mu_{it} \tag{4.2}$$

R_i represents the return of stock i and R_f is the risk-free rate. Rm represents the market excessive return as Capital Asset Pricing Model. SMB is 'Small Minus Big' variable, meaning the risk premium from different size. HML is 'High Minus Low' variable, meaning the risk premium from different company size. T represents the time periods. b_i, s_i and h_i are the portfolios' sensitives to the market.

4.2 Data and Variable

The dissertation uses time-series data from multiple databases including Amedeus, China Center for Economic Research (CCER), Datastream, European Central Bank and The National Bank of Poland. The series includes the data from 2007 to 2018 for China and Poland. The market risk premium is calculated based on MSCI data and Shanghai Security Stock Market Index obtained from Datastream.

In the one-factor test model, the dependent variable is abnormal return of the portfolio return in month t. The independent variable is weighted average figure of all single asset in portfolio p in period t-1 and unsystematic risk of each single asset in portfolio p in period t-1.

This dissertation follows Phillips, Wu and Yu (2011) and the risk-free rates are the monthly U.S. Treasury Bill rates supplied by Professor Robert Grauer. in both Chinese and Polish stock market due to high reliability and comparison purpose. For Polish stock market, Urbański (2017) ever applies Warsaw Interbank Offered Rate as risk-free rate but it only covers Polish research that is not proper for our empirical test as our research include two markets so we still choose monthly U.S. Treasury Bill rates supplied by Professor Robert Grauer as risk-free rate in Poland stock market of our research following the research of Czapiewski (2013) in emerging European stock markets. This dissertation deletes financial companies due to its higher financial gearing and this means financial abnormity for non-financial companies, making our research not comparative. The missing values have been eliminated to fit our data analysis.

The sample periods for CAPM and Fama-French Three-Fator Model are different but follow the same principles of companies (samples) selection:

(1) Eliminating financial companies. In normal operation, financial companies have higher financial gearing but this means financial abnormity to non-financial companies.
(2) Eliminating companies with missing values in some periods. Data should be complete during one sample period.
(3) Eliminating public companies with insolvency and risk of insolvency.
(4) Eliminating companies of which listing date is in the first month of one period. Outliers tend to exist in the first date of public offering.

This dissertation trying to keep consistent with data in previous research to make our results comparative in both markets. The size of samples in China is larger than that of Poland but the mean value of is higher.

Table 3 and 4 list the sample periods and figures of return over these periods in Chinese and Polish stock markets. The variance analysis of Chinese stock market reveals that first stage has higher stock index and market return. The three-fold standard deviation in the first period of Chinese market reflect that financial crisis period (2007-2009) is the most fluctuated and volatile period of samples. In second stage, due to damages in financial crisis, Chinese stock market seems experiencing lower return and most investors' decision preference is conservative. In third stage, Chinese stock market recovers and both index and return remain normal as stationary period (2000-2006) as data presented by Phillips, Wu and Yu (2011).

In Polish stock market, the sizes of two markets are different so their return and index has big difference. However, the standard deviation during financial crisis period is higher indicating higher risk during this period, which is corresponding with Chinese stock market.

Table 3 Periods Description in Different Stages in China Stock Market

		First Stage	Second Stage	Third Stage
Portfolio Forming Period		2004.01-2005.12	2008.01-2009.12	2012.01-2013.12
Initial Estimation Period		2006.01-2006.12	2010.01-2010.12	2014.01-2014.12
Final Test Period		2007.01-2010.12	2011.01-2014.12	2015.01-2018.12
Shanghai Stock Index	Mean	3214.90	2308.95	2145.45
	Std. Div.	962.19	270.66	385.34
Market Return	Mean	3.09%	-0.05%	0.21%
	Std. Div.	8.52	0.09	0.75

Table 4 Periods Description in Different Stages in Poland Stock Market

		First Stage	Second Stage	Third Stage
Portfolio Forming Period		2004.01-2005.12	2008.01-2009.12	2012.01-2013.12
Initial Estimation Period		2006.01-2006.12	2010.01-2010.12	2014.01-2014.12
Final Test Period		2007.01-2010.12	2011.01-2014.12	2015.01-2018.12
MSCI Poland Index	Mean	1811.61	1703.37	1559.273
	Std. Div.	463.55	131.26	174.29

Market Return	Mean	-0.2%	-0.33%	0.13%
	Std. Div.	0.082	0.047	0.049

In section 3.1.2, the portfolios grouping methodologies have been illustrated. After portfolios formation, table 5 presents the variables used in Fama-French three factor model. This dissertation will apply Black-Jensen-Scholes time-series regression method for 25 portfolios. The dependent variable is R_{it}-R_{ft} and independent variable is market excess return, SMB and HML. Therefore, these data will form 25 portfolios as our datasets.

Table 5 Definitions of Variables in Model.

Variables	Definitions of Variables
R_i	Monthly return of stock
R_{m}	Monthly return of market
R_f	Risk-free return rate (One-year deposit rate)
BE	Book-value of equity at the end of each year
ME	Market value (for size and B/M calculation)
R_i - R_f	Excess return rate of portfolio i
R_{m} - R_f	Excess return rate of stock market
SMB	Size Factor (Size difference)
HML	Value Factor (B/M ratio difference)

4.3 Sample Periods

The testing periods are long and time of initial public offering stocks are different. Asset reorganization and listing of stocks will affect our testing. However, the datasets will be poor if we promise no missing values of stocks during the whole sample periods. Considering this, this thesis employs grouping method by Fama-MacBeth (1973) and divide our sample periods into three stages and make full advantage of all available stocks for our testing.

Since the thesis tests CAPM in Chinese and Polish stock markets, we divide our sample periods by considering the trend of stock market index. The MSCI Poland Index is designed to measure the performance of the large and mid-cap segments of the Polish market, which is corresponding with Chinese stock market index for market A (large and mid-cap segments). They represent the volatility of total stock price within two markets. Chart 1 and 2 present the market trend of two emerging markets over the sample periods (2004-2018). The index in Polish stock market rise dramatically during 2007-2009, indicating over-volatility over financial crisis period. While in Chinese stock market, there are two peaks (2007-2009, 2014-2015). These represent two financial crisis events in Chinese stock markets.

According to Fama and MacBeth (1972), the whole sample periods should be divided into continuous sub period in average. The chart present that the mutation of index in both Chinese and Polish stock market during financial crisis period (2007-2009) should be divided separately to reach better testing effect. This thesis will conduct empirical test of CAPM in three periods.

Chart 1 Trend of MSCI Poland Index picture

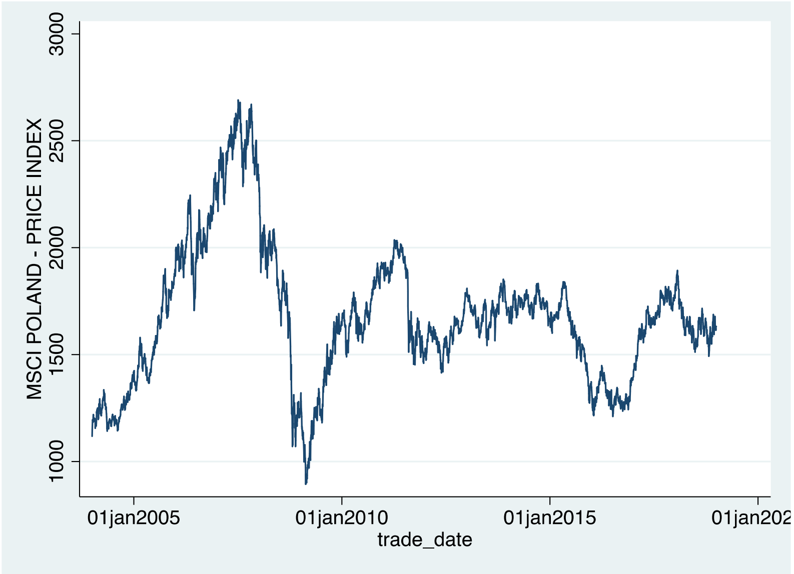
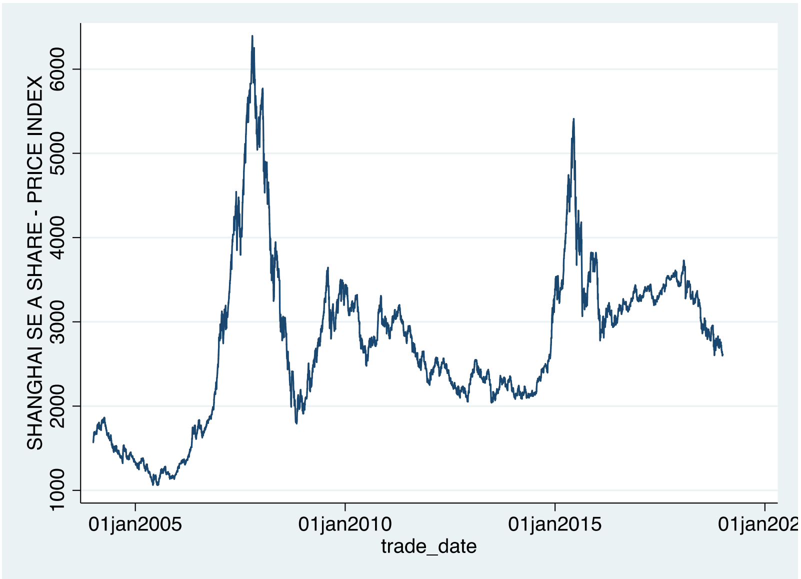


Chart 2 Trend of Chinese stock market Index



4.4 Estimation Strategy

In summary, this dissertation estimates the CAPM and Fama-French three factor model using Fama-MacBeth (1972) cross section method. As supplement to asset pricing in emerging markets, the thesis tests volatility in stock market following Phillips, Wu and Yu (2011) based on GARCH model (Bollerslev, 1986).

Firstly, this dissertation will test CAPM in Polish and Chinese stock market during three distinguished eras (2007-2009, 2010-2014, 2015-2018). In each period test, portfolios formations will be conducted firstly according to their beta in initial period. After obtaining beta for new portfolio, we will run new cross-sectional regression for each portfolio.

Secondly, this dissertation will run Fama French three factor model following Fama and French (1993, 2011). Firstly, the portfolios will be constructed by its size and book-to-market value. Then time-series regression will be run for each portfolio in different periods. Comparative analysis of Chinese and Polish stock market will be followed by the empirical results.

Thirdly, this dissertation will test volatility of stock prices in stock markets as the supplement of testing CAPM and Fama-French three factor model. To begin with, this dissertation will run GARCH model test as a tool to measure volatility of stock price and obtain the degree of volatility in both stock market. The conditional variance will be obtained to analyze the periods of over-volatility. Since the over-volatility exists in both Chinese and Polish market, the thesis follows Phillips Wu and Yu (2011) and Deng (2013) to run bubble tests in the two emerging markets, namely supreme ADF and KSS test.

5 Results and Relevant Check

This Chapter computes empirical results of testing CAPM and Fama-French Three Factor Model. The thesis also explores volatility and bubbles in stock price based on our empirical results in 5.1 and 5.2. In each part, descriptive statistics and regression results of two countries will be presented and discussed respectively. This dissertation will compare the testing results in sub periods as stated in section 4.3 and efficiency of two models in explaining the variance on expected return in Chinese and Polish stock markets.

5.1 Results of Testing Capital Asset Pricing Model

This section will present the results of testing CAPM in Polish and Chinese stock market respectively. Since this dissertation divides sample periods into three groups as grouping in section 4.3, the regression results will be presented by three periods. In each sample period (7 years per sub period) of this chapter, portfolio formation periods will be the first 24 months. The initial estimation period (for calculating beta of each portfolio) will be the next 12 months. The last 48 months will be the final estimation period (CAPM test period).

5.1.1 Descriptive Statistics

Table 6 presents the $\hat{\beta}_{p,t-1}$ and their standard deviation $s(\hat{\beta}_{p,t-1})$ of each portfolio (10 portfolios) in Polish stock market within five years. To investigate the charateristics of each portfolio, this dissertation also calculates the correlation between portfolio return and market return. $s(R_p)$ represents standard deviation of return of each portfolio. $s(\hat{\varepsilon}_p)$ is the standard deviation of errors after regression of return of market and return of portfolios. Particularly, $s(\hat{\beta}_{p,t-1})$ is the weighted average figure of standard deviation of single stock in each portfolio. Based on section 3.1, we obtain the descriptive statistics of each portfolio in sample periods.

The figure of $s(\hat{\varepsilon}_p)/\hat{s}_{p,t-1}(\hat{\varepsilon}_i)$ ranges between 0.35 to 0.6, indicating that the standard deviation of estimated portfolios' beta is approximately 50% lower than that of single assets' beta. This. evidence reveals that portfolio estimation for testing CAPM is more accurate than single assets. From the regression results, $s(\hat{\varepsilon}_p)/\hat{s}_{p,t-1}(\hat{\varepsilon}_i)$ in each period is around 0.5, meaning the more accurate beta obtained for portfolios estimation than for single assets in our research.

However, the thesis also figures out that time varying effect may exist in $\hat{\beta}_{p,t-1}$ as the estimated figures changed dramatically from 2006-2014 periods to 2014-2018 in Polish stock market. The reasons may be that Polish stock market is not developed as developed stock market. The emerging market will be more volatile and betas of stocks in the market are more likely to become time-varying as Jawadi (2019) suggests.

Table 7 presents the description of statistics in Chinese stock market. Compared with Polish stock market, Chinese stock market also sees more accurate explanatory power of portfolios instead of single assets on the average return because of all figures of $s(\hat{\varepsilon}_p)/\ \hat{s}_{p,t-1}(\hat{\varepsilon}_i)$ are ranged between 0.34 and 0.6. The similar trend of beta time-varying problems also identified in Chinese stock market. The variance of estimated beta changed dramatically over the whole period. A big difference is that the correlation between market and portfolio return (around 0.85) of Chinese stock market is much higher than that in Polish stock market (approximately 0.6). This result indicates that Chinese stock market return has more explanatory power on portfolios' return, which we will discuss in Fama-French three-factor model section. The variance of other factors (statistics) see small difference between two markets according to the estimation results.

Table 6 Statistics in three estimation periods in Polish stock market

Statistics	1	2	3	4	5	6	7	8	9	10
					2006-2010					

$\hat{\beta}_{p,t-1}$	0.730	0.934	1.084	0.964	1.041	0.871	0.815	1.079	1.079	0.980
$s(\hat{\beta}_{p,t-1})$	0.111	0.138	0.198	0.149	0.201	0.197	0.128	0.162	0.237	0.265
$r(R_p, R_m)$	0.570	0.628	0.602	0.614	0.606	0.549	0.641	0.661	0.555	0.582
$s(R_p)$	0.121	0.145	0.198	0.164	0.192	0.197	0.135	0.176	0.223	0.253
$s(\hat{\varepsilon}_p)$	0.055	0.067	0.089	0.080	0.086	0.087	0.064	0.083	0.107	0.100
$\hat{s}_{p,t-1}(\hat{\varepsilon}_i)$	0.111	0.131	0.173	0.145	0.170	0.166	0.119	0.158	0.185	0.205
$s(\hat{\varepsilon}_p)/\ \hat{s}_{p,t-1}(\hat{\varepsilon}_i)$	0.494	0.513	0.513	0.549	0.507	0.522	0.541	0.523	0.577	0.487
					2010-2014					
$\hat{\beta}_{p,t-1}$	0.676	0.798	0.839	0.605	0.719	0.858	0.762	0.728	0.745	0.966
$s(\hat{\beta}_{p,t-1})$	0.102	0.116	0.122	0.124	0.108	0.119	0.107	0.109	0.125	0.130
$r(R_p, R_m)$	0.448	0.619	0.724	0.711	0.780	0.754	0.755	0.779	0.754	0.775
$s(R_p)$	0.124	0.125	0.138	0.133	0.122	0.141	0.135	0.140	0.155	0.180
$s(\hat{\varepsilon}_p)$	0.043	0.048	0.043	0.044	0.040	0.052	0.054	0.054	0.062	0.074
$\hat{s}_{p,t-1}(\hat{\varepsilon}_i)$	0.111	0.112	0.121	0.114	0.107	0.125	0.116	0.121	0.134	0.151
$s(\hat{\varepsilon}_p)/\ \hat{s}_{p,t-1}(\hat{\varepsilon}_i)$	0.390	0.430	0.353	0.383	0.374	0.414	0.462	0.444	0.465	0.491
					2014-2018					
$\hat{\beta}_{p,t-1}$	0.210	0.262	0.145	0.223	0.327	0.428	0.589	0.386	0.515	0.533
$s(\hat{\beta}_{p,t-1})$	0.109	0.100	0.125	0.092	0.167	0.092	0.130	0.103	0.116	0.113
$r(R_p, R_m)$	0.039	0.271	0.204	0.382	0.379	0.653	0.590	0.515	0.589	0.559
$s(R_p)$	0.118	0.115	0.125	0.094	0.154	0.096	0.130	0.116	0.130	0.139
$s(\hat{\varepsilon}_p)$	0.034	0.037	0.042	0.029	0.043	0.027	0.041	0.044	0.046	0.061

$\hat{s}_{p,t-1}(\hat{\varepsilon}_i)$	0.112	0.109	0.115	0.085	0.124	0.089	0.113	0.106	0.121	0.127
$s(\hat{\varepsilon}_p)/\ \hat{s}_{p,t-1}(\hat{\varepsilon}_i)$	0.300	0.338	0.363	0.344	0.346	0.304	0.366	0.416	0.375	0.482

Table 7 Statistics in three estimation periods in Chinese stock market

Statistics	1	2	3	4		5		6	7	8
					2006-2010					
$\hat{\beta}_{p,t-1}$	0.818	0.848	0.792	0.883	1.039	1.035	0.989	0.963	0.938	1.062
$s(\hat{\beta}_{p,t-1})$	0.118	0.099	0.112	0.121	0.136	0.101	0.136	0.114	0.112	0.125
$r(R_p, R_m)$	0.832	0.902	0.807	0.852	0.884	0.912	0.904	0.894	0.911	0.952
$s(R_p)$	0.133	0.125	0.129	0.141	0.160	0.141	0.161	0.142	0.141	0.160
$s(\hat{\varepsilon}_p)$	0.052	0.039	0.057	0.054	0.055	0.047	0.048	0.049	0.043	0.036
$\hat{s}_{p,t-1}(\hat{\varepsilon}_i)$	0.103	0.091	0.101	0.108	0.119	0.092	0.123	0.101	0.100	0.110
$s(\hat{\varepsilon}_p)/\ \hat{s}_{p,t-1}(\hat{\varepsilon}_i)$	0.507	0.433	0.569	0.502	0.464	0.506	0.387	0.483	0.429	0.331
					2010-2014					
$\hat{\beta}_{p,t-1}$	0.627	0.602	0.697	0.896	0.809	1.029	0.980	0.981	1.011	1.116
$s(\hat{\beta}_{p,t-1})$	0.096	0.087	0.099	0.087	0.095	0.084	0.097	0.094	0.090	0.098
$r(R_p, R_m)$	0.621	0.726	0.771	0.828	0.838	0.918	0.925	0.871	0.897	0.940
$s(R_p)$	0.107	0.101	0.115	0.113	0.114	0.117	0.123	0.127	0.124	0.141
$s(\hat{\varepsilon}_p)$	0.052	0.046	0.045	0.043	0.041	0.031	0.030	0.042	0.038	0.035
$\hat{s}_{p,t-1}(\hat{\varepsilon}_i)$	0.096	0.087	0.096	0.091	0.090	0.090	0.098	0.100	0.096	0.100
$s(\hat{\varepsilon}_p)/\ \hat{s}_{p,t-1}(\hat{\varepsilon}_i)$	0.538	0.526	0.470	0.471	0.461	0.351	0.306	0.421	0.389	0.347

	2014-2018									
$\hat{\beta}_{p,t-1}$	0.899	0.918	0.941	1.007	1.112	0.933	1.003	1.028	1.093	1.124
$s(\hat{\beta}_{p,t-1})$	0.093	0.093	0.083	0.097	0.094	0.090	0.106	0.090	0.106	0.108
$r(R_p, R_m)$	0.767	0.784	0.909	0.889	0.941	0.903	0.884	0.933	0.897	0.926
$s(R_p)$	0.110	0.109	0.102	0.114	0.114	0.106	0.120	0.111	0.124	0.133
$s(\hat{\varepsilon}_p)$	0.043	0.045	0.028	0.034	0.026	0.030	0.036	0.027	0.036	0.033
$\hat{s}_{p,t-1}(\hat{\varepsilon}_i)$	0.094	0.089	0.077	0.089	0.085	0.083	0.094	0.083	0.097	0.101
$s(\hat{\varepsilon}_p)/\ \hat{s}_{p,t-1}(\hat{\varepsilon}_i)$	0.459	0.506	0.360	0.379	0.305	0.363	0.380	0.323	0.373	0.329

For regression model (4.1): $R_{pt} - R_{ft} = \hat{\gamma}_{ot} + \hat{\gamma}_{1t}\hat{\beta}_{p,t-1} + \hat{\gamma}_{2t}s_{p,t-1}(\hat{\varepsilon}_i) + \hat{\eta}_{pt}$, the thesis will run cross section regression for R_{pt}-R_{ft}, $\hat{\beta}_{p,t-1}$ and $s(\hat{\beta}_{p,t-1})$. For each year, estimated figures ($\hat{\gamma}_o, \hat{\gamma}_1\ and\ \hat{\gamma}_2$) will produce a series of section estimations ($\hat{\gamma}_o, \hat{\gamma}_{1t}\ and\ \hat{\gamma}_{2t}$). The testing methods is to test whether the coefficients of model will be significantly equal to zero and whether the model 4.1 qualifies for the assumptions of Capital Asset Pricing Model.

The estimated series of three coefficients ($\hat{\gamma}_o, \hat{\gamma}_1\ and\ \hat{\gamma}_2$) in Polish and Chinese stock markets are presented in chart 1 and 2 perspectively.

In polish stock market, all three estimations are fluctuated between zero except for financial crisis period (2007-2009). Over this period, the variances of statistics are highest for all three statistics, indicating the severe effects of financial crisis in Polish stock market. The trend of estimated statistics remains stable after financial crisis period.

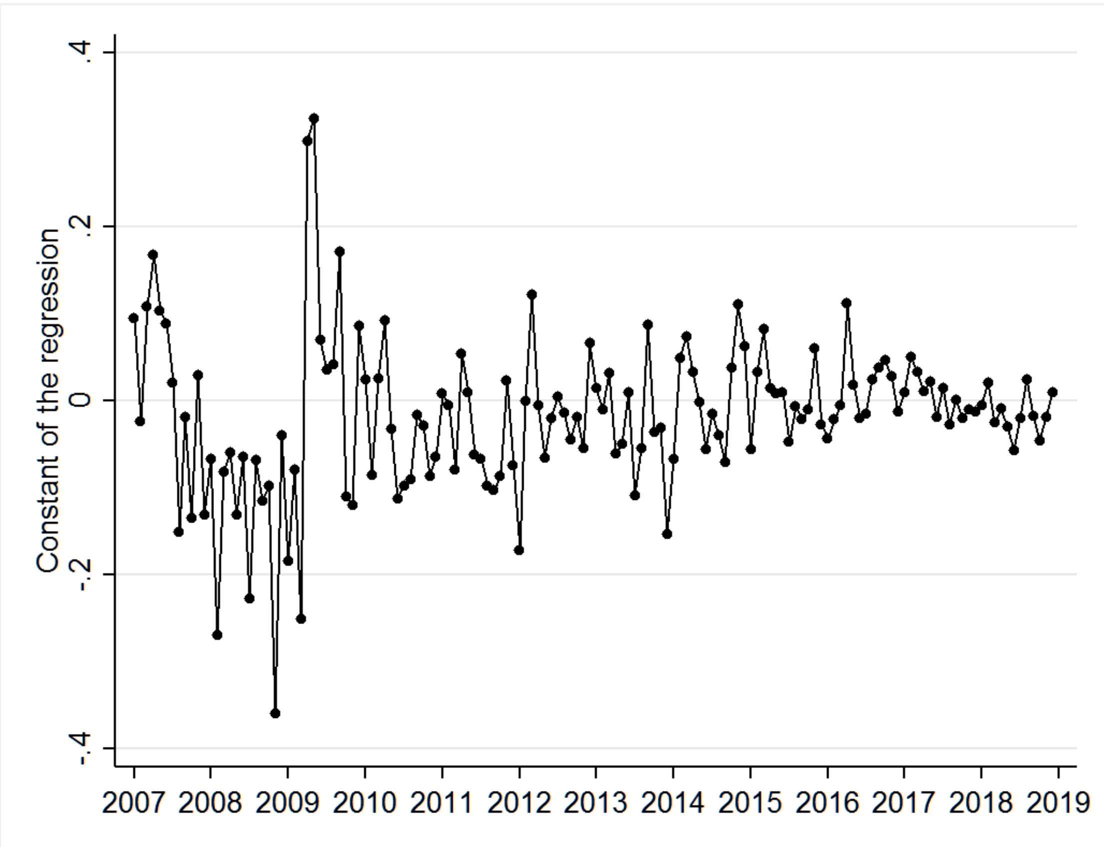
Compared with Polish stock market, the beta in Chinese stock market is less fluctuated, meaning less market risk than Poland. All three variables are more fluctuated during financial crisis and remain stable after 2010. More specifically, the $\hat{\gamma}_{2t}$ is more fluctuated in Polish stock market during 2013, meaning risk of single assets increase remarkably. However, it saw a decrease at the end of year and the stock market remains stable after that. For Chinese stock market, the $\hat{\gamma}_{2t}$ is more fluctuated over the period of 2015-2017, which broke the financial crisis within Chinese stock market, resulting in high variance on single assets' risk.

In all, due to local markets policy or crisis reasons, the trends of statistics in two countries are different but saw same fluctuation during global financial crisis. For investors' decisions, Chinese stock market would be more stable than Polish stock market according to the picture presented.

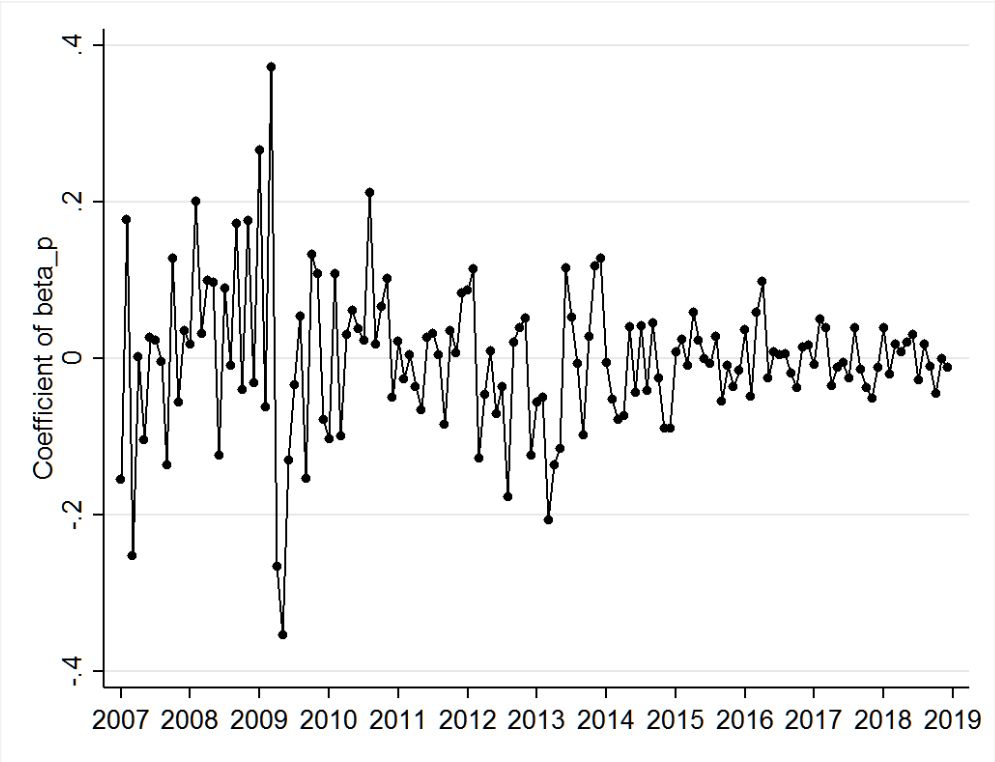
Next, the thesis will run capital asset pricing model using equation (4.1) to test its applicability in Chinese and Polish stock markets.

Chart 3 Statistics in three estimation periods in Polish stock market

$Time\ series\ of\ \hat{\gamma}_{ot}$



$Time\ series\ of\ \hat{\gamma}_{1t}$



$Time\ series\ of\ \hat{\gamma}_{2t}$

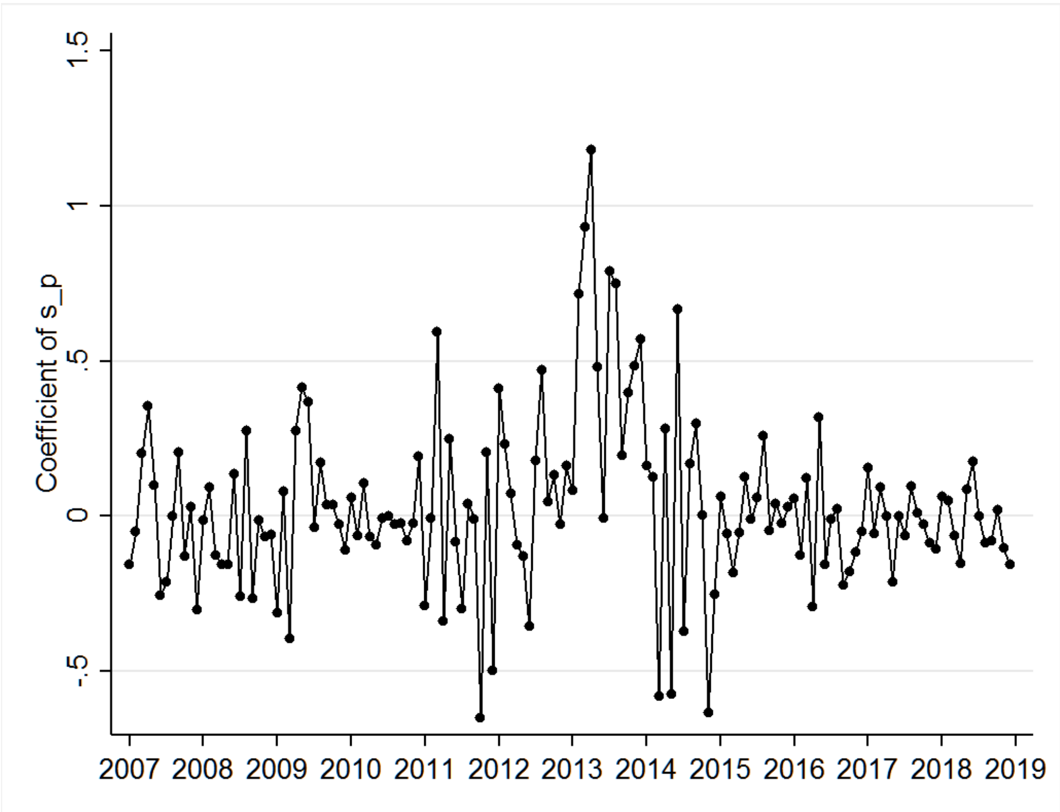
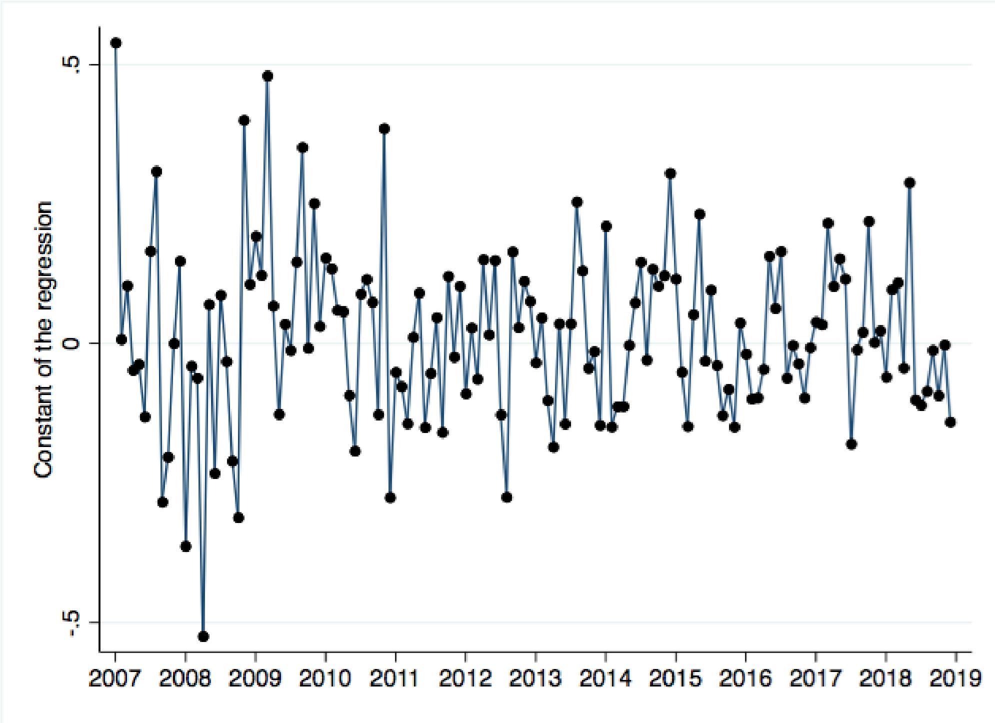
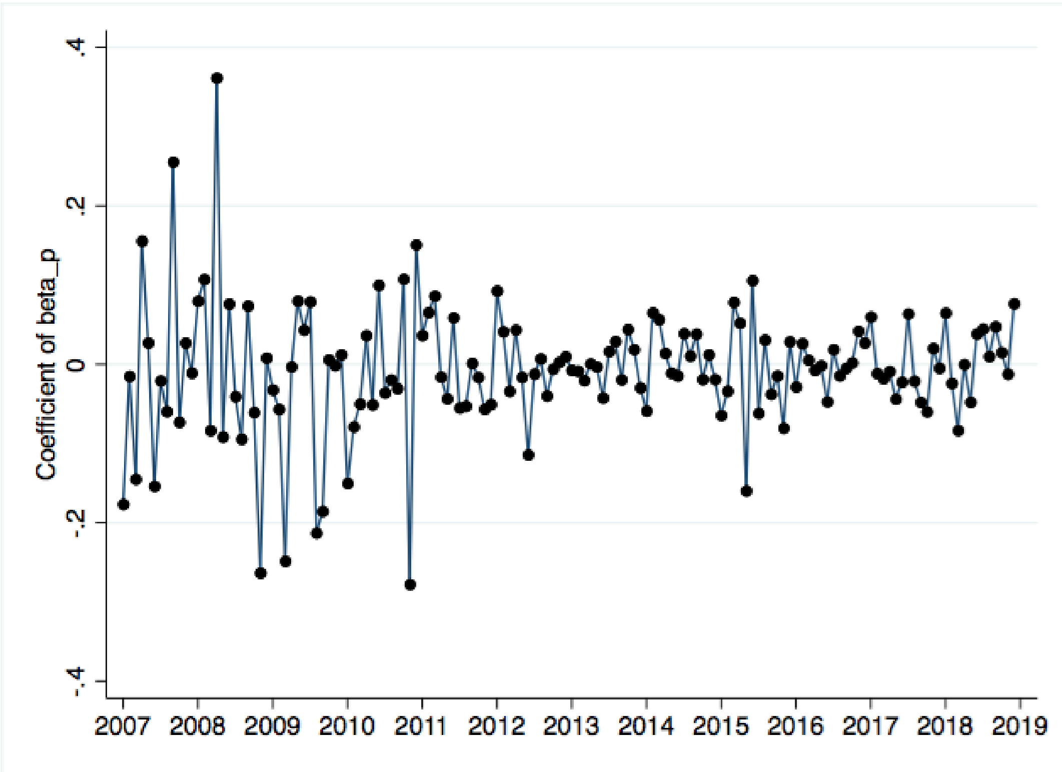


Chart 4 Statistics in three estimation periods in Chinese stock market

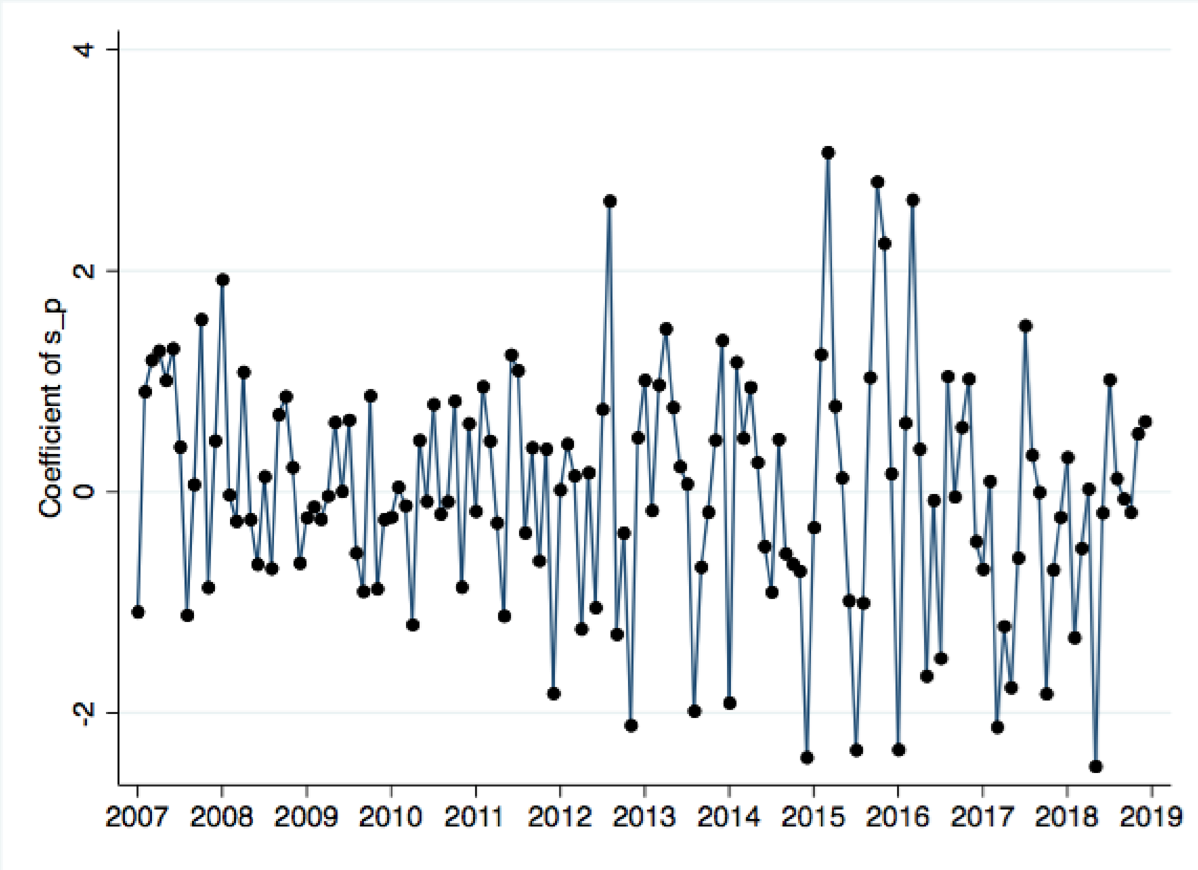
Time series of $\hat{\gamma}_{ot}$



Time series of $\widehat{\gamma}_{1t}$



Time series of $\hat{\gamma}_{2t}$



5.1.2 Estimated Coefficient and Regression Results

Table 10 and 11 present the regression results of our Capital Asset Pricing Model using equation (4.1). Our results select five periods for discussion. First three comparison periods are used for testing applicability in different periods and provides grouping methodology for Fama French three factor model regression. The forth one is regression for whole sample period. The last period is to make other sub sample periods in contrast with financial crisis period because testing results of both CAPM and Fama-French three factor model can't support previous findings in the crisis period (Czapiewisk, 2013).

For each sub period and model, this dissertation provides results of following variables:

$\overline{\hat{\gamma}_J}$: Weighted Average figure of regression co-efficient ($\hat{\gamma}_o, \hat{\gamma}_1$ *and* $\hat{\gamma}_2$) for rolling months;

s($\hat{\gamma}_j$): Standard Deviation of monthly coefficients ($\hat{\gamma}_o, \hat{\gamma}_1$ *and* $\hat{\gamma}_2$) estimations;

$\overline{r^2}$: Coefficient of determination for monthly rolling cross section regression model;

$\rho_0(\hat{\gamma}_0)$, $\rho_M(\hat{\gamma}_1)$, $\rho_0(\hat{\gamma}_2)$: First-order serial correlation coefficient based on monthly changes;

$t(\hat{\gamma}_j)$: Constructed t-statistics when assumed that $\bar{\hat{\gamma}}_j$=0.

Non-market factors will affect stock markets in several periods (Fama and French, 1973; Lardy, Nicholas and Arvin, 2013). In Polish stock market, we consider the $\hat{\gamma}_2$ in equation firstly (4.1). As we assumed, if E($\hat{\gamma}_2$)=0, the systematic risk does not exist in our empirical model and only beta (systematic risk) will affect cross section return. From our results, this hypothesis is only accepted during the period of 2015 to 2018 ($t(\hat{\gamma}_2)$ is less than critical value). In other periods, the null hypothesis is rejected and this indicates that non-systematic factors exist, meaning the results is contradict with assumption of CAPM. The findings are corresponding with Fama and MacBeth (1973) in developed markets.

In section 3, we assume that E ($\bar{\hat{\gamma}}_1$) $= E(R_{mt}) - E\left(R_{ft}\right) > 0$. This means the excessive market return is positive and expected return is higher than risk free return, which is corresponding with the fact. Most estimated $\bar{\hat{\gamma}}_1$ is positive except the period of 2011 to 2014 (-0.018 and significantly lower than zero). This is because in the period of new development after financial crisis, investors tend to hold assets with lower risk. Their expectations towards stock return is conservative. Although the thesis obtains most positive $\bar{\hat{\gamma}}_1$, only $\bar{\hat{\gamma}}_1$period of 2015 to 2018 is significant at the level of 10%.

It is also obvious that lower t-statistics can reflect the variance of these parameters. For example, during the period of financial crisis, $\bar{\hat{\gamma}}_1$ is 0.006. The economic meaning of this figure is that stock cross section return will increase by 0.6% when stock risk rise by 1 unit. Due to the volatility of $\bar{\hat{\gamma}}_1$ as chart and table shown, the s($\hat{\gamma}_1$) in the period of financial crisis is 15.2%. The large value of s($\hat{\gamma}_1$) will lead to lower t-statistics.

Based on analysis above, this dissertation concludes that the empirical evidence of Polish stock market can't support Capital asset pricing model (4.1) although the cross-section tests over the period of 2015 to 2018 support the theory. We also observe that results of sub period 2011 and 2014 reject CAPM. The possible reasons can be that the expectation of investors did not rise back to that in stationary period (2003-2006), which is tested in the research of Urbanski (2011).

Compared with Polish stock market, the parameters in Chinese stock market have similar characteristics with those in Polish stock market. The difference is the trend of $\hat{\gamma}_2$. If E ($\hat{\gamma}_2$) is equal to zero, the non-systematic risk does not exist and only beta (systematic risk) will affect the return of cross section. While this null hypothesis is not rejected during the period of 2015-2018, the $t(\hat{\gamma}_2)$ over this period is lower than critical value. This indicates that non-systematic risk and other crashes exist during financial crisis period (2007-2009) and recovery period (2010-2014). This is corresponding with Fama and French (2011)'s findings in stationary period in developed markets.

Chinese stock market experienced crash between 2014 and 2015. However, we still observe that only $\overline{\hat{\gamma}_1}$ of period during 2015 to 2018 is significant at the level of 10%. Similar with Polish stock market (negative $\overline{\hat{\gamma}_0}$) , investors in Chinese stock market tend to hold assets with lower risk and their preferences of investment decisions are likely to be risk-appetite. The variance during financial crisis period is higher but although Chinese stock market experienced crash during 2014-2015, the empirical results still favour CAPM. This empirical evidence shows the same results as Polish stock market.

Then, the thesis will derive and obtain market characteristics of Chinese and Polish stock markets in different sub period to make further conclusions

Table 8 Regression Results of CAPM in Polish Stock Market

Period	Statistics

	$\bar{\hat{\gamma}}_0$	$\bar{\hat{\gamma}}_1$	$\bar{\hat{\gamma}}_2$	$s(\hat{\gamma}_0)$	$s(\hat{\gamma}_1)$	$s(\hat{\gamma}_2)$	$\rho_0(\hat{\gamma}_0)$	$\rho_M(\hat{\gamma}_1)$	$\rho_0(\hat{\gamma}_2)$
2007.01-2010.12	-0.034	0.013	-0.006	0.132	0.138	0.181	0.317	-0.179	0.018
2011.01-2014.12	-0.019	-0.018	0.123	0.063	0.078	0.420	0.236	0.262	0.192
2015.01-2018.12	0.001	0.002	-0.018	0.034	0.032	0.122	0.222	-0.018	-0.192
2007.01-2018.12	-0.017	-0.001	0.033	0.088	0.094	0.279	0.315	-0.051	0.186
2007.01-2009.12	-0.032	0.006	-0.008	0.149	0.152	0.204	0.313	-0.189	0.032

Period	Statistics						
	$t(\hat{\gamma}_0)$	$t(\hat{\gamma}_1)$	$t(\hat{\gamma}_2)$	$p(\hat{\gamma}_0)$	$p(\hat{\gamma}_1)$	$\rho_M(\hat{\gamma}_1)$	$\overline{r^2}$
2007.01-2010.12	-1.771	0.659	-1.245	0.083	0.513	0.808	0.213
2011.01-2014.12	-2.118	-1.578	2.034	0.040	0.121	0.048	0.258
2015.01-2018.12	0.285	1.734	-0.996	0.777	0.740	0.324	0.180
2007.01-2018.12	-2.366	-0.126	1.426	0.019	0.900	0.156	0.217
2007.01-2009.12	-1.283	0.248	-1.235	0.208	0.806	0.815	0.230

Table 9 Regression Results of CAPM in Chinese Stock Market

Period	Statistics								
	$\bar{\hat{\gamma}}_0$	$\bar{\hat{\gamma}}_1$	$\bar{\hat{\gamma}}_2$	$s(\hat{\gamma}_0)$	$s(\hat{\gamma}_1)$	$s(\hat{\gamma}_2)$	$\rho_0(\hat{\gamma}_0)$	$\rho_M(\hat{\gamma}_1)$	$\rho_0(\hat{\gamma}_2)$
2007.01-2010.12	-0.110	0.013	0.229	0.131	0.150	0.850	0.089	-0.041	-0.087
2011.01-2014.12	-0.022	-0.021	0.425	0.050	0.049	1.108	0.123	0.218	0.098

2015.01-2018.12	-0.004	0.025	-0.216	0.091	0.101	1.399	0.030	0.299	-0.219
2007.01-2018.12	-0.011	0.010	0.119	0.087	0.111	1.198	0.093	0.067	-0.039
2007.01-2009.12	0.005	0.017	0.293	0.121	0.134	0.719	0.054	0.149	0.051

Period	Statistics						
	$t(\hat{\gamma}_0)$	$t(\hat{\gamma}_1)$	$t(\hat{\gamma}_2)$	$p(\hat{\gamma}_0)$	$p(\hat{\gamma}_1)$	$\rho_M(\hat{\gamma}_1)$	$\overline{r^2}$
2007.01-2010.12	-0.594	0.540	1.594	0.540	0.593	0.083	0.134
2011.01-2014.12	-2.841	-1.649	2.394	0.008	0.119	0.021	0.297
2015.01-2018.12	-0.298	1.898	-1.093	0.731	0.049	0.294	0.183
2007.01-2018.12	-1.710	1.112	1.394	0.049	0.139	0.081	0.185
2007.01-2009.12	0.159	0.593	1.695	0.496	0.296	0.059	0.139

5.1.3 Market Characteristics

Table 9 and 10 presents several characteristics of stock markets in different periods and $\hat{\gamma}_1$ as well as $\overline{\hat{\gamma}_0}$. All estimations calculation is same as Table 8. If CAPM model (4.1) is efficient, E $(\overline{\hat{\gamma}_0})$ = 0. Likewise, the expected risk premium of beta should follow: $\mathrm{E}\left(\overline{\hat{\gamma}_1}\right) = E(R_{mt}) - E(R_{ft})$. From the empirical results, the estimations of $\overline{\hat{\gamma}_0}$ are all negative in each sample period except the period between 2015 and 2018. This indicates that before 2015, investors tend to be risk appetite and speculative. They tend to seek higher return from higher risk. The figure of $t(\hat{\gamma}_0)$ tends to be higher during 2011 to 2014, meaning the $\hat{\gamma}_0$ is significant during these periods. During stationary period (tested in 5.1.2) 2015 to 2018, the $t(\hat{\gamma}_0)$ is lower. Therefore, the selected risk-free rate has no statistical difference with real risk-free rate.

From the table 8 and 10, only $\overline{\hat{\gamma}_1}$ during 2015-2018 is significant different from zero, indicating that $\mathrm{E}(\overline{\hat{\gamma}_1}) = E(R_{mt}) - E(R_{ft})$ equation holds. For Capital Asset Pricing Model, the linear relationship of beta is established during this period. In other periods, the estimation of $\hat{\gamma}_1$ is insignificant. The risk factor can't explain the market return and we should reject CAPM.

Table 11 presents the market characteristics of estimations in Chinese stock market. If model (4.1) is efficient in Chinese stock market, E $(\overline{\hat{\gamma}_0})$ = 0. The estimated coefficients of $\overline{\hat{\gamma}_0}$ are all negative in each period or the whole sample periods. The results are corresponding with findings in Polish stock markets. Investors in this market prefer highly risky investments and speculative. Apart from this, the figure of $t(\hat{\gamma}_0)$ is higher during period of 2011 to 2014 and the whole sample period. Compared with Table 9, the results indicate that $\hat{\gamma}_0$ is significant during these periods. Only between 2015 and 2018, the thesis can't reject the null hypothesis of E (($\hat{\gamma}_0$)=0. Likewise, the risk-free rate has no significant difference with real risk-free rate.

As for equation: E $(R_{mt}) - E(R_{ft}) = E(\overline{\hat{\gamma}_{1t}})$, the equation only holds during 2015 to 2018, which is the same as Polish stock market. Only the datasets over period of 2015 to 2018 favours Capital Asset Pricing Model as Lee (2014) estimated.

Table 10 Market Variables and Estimation of Parameters in Polish Stock Market

Period	Statistics							
	$\bar{R}_m$	$\overline{R_m - R_f}$	$\overline{\hat{\gamma}_1}$	$\overline{\hat{\gamma}_0}$	$\bar{R}_f$	$\dfrac{\overline{R_m - R_f}}{s(R_m)}$	$\dfrac{\overline{\hat{\gamma}_1}}{s(R_m)}$	$s(R_m)$
2007.01-2010.12	0.009	-0.025	0.013	-0.034	0.034	-0.353	0.184	0.072
2011.01-2014.12	-0.002	-0.028	-0.018	-0.019	0.027	-0.420	-0.263	0.067
2015.01-2018.12	0.002	-0.009	0.002	0.001	0.011	-0.200	0.034	0.046
2007.01-2018.12	0.003	-0.021	-0.001	-0.017	0.024	-0.334	-0.016	0.063

2007.01-2009.12	0.009	-0.025	0.006	-0.032	0.034	-0.336	0.085	0.074

Period	Statistics							
	$s(\hat{\gamma}_0)$	$s(R_f)$	$t(\bar{R}_m)$	$t(\overline{R_m - R_f})$	$t(\hat{\gamma}_1)$	$t(\hat{\gamma}_0)$	$\rho_m(\hat{\gamma}_1)$	$\rho_0(\hat{\gamma}_0)$
2007.01-2010.12	0.132	0.009	1.165	-3.148	0.659	-1.771	-0.179	0.317
2011.01-2014.12	0.063	0.012	-0.215	-3.685	-1.578	-2.118	0.262	0.236
2015.01-2018.12	0.034	0.009	0.317	-1.818	1.534	0.285	-0.018	0.222
2007.01-2018.12	0.088	0.014	0.772	-5.118	-0.126	-2.366	-0.051	0.315
2007.01-2009.12	0.149	0.009	1.000	-2.769	0.248	-1.283	-0.189	0.313

Table 11 Market Variables and Estimation of Parameters in Chinese Stock Market

Period	Statistics							
	$\bar{R}_m$	$\overline{R_m - R_f}$	$\bar{\hat{\gamma}}_1$	$\bar{\hat{\gamma}}_0$	$\bar{R}_f$	$\frac{\overline{R_m - R_f}}{s(R_m)}$	$\frac{\bar{\hat{\gamma}}_1}{s(R_m)}$	$s(R_m)$
2007.01-2010.12	0.025	0.019	0.011	-0.116	0.006	0.159	0.110	0.120
2011.01-2014.12	0.005	-0.007	-0.012	-0.024	0.009	-0.092	-0.239	0.060
2015.01-2018.12	0.020	0.015	0.029	-0.005	0.006	0.226	0.450	0.070
2007.01-2018.12	0.019	0.010	0.011	-0.015	0.008	0.114	0.113	0.080
2007.01-2009.12	0.036	0.030	0.018	0.004	0.009	0.208	0.143	0.139

Period	Statistics							
	$s(\hat{\gamma}_0)$	$s(R_f)$	$t(\bar{R}_m)$	$t(\overline{R_m - R_f})$	$t(\hat{\gamma}_1)$	$t(\hat{\gamma}_0)$	$\rho_m(\hat{\gamma}_1)$	$\rho_0(\hat{\gamma}_0)$

2007.01-2010.12	0.121	0.003	1.549	1.133	0.571	-0.671	-0.041	0.098
2011.01-2014.12	0.059	0.001	0.489	-0.659	-1.655	-2.933	0.234	0.131
2015.01-2018.12	0.123	0.000	2.090	1.489	1.939	-0.329	0.311	0.038
2007.01-2018.12	0.091	0.003	2.369	1.390	1.073	-1.674	0.073	0.093
2007.01-2009.12	0.139	0.003	1.694	1.319	0.641	0.671	0.149	0.069

In summarize, the empirical evidence does not unambiguous support CAPM in both stock markets while empirical results in Chinese and Polish stock markets over sub period of 2015 to 2018 still favour the testing model and support CAPM. Comparing two stock markets, the estimations of coefficients present similar market characteristics.

During financial crisis period (2007-2010), only $\hat{\gamma}_2$ is significant. Only non-systematic factor can cause stock cross-sectional returns fluctuating. Other parameters reflecting rational expectations in CAPM is invalid during this period. The market is inefficient and the empirical evidence during this period is against CAPM.

During crisis recovery period (2011-2014), three parameters are almost all insignificant while $\hat{\gamma}_0$ is negative and speculations exist in stock market. Both $\hat{\gamma}_0$ and $\hat{\gamma}_1$ are positive, indicating there is weighing gaming between risk and return in Chinese and Polish stock markets. Due to speculation factor and non-systematic risk factors, Capital Asset Pricing Model is against.

During stationary period (2015-2018), $\hat{\gamma}_0$ has no significant difference with zero. There is no significant difference between the mean of $\hat{\gamma}_1$and excessive market return. The cross-section return can be perfectly explained by CAPM. $\hat{\gamma}_2$ is not significant, indicating that non-systematic risk can't explain cross section return during this period. Therefore, Capital Asset Pricing Model is supported in the two stock markets during this period.

5.2 Fama-French Three-Factor Regression Results

All data of Poland used in this section are from Datastream, European Central Bank, Poland National Bank and Amendeus database. The datasets of China's stock market are from CCER China Economic Database and Datastream. This dissertation selects data over the period from 2007 to 2018. The portfolio return will be the monthly return weighted averaged by samples' size (circulated stock value) variable.

5.2.1 Descriptive Statistics of Variables

According to section 3.1.2, this dissertation constructs 25 portfolios in Poland and China's stock market using the 5*5 method. Table 12 and 13 presents the descriptive statistics of our stock portfolios in two markets.

Although the sample stocks in Polish stock market are limited, the number of stocks in each portfolio in early financial crisis is small but grows after global financial crisis. Table 6 and table 7 present the descriptive statistics (Size mean and Book to market ratio mean) of portfolios in Polish and Chinese markets perspectively. In Polish market, the size of each portfolio sees big difference. However, the companies with higher size own much larger market capitalization than the companies with lower size. The market return is calculated based on average weight of market capitalization. Therefore, the volatility of total stock market is likely to be determined by companies with higher market capitalization (Phillips, Wu and Yu, 2011)

As for the factor of HML, the difference of B/M ratio of biggest size portfolio and lowest size portfolio is small (0.05 and 0.2), indicating that there is no obvious difference of book to market ratio between portfolios with same B/M ratio.

Table 12 Descriptive Statistics of Portfolios in Polish Stock Market

SIZE	B/M									
	L	2	3	4	H	Low	2	3	4	High
	SIZE Mean (1 billion)					B/M Mean				
S	85.4	64.9	30.5	17.5	15.5	0.28	0.57	0.89	1.15	2.29
2	285.99	189.4	70.53	54.2	30.1	0.29	0.59	0.74	1.15	2.21
3	501.49	477.5	353.1	154.3	63.7	0.24	0.55	0.79	1.17	2.07
4	1290.5	1234	337.8	289.5	155.4	0.29	0.56	0.81	1.17	2.05
B	6948.4	9094	2997	2877	2851	0.24	0.57	0.98	1.15	2.04

Compared with average figures of size in Polish stock market, the size in Chinese market sees higher figure. The portfolios with larger size own nearly 80% of the market capitalization. This tends to result that larger size portfolios can determine the volatility of whole market's stock price. The difference of B/M of biggest size portfolio and lowest size portfolio sees the same trend with Polish market. Their difference is 0.88% and 5.13% respectively. Therefore, there is no obvious difference of book to market ratio between five portfolios in Chinese market as well.

Table 13 Descriptive Statistics of Portfolios in Chinese Stock Market

SIZE	B/M									
	L	2	3	4	H	Low	2	3	4	High
	SIZE Mean (100 billion)					B/M Mean (%)				
S	15.84	16.17	16.56	16.07	17.54	6.07	10.41	13.62	17.54	25.26
2	28.01	22.19	29.34	28.51	29.05	7.01	11.45	14.85	18.91	27.54
3	44.93	42.49	45.12	45.31	45.12	6.53	10.91	14.12	18.98	29.43

4	77.91	75.34	74.50	77.84	79.56	5.81	9.91	13.51	18.31	31.12
B	301.94	401.9	509.5	793.1	459.41	5.19	9.41	13.54	18.81	30.39

After portfolio grouping and sorting, the SMB and HML variable is easy to calculate based on the data (B/H, B/M, B/L, S/H, S/M and S/L) we obtained. Before regression, we will obtain the line chart of SMB, HML, R_m-R_f and R_i-R_f to see whether missing values or outliers exist.

5.2.2 Stationarity Test

For regression model (3.2), table 16 present the stationarity test of SMB, HML and excess market return. The t-statistics of all three variables are less than critical value and reject null-hypothesis. All three variables are stationary series and no unit-root exists over the whole sample periods.

Before regression, table 14 and 15 compute the descriptive statistics of excessive return of each portfolio as well as their stationarity test results in both Polish and Chinese stock markets. From the results, there is obvious difference between excessive return of big size and small size portfolios. The figure of return of small-size companies is higher than that of big size (mean and maximise figure) with high standard deviation figure (more volatile), which is corresponding with Fama and French (1977, 1992). When controlling the size of portfolios, the portfolio with higher book to market ratio has higher return than that with lower ratio.

Compared with Polish stock market, the effects of higher size and book to market ratio on return are more obvious in Chinese stock market. The larger size and book to market ratio tend to lead to higher market excessive return of portfolio.

In next stage, this thesis will run regression to test the applicability of Fama and French three factor model in Polish and Chinese stock market respectively and compute the empirical results.

Table 14 Descriptive Statistics and Stationary Test of Rp-Rf in Polish Stock market

SIZE	B/M									
	L	2	3	4	H	Low	2	3	4	High
	Mean					Standard Deviation				
S	-0.008	-0.007	0.008	0.005	0.008	0.073	0.062	0.053	0.052	0.086
2	0.01	-0.005	-0.008	-0.016	-0.003	0.057	0.050	0.048	0.044	0.059
3	0.002	0.007	-0.009	-0.002	0.003	0.052	0.048	0.037	0.052	0.052
4	0.005	-0.001	0.005	-0.001	0.011	0.074	0.048	0.046	0.043	0.052
B	-0.011	0.007	0.011	0.002	0.007	0.060	0.059	0.068	0.054	0.048
	Maximum					Minimum				
Small	0.333	0.134	0.117	0.160	0.236	-0.11	-0.12	-0.09	-0.10	-0.15
2	0.175	0.105	0.085	0.101	0.137	-0.13	-0.13	-0.13	-0.09	-0.17
3	0.112	0.074	0.064	0.082	0.169	-0.08	-0.11	-0.08	-0.21	-0.15
4	0.167	0.167	0.151	0.758	0.126	-0.19	-0.11	-0.09	-0.12	-0.11
Big	0.163	0.106	0.183	0.161	0.109	-0.11	-0.13	-0.12	-0.10	-0.10

	ADF Statistics				
	Low	2	3	4	5
Small	-6.000^{***}	-5.667^{***}	-5.629^{***}	-5.754^{***}	-5.331^{***}
2	-5.732^{***}	-4.801^{***}	-4.762^{***}	-5.945^{***}	-4.763^{***}
3	-5.137^{***}	-5.811^{***}	-6.395^{***}	-5.104^{***}	-6.098^{***}

4	-6.33***	-6.377***	-5.73***	-4.702***	-5.164***
Big	-5.984***	-6.624***	-6.637***	-5.683***	-7.065***

Table 15 Descriptive Statistics and Stationary Test of Rp-Rf in Chinese Stock market

SIZE	B/M									
	L	2	3	4	H	Low	2	3	4	High
	Mean					Standard Deviation				
S	0.012	0.014	0.015	0.015	0.012	10.44	10.16	10.25	10.10	10.02
2	0.007	0.013	0.013	0.013	0.012	10.35	9.90	9.73	10.13	9.55
3	0.007	0.099	0.098	0.011	0.012	9.76	9.72	9.65	9.85	9.36
4	0.006	0.009	0.010	0.011	0.099	9.24	9.71	9.48	9.62	9.29
B	0.005	0.006	0.008	0.007	0.007	8.44	8.52	9.00	8.56	8.15
	Maximum					Minimum				
Small	0.32	0.29	0.38	0.37	0.45	-0.35	-0.31	-0.30	-0.31	-0.32
2	0.35	0.33	0.33	0.41	0.42	-0.33	-0.31	-0.32	-0.30	-0.29
3	0.30	0.35	0.36	0.36	0.35	-0.32	-0.32	-0.32	-0.30	-0.27
4	0.30	0.32	0.41	0.39	0.43	-0.30	-0.32	-0.30	-0.29	-0.26
Big	0.27	0.27	0.42	0.34	0.30	-0.26	-0.30	-0.28	-0.28	-0.29

	ADF Statistics				
	Low	2	3	4	5

Small	-9.29***	-9.09***	-9.54***	-9.31***	-8.76***
2	-9.87***	-8.95***	-9.01***	-8.94***	-9.05***
3	-8.84***	-9.51***	-8.67***	-8.54***	-8.61***
4	-5.51***	-8.54***	-8.81***	-5.49***	-8.48***
Big	-9.16***	-8.51***	-10.32***	-5.43***	-5.61***

Table 16 Descriptive Statistics of SMB and HML (First is Poland and Second is China) (%)

Variable	Mean	Std. Div.	Max	Min	ADF
SMB	-0.27655	0.35934	11.31928	-7.95562	-8.390***
HML	0.25568	0.33201	13.43942	-12.23549	-10.751***
Variable	Mean	Std. Div.	Max	Min	ADF
SMB	0.4385731	0.2469149	19.48492	-16.73043	-13.399***
HML	0.2767113	0.2184076	16.35178	-15.568	-14.695***

Chart 5 Time-series of SMB in China's Market (%)

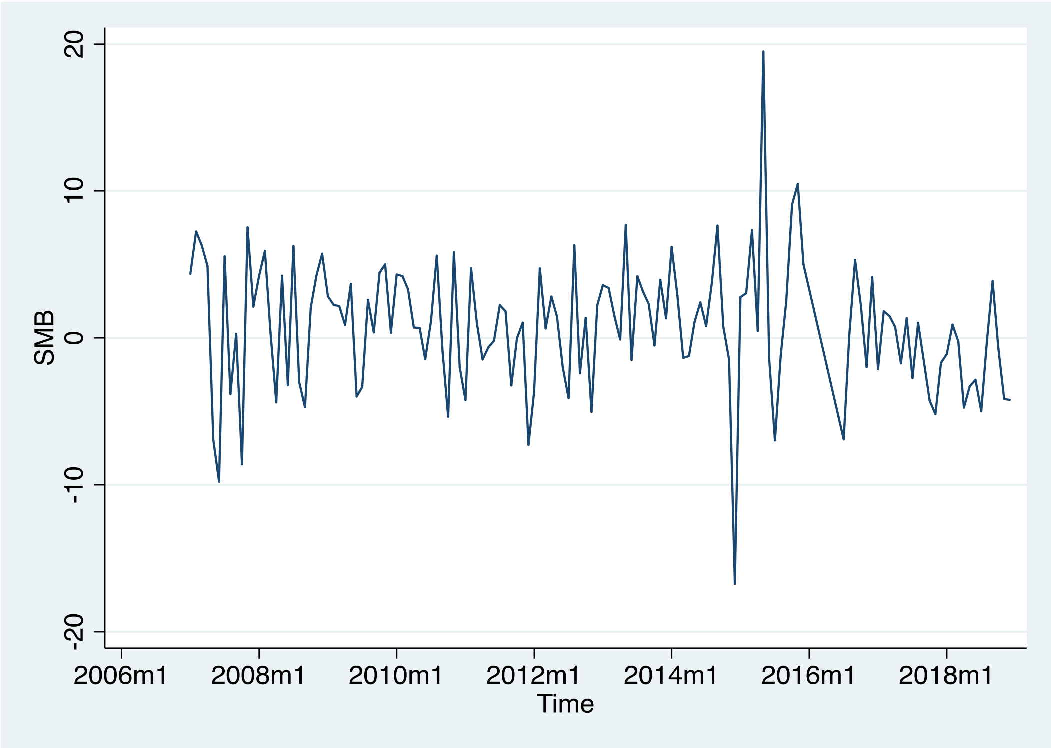


Chart 6 Time-series of HML in China's Market

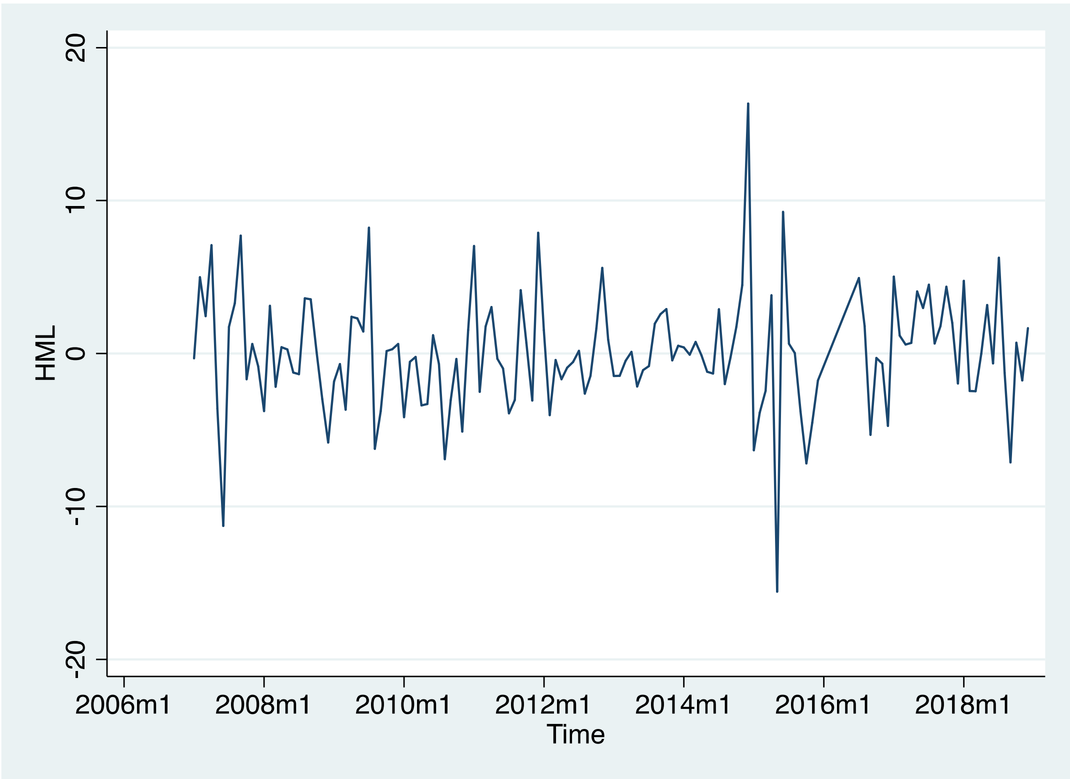


Chart 7 Time-series of SMB in Poland's Market

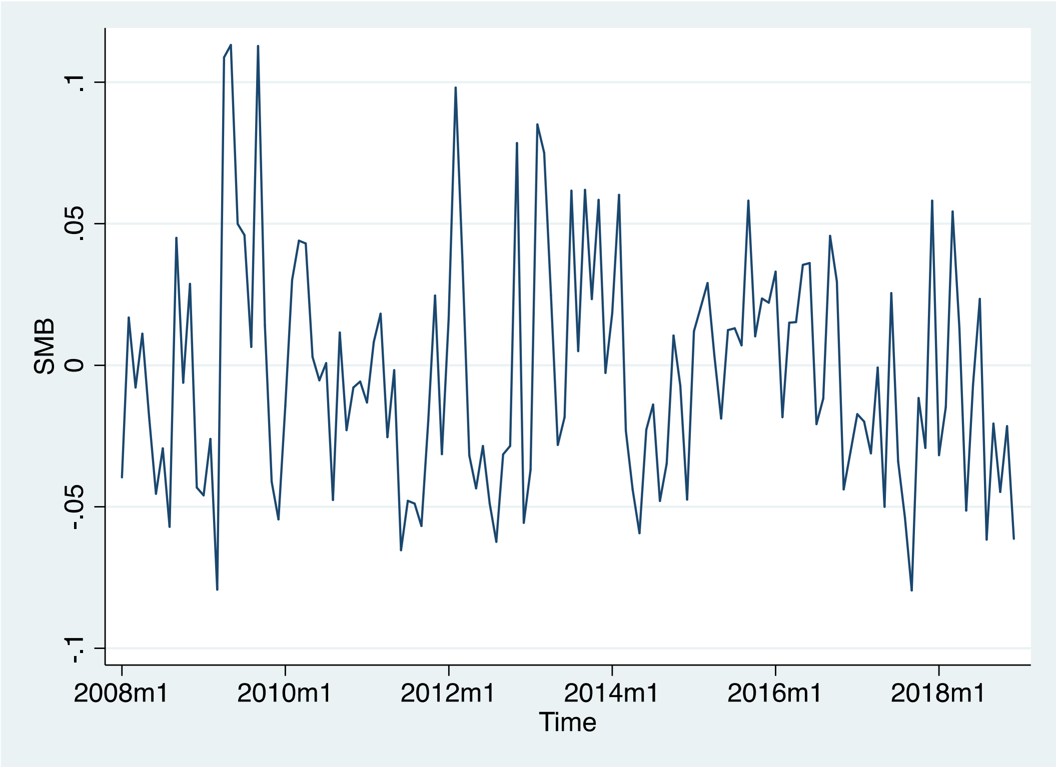
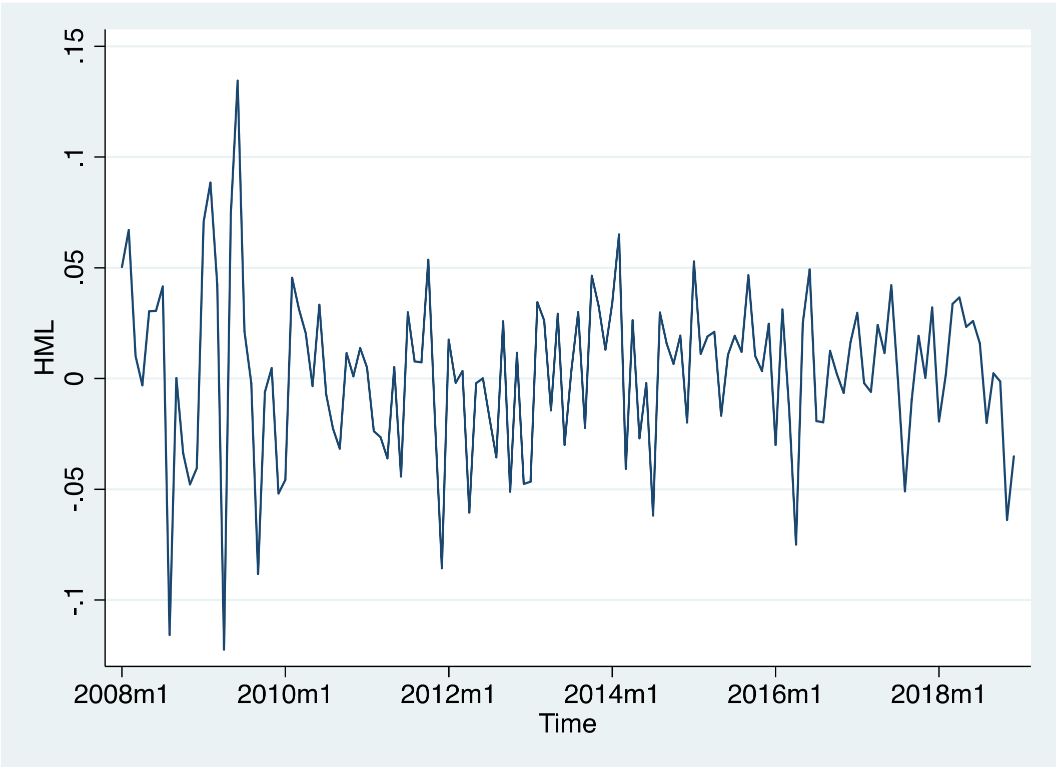


Chart 8 Time-series of HML in Poland's Market



5.2.3 Regression Results

The regression Results will be discussed in three periods: Financial Crisis period (2007-2009), Recovery period (2010-2014), Stationary period (2015-2018) as we distinguished in section 4.3. This dissertation aims to test CAPM using different sub period following Fama and French (1992, 1996) to obtain empirical evidence to support CAPM in different sub periods.

In the period of financial crisis, the range of China's stock market volatility is much more fluctuating than it in stationary period. The explanatory power of size factor (SMB) is higher than market value factor (HML), which is corresponding with the results in other emerging markets. Beltratti and Tria (2002) suggest that cross section regression is more applicable to testing CAPM in emerging markets and that consists of our research methodology. From the estimated results of 25 portfolios, the coefficient of abnormal return (R_{mt}-R_{ft}) ranges between 0.954048 and 1.0850919 and all of them are significant, indicating market risk can perfectly explain the stock return variance in China's stock market. Most of size factor (SMB) variable is significant expect portfolio P52, P53 and P54 group. The coefficient (s) of size factor shows a decreasing trend indicating the existence of scale effect in Three-Factor Model. Approximately half of HML coefficient is insignificant at the level of 10%, meaning the weak interpretation of HML on stock return during financial crisis in China's market. In summary, during financial crisis period, Fama-French three-factor model could not perfectly explain the variance on stock returns. The intercept of P15, P32, P53 are significant, indicating that CAPM assumption is not satisfied during financial crisis period. The possible reasons may include: samples selection, observation errors. The financial crisis will stimulate stock speculation behaviour and the expectation of investors tend to be influenced, resulting in the stock price can't be explained by three-factor model.

Table 17 Estimated Results of Chinese Stock Market in 2007-2009

Size	B/M low	2	3	4	5
			b		
	0.99492***	0.930824***	0.998494***	1.023008***	1.055368***
Small	(12.64243)	(18.75559)	(38.69606)	(47.15873)	(42.41422)
	1.051082***	0.985531***	0.967373***	1.0432***	1.041482***
2	(16.73848)	(29.3226)	(25.4213)	(39.16161)	(38.63031)
	1.012919***	1.015908***	1.047915***	1.068821***	.1.028157***
3	(26.35516)	(31.59983)	(28.22498)	(37.41481)	(34.92392)
	0.980816***	1.05944***	1.034065***	1.07812***	1.085092***
4	(24.48082)	(32.62984)	(29.38412)	(46.43163)	(30.5456)
	0.981433***	1.057049***	1.112396***	1.046926***	0.954048***
Big	(30.2462)	(62.25303)	(23.52501)	(33.48549)	(12.35172)
			SMB		
	1.171696***	1.195114***	1.183987***	1.183989***	1.187562***
Small	(6.7629)	(8.4416)	(10.72577)	(11.97567)	(12.99305)
	1.212842***	0.903944***	0.935487***	1.21417***	0.940623***
2	(7.1227)	(7.1845)	(7.5247)	(11.0501)	(11.0535)
	0.753***	0.85442***	0.81977***	0.93274***	0.671472***
3	(7.3975)	(11.2023)	(11.1204)	(7.07002)	(6.49602)

	0.55218^{***}	0.76683^{***}	0.6806^{***}	0.74898^{***}	0.41414^{***}
4	(5.0449)	(6.5412)	(4.6083)	(9.7217)	(4.50112)
	-0.25291^{*}	-0.0707	-0.0755	-0.066	-0.4401^{***}
Big	(-1.7967)	(-0.8413)	(-0.4195)	(-0.4488)	(-3.0726)
			HML		
	-0.31365	-0.2569	-0.17037^{**}	-0.14803	0.28689^{*}
Small	(-0.9281)	(-2.0047)	(-2.1067)	(-1.9299)	(1.91637)
	-0.52511^{**}	-0.0093	-0.29619^{**}	0.103319	0.26686^{**}
2	(-2.6764)	(-0.06064)	(-2.18238)	(0.869928)	(2.553437)
	-0.80211^{***}	-0.41448^{***}	-0.16924^{*}	-0.03746	0.39085^{***}
3	(-4.8388)	(-3.24686)	(-1.75729)	(-0.35354)	(3.20913)
	-0.85523^{***}	-0.28951^{**}	0.07953	0.17473	0.41457^{**}
4	(-5.37668)	(-2.09235)	(0.505592)	(1.97631)	(2.167488)
	-0.8185^{***}	-0.66^{***}	0.0071	0.4416^{***}	0.491788^{**}
Big	(-5.97579)	(-6.58985)	(0.0305)	(3.81303)	(2.60795)
			S(e)		
Small	0.0787	0.049629	0.025803	0.021693	0.024882
2	0.062794	0.03361	0.038054	0.026615	0.02696
3	0.038433	0.032149	0.037127	0.028567	0.02944
4	0.040065	0.032468	0.035191	0.02322	0.035524
Big	0.032448	0.01698	0.047286	0.031265	0.07724

	a				
	-0.4383	-2.6427	-0.2921	-1.5095	4.4790 ***
Small	(-0.2486)	(-1.6416)	(-0.1913)	(-0.8486)	(2.4493)
	-0.0583	-0.6062	-3.7857	-0.6761	0.0058
2	(-0.0521)	(-0.4898)	(-1.6940)	(-0.6740)	(0.0026)
	0.9387	-3.1093 ***	-0.6609	0.0386	3.0884
3	(0.3517)	(-2.8026)	(-0.3385)	(0.0291)	(1.1186)
	1.8901	-1.6347	-1.1452	2.1186	-1.1526
4	(0.8241)	(-0.8496)	(-0.8469)	(0.9164)	(-0.9717)
	0.0128	-0.4459	-3.6777 ***	-1.4735	0.1805
Big	(0.0079)	(-0.4376)	(-2.8647)	(-1.2979)	(0.1629)
	Adjusted R^2				
Small	0.912	0.945	0.923	0.951	0.974
2	0.925	0.964	0.959	0.963	0.961
3	0.954	0.887	0.931	0.931	0.941
4	0.811	0.902	0.906	0.954	0.945
Big	0.910	0.909	0.806	0.911	0.936

Table 18 Estimated Results of Chinese Stock Market in 2010-2014

	B/M				
Size	low	2	3	4	5

			b		
	1.033614***	0.973364***	0.997081***	1.01992***	0.9851***
Small	(21.33073)	(21.88483)	(32.68344)	(25.62844)	(20.0599)
	1.123123***	0.979904***	1.0624***	1.03945***	1.02214***
2	(31.90797)	(22.0966)	(33.2893)	(27.3332)	(31.1774)
	0.97798***	0.987233***	1.0787***	1.05519***	1.14173***
3	(19.5241)	(41.2467)	(28.499)	(21.87999)	(33.35432)
	0.96785***	1.09241***	1.13027***	1.2637***	1.146582***
4	(32.724)	(33.4806)	(34.6102)	(38.40658)	(39.71138)
	0.9827***	1.195439***	1.1847***	0.8682***	0.9837***
Big	(28.8199)	(23.2767)	(28.561)	(15.7612)	(37.0552)
			SMB		
	0.81241***	1.0492***	1.09435***	0.94692***	0.95313***
Small	(6.7039)	(10.9101)	(10.0796)	(12.9609)	(10.8891)
	0.8821***	0.8472***	0.8151***	0.89154***	0.81414***
2	(10.1382)	(13.2215)	(9.6983)	(12.9637)	(12.5319)
	0.64625***	0.8083***	0.7757***	0.7342***	0.5001***
3	(5.3227)	(11.048)	(10.2944)	(7.3269)	(4.5506)
	0.4759***	0.4934***	0.4929***	0.2659***	0.2123***
4	(5.4814)	(4.6417)	(6.8788)	(3.1574)	(2.6357)
	-0.4664***	-0.19662**	-0.1481	-0.0521	-0.30314***

Big	(-6.7431)	(-2.6392)	(-1.5433)	(-0.4383)	(-6.10863)
			HML		
	-0.49078***	-0.3509***-	-0.2006*	-0.3279***	-0.06975
Small	(-3.60918)	(-2.7153)	(-1.9793)	(-3.1009)	(-0.57873)
	-0.40421***	-0.3975***	-0.43624***	-0.1057**	0.22241**
2	(-4.897)	(-6.074)	(-3.8778)	(-0.78254)	(2.271)
	-0.7116***	-0.4606***	-0.3213***	-0.1474	0.1085
3	(-5.1248)	(-5.5951)	(-3.4823)	(-1.1408)	(0.88674)
	-0.8642	-0.6024***	-0.367***	-0.2788**	0.23327**
4	(-11.5356)	(-3.8278)	(-4.3615)	(-2.49951)	(2.5348)
	-1.2557***	-0.5787***	-0.1077	0.4788***	0.5396***
Big	(-13.3121)	(-5.2904)	(-0.85302)	(3.595)	(6.2661)
			S(e)		
Small	0.048	0.0445	0.0305	0.0398	0.0491
2	0.0352	0.0443	0.0319	0.0380	0.0328
3	0.0201	0.0239	0.0379	0.0501	0.0239
4	0.0296	0.0326	0.0327	0.0329	0.0289
Big	0.0341	0.0514	0.0415	0.0551	0.0265
			a		
	0.2601	0.3628	0.6444	-0.1629	-0.1354
Small	(0.2072)	(0.4313)	(1.0459)	(-0.2120)	(-0.1661)

	0.2911	0.5503	0.0511	-0.0987	-0.5262
2	(0.3238)	(0.6679)	(0.0786)	(-0.1325)	(-0.6611)
	0.4269	1.4263	0.4029	-0.0729	-1.3083
3	(0.4745)	(2.4307)	(0.5510)	(-0.1134)	(-2.1705)
	0.0594	0.0595	2.0742	-0.2663	0.4509
4	(0.0494)	(0.0792)	(1.3445)	(-0.4020)	(0.3154)
	-0.0055	0.3863	-0.3944	-1.6629	1.1034
Big	(-0.0150)	(0.3227)	(-0.5868)	(-1.8943)	(1.6675)
			Adjusted R^2		
Small	0.861	0.926	0.933	0.835	0.895
2	0.942	0.931	0.949	0.945	0.954
3	0.915	0.885	0.941	0.899	0.939
4	0.806	0.898	0.931	0.931	0.894
Big	0.898	0.906	0.871	0.959	0.889

Table 19 Estimated Results of Chinese Stock Market in 2015-2018

Size	**B/M**				
	low	2	3	4	5
			b		
	0.97153***	1.0780***	0.9662***	0.9739***	1.0004***
Small	(26.4533)	(19.557)	(20.4565)	(27.4269)	(20.8125)
	0.9582***	0.9802***	1.02001***	0.9785***	1.0211***

2	(26.5695)	(28.7133)	(27.4026)	(26.2354)	(29.808)
	1.0297***	1.0067***	0.945***	1.0193***	0.9966***
3	(23.5323)	(23.0799)	(18.283)	(29.779)	(23.453)
	0.9684***	1.0331***	0.9855***	1.0926***	0.9938***
4	(14.339)	(22.4868)	(18.162)	(39.946)	(24.3309)
	1.0002***	0.9404***	1.0361***	1.0872***	0.9596***
Big	(29.755)	(20.0913)	(26.098)	(16.879)	(18.342)
			SMB		
	1.0201***	0.9784***	0.9985***	0.8628***	0.8373***
Small	(8.6109)	(8.6116)	(7.9225)	(21.9739)	(5.3650)
	1.0056***	0.8535***	0.8293***	0.9565***	0.7678***
2	(14.5994)	(10.6141)	(5.5713)	(6.7333)	(6.8534)
	0.7657	0.7429	0.67005	0.7169	0.5598
3	(6.9866)	(4.4061)	(7.0175)	(8.4876)	(4.7522)
	0.3328*	0.18823	0.2968***	0.2921***	0.4635***
4	(1.4388)	(1.5604)	(2.6892)	(4.0873)	(5.1681)
	-0.6403***	-0.211*	-0.1198	-0.3253**	-0.2352***
Big	-3.9068	-1.7601	-1.3192	-2.6727	-5.139
			HML		
	-0.4562***	-0.2222*	-0.3925***	-0.3751***	0.0495
Small	(-4.921)	(-1.8389)	(-5.6936)	(-6.0219)	(0.3708)

	-0.5135***	-0.5358***	-0.1298	-0.089***	0.2502***
2	(-6.607)	(-6.251)	(-0.7344)	(0.6055)	(2.7708)
	-0.5531***	-0.4867**	-0.2377	-0.0858**	0.1876**
3	(-4.048)	(-4.623)	(-2.451)	(-1.069)	(2.1517)
	-0.877***	-0.602***	-0.3659***	-0.051	0.399***
4	(-4.087)	(-4.954)	(-3.499)	(-0.454)	(6.4134)
	-1.2602***	-0.4506***	-0.138*	0.056	0.615***
Big	(-9.046)	(-3.643)	(-1.98)	(0.35)	(7.79)
			S(e)		
Small	0.037	0.035	0.037	0.036	0.028
2	0.036	0.034	0.037	0,037	0,034
3	0.043	0.044	0.052	0.034	0.042
4	0.068	0.046	0.054	0.047	0.041
Big	0.069	0.047	0.059	0.065	0.052.
			a		
	0.8622	1.1246	1.6553	0.9203	-0.5244
Small	(0.9006)	(2.1457)	(2.3571)	(1.1048)	(-0.3674)
	2.1226	0.3888	0.0714	-1.0911	0.1421
2	(2.7672)	(0.5648)	(0.0943)	(-2.3433)	(0.2442)
	0.8749	0.8849	-0.3660	0.4054	1.2880
3	(1.3586)	(1.1819)	(-0.6244)	(0.6663)	(2.2806)

	1.4145	0.3080	1.4814	0.5935	1.1416
4	(1.2233)	(0.4504)	(3.0252)	(1.0967)	(1.2282)
	-0.6835	0.5252	1.5954	0.2582	0.7145
Big	(-1.2630)	(1.1203)	(2.0487)	(0.5761)	(1.1954)
			Adjusted R^2		
Small	0.931	0.961	0.969	0.965	0.956
2	0.946	0.957	0.955	0.964	0.962
3	0.950	0.960	0.957	0.960	0.951
4	0.933	0.939	0.944	0.950	0.953
Big	0.941	0.932	0.922	0.910	0.940

To recover from financial crisis, China had their plans to stimulate economic growth (Phillips and Yu, 2011; Lardy, Nicholas and Arvind, 2011). Under Proactive fiscal policy and loose monetary policy, the China stock market began to see stability. In the end of 2009, the index steadily grew to 3300 and then dropped between 2000 and 3000 and remained stable. In the period of 2010 and 2014, the China stock market index saw highest figure of 3282 and lowest figure of 1950. The range is between -10% and 10%. This period is more stationary than financial crisis period (2007-2009). Fama and French (1996) point out that the size of public firms has negative effect on expected return. The size effect in small firms is corresponding with most research results. That is the risk of small and medium enterprise is higher so the investors require higher return. The regression results indicate that SMB factors are all significant. When controlling market value factor, the coefficient sees no decreasing trend with the decline of size, indicating that there is no size effect during financial crisis period.

Almost all coefficient of intercept (a) is significantly equal to zero, indicating the explanatory power of three-factor model.

In the period of post financial crisis period (2015 to 2018), the explanatory power of SMB and HMB is weaker. This is because of crash in Chinese stock market in 2015 for a short time but government quickly implement relevant policy and the stock market recovered from the end of 2015 and the stock index remained steady range between 2000 and 3000. However, size effect and market value effect all exist during this period, which is corresponding with our findings.

In summarize, the results of test in Chinese stock market show empirical evidence that our results do not ambiguously support Fama-French three factor model and it can only explain the cross section return over the period of 2015 to 2018 to a lesser extent.

Table 20 Estimated Results of Poland's Stock Market in 2007-2009

	B/M				
Size	low	2	3	4	5
			b		
Small	0.855384***	0.528633***	0.851335***	0.546635***	0.465894***
	(4.21973)	(3.89248)	(7.28062)	(3.23645)	(2.97709)
2	0.82861***	0.696861***	0.61519***	0.680193***	0.60832*
	(4.308867)	(5.903809)	(3.437723)	(4.534461)	(1.486787)
3	0.556367***	0.679305***	0.697919***	0.936208***	1.194026***
	(3.837824)	(5.396078)	(5.53637)	(13.99624)	(5.188129)
4	0.784232***	0.77996***	1.219787***	0.754228***	0.791126***
	(3.952817)	(2.955177)	(6.933794)	(4.31114)	(12.5509)

	0.912302***	0.601271***	0.85704***	0.784184***	0.805079***
Big	(10.33241)	(10.8241)	6.854756	(5.97676)	(4.344678)
			SMB		
	1.610886***	1.197437	0.601145*	-0.02126	0.005301
Small	(10.142)	(1.60188)	(2.03419)	(-0.0875)	(0.0232)
	1.022576**	0.872371***	1.122573***	1.199253***	0.408046
2	(2.57457)	(3.06757)	(4.82952)	(6.309278)	(0.62779)
	0.435129	0.553106	0.468499	0.885301***	1.39119***
3	(1.5157)	(1.414355)	(1.63999)	(3.749354)	(2.959959)
	0.593753*	0.484749	0.392043	1.240666***	0.578699***
4	(1.90123)	(1.30186)	(1.10291)	(4.35259)	(2.9777)
	-0.1976	0.014197	-0.26868	0.040624	0.037336
Big	(-0.68649)	(0.068371)	(-1.12826)	(0.1293)	(0.2473)
			HML		
	-0.66427**	-0.59038*	-0.75906***	-0.54545**	0.338673
Small	(-2.23989)	(-1.81847)	(-3.5637)	(-2.26095)	(0.833033)
	-0.41316	-0.25251	0.138106	0.197974	-0.06344
2	(-1.21341)	(-1.40922)	(0.444788)	(0.880339)	(-0.11426)
	0.614226	0.446146	0.288285	0.531224	1.689473
3	(1.510101)	(1.455348)	(1.543855)	(2.158021)	(3.02157)
	-0.37672	0.443256	0.248722	0.398951	0.582906

4	(-1.7004)	(1.384834)	(1.238192)	(1.326762)	(1.967036)
	-0.29586	-0.7122	0.756382	0.41153	0.559446
Big	(-0.95254)	(-4.8885)	(4.262753)	(1.539109)	(3.142295)
			S(e)		
Small	0.20271	0.135809	0.116932	0.168899	0.156492
2	0.192303	0.118036	0.178953	0.150005	0.40915
3	0.144969	0.125889	0.126061	0.06689	0.230146
4	0.198398	0.26393	0.175919	0.174949	0.063033
Big	0.088295	0.055549	0.125029	0.131206	0.185302.
			a		
	0.2796	0.8779	0.3962	0.4161	0.2257
Small	(0.3500)	(1.4485)	(0.8559)	(1.1018)	(0.5279)
	-0.7176	0.6940	0.3601	0.3979	0.7045**
2	(-1.3333)	(1.2784)	(0.5474)	(1.1650)	(2.1441)
	-0.1773	-0.0259	-0.0199	0.4825	0.3578
3	(-0.4133)	(-0.0573)	(-0.0586)	(1.1761)	(0.7532)
	0.0155	0.1395	0.3370	0.0519	0.2964
4	(0.0220)	(0.2919)	(0.5227)	(0.1067)	(0.6141)
	0.4385	0.1093	0.4908	0.8574	0.1424
Big	(0.7841)	(0.2241)	(0.6998)	(1.9155)*	(0.1778)
			Adjusted R^2		

Small	0.794	0.896	0.719	0.715	0.794
2	0.765	0.884	0.796	0.840	0.760
3	0.811	0.894	0.895	0.850	0.759
4	0.756	0.867	0.893	0.869	0.674
Big	0.691	0.840	0.839	0.853	0.811

Table 21 Estimated Results of Poland's Stock Market in 2010-2014

Size	**B/M**				
	low	2	3	4	5
			b		
Small	0.63174***	0.681326***	0.751207***	1.0029***	0.95543***
	(4.3561)	(4.1041)	(5.9515)	(7.2737)	(6.9079)
2	0.93699***	0.87205***	0.70697***	0.886792***	0.38329***
	(6.7222)	(7.0191)	(5.6901)	(5.56297)	(3.9362)
3	0.94771***	0.734976***	0.642927***	0.675037***	0.559024***
	(6.9794)	(8.7183)	(4.8723)	(5.1196)	(5.1715)
4	0.86339***	0.68053***	1.2573***	0.6573***	1.1453***
	(5.4486)	(4.7881)	(4.4249)	(4.7364)	(5.1576)
Big	0.7493***	0.7766***	0.8579***	0.4153***	0.6273***
	(15.3402)	(3.0081)	(9.8803)	(2.7348)	(8.0327)
			SMB		

	1.126819***	0.72196***	0.8152***	1.0601***	0.8548***
Small	(4.382)	(4.798)	(6.137)	(6.896)	(3.656)
	1.3259***	0.9973***	0.7715***	1.0438***	0.9489***
2	(8.003)	(6.571)	(4.934)	(7.559)	(5.710)
	0.7435***	1.0101***	0.8303***	0.3616**	0.199
3	(5.326)	(6.106)	(4.704)	(2.270)	(1.096)
	0.65262*	0.346024**	0.833186***	0.2633	0.607***
4	(1.682)	(2.177)	(3.456)	(1.430)	(3.747)
	-0.0861	0.6497**	-0.3343	0.1319	0.1847
Big	(-0.824)	(2.591)	(-1.670)	(0.900)	(1.609)
			HML		
	-0.5027*	-0.1575	-0.2330	-0.1621	0.7612***
Small	(-1.9851)	(-0.3883)	(-1.1932)	(-0.8118)	(2.7696)
	-0.7527***	-0.0637	0.3995**	0.3125	0.4779**
2	(-4.2629)	(-0.3176)	(2.1805)	(1.166)	(2.296)
	-0.1572	-0.27415**	0.5342	0.2836*	0.0483**
3	(-0.879)	(-1.774)	(2.628)	(1.368)	(0.205)
	-0.3231	0.0465	-0.5637	-0.0501	0.4536
4	(-0.899)	(0.255)	(-1.611)	(-0.259)	(2.146)
	-0.3684**	-0.6132***	0.1056	0.0079	0.4073***
Big	(-4.441)	(-1.338)	(0.468)	(0.034)	(3.172)

S(e)					
Small	0.145	0.166	0.126	0.138	0.138
2	0.139	0.124	0.124	0.159	0.098
3	0.136	0.084	0.132	0.132	0.108
4	0.158	0.142	0.284	0.139	0.222
Big	0.049	0.258	0.087	0.152	0.078.

a					
	0.0758	0.0939	0.1777	0.1979	-0.2896
Small	(0.2860)	(0.4303)	(0.8688)	(0.8180)	(-1.1576)
	0.0299	-0.2101	0.1567	-0.0653	-0.2282
2	(0.1822)	(-1.0844)	(0.7147)	(-0.3059)	(-0.8963)
	-0.1705	-0.1824	-0.3515	-0.1200	-0.2334
3	(-0.6598)	(-1.0535)	(-1.7629)	(-0.4566)	(-1.2110)
	-0.1957	-0.2788	-0.0373	-0.0488	-0.0898
4	(-0.9370)	(-1.1531)	(-0.1710)	(-0.2199)	(-0.3771)
	0.2683	-0.5455	-0.3527	-0.2683	-0.0335
Big	(1.1763)	(-1.2865)	(-1.2474)	(-1.2206)	(-0.1761)

Adjusted R^2					
Small	0.811	0.859	0.819	0.689	0.840
2	0.803	0.754	0.759	0.798	0.813
3	0.832	0.733	0.729	0.749	0.795

4	0.832	0.729	0.733	0.813	0.758
Big	0.759	0.810	0.811	0.830	0.793

Table 22 Estimated Results of Poland's Stock Market in 2015-2018

Size	**B/M**				
	low	2	3	4	5
			b		
Small	1.0462***	1.0169***	0.4256**	0.2517**	0.8669**
	(3.666)	(6.245)	(2.644)	(1.692)	(1.834)
2	0.7268***	0.7577***	0.5801***	0.6042***	0.9557***
	(6.257)	(6.498)	(4.351)	(4.888)	(4.789)
3	0.5661***	0.7233***	0.5982***	0.6194***	0.8459***
	(3.190)	(3.243)	(5.429)	(3.155)	(6.248)
4	0.7918***	0.4499***	0.7461***	0.7758***	0.5668***
	(3.085)	(4.298)	(4.309)	(7.934)	(3.352)
Big	0.5213***	0.7667***	0.9475***	0.856***	0.611***
	(4.824)	(5.298)	(6.488)	(4.387)	(3.586)
			SMB		
Small	1.346***	1.270***	0.843***	0.465*	0.840*
	(3.203)	(7.195)	(3.968)	(1.676)	(1.706)
	1.278***	0.931***	1.023***	0.618***	1.044***

2	(8.966)	(5.037)	(3.951)	(3.712)	(2.961)
	0.736**	0.849***	0.613***	0.973***	1.076***
3	(2.179)	(4.179)	(5.817)	(3.403)	(3.525)
	0.459*	0.383**	0.951***	0.997***	0.639*
4	(1.084)	(2.103)	(4.490)	(6.631)	(1.954)
	-0.45311**	-0.27417*	-0.025	-0.178	-0.189*
Big	(-2.321)	(-1.584)	(-0.111)	(-0.722)	(-0.925)
HML					
	-1.013**	-0.307	-0.593**	-0.237	0.809*
Small	(-2.043)	(-1.502)	(-2.264)	(-0.879)	(1.945)
	-0.324**	-0.166	-0.325***	0.078	0.679***
2	(-2.131)	(-0.689)	(-2.879)	(0.582)	(3.064)
	-0.059	-0.198	-0.132	0.249	-0.149
3	(-0.250)	(-0.597)	(-1.008)	(1.152)	(-0.545)
	-0.601*	-0.128	-0.349*	0.129	0.216
4	(-1.915)	(-0.549)	(-1.883)	(1.295)	(0.854)
	-0.613***	-0.299	-0.024	0.526**	0.301
Big	(-2.835)	(-1.611)	(-0.111)	(2.406)	(1.139)
S(e)					
Small	0.285	0.163	0.161	0.149	0.473
2	0.116	0.117	0.133	0.124	0.199

3	0.177	0.223	0.110	0.196	0.135
4	0.257	0.105	0.173	0.098	0.169
Big	0.108	0.145	0.146	0.195	0.170.
			a		
	0.2099	0.6430	0.3250	0.5810	0.2190
Small	(0.7169)	(1.7579)	(1.4578)	(1.8364)	(1.0778)
	-0.2574	0.2264	0.1447	0.3020	-0.0793
2	(-1.5982)	(0.9615)	(0.7137)	(1.2242)	(-0.2801)
	-0.3403	0.1129	-0.2413	-0.0958	0.1158
3	(-1.2045)	(0.3532)	(-1.1347)	(-0.4303)	(0.7821)
	-0.4554	-0.2298	-0.4245	0.0428	-0.2386
4	(-1.1404)	(-0.9028)	(-1.6522)	(0.1760)	(-1.4350)
	0.6118	0.3057	-0.0472	0.2890	0.1802
Big	(1.6374)	(1.1734)	(-0.2067)	(0.6286)	(1.0308)
			Adjusted R^2		
Small	0.812	0.793	0.849	0.874	0.748
2	0.839	0.735	0.854	0.734	0.813
3	0.841	0.751	0.895	0.769	0.769
4	0.834	0.698	0.713	0.841	0.827
Big	0.829	0.813	0.811	0.753	0.873

Compared with Chinese Stock market, Polish stock market saw a different picture .Unlike high R-square figure of CAPM in Chinese stock market, the goodness of fit is less than that in Chinese market in our empirical research over the whole sample periods.

The global financial crisis (2007-2009) affected European capital market severely, including Polish stock market. The empirical results (Table 9) suggest that market excess returns are significant in this period but nearly half of SML variables and most HML variables can't explain the excess return. The intercept of P25 and P54 portfolio is significantly different from zero, which rejects the Fama-French three factor model.

Over the period between 2010 and 2014, all intercepts of model are insignificantly different from zero, accepting null hypothesis. Meanwhile, all of coefficients of market excessive return is significant. Only the SMB of P35, P44, P51 and P54 portfolios can't explain the return. As for HML, less than half of HML variables can explain Polish stock market. Therefore, in the period of 2010 to 2014, only SMB variable can explain the market return especially for those small and median size companies. In addition to comparing Polish with Chinese stock markets, size effect is not observed in our samples. This shows empirical evidence to reject Fama French three factor model over this sub period.

In the period of post financial crisis (2014-2018) as we distinguished before, most intercepts for all portfolios are insignificant except for P13, P24, P35 and P43. Most SMB variables can explain the market return except big-size firms. The size effect does not exist in these samples over the period. HML variables can't explain the stock returns well as it is during recovery period. These findings are totally contradictory with Foye, Mramor, and Pahor's findings (2013) because their results show SMB is less explanatory. The major reasons are that the sample periods we chose are different. Their research consists of the financial crisis periods, which is different from ours.

Thus, the results during 2015 to 2018 in Polish stock market are against Fama-French three-factor model.

In summarize, SMB variable has explanatory power in Polish stock market over the period of 2010 to 2018 while HML can't explain the return over all sub periods. The HML insignificant results and significant intercepts reject three factor model in Polish stock market.

When comparing two emerging markets, there are still some weaknesses in the design of empirical research. The selection of periods may not be divided properly as this dissertation does not consider the actual local financial market situation. The results in Chinese stock market support Fama and French three-factor model over the sub period of 2015-2018 while results in Polish stock market reject Fama and French three-factor model in all sub sample periods.

As for other results, expected return is negatively correlated with size in Chinese market, which means size effect exists in Chinese stock market. However, from the empirical results, this dissertation suggests no size effect exist in Polish stock market. The HML variables in Chinese stock market are characterized in stage and unrelated to market risk. It is not explanatory in the period of financial crisis but the results over sub period 2015-2018 support the Fama-French three factor model. Over-volatility and Bubble Test Results

The thesis has tested CAPM and three factor model using cross section method. Next, this dissertation will follow Phillips, Wu and Yu (2011) to test over-volatility in Polish and Chinese stock market. This section will briefly discuss over-volatility in emerging markets. Section 5.3.1 will present over-volatility test in Polish an Chinese stock market and section 5.3.2 will test bubbles in stock price in two markets respectively. The results will be discussed in the following tests (GARCH model test, Stationary test and Supreme ADF test).

5.2.4 GARCH Model Test

Chart 1 presents the trend line of stock price in China's stock market. It is obvious that China's stock market experience high fluctuation indicating over-volatility may exist in the stock market. Since constructing GARCH model requires observing agglomeration fluctuation, this dissertation select daily China's stock market time-series index over the period of 2001 to 2018 as research samples as monthly data can't reflect the agglomerate characteristics. The highest observation over this period is 6395 and the lowest figure is 1062. Assuming that Pt is the closing price of stock index in trading day t, the return can be calculated as $R_t = (P_t-P_{t-1})/P_{t-1}$. The chart indicate that agglomeration fluctuation may exist in the China's stock market and it is likely to happen during financial crisis and 2016. We use unit-root test for the return series data and obtain ADF-statistics is -67.114 and reject the null hypothesis at the level of 1%. The return data of China's market is stationary series.

Chart 2 presents the trend line of stock price in Poland's stock market. Different from China's stock market, Poland stock market may experience higher fluctuation. To observe over-volatility in Poland market, this dissertation selects daily MSCI-Poland data over the period of 2000 to 2018 from Datastream as it presents the performance of stock market in Poland. The highest observation over this period is 2690 and the lowest figure is 720. This dissertation employs ADF statistics to test the return series data and obtain ADF-statistics is -63.832 and reject the null hypothesis at the level of 1%. The return data of Poland's market are also stationary series.

In testing over-volatility in stock market, GARCH model (Bollerslev, 1986), the model we discussed before, is likely to be employed to estimate the outliers and test the over-volatility.

Chart 9 Daily Return of China's Stock Market

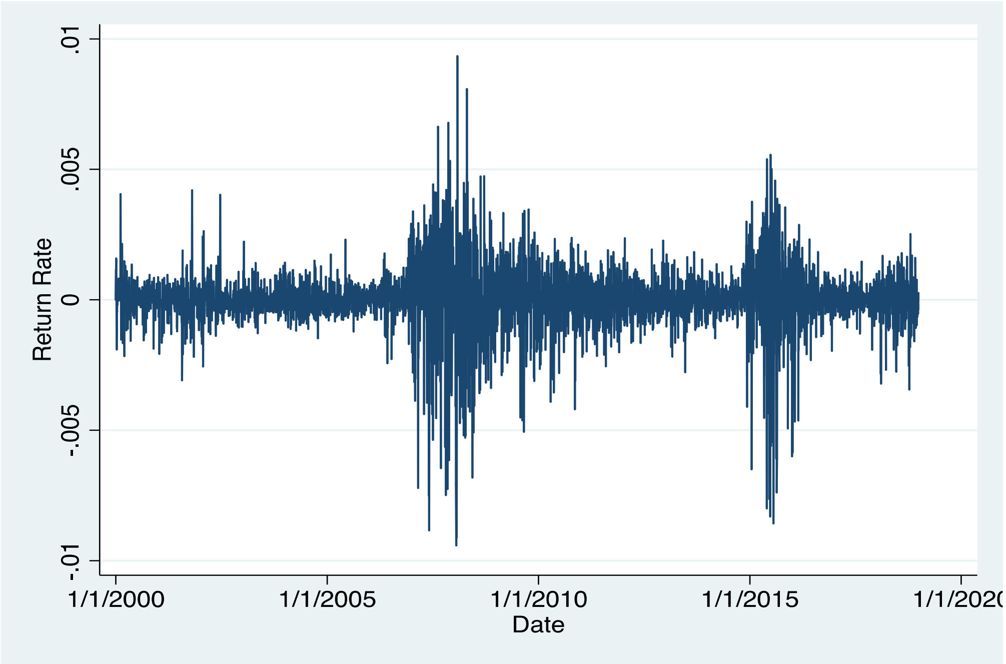
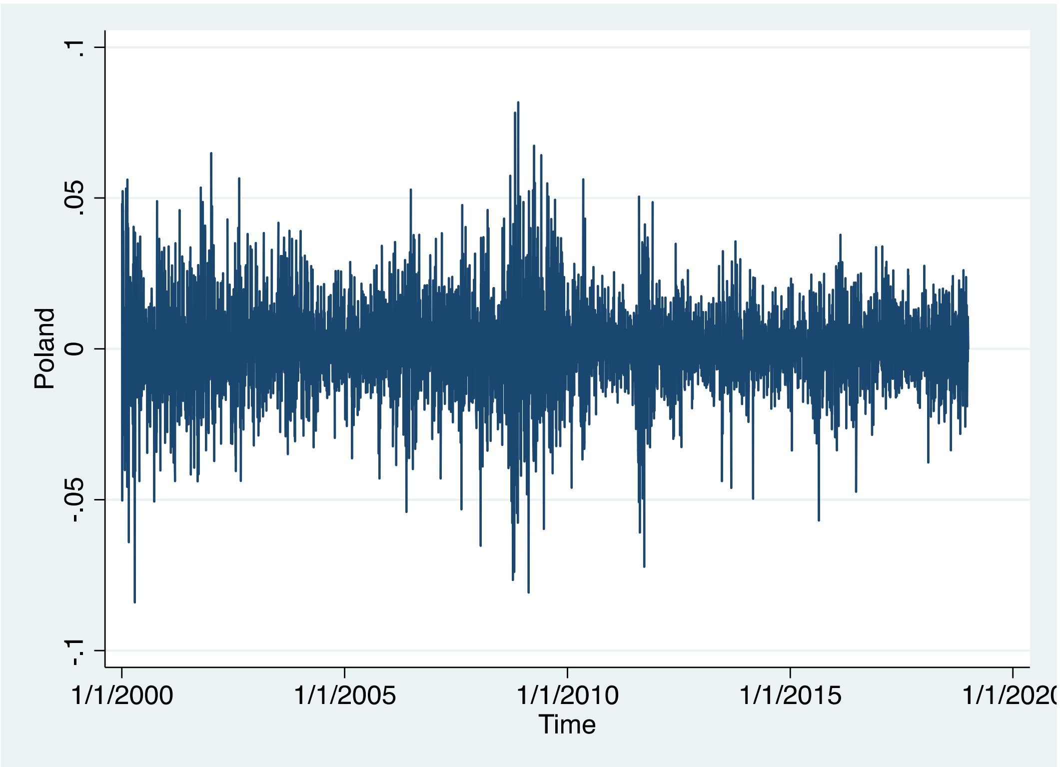


Chart 10 Daily Return of Poland's Stock Market



The variance obtained from GARCH model is conditional variance based on historical information, including variance on market return, change on company assets, new market policy and etc. (Pati and Rajib, 2010; Xiao and Yoon, 2019). However, the expectations of investors are likely to change with the change of conditional volatility. Thus, this dissertation employs conditional variance variable to improve model fitting accuracy. After considering previous research methodologies, this dissertation will use GARCH (1,1)-M model to estimate the volatility in China and Poland's stock market.

The GARCH (1,1) – M model in China's stock market is estimated as:

$$R_t = -0.0367 + 0.0351\,\sigma_t^2 + \varepsilon_t$$

(-0.783). (1.826).

$$\sigma_t^2 = 0.0354 + 0.0701\varepsilon_{t-1}^2 + 0.9078\sigma_{t-1}^2$$

(5.53) (13.314) (234.5558)

From the estimated results, the coefficient of σ_t^2 is 0.0351 and t-statistics is 1.826, estimated value significantly different from zero. This indicates that expected risk in stock market increase by 1%, the expected return will respectively increase by 0.0351%. This dissertation run autocorrelation test for the time-series data and it also passes ARCH test, which indicates GARCH (1,1)-M model can perfectly simulated heteroscedasticity in Chinese stock market.

Thus, this dissertation obtains the conditional variance line chart of GARCH model in China's stock market. During global financial crisis (2007-2009), the over-volatility exists in China's stock market. The stock market index surged from 3000 to 6000 during that period and then drop rapidly, which shows severe fluctuation in stock price and speculation behaviour is more frequently at the same time. The irrational expectation also exists during 2015 in China's stock market as well. The index dropped from 5380 to 2980 during two months. However, this market crash is because of the inappropriate policy in China. Chinese government seriously misread the policy intention of vigorously developing the capital market, distorted understanding of the strategic value of the capital market, and believed that the key development of the capital market is to push up the stock price while the rapid expansion of the scale of market allocation and high leverage had driven the stock market to rise rapidly (Phillips and Yu, 2015). Meanwhile, the risk increased significantly and the market price was full of bubbles (Tomanova, 2016).

The GARCH (1,1) – M model in Polish stock market is estimated as:

$$R_t = -0.0251 + 0.0003\,\sigma_t^2 + \varepsilon_t$$

(-0.619). (1.55).

$$\sigma_t^2 = 0.0270 + 0.0417\varepsilon_{t-1}^2 + 0.94348\sigma_{t-1}^2$$

(5.929) (6.636) (226.4173)

The regression results and chart of conditional variance show the over-volatility in Polish market and it existed during financial global crisis. Different from Chinese stock market, Polish stock market recover from global financial crisis and develop in a stable trend after the crash in 2009. Table 12 presents the autocorrelation and ARCH test of two models and it show that GARCH model can explain characteristics of heteroscedasticity in Chinese and Polish stock markets.

Table 12 Autocorrelation and ARCH test

Statistics	D-W Statistics	AIC	SC
Polish Stock Market	1.9321	-5.801	-5.797
Chinese Stock Market	1.9627	-5.746	-5.741

Note: GARCH models in both markets pass autocorrelation-test and ARCH test by Eviews 9.0

Chart 11 Conditional Variance of Chinese Stock Market Price

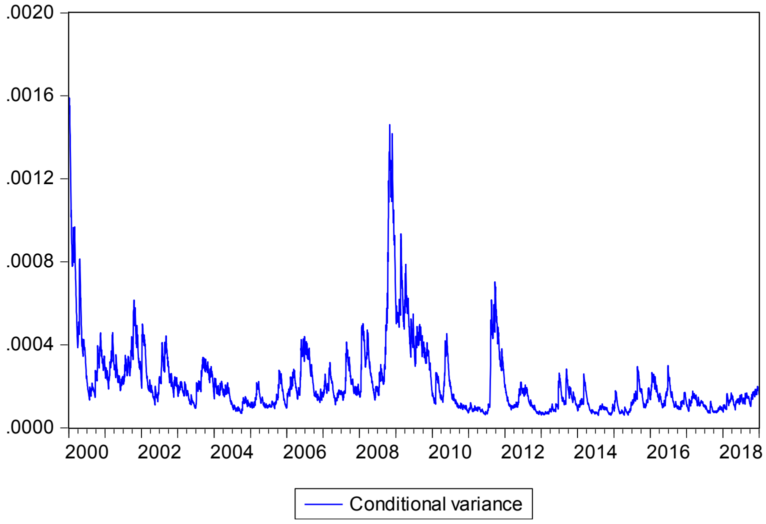
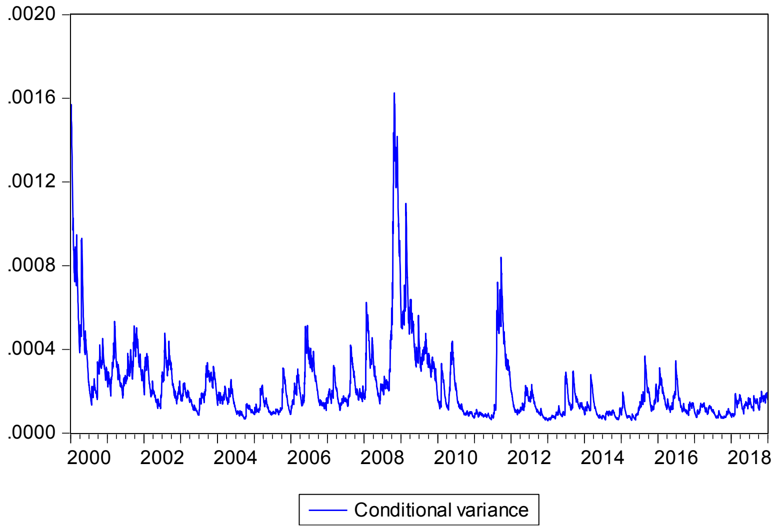


Chart 12 Conditional Variance of Polish Stock Market Price



5.2.5 Bubble Test in Stock Market

In the past few years, scholars define over-volatility as bubbles in their new research (Mankiw, 1985; West, 1987, Grossman, 1988, Phillips, Wu and Yu, 2011). To test the bubbles in developed countries, supreme ADF test has been widely used as we mentioned above. To test the bubbles in Polish and Chinese stock market, this dissertation uses daily date of MSCI polish stock market index from Datastream and China Stock Index from CCER database over the period of January, 2000 to December, 2018. Following Phillips and Yu (2011, 2015), this dissertation uses the critical values of asymptotic distribution as the samples are large enough (each larger than 4800 observations). The critical value is obtained from Phillips and Yu (2011, 2015) and Deng (2013).

This dissertation uses EVIEWS 9.0 to estimate Sup ADF and KSS ADF statistics and obtains right-tail critical value of each statistics from Phillips, Wu and Yu (2011, 2015) and Deng (2013).

Table 13 Supreme ADF statistics at the 95% significance level

Statistics	Poland	China	Critical Value
Supreme ADF (r)	4.337595	5.194952	1.5936
GS(KSS) ADF(r)	3.205860	6.815965	2.2674

From the chart results, both statistics of indices are significantly higher than critical value. These results indicate that supreme ADF and supreme KSS test both proves the bubbles exist in the China and Poland stock market.

From the regression results, this dissertation identifies obvious bubbles in both China and Poland stock market. The tests indicate bubbles exist in both stock market but it does not frequently happen. For Chinese stock market, when the index is stable between 2000 and 3000 (2015-2018) without any crashes, the results can support CAPM and Fama-French three factor model. At this period, bubbles do not exist and over-volatility phenomenon does not exist. Correspondingly, Chinese and Polish stock market saw over-volatility during crisis time but remains stable.

6 Conclusion

This dissertation tests capital asset pricing model as well as Fama-French three factor model in Chinese and Polish stock markets and presents testing methods, aiming to see whether the results in emerging markets are corresponding with previous findings in developed markets. In the research whose datasets covers sub period before 2007 (global financial crisis), China and Poland were both in stationary development and the external financial shock was lack of power to crash the local capital markets. In our research, the test results of both Chinese and Polish stock markets do not unambiguously support CAPM and Fama-French three factor model. Global financial crisis in 2008 is proved to cause irrational behaviour of investors in stock markets. The thesis considers this factor and, therefore, divides sample periods into three sub periods (financial crisis period, recovery period and stationary period). The time-series test results over the period of 2015 to 2018 favour the CAPM in both stock markets while only results of Chinese stock market support Fama-French three factor model during 2015-2018 to a lesser content. The cross-sectional test results in Poland reject Fama-French three-factor model. Although Chinese stock market suffered crash at the beginning of 2015, the results of stock index and variance on stock returns also show that economy has been recovered quickly and the influence of external crash became lighter after 2015. The market risk factor is the main factor to explain cross section return.

Secondly, we identify stock risk factor can no longer explain market returns during financial crisis period. Over this period, both Polish and Chinese stock markets are damaged by external crash and the motivations of investors on short term speculations are strong. The policy of Poland affected by European Union worsened the over-volatility in Polish stock markets. Over this period, cross section tests reject both CAPM and Fama-French three factor model. During recovery period (2011-2014), the effects of financial crisis still affect the stock market. Therefore, the systematic and non-systematic affect the cross section return together over this period. The results also indicate that investors in both Chinese and Polish markets seek high return from higher risk investment, which is corresponding with Black (1972)'s findings. According to the results that can't support CAPM, this thesis suggests that time-varying characteristics of beta may affect our empirical results and conclusions. Since emerging markets is not developed and may be affected by many other factors including policy, the errors may influence the results of portfolios formation and cross section return estimation tests.

Based on analysis of this dissertation, different factors asset pricing models and forms of consumer asset pricing model are likely to develop the structure of asset pricing theory in further research. Emerging markets, as new potential stock markets in world economy, are likely to affect the world economy and attract more and more investors. East European countries and China are now collaborating with each other in many economic perspective (i.e. One-belt-one-road policy). Therefore, in financial perspective, this dissertation aims to give investors more suggestions for their decisions in emerging markets. However, most financial research only focuses on developed market but ignoring the development of emerging markets. Therefore, future research can compare two regions (like Asian and Eastern European emerging markets) though it will large the datasets and needs more steps for data processing.

To enhance the research on asset pricing in emerging markets, this dissertation gives several further suggestions to improve it. Firstly, considering the comparability of samples is an improvement approach. This dissertation only selects one major stock market in China. Further studies can consider other types of stock markets in China for regression. Secondly, modifying or replacing the factors could be an alternative way. Our results show Fama-French three factor model is rejected in Polish stock market but adding more factors or replacing some of them might improve the explanatory power on cross section return. Thirdly, the emerging stock markets are different from developed markets, the stability and time-varying characteristics of beta in emerging markets may affect our analysis because we can't judge whether the results are attributed to beta or irrational behaviour of investors. Finally, this research concentrates more on CAPM and Fama-French three factor model. As we discussed before, more testing methods and models can be applied to fulfil the research in emerging markets. Future research can focus more on irrational behaviour and pricing in emerging markets. To improve our testing approaches, time-varying characteristics of risk factor can be considered. An alternative method might be using variance as proxy of risk and considering cross section return in different variance. Testing CAPM by extending sample periods and, to make portfolios more accurate and closed to market portfolios.

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