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US versus China, a classic derby

The level of inefficiency in Chinese stock markets compared to US stock markets

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PREFACE AND ACKNOWLEDGEMENT

The desire for this research work has originally come from my appetite for stock markets. I trade in stocks by myself with the current sentiment my positions are all turning green. Furthermore, I like to research stock markets as my profile paper of the secondary school was already about stocks, videlicet the flash crash on May 6th, 2010. Besides, the rising tensions between China and US captured my attention, since I believe China will become the largest economy one day.

Also, this lengthy work was impossible with the teamwork of our institution Erasmus University in Rotterdam, which became visible in the person of Ms. A. Li. Her amount of hard work is truly commendable. Thanks to my family as well, especially my brothers and sisters-in-law, for consulting and supporting me during the hard times.

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“Research means that you don’t know, but are willing to find out”

- *Charles F. Kettering* -

ABSTRACT

This paper is based on two observations in the finance literature. On one hand, the ongoing discussion about the efficiency of the US and Chinese stock markets. On the other hand, the more restricted Chinese stock markets compared to the 'free' US stock markets. The results provide evidence for a more inefficient Chinese stock market measured by a difference in abnormal returns. This is measured by the low-volatility effect, the momentum effect and the contrarian effect. However, the liquidity effect does not show such a difference in abnormal returns. The efficiency difference is caused by, for example, a daily trading limit, non-tradable shares, a lack of management and different stock types in the Chinese stock market. Furthermore, the data show inefficient US stock markets in recent years, which has not been observed very often.

Keywords:

Market inefficiency; Stock returns; Asset pricing model; Abnormal returns; Trading strategies

JEL classification:

F20; G11; G12; G14; G15; G40

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CHAPTER 1 Introduction

Could a stock market be an efficient market? Is it possible that a system created by human interaction is rational, reflecting all available information? The question in itself already incorporates an antithesis; therefore the follow-up question arises: are there certain levels of inefficiency indicating significant differences? For many decades researchers argue about these questions and yet there is a lot unanswered. One of the main contrasts is the difference between the young emerging markets and the old fully established markets. Thereupon, the link to the US versus Chinese stock markets is easy to make. Both markets have their characteristics, creating two different environments, possibly followed by inequivalent levels of inefficiency.

1.1 Research context

The main essence of this paper is the difference in the degree of efficiency between the Chinese and the US stock markets and possible clarifications for it. The two countries highlighted are China and the US. These two countries differ from each other through history, governance and traders. The Chinese stock markets are much younger than the US stock markets and more regulated than the US stock markets, the daily limit for example. Besides, at the Chinese stock markets, traders are seeking short-term opportunities, while at the US stock markets institutional long-term investments take place. China has during the tested period mostly emerging stock markets and the US stock markets are mature. Besides, Chinese stocks are largely owned by the state, divided into two different stock classes, which causes inefficiency following Balsara et al. (2007).

Another difference between these two is the financial environment. Yang (2020) states that the Chinese stock markets have solid investment opportunities, but a lack of external environment development. This causes an inefficient market. Furthermore, Chinese stock markets have a daily trading limit causing much more volatile markets than the US stock markets. Intervention in the US stock markets is a curtailment of free capitalism and is out of scope. Although, inefficient stock markets are obtainable in the US as well, as Schwert (2003) found inefficient US stock markets between 1982 until 2002.

Inefficient stock markets could be measured on grounds of abnormal return since, abnormal return reflects the profit of a portfolio above another portfolio with the same risk as the stock index (Malkiel, 1989). Abnormal return is subservient with the efficient market hypothesis of Fama (1973). In this thesis, different trading strategies are tested whether they generate abnormal returns, implicating inconsistency with the efficient market hypothesis. The trading strategies which are examined are the low-volatility effect, the momentum effect, the contrarian effect and the liquidity effect

The main reason for these strategies is the scientific basis. Wu (2011), Dhankar and Maheswari (2014), Soares and Serra (2005), Baker et al. (2011), Li et al. (2014), Liu (2006) and Han and Lesmond (2011) all emphasize the significance of the chosen strategies. In those papers, the strategies are always tested for factor models like Fama and French (1993), which make the evidence of the strategies much more reliable. In addition, these strategies are easy to excess. They are obtainable by just using the prices and trading volume of the stock. It does not need any hard-to-find accounting data, which makes it easier to apply in practice.

The first strategy is the low-volatility effect, found by Blitz and Van Vliet (2007). They argue that portfolios with the lowest volatility significantly outperform the other portfolios, while the highest volatility portfolios significantly underperform. There are different explanations like the leverage restriction and limits on arbitrage causing mispriced stocks.

Second, the momentum effect is used as a trading strategy. Evidence is found by Jagadeesh and Titman (1993, 2001) that the best-performing stocks of the past 12 to 2 months significantly outperform the worse stocks in the coming month. Novy-Marx (2012) argues that 12 to 7 months is a better time frame due to higher significant abnormal returns. Most researchers agree that the slow incorporation of information in prices causes underreaction and therefore the momentum effect.

Third, the contrarian effect was observed by De Bondt and Thaler (1985). The worst-performing stocks in the last 5 or 3 years will outperform the best-performing stocks in the next 5 or 3 years. The right period before and after the formation period is often criticised. For example, Soares and Serra (2005) claim a 2-year timespan. The main reason for the abnormal return is the overreaction, caused by the representative heuristic of the investors.

Finally, the liquidity effect is used to chase abnormal returns. Amihud and Mendelson (1986) obtained prices too low for illiquid stocks because investors do not estimate the justified compensation for illiquidity thereupon, the prices will fall and stocks are undervalued. The tricky part of the liquidity effect is measuring liquidity because there does not exist a perfect measurement.

1.2 Problem statement

The subject of this paper is based on two different contradictions in the literature. First, many scientists have researched to what degree the US stock markets and Chinese stock markets are inefficient. Therefore, abnormal returns are present through time. The US stock markets have been found inefficient by Banz (1981) and in recent data by Verheyden et al. (2015) and Novy-Marx (2012). However, Granger and Morgenstern (1963) and later Rehman et al., (2018) found efficient stock markets in the US based on abnormal returns. Su and Fleisher (1998) and Wang et al. (2010) conclude that the Chinese stock markets are inefficient, in contrast to Bailey (1994) and Chen and Li (2006), who found an efficient stock market.

The second contradiction lies in the different underlying structures of the stock markets of both countries. On one hand is the US, liberal mature stock markets and on the other hand, China which has heavily regulated emerging stock markets. Yang (2020) states that the Chinese stock markets have relatively less extrinsic environment governance. In addition, the different stock types at the Chinese stock markets cause a lack of liquidity and market capitalisation (Tabak, 2004). Furthermore, the daily limit and many non-tradable shares add up to the list of interruptions of the Chinese stock markets, which do not exist in the US stock markets (Chang, 2021).

All in all, this research is based on these contradictions in the literature. There is no clear answer in the literature in terms of efficiency in both the US stock markets and the Chinese stock markets. However, the differences in regulation between both stock markets do imply that the level of efficiency is not equivalent. This leads to the following research question:

Are the Chinese stock markets more inefficient than the US stock markets and which trading strategy can exploit these potential inefficiencies?

To answer the research question low-volatility effect, momentum effect, contrarian effect and liquidity effect are used as trading strategies. The incorporation of the four strategies causes a broad spectrum to catch the inefficiency of the stock markets. They are executed by portfolio construction, based on different elements of the trading strategies, like Schwert (2003). However, in this paper different trading elements are used videlicet volatility, past returns and liquidity. The difference in future return between the highest and lowest decile is used to calculate the abnormal return, because of a long-short strategy. These difference returns are then regressed against factor models, testing whether the returns are not caused by risk factors. Thereupon, one can state the level of efficiency. Afterwards, the Chinese and US stock markets are compared to confirm possible significant differences between the level of efficiency.

The data in this research is from 1991 to 2021 and shows a higher level of inefficiency in the Chinese stock markets than in the US stock markets, confirming Chang (2021). The low-volatility effect, momentum effect and contrarian effect show significantly higher abnormal returns in the Chinese stock market than in the US stock markets. The liquidity effect however does not find such a result. The main trading effects causing the highest difference between the stock markets are the momentum effect and the contrarian effect. Furthermore, the US stock markets only had significantly abnormal returns in the last few years, which is in disagree with recent papers, like Carporale et al. (2019). Another remarkable result is the efficiency of both stock markets during 2000-2006, leading to no significant differences in abnormal returns during this period.

1.3 Research motivation

This paper is mainly scientifically relevant. First, the newest data is used, which is from January 1991 till December 2020. This is one of the first papers that will cover 2020 for the US as well as for the Chinese stock markets. If the same trend continues in this paper, it will confirm the trend in the other papers (Blau et al., 2018; Blizt et al., 2019; Caporale et al., 2019; Imran et al., 2020). They all conclude that the abnormal returns by these trading strategies disappear slowly over time due to arbitrage. However, if there is a trend disruption in 2020 this would be one of the first papers that will confirm abnormal returns for these particular trading strategies in the last measurable years. So, that one can find out where more risk-free returns can be achieved.

Second, this research can teach more about Behavioural Finance. The fact that strategies are delivering abnormal returns depends on the irrationality of a market, like the overconfidence of the investors (Daniel & Titman, 1999). If this paper finds such abnormal returns, it will confirm that people act irrational, because in a rational world there cannot be a return without risk. This research will go even a level deeper. It will compare different countries and the rationality of the markets will be compared to each other based on obtainable abnormal returns.

Last, the research draws up the differences between the Chinese and US stock market, especially for the different trading strategies. It will explain possible causes of the similarities and differences found in the results. Such a clear description of these distinctions and affinities of these markets is not yet in the literature, especially with correspondence of the recent dataset that is used.

This paper is besides being scientifically relevant, also socially relevant. The main social importance is for stock traders because it will give a conclusion which markets work more rationally. This means that a broker can use an advantage to make higher abnormal returns. For example, if the low-volatility effect is more useful for the Chinese stock markets, a broker could make more return without risk, because of a long-short strategy.

The paper is structured as follows. The 2nd chapter describes the theoretical framework of an efficient market, the four different trading strategies and the different characteristics of the Chinese and US stock markets are provided. Chapter 3 covers the data selection given by CRSP and CSMAR; it also declares the data adjustments to prepare the dataset. Chapter 4 discusses how the practical implementation of the problem statement is executed. In chapter 5 the results are shown, provided with a scientific basis. Last, chapter 6 concludes the research, in addition to discussing limitations and avenues for further research.

CHAPTER 2 Theoretical framework

Chapter 2 elaborates the theoretical framework. First, section 2.1 explains the efficiency of stock markets. Second, 2.2 builds upon the characteristics and differences of the US and Chinese stock markets. Last, section 2.3 discusses the four different trading strategies, being: low-volatility effect, momentum effect, contrarian effect and liquidity effect.

2.1 Efficient markets and non-random walks

Fama (1970) developed the efficient market hypothesis stating: “the theory of efficient markets is concerned with whether prices at any point in time “fully reflect” available information” (Fama, 1970, p. 413). The market is defined to be efficient when information, revealed to all participants, will not change the stock prices. Efficiency towards information sets like these implies that trading based on the information set will not generate any return. Putting this into practice means that neither historical analysis of stock prices nor analysing company financials (EBITDA, cash flow, etc. to determine fundamental value) assisting investors in selecting undervalued stocks, would facilitate returns higher than obtained by holding random stocks, at least not with the same risk (Malkiel, 1989).

Abnormal returns are not obtainable under the efficient market hypothesis. Abnormal returns are defined by Malkiel (1989): “portfolio profits over and above those attainable by buying and holding a diversified portfolio of stocks with similar risk such as those that make up the stock index” (p. 13). De Bondt and Thaler (1985), Strong (1992) and Baker et al. (2011) find abnormal returns implying that stock markets are not efficient and the efficient market hypothesis does not hold. Fama (1970), anticipated a possibility of such phenomena recognising three categories, which are the strong, semi-strong and weak-form. The construction of the categories depends on the nature of the information set.

First, the strong-form of the efficient market hypothesis is defined as the stock prices reflecting all information available by any market participant. Hence, no one with privileged information has an advantage over others without this information. The strong-form is too unrealistic, it can serve as a benchmark to what extent a market deviates from market efficiency (Fama, 1970). A less restrictive form is the semi-strong-form: the stock prices reflect all historical information and publicly available information. Technical analysis will not allow a better-informed position than other market participants (Fama, 1970).

Last, the weak-form stated by Fama (1970) as, stock prices reflect all information in the past sequences of prices. Investors are not able to obtain abnormal returns by analysing past pathways of price, because stock prices fluctuate by a random walk. Fama (1970) found statistically significant results for the random walk. The idea of a random walk originates from Bachelier (1900), who did not find any relation between the past and the current stock prices. Cowles and Jones (1937) come to the same conclusion for the US stock market in the 20's and 30's. Granger and Morgenstern (1963) tested different techniques of spectral analysis and neither found any relationship between historical and future stock prices. In addition, the random walk is supported by recent papers (Rehman et al., 2018; Lawal et al., 2017).

Certain researchers disagree with stock prices following a random walk. Basu (1977, 1983) found that historical price to earnings ratios can predict the future stock price for the NYSE in the 60's and 70's. Banz (1981) discovered a higher adjusted return on average for smaller firms than for larger companies, also known as the small-firm effect. He found evidence for the small-firm effect on the NYSE from the 40's till the 80's. Banz's (1981) research even controlled for transaction costs, as they are generally higher for small firms. Nowadays, the abnormal returns in stock markets are still visible, as proven by Verheyden et al. (2015) at different US stock markets.

These contradictory papers need an explanation, stating that abnormal returns are obtainable. Daniel and Titman (1999) argue the abnormal return is a consequence of overconfidence, which can be split into direct and indirect effects. Daniel et al. (1998) clarify the direct effect as people put too much weight on the information that is collected by themselves. These kinds of investors underrate the value of analysis given by others (e.g., accountants). The indirect effect is described as people filtering out information, such that their confidence stays untouched and even got a bit improved.

De Bondt and Thaler (1985) found in their empirical study clear indications of the existence of an overreaction to information. When people adjust their probability distribution to new information it will happen in line with the representativeness heuristic, not with the statically justified Bayes' rule. The Bayes' rule explains how a rational individual should react to new information. However, Grether (1980) like De Bondt and Thaler (1985) comes to the empirical conclusion, that people do not act based on the Bayes' rule but in line with the representativeness heuristic. In other words, people mainly focus on one certain event instead of all events present in an information set (Kahneman & Tversky, 1982).

The overconfidence and repressiveness heuristic are not likely to be present equally in all situations. Experimental evidence suggests that overconfidence and representativeness heuristic are much more present when information is fairly vague (Daniel & Titman, 1999). When the information is more rock-solid, Daniel and Titman (1999) obtain less evidence for overconfidence and representativeness heuristic, implying that companies with subjective information sets should be more mispriced than companies with concrete information sets.

In the 90's and 00's, abnormal returns became well-known and trading strategies were developed to harvest abnormal returns, examples include the small-firm effect or the momentum effect. The momentum effect is described as going long in the winning stocks and short in the losing stocks, resulting in positive returns without taking any risk (Jagadeesh and Titman, 1993). Especially hedge funds started using the phenomenon and used arbitrage to trade on these advantages. The effects were becoming less present and the markets became more efficient (Lo, 2005; Taylor, 2014).

However, it is still possible to obtain abnormal returns in the market with the momentum effect or small-firm effect based on the paper of Sadka (2003). She states that the liquidity level is important for asset pricing and limits arbitrage. Higher returns will make the winning portfolio more liquid and easier to trade with than with the losing portfolio. Besides the liquidity level, the costs of short selling are also a reason why it remains possible to obtain abnormal returns. Ofek et al. (2004) conclude that the costs of short selling have a significant impact on the returns of a portfolio. Therefore, perfect market equilibrium is not profitable contrary to the weak-form of the efficient market hypothesis.

Furthermore, testing the efficient market hypothesis is challenging for both, investors and researchers in an inefficient stock market. The challenge depends on which model one tests their strategy. The most commonly applied model is the capital asset pricing model (CAPM) of Sharp (1964). CAPM only builds upon the market factor and therefore is not as accurate as larger factor models. Fama and French (1993) create the 3-factor model (FF3), which is a lot better. Later on, additional many factor models were constructed from which the 4-factor model of Carhart (1997) and the 5-factor model of Fama and French ((2015) are most famous. Furthermore, Elton (2003) created a 99-factor model, very accurate but the effect cannot be underlined due to factor correlation (Fama and French, 2015).

These factor models receive a lot of critiques. Roll (1977) states that the CAPM has not been tested well. It is only tested right when all individual assets are used and not by portfolio testing. Lam (2005) states that the FF3 is also incorrect when using better methodologies to test the model. However, almost every hedge fund or asset management department uses one of these models, as these are closest to reality and easy to access. Clarke (2021), Kubota and Takehara (2018) and Chai et al. (2019) all agree that these factor models are the best models available at the moment.

2.2 US and Chinese stock markets

Critical for this research is to analyse and understand to what extent the stock markets of China and the US differ and correspond. Especially the implications of the differences in characteristics are interesting because these could potentially explain the differences in abnormal return resulting from one of the different trading strategies.

First, the age of both stock markets differs and therefore the markets are not parallel through time. The NYSE is the first US stock market and was founded in 1792, in contrast to the first Chinese stock market founded in 1990. The Chinese stock markets developed as a high-speed emerging market. Especially in the 90's and 00's, therefore the market was riskier and more volatile than the US stock markets. Lin and Song (2001) conclude that the regulations of China are neither efficient nor effective due to the immature status of the Chinese stock market. Guo et al. (2013) conclude that the Chinese monetary policy adjustments increase the volatility instead of stabilizing it. The Chinese government used the tools for a mature stock market while the Chinese stock markets were still in an emerging phase.

The emerging status of the Chinese stock markets in the 90's and 00's does not mean that it was an inefficient market. Bailey (1994), Liu et al. (1997), Xu (2000) and Chen and Li (2006) conclude that the Chinese stock markets are weak-form efficient. However other researchers like, Su and Fleisher (1998), Kang et al. (2002) and Balsara et al. (2007) disagree with the efficient Chinese stock markets. Groenewold et al., (2004) eventually point out that it is the characteristics of the sample periods which lead to different outcomes.

Chong et al. (2012) use the recommendations of Groenewold et al. (2004), which translates into a longer sample period of 20 years. In addition, they used a different method for the analysis (autoregressive model) than the most commonly applied method (a linear regression model). Chong et al. (2012) find an improvement in stock markets efficiency over time. Before 2005, the stock markets were more inefficient and later on, when the state-owned enterprises are reformed, the stock markets became more efficient. The Chinese government has a significant impact on the many state-owned enterprises. From 2003 till 2005 the Chinese government reformed the state-owned enterprises; more in line with commercial enterprises. The Chinese owned companies changed their focus to profit-making. This change in focus led to a more efficient stock market. Wang et al. (2010) confirmed the findings of Chong et al. (2012), observing efficient stock markets after the state-owned enterprise reformation.

However, not all researchers find comparable results, like Qi et al. (2000) even before the enterprise reformation. They conclude that there is a weak correlation between returns and the outstanding equity in tradable state-owned enterprises, which causes no large change in the efficiency of stock markets after a reformation. Young and McGuiness (2001) supported the results of Qi et al. (2000) stating that the dominance of non-tradable shares, which are part of state-owned enterprises, are low in comparison to the overall stock markets consequently, the reformation has a low impact.

Besides the inefficient state-owned enterprises in China, the lack of management of the Chinese stock markets caused a low-efficiency of extrinsic environment governance found by Yang (2020). He clarifies the external governance environment issues in three root causes. First, the development of the legal system lags the development of the stock market, therefore reformations are ineffective and inefficient. Furthermore, the credit rating system information can be influenced by major shareholders and they were able to withdraw financial information before small shareholders, leading to information discrepancies and inefficiencies. Last, the administrative bureaucracy caused too much control and therefore the stock markets could not become efficient (Yang, 2020).

Another significant characteristic of the Chinese stock markets is the different stock types, being A-shares and B-shares. The A-shares are quoted in Chinese yuan or renminbi, which are only available for Chinese nationals and the B-shares are quoted in foreign currencies, only accessible for non-Chinese residents, Hongkongers, Taiwanese and Macau people. Lock (2007) finds that the A-shares are efficient and the B-stocks are inefficient. He tests against the MacKinlay variance ratio test. Lima and Tabak (2004) argue that the difference in efficiency is due to a lack of liquidity and market capitalisation, which are problems in the A-stocks market. However, Chen et al. (2011) did not find efficiency in both stock markets, even not after the reformation of the state-owned enterprises. They find a positive correlation between both markets, especially after the reformation. Consequently, both stock markets will convergence much faster, confirming the inefficiency in both markets, resulting in the occurrence of more complex shock transmission mechanisms.

The US stock markets are different, especially because major events on the stock market for example, state-owned enterprise reformations, are very rare. However, the stock market regulation is not entirely fixed. For example, Ramiah et al. (2015) observed the consequences of the Obama effect, which is incorporating green policies in the economy. Ramiah et al. (2015) obtained a negative abnormal return and a rise in systemic risk for large polluters, whereas green corporates are less affected by the green policies. In addition, the regulation of fair disclosure, which caused a positive impact on the efficiency of stock markets according to Jiang and Kim (2005). However, Rehman et al., (2018) concluded that the US stock markets are weak-form efficient in recent years.

In a recent study by Chang (2021) the comparison of the US stock markets and the Chinese stock markets is examined with a conclusion in threefold. First, the stock markets of China are highly impacted by the regulations. Chinese stock markets have a daily limit, which manages the high and low boundaries of trading fluctuations. The US stock markets regulator does not intervene in the market in such a way. However, the US supervision mechanism, which guarantees the efficient operation of the stock markets is worse than the Chinese supervision system, confirmed by Liu (2018). The main reason for this is the position of the Chines Securities Regulatory Commission, which is a ministerial-level public institution, leading to direct intervention of the government. This is in contrast to the US, where direct interventions are uncommon, causing inefficiency.

Second, Chang (2021) concludes that in China the government is the largest shareholder via the state-owned enterprises, resulting in a significant amount of non-tradable shares, which caused many fluctuations. In the US, the government only invests in pensions or social funds, managed by professional companies, which creates only a small insignificant effect. Last, at the Chinese stock markets, the major group of investors are retail investors, whose purpose is to harvest short-term profits. Auxiliary, the dividends are low causing a more volatile market. This is different compared to the US stocks markets, which are dominated by institutional investors focussing on the long-term.

2.3 Trading strategies

This paper tests the efficient market hypothesis and tries to find abnormal returns in the US or Chinese stock market. To test the hypotheses, different trading strategies are used to obtain abnormal returns. The strategies are low-volatility effect, momentum effect, contrarian effect and liquidity effect.

2.3.1 Low-volatility effect

First of all, the low-volatility effect, commonly known as the portfolio with the lowest volatility earns a higher future return than the portfolio with the highest volatility. This originates from the ideas of Black (1972) and Haugen and Heins (1975). They all conclude that the relationship between risk and return is much flatter than the CAPM predicts. Fama and French (1992) extend this phenomenon and conclude that the effect is captured by size and book-to-market equity. Ang et al. (2006) are the first ones with a specific conclusion regarding the low-volatility effect: a low volatility portfolio has a higher return than all the other ones. This is confirmed for countries outside the US by Dutt and Humphery-Jenner (2013).

The low-volatility effect became famous in the work of Blitz and Van Vliet (2007). They conclude that the lowest quintile of volatility has a significantly higher return than the market portfolio. Likewise, the highest quintile of volatility significantly underperforms the market. Blitz and Van Vliet’s (2007) explanations for this effect are leverage restrictions and behavioural bias towards risky stocks. Baker et al. (2011) declare that the low-volatility effect is the result of limits on arbitrage. Institutional investors have fixed benchmarks to offset irrational demand for risk, which discourages low-volatility investments, resulting in under and overpriced stocks.

The main evidence for the existence of the low-volatility effect is the use of FF3 by Blitz and Van Vliet (2007) to test the low-volatility and even then, the effect is still significant for the lowest and highest quintile. Ang et al. (2009) include regional factors and came to the same conclusion as Blitz and Van Vliet (2007). One of the most recent studies from Blitz et al. (2019) finds evidence of the latest dataset for the low-volatility effect, their results are robust for different factor models including the four-factor model of Carhart (1997). At the Chinese stock markets, the low-volatility effect for A-shares is significantly present. Blitz et al. (2021) test the low-volatility effect for Chinese stock markets against the FF3 and FF5 and it is still robust even over a longer period and different sectors. The effect for the whole market is demonstrated by Chen (2009).

In line with the findings of Blitz and Van Vliet (2007) and Chen (2009) on the low-volatility effect, similar results are expected at the US and Chinese stock markets. Thus, abnormal returns for the US and Chinese stock markets, which are caused by inefficient stock markets. However, the Chinese stock markets have an inefficient environment Chang (2021), causing inefficiency implying higher abnormal returns of the low-volatility effect, leading to the following hypothesis:

Hypothesis 1: The low-volatility effect leads to an overall higher abnormal return in China than in US stock markets.

2.3.2 Momentum effect

The basis of the momentum effect is that good performing stocks in the past 12 to 1 months outperform bad performing stocks in the same period. It originates from De Bondt and Thaler (1985), concluding that investors overreact. This finding triggered Jagadeesh and Titman (1993) to research underreaction in the stock market. They concluded that the best stocks over the last 12 to 1 months have significantly higher returns than the worst performing stocks in the next month. It is considered by Fama and French (1996) as "the main embarrassment of the three-factor model" (p.81). Indicating that it is not explainable by their 3-factor model. The four-factor model of Carhart also cannot explain the momentum as Eggins and Hill (2010) concluded. Although, Novy-Marx (2012) found the same observation based on the worst and best performing stocks over the last 12 to 7 months. The winner portfolio compared to the loser one of Novy-Marx (2012) has a higher positive return than the winner portfolio of Jagadeesh and Titman (1993). The short-term reversal effect completes the momentum effect by buying last month's losers and selling last month's winners generating positive returns (Jegadeesh, 1990; Da et al., 2014).

Various explanations are presented for the abnormal profitability of the momentum effect, which can be roughly divided into two groups. Both groups are incorrect responses to information. First, underreaction documented by Moskowitz and Grinblatt (1999), arguing that the information that will come available is gradually incorporated in the prices and is adjusted to their fair value over time. Second, overreaction found by De Long et al. (1990), they declared overreaction with positive-feedback trading, a later in time reversal of return. Different possibilities could cause overreaction, for example, a boom of a temporary aspect is mistakenly treated as permanent. Another example is trend-chasing without fundamental support. These explanations are the result of cognitive shortcomings or deficiency of news processing (Hong & Stein, 1999).

The first proof for the momentum effect over a long period, 1965 till 1998, is from Jegadeesh and Titman (1993, 2001). They found a 1% per month abnormal return for the US. Rouwenhorst (1998) found evidence for momentum in Europe and Chui et al. (2010) all around the biggest world indices. Imran et al. (2020) also found the momentum effect in 40 different countries with recent data, however, the momentum effect decreases over time, although still significant. For the Chinese market, Li et al. (2017) found a momentum effect with significant evidence causing pressure on the pricing of index options.

Since momentum is found to create robust abnormal returns in the US stock markets (Da et al., 2014) and for the Chinese stock markets (Li et al, 2017), abnormal returns are expected for the data set tested in this paper, caused by inefficient stock markets. Although, the Chinese markets are seen as less inefficient, due to disabilities for example the lack of management (Yang, 2020), which makes the following hypothesis:

Hypothesis 2: The momentum effect leads to an overall higher abnormal return in China than in US stock markets.

2.3.3 Contrarian effect

The essence of the contrarian investment strategy is comparable to the momentum effect. The main difference is that it is over a longer period and flips the winner and loser portfolio. As the contrarian effect is not driven by underreaction but, overreaction. Consequently, one looks back two to five years in time and determines the winner and loser portfolios. One will then go long in the loser portfolio and short in the winner portfolio. De Bondt and Thaler (1985) were the first ones to create a testing framework on an aggregated level of the market, including a time frame from 1926 till 1982. The researchers argue a lot about the timespan, that will be used to structure the portfolios and the holding period. Campbell and Limmack (1997) for example use two to five years as formation period and two years as holding period. Where De Bondt and Thaler (1985) used two to five years prior to formation and use zero to five years as a holding period. The more recent papers, like Soares and Serra (2005) used at least two years before portfolio creation and two years for the holding period. They even tested the strategy against Fama and French factors and found significant results.

The founding fathers, DeBondt and Thaler (1985), of the contrarian effect try to explain the effect and argue that it is an overreaction to provided information. Investors price the stocks higher or lower than the initial value, over time the stocks will find their initial value and a zero-risk strategy arises. Where DeBondt and Thaler (1985) attribute the overreaction to representative heuristic, Howe (1986) attributes it to the tendency of the markets. Another explanation for the contrarian effect is from Chan (1988): the sum of leverage effect and small firm effect, causing overreaction. Consequently, Chan (1988) questioned the existence of the contrarian effect. However, Chopra et al. (1992) researched the contrarian effect as well, taking into account the leverage and small firm effect and did find significant abnormal returns.

The above-stated papers are all tested for US stock markets, although the effect is measured around the world. For example, Kato (1990) found evidence for the contrarian effect and obtained significant abnormal returns for the Japanese market. Besides, Shi and Zou (2017) researched the Chinese stock market and concluded that the contrarian effect existed from 1991 till 2015-for A-shares. Fung (1999) did observe significant abnormal returns using the contrarian strategy for B-shares. However, that was before the state-owned enterprise reformation took place. Ramiah et al. (2011) did examine the period after the reformation and obtained abnormal returns for the B-shares, quite profitable with 6,08 % return per month.

The same results as Soares and Serra (2005) for the US markets and Ramiah et al. (2011) for the Chinese stock market are expected in this thesis. So, abnormal returns should be obtainable for the US and Chinese stock markets, induced by inefficient stock markets. However, the Chinese stock markets do not have a very good environment. For example, non-tradable shares cause inefficiency in the Chinese stock market (Qi et al., 2000). This inefficiency implies that the contrarian effect will generate higher returns. The observed contrarian effects in combination with a poor market environment leads to the following hypothesis:

Hypothesis 3: The contrarian effect leads to an overall higher abnormal return in China than in US stock markets.

2.3.4 Liquidity effect

The last trading strategy to be discussed is the liquidity effect. Its meaning is: illiquid assets will have a significantly higher return than liquid assets. Amihud and Mendelson (1986) are the first ones to investigate this phenomenon and found evidence in support of this. The liquidity measure used by them is the bid-ask spread although, researchers are still arguing about the best measure for liquidity. Lesmond et al. (1999), Amihud (2002) and Holden (2009) all created their own liquidity measurement. Goyenko et al. (2009) compared many different measures of liquidity and the best measure is not a simple measure. However, Atiken and Comerton-Forde (2003) concluded a very different measure as the best measure. All in all, there does not exist a perfect liquidity measure, only indications of good and worse ones. An accessible liquidity measure, besides the bid-ask spread, is the trade volume. Sarr and Lybek (2002) conclude that a volume-based measure is a good proxy for liquidity measure. Their measurement does not need any hard-to-find accountant data and distinguishes it therefore from Amihud’s (2002) or Holden’s (2009) measurement.

The rationale behind the liquidity effect is according to Amihud and Mendelson (1986), that investors are likely to ask for higher returns as compensation for the fact that they cannot liquidate their stocks at the justified timing. This compensation is estimated higher than it should be, therefore investors do not want to invest in such stocks. The overestimation for the illiquid stocks could be caused by loss-aversion. Tversky and Kahneman (1991) describe that people are willing to pay more for preventing a potential loss than for the same amount of profit. In this case, investors are overestimating the compensation value of illiquid stocks.

When generating abnormal returns, risk needs to be taken into account. Brennan and Subrahmanyam (1996) adjust the liquidity effect for the risk using Fama and French 3-factor model and account for the stock price level. They discovered a convex relationship between the premium of illiquid stocks and the estimated costs, confirming the liquidity premium. The liquidity effect is still significant but declining, which follows from the results of Ben-Rephael et al. (2015). An et al. (2020) researched the Chinese stock market and found an increase in the liquidity effect from 2011 and a declining effect for the US stock market from 1995. The main reason is that liquidity on an overall level decreased in China and increased in the US, which caused a higher or lower degree of mispricing.

In line with the findings of Ben-Rephael (2015) and An et al. (2020) regarding the liquidity effect, comparable results are expected in the data sample used in this paper. Thus, abnormal returns for the US and Chinese stock markets when the liquidity effect is executed. Moreover, higher abnormal returns will be supposed, because the Chinese market has a restricted environment, like the daily limit, highlighted by Chang (2021), causing higher inefficiency. The combination of both observations leads to the last hypothesis:

Hypothesis 4: The liquidity effect leads to an overall higher abnormal return in China than in US stock market.

CHAPTER 3 Data

Section 3 elaborates the data, section 3.1 explains what kind of data is used, how it is prepared and where it is from. Section 3.2 discusses the descriptive statistics of the dataset.

3.1 Data accountability

The data used for the research contains monthly stock data from January 1991 until December 2020 from the database Wharton Research Data Services (WRDS). The timespan is in line with the origin of the Chinese stock market and the last available data at WRDS. Monthly data has various advantages as it is barely subjective to errors.

The Stock data is deducted from the Centre of Research in Security Prices (CRSP) and the Chinese Stock Market and Accounting Research (CSMAR). The US stock data is from CRSP, containing the AMEX, NYSE and NASDAQ. In addition, the Chinese data is from CSMAR consisting of the Shanghai and Shenzhen exchange including A-shares and B-shares. Both samples are restricted to common stocks only. Furthermore, the sample is excluded from financial firms, as these are bounded by regulations and high leverage. Besides, stocks that were delisted during the period are not removed from the dataset to prevent survivorship bias. The influence of outliers in the data is prevented through winsorisation of the data at the 1^{st} and 99^{th} percentile. For some trading strategies, an observation period of 3 years and a holding period of 3 years is used, therefore the data that is tested starts in January 1994 and ends in December 2017. This will lead to consistency during the research. Taking these data adjustments into account, the final sample of the US consists of 13,869 stocks and the Chinese sample has 3,247 stocks from 1994 until 2017.

The value-weighted return, including dividends, is used as a return measure because it gives the best representation of the returns an investor would obtain. In addition: the shares outstanding, the monthly trade volume and the stock price are abstracted from CRSP and CSMAR. The monthly trade volume and the stock price generate the trade volume per stock in US dollars. Moreover, the stock price and the shares outstanding create the market value per stock in US dollars. These market values and trade volumes are used to calculate the liquidity measure for the liquidity effect.

Furthermore, the five factors of Fama and French are used in this paper. The factors are market, value, size, investment and profitability. The factors for the US markets are deducted from Kenneth French's data library. The emerging-market factors of Kenneth French's data library are used for the Chinese stock markets because the factors for China are not available. The construction of the emerging market factors includes Chinese stocks as well, which justifies them.

3.2 Descriptive statistics

The descriptive statistics of the variables: return, market value and trade volume are presented in table 3.1. The first eye-catcher is the difference between the observations of the US and Chinese stocks, which is almost a million. The clarification is that the Chinese stock markets are founded at the start of the dataset, consequently, it began with just a few firms and the total growth is captured in the dataset. The US market exists much longer, whereupon it started already with many stocks. Besides, the mean of the returns is almost zero, which is in line with the return one could obtain on a market index. Moreover, the trade volume is higher than the market value, implicating that a stock is traded a couple of times during the month. In addition, the trade volume in the US is higher than in China, this higher trading activity is mainly caused by the status of the US market, which is confident and efficient.

Table 3.1 demonstrates the descriptive statistics of the variables, divided into US stocks and Chinese stocks. The market value and the trade volume are for both the Chinese and US stocks in US dollars.

Variables	**Observations**	**Mean**	**Standard Deviation**
US Stocks			
Return	1,469,856	0.010	0.043
Market Value *in US dollars*	1,469,856	4.79E+08	3.24E+09
Trade Volume *in US dollars*	1,469,856	2,967,027	1.88E+07
Chinese Stocks			
Return	514,039	0.013	0.144
Market Value *in US dollars*	514,039	3.28E+08	9.26E+08
Trade Volume *in US dollars*	514,039	1,655,257	7,804,352

CHAPTER 4 Methodology

This section explains the methodology. First, section 4.1 describes how the different trading strategies are formed, one by one. Section 4.2 builds upon testing of the trading strategies relative to the factor models, which adjust risk. Last, section 4.3 creates a framework to compare the abnormal returns of the US and Chinese stock markets.

4.1 Constructing trading strategies

The research is similarly done as Schwert (2003), he researched inefficiency based on trading strategies as well. All four hypotheses, stated in section 2.3, have a trading strategy incorporated, thereupon they are tested in almost the same framework. The trading strategies are constructed by one or two papers. Therefore, the strategies contain scientific evidence and these methods are used in common situations. All strategies are built upon portfolio construction based on the concerned strategy and afterwards ranked from high to low. The utmost portfolios are used to generate positive returns, by a long-short strategy. A long-short strategy pursues minimizing market exposure while earning from gains in the long portfolio together with decreasing prices in the short portfolio.

4.1.1 Low-volatility effect

The low-volatility effect is tested following the paper of Blitz and Van Vliet (2007). However, Blitz and Van Vliet (2007) only tested it using three year and one-year prior formation volatility data. In this research, the volatility is measured over the past three, two and one years. The volatility is calculated by the formula of standard deviation. Based on the level of volatility ten portfolios will be constructed. The stocks with the highest volatility are classified as top decile, stocks with the lowest volatility are assigned to the bottom decile. For each decile, the return for the next month is calculated. Then the difference of the highest and lowest portfolio is computed, because one will go long in the portfolio with low volatility and short in the high volatility portfolio, following the long-short strategy.

4.1.2 Momentum effect

The construction of the momentum effect is based on the paper of Jagadeesh and Titman (1993) and Novy-Marx (2012), who uses a different timespan. Consequently, every month the cumulative return over the past twelve to one month, twelve to seven months and six to one month are computed. In addition, a formation period of one month is taken into account to have a look at the short-term reversal effect. The degree of cumulative return indicates in which portfolio stocks are assigned. The best-performing stocks are in the top decile and the worst performing in the bottom decile. After this, the return of the next month is obtained and the difference of the best and lowest portfolio is computed since one would go long in the winning portfolio and short the losing portfolio.

4.1.3 Contrarian effect

For investigation of the contrarian effect, the same method as De Bondt and Thaler (1985) is used, only with different timespans. The timespans here are motivated by Soares and Serra (2005). For every month the cumulative return of the previous three to one year and two to one year is calculated. Again, ten portfolios are constructed, also based on the cumulative return. Stocks with the best cumulative returns are in the top decile and the worst stocks are in the bottom decile. The cumulative returns of every portfolio are computed over the next 2 and 3 years. Afterwards, the difference between the top decile and the bottom decile is calculated, because one would go long in the losing portfolio and short in the winning decile.

4.1.4 Liquidity effect

The framework of the liquidity effect is in line with the research of Amihud and Mendelson (1986). For each month the liquidity of the past 5 months is computed. The liquidity measure in this paper is from Sarr and Lybek (2006):

$$L = \frac{\frac{P_{MAX} - P_{MIN}}{P_{MIN}}}{\frac{V}{M}}$$

The liquidity is based on a few elements, consisting of the maximum and minimum price over the five months, the trade volume over the prior five months and the market value of the particular stocks. Build upon the level of liquidity, ten portfolios are created. The top decile is represented by the highest liquidity and the bottom one with the lowest liquidity. Afterwards, the return of the next month and the cumulative return of the future 5 months is calculated. Then, the difference of the top and bottom decile is generated, while the investor would go long in the lowest liquidity portfolio and go short in the highest liquidity portfolio.

4.2 Testing trading strategies

All strategies have difference returns, of either high minus low or low minus high portfolios, which are used to test the four hypotheses. The difference return could be caused by extra risk. If one will have extra risk, the return will be higher and no abnormal return is gained. In other words, the efficient market hypothesis of Fama (1970) will still be valid. Therefore, the difference returns are tested for the risk factors. Schwert (2003) only used the CAPM to test the strategies, however here other factor models are tested as well.

First, the returns are regressed against the CAPM of Sharpe (1964), which uses the market return factor. Second, the difference returns are tested against the FF3. The FF3 is an extension of CAPM, consisting of two new factors, namely the size and value factor. At last, the FF5 is used to test the difference returns. This model adds two factors, the profitability and investment factor. Afterwards, the GRS test of

Gibbons et al. (1989) is performed to test if these factor models with the extra effect are efficient. If the GRS test concludes that a model is inefficient, no valid conclusion can be reached. All the efficient factor models examine if the difference returns are accumulated by risk or by abnormal return, causing inefficiency on the particular stock market.

4.3 Comparison framework

All the above strategies are separately performed on the US and Chinese stock markets. To compare both stock markets and test the hypotheses which, answer the research question, the results of these strategies are put next to each other. Then, for every strategy, an independent sample t-test between the Chinese and US results is executed. This test shows if there is a significant difference between the results. It concludes if a market is more sensitive to the specific strategy than the other market. Furthermore, the sum of all abnormal returns is computed and again a t-test between China and US is executed. Consequently, the conclusion of the paper can be drawn.

Besides, the sample is divided into four timespans. The first period is from 1994 to 2000 because here the first years of the Chinese stock market are captured. The next one is from 2000 to 2006, because of the state-owned enterprise reformation in 2005. The third period starts in 2005 up to 2011 while from 2011 the consequences of the financial crisis of 2008 are almost disappeared. Last, the timeframe from 2011 to 2018 is highlighted. All trading strategies per stock market are tested for every timespan. In addition, the comparison of the stock markets is researched in the different timespans therefore, the outcome can be specified for a certain period.

CHAPTER 5 Results

The following section elaborates the results generated by using the methodology of section 4. First, section 5.1 explains the results regarding the GRS-test. Next, section 5.2 presents the results of the different trading strategies. Section 5.3 builds upon the comparison of the Chinese and US stock markets, highlighting causes for the differences.

5.1 GRS-test

Before one could argue about the outcome of the different trading strategies, the efficiency of the different models is tested. Concerning the results in table 5.1, the models for the US are all significant at a p-value of 0.05, which means that all the models are efficient and appropriate to use during the research. However, not all models are efficient at a p-value of 0.01, especially the CAPM models are not significant anymore, which is in line with the theory of Fama and French (1996). They state that the market factor alone cannot fully explain the expected return.

Table 5.1 shows p-values of the GRS-tests. The GRS-test is executed on all the regression models containing the difference portfolio, which is the difference of the utmost deciles. The CAPM, FF3 and FF5 are used to test the different trading strategies with all their variations. Thereupon every variation has its model, which needs to be tested by a GRS-test.

		US			China		
		CAPM	FF3	FF5	CAPM	FF3	FF5
Volatility							
12 months prior		.000	.002	.000	.000	.000	.000
24 months prior		.002	.001	.001	.007	.007	.006
36 months prior		.014	.003	.000	.022	.018	.015
Momentum							
1 month prior		.021	.011	.003	.032	.025	.023
6-2 months prior		.002	.003	.000	.048	.045	.039
12-7 months prior		.003	.015	.002	.582	.569	.520
12-2 months prior		.021	.002	.002	.623	.426	.378
Contrarian							
24 months prior	24 months holding	.000	.000	.000	.000	.000	.000
	36 months holding	.001	.000	.002	.001	.002	.001
36 months prior	24 months holding	.000	.002	.000	.000	.001	.000
	36 months holding	.000	.000	.001	.001	.001	.001
Liquidity							
1 month holding		.002	.000	.000	.000	.001	.000
5 months holding		.021	.013	.005	.041	.037	.028

For the Chinese factor models, the results are mainly the same. The volatility, contrarian and liquidity effect are significantly efficient at a p-value of 0.05. However, the momentum effect is not significant for the period of 12-7 and 12-2 months before portfolio formation, meaning that these models are not efficient and therefore unusable to test the trading strategy. Although, the 6-12 months formation period and the short-term reversal effect are significant and can therefore be used to test momentum for China.

At a p-value of 0.01 more models of different strategies become insignificant. Remarkable at this p-value level is the significance of the CAPM, if the CAPM is insignificant all the other models are also insignificant, however the p-value declines if more factors are added, which confirms Fama and French (1996). In line with this, the lowest p-value for every model is obtained with an FF5 model, therefore FF5 is used as a reference point throughout the rest of the results section and the different periods are solely tested against the FF5 model.

5.2 Trading strategies

The 4 researched trading strategies have their own results and are mainly analysed concerning the FF5 model because it is more accurate than the other models (Fama and French, 1996) and therefore more efficient, see section 5.1. However, the FF3 and CAPM are still presented to check whether any results stand out. The hypotheses related to the effects are accepted or rejected in section 5.3, where the complete comparison between the two markets is discussed.

5.2.1 Low-volatility effect

The results in table 5.2 are all positive, indicating that the portfolio with the lowest volatility generates a higher return than a portfolio with higher volatility. The full period generates for both markets positive significant results, meaning that the low-volatility effect generates abnormal returns in the examined period. The highest returns are obtained if the portfolio is formed based on the previous year, which is in contradiction to Blitz and Van Vliet (2007). They observed higher returns in de previous 3 years instead of 1 year, possibly caused by different sorting methods. Whereas Blitz and Van Vliet (2007) found evidence for double sorted portfolios these results are single sorted. Focussing on the difference between the US and Chinese stock markets, almost every Chinese observation is higher than for the US, which is in favour of the first hypothesis.

When the sample is separated the US volatility effect for 2006 – 2011 for a 2- and 3-years formation period gives only significant results, what the overall significant results drives. The US volatility effect based on 1 year is most of the time significant however, the effect declines through time. Like Caporale et al. (2019) state that the abnormal returns such as the low-volatility disappear over time. However, this is in contrast to the Chinese stock markets. The low-volatility effect is the highest in the last period, caused by on average lower volatility in this period. Blitz et al. (2013) conclude the same, stating that higher abnormal returns are related to the increased delegated portfolio management in emerging markets, causing less volatility.

Table 5.2 presents monthly abnormal returns of the difference portfolio according to the low-volatility effect. The results shown are the difference portfolios, so the lowest volatility stocks minus the highest volatility stocks. The low-volatility effect is tested against the CAPM, FF3 and FF5. The FF5 model is used to test the low-volatility effect against multiple periods to track the abnormal returns over time.

			FF5			**FF3**	**CAPM**
	'94-'99	**'00-'05**	**'06-'11**	**'12-'17**	**Full**	**Full**	**Full**
China							
12 months prior	.046***	.019	.043***	.068***	.048***	.055***	.057***
	(.007)	(.013)	(.007)	(.006)	(.004)	(.004)	(.005)
24 months prior	.039***	.010	.037***	.061***	.041***	.049***	.051***
	(.007)	(.012)	(.007)	(.005)	(.004)	(.004)	(.005)
36 months prior	.035***	.011	.033***	.057***	.038***	.046***	.047***
	(.006)	(.011)	(.006)	(.005)	(.003)	(.004)	(.005)
US							
12 months prior	.042**	.022	.038***	.028**	.039***	.037***	.038***
	(.018)	(.024)	(.014)	(.012)	(.009)	(.009)	(.008)
24 months prior	.021	.016	.028**	.012	.022**	.023***	.023***
	(.032)	(.022)	(.011)	(.010)	(.009)	(.009)	(.009)
36 months prior	.007	.019	.025**	.007	.017**	.015**	.015**
	(.018)	(.022)	(.011)	(.010)	(.007)	(.007)	(.007)

** p< 0.10; ** p< 0.05; *** p< 0.01*

Another observation is the insignificant results from 2000 to 2006, especially for the Chinese stock markets, the other results are all significant at a p-value of 0.01. One could address this to a macro-economic event because it is intermarket. However, Aggarwal et al. (1999) say that only local events can shift the volatility-effect in emerging stock markets. Looking at the Chinese stock market reveals that in these years the Chinese stock market was reforming the stock market by selling previously untraded government holdings of shares in listed companies and aligning state-owned enterprises with commercial companies, this event helps shift the volatility-effect. Yet, the Chinese stock market does not become more efficient due to this reform, confirming Chen et al. (2011).

5.2.2 Momentum effect

The results of the GRS-test (section 5.1) impact the analysis of the momentum effect because the GRS-test labels six models as inefficient. The results of the Chinese momentum effect for the formation period of 12-7 and 12-2 months are inefficient for the CAPM, FF3 and FF5 model, therefore these returns are uninterpretable. However, the other models following the momentum effect are efficient, therefore it is justified to interpret these results.

In table 5.3 the US momentum effect does generate insignificant abnormal returns, which is contrary to Jagadeesh and Titman (1999) and Novy-Marx (2012). A possible clarification is a different period however, the period from 1994 to 2006 does not generate abnormal and is incorporated in Novy-Marx's (2012) work as well. Another reason for this phenomenon is survivorship bias because here all stocks are taken into account, also the ones of companies in default. Wermers (1997) found evidence that momentum is more present if survivorship bias occurs. All in all, the results are insignificant implicating a weak-from efficient stock market, which is in line with Dias et al. (2020). However, the momentum of 6-2 months before formation in the Chinese stock markets is significant at a p-value of 0.01 confirming Li et al. (2017), which implicates an inefficient market. The significant results of the US stock markets versus the insignificant results of the Chinese stock markets are a support for the second hypothesis.

Table 5.3 demonstrates monthly abnormal return of the difference portfolio according to the momentum effect. The results shown are the difference portfolios, so the best performing stock minus the losers. The momentum effect is tested against the CAPM, FF3 and FF5. The FF5 model is used to test the momentum effect against the different periods to track the abnormal returns over time. In addition, the one-month reversal effect is taken into account.

			FF5			**FF3**	**CAPM**
	'94-'99	**'00-'05**	**'06-'11**	**'12-'17**	**Full**	**Full**	**Full**
China							
1 month prior	-.024***	-.040	-.016*	.003	-.018***	-.014***	-.014***
	(.006)	(.026)	(.008)	(.004)	(.005)	(.005)	(.005)
6-2 months prior	.029***	-.001	.016***	.037***	.025***	.029***	.030***
	(.005)	(.014)	(.005)	(.005)	(.004)	(.004)	(.004)
12-7 months prior	.026***	.009	.016***	.030***	.023***	.027***	.027***
	(.004)	(.012)	(.005)	(.004)	(.003)	(.003)	(.003)
12-2 months prior	.037***	.002	.021***	.042***	.031***	.036***	.036***
	(.006)	(.015)	(.006)	(.005)	(.004)	(.004)	(.004)
US							
1 month prior	-.012	.007	-.022***	-.030***	-.014**	-.016**	-.015**
	(.027)	(.013)	(.008)	(.008)	(.007)	(.007)	(.007)
6-2 months prior	.002	.006	.018**	.013**	-.005	-.007	-.006
	(.018)	(.012)	(.007)	(.006)	(.005)	(.005)	(.005)
12-7 months prior	-.003	.021	-.002	.004	.003	.002	.002
	(.012)	(.018)	(.007)	(.005)	(.004)	(.004)	(.004)
12-2 months prior	-.006	.019	.018**	-.009	-.003	-.005	-.005
	(.018)	(.013)	(.009)	(.006)	(.006)	(.006)	(.005)

** p< 0.10; ** p< 0.05; *** p< 0.01*

Focusing on the different timespans, the US stock markets generate for the formation period of 6-2 months significant returns from 2006 to 2018, which Imran et al. (2020) found as well. For the Chinese stock markets, the results are significant during the whole sample except the second period, likewise with the low-volatility effect. The state-owned enterprise reformation could be again a valid explanation, since before and during the reformation, the information uncertainty was very high. Cheema and Nartea (2014) state that higher information uncertainty in the Chinese stock market leads to a lower momentum effect. The Chinese momentum effect peaks in the last period and again gives evidence for less efficient markets after the state-owned enterprise, confirming Chen et al. (2011).

Last, in table 5.3 the short-term reversal effect is tested by shorting and buying the stocks relative to last month's results. A negative sign is in line with the effect since it is a reversal. Significant evidence can be seen in the US stock markets and the Chinese stock markets, confirming Da et al. (2014). Merely, the effect is higher in the US stock markets than in the Chinese stock markets, implicating higher efficiency in Chinese stock markets. Analysing the results in different timeframes shows that the Chinese results are driven by the first period, the other periods are insignificant. The US results are driven by the last two periods therefore, a period-on-period comparison is not suitable.

5.2.3 Contrarian effect

Table 5.4 shows the results of the contrarian effect. Regarding the full sample, all results are significant at a p-value of 0.001, which is in favour of De Bondt and Thaler (1985), Soares and Serra (2005) and Shi and Zou (2017). Remarkable are the small, though significant, results for the US Stock market. If we compare this to the Chines stock market much higher returns are obtained in the sample period. Besides, the standard errors are for all results very small, causing reliable results. These results are supportive of the third hypothesis, taking the difference and small standard errors into account.

The highest returns are obtained, when using 24 months holding period, contradicting De Bondt and Thaler (1985), who got the higher returns when using 36 months holding period. However, Soares and Serra (2005) found the highest returns with a formation period of 24 months continued with a 24 month holding period. Fung (1999) researched it for the Chines stock market and did also find higher returns after 24 months, because of the adjustments of the markets after the overreaction.

Looking at multiple periods, the first thing highlighted is the insignificant results of the US during 2006 to 2012, containing the financial crisis. Such a result is found by O'Keefe and Gallagher (2017) as well for the Greece stock market during the financial and euro crisis. The main reason given by O'Keefe and Gallagher (2017) is the tempered trading spirit of the investors during this period, declining overreaction. Furthermore, the Chinese results are again generating the highest return in the last period, implicating rising inefficient stock markets in the recent years, approving the paper of Chang (2021).

Table 5.4 shows monthly abnormal return of the difference portfolio according to the contrarian effect. The results shown are the difference portfolios, so the worst-performing stock minus the winners. The contrarian effect is tested against the CAPM, FF3 and FF5. The FF5 model is used to test the contrarian effect against the different periods to track the abnormal returns over time. The returns of the holding periods are converted to monthly returns.

				FF5			FF3	CAPM
		'94-'99	**'00-'05**	**'06-'11**	**'12-'17**	**Full**	**Full**	**Full**
China								
24 months prior	24 months holding	.014***	.008**	.024***	.045***	.023***	.023***	.023***
		(.001)	(.004)	(.001)	(.001)	(.001)	(.001)	(.001)
	36 months holding	.012***	.006***	.015***	.030***	.017***	.016***	.016***
		(.001)	(.002)	(.001)	(.001)	(.001)	(.001)	(.001)
36 months prior	24 months holding	.019***	.011***	.029***	.054***	.029***	.028***	.028***
		(.001)	(.003)	(.001)	(.002)	(.001)	(.001)	(.001)
	36 months holding	.015***	.011***	.017***	.036***	.021***	.020***	.020***
		(.001)	(.002)	(.001)	(.001)	(.001)	(.001)	(.001)
US								
24 months prior	24 months holding	.010***	.004**	.002	.010***	.007***	.006***	.006***
		(.003)	(.002)	(.001)	(.001)	(.001)	(.001)	(.001)
	36 months holding	.008***	.001	.000	.003***	.003***	.003***	.003***
		(.003)	(.001)	(.000)	(.001)	(.001)	(.001)	(.001)
36 months prior	24 months holding	.012***	.010***	.000	.011***	.009***	.009***	.009***
		(.004)	(.003)	(.001)	(.001)	(.001)	(.001)	(.001)
	36 months holding	.006**	.006***	.002***	.004***	.005***	.004***	.004***
		(.003)	(.002)	(.000)	(.001)	(.001)	(.001)	(.001)

** p< 0.10, ** p< 0.05, *** p< 0.01*

5.2.4 Liquidity effect

In table 5.5 the results of the liquidity effect are presented. All results of the full sample are significant at a p-value of 0.05, confirming the theory of Amihud and Mendelson (1986). These significant results implicate that the markets are indeed inefficient, confirming the papers of Balsara et al. (2007) and Nguyen and Pham (2021). The 1 month holding return for China is lower than for the US, which implicates a more efficient market in the US however for 5 months, this is the other way around at almost the same level. These abolishing results are somewhat in contrast with the fourth hypothesis.

Remarkable are the high results of a 1 month holding period in contrast to the lower results of 5 months holding. An et al. (2020) did take a 5 month holding period into account and obtained lower returns as well, although not such a difference as in this paper. They argue that the mispricing decreases over time, especially in liquid markets. This is visible in table 5.5 since, the difference in abnormal returns between 1 and 5 months holding period for the US stock markets is higher than the Chinese stock markets, implicating that the US stock markets are more liquid and the Chinese stock markets. Mensi et al. (2016) discovered higher liquidity in the US than in China from 1997 to 2014.

Table 5.5 demonstrates monthly abnormal return of the difference portfolio according to the liquidity effect. The results shown are the difference portfolios, so the worst liquidity stocks minus the best liquidity stocks. The liquidity effect is tested against the CAPM, FF3 and FF5. The FF5 model is used to test the liquidity effect against the different periods to track the abnormal returns over time. The returns of the holding periods are converted to monthly returns.

	FF5					FF3	CAPM
	'94-'99	**'00-'05**	**'06-'11**	**'12-'17**	**Full**	**Full**	**Full**
China							
1 month holding	.064***	.044***	.042***	.041***	.050***	.052***	.052***
	(.005)	(.011)	(.006)	(.003)	(.003)	(.003)	(.003)
5 months holding	.008***	.008***	.019***	.023***	.015***	.015***	.015***
	(.002)	(.002)	(.002)	(.001)	(.001)	(.001)	(.001)
US							
1 month holding	.087***	.057***	.043***	.047***	.058***	.055***	.056***
	(.015)	(.016)	(.006)	(.007)	(.005)	(.005)	(.005)
5 months holding	-.007	.007*	.001	.006***	.003**	.003**	.003**
	(.004)	(.002)	(.003)	(.001)	(.001)	(.001)	(.001)

** p< 0.10, ** p< 0.05, *** p< 0.01*

Concentrating on the different periods, the highest abnormal returns for both stock markets were obtained during the first period, following a 1 month holding period. Afterwards, the abnormal returns decrease over time, meaning that the effect is less present. Such a decrease could be caused by arbitrage, because investors know about this effect, confirming Ben-Rephael et al. (2015). However, this is unlikely, since the effect is still visible at high levels. In addition, the abnormal return of 5 months holding period increase over time, leading to an antithesis. Moreover, the significant 5 months holding period result for the full US stock market sample is mostly driven by the results positive abnormal return obtained in the period 2012 to 2018.

5.3 Comparing US and Chinese stock markets

To compare US and Chinese stock markets, analyses are made between the US and Chinese stock markets, whether they are efficient. This is based on the abnormal returns generated by the different trading effects, which are presented in table 5.6. Both stock markets are significantly inefficient during the whole sample, contrasting with the weak-from efficient market hypothesis of Fama (1970). However, they are in line with papers as Kang et al. (2002), Balsara et al. (2007), Verheyden et al. (2015) and Sadka (2003), who as well found inefficient stock markets for the US and Chinese stock markets.

When looking at the timespans the US stock markets are efficient for the period 1994 to 2012, confirming the weak-from efficient market hypothesis. The US is not efficient in the last period, which causes the full sample insignificance. The efficient stock market period of 1994 to 2012 agrees with the paper of Verheyden et al. (2015), which included data till 2013.

However, the last inefficient period of the US stock markets is in contrast with papers like Blau et al. (2018) and Blizt et al. (2019). This concludes decreasing abnormal returns in the US stock markets over time. However, Boya (2019) researched it for the French market and he found no evidence for an efficient stock market as well, which is supportive to the results found here. He mentioned that the behaviour of humans is reflected in stock markets, which is irrational (Daniel & Titman, 1999) and therefore it could never be efficient. Boya (2019) states that the French stock market is in line with the adaptive market hypothesis of Lo (2005). He incorporated these behavioural biases as Daniel and Titman (1999) mentioned.

Table 5.6 presents efficiency of the stock markets measured in abnormal returns, based on all effects tested against FF5. Only efficient models are used regarding the GRS-test.

	'94-'99	**'00-'05**	**'06-'11**	**'12-'17**	**Full**
China	.024***	.016	.018***	.024***	.021***
	(.004)	(.010)	(.005)	(.004)	(.003)
US	.009	.010	.007*	.009***	.008**
	(.007)	(.007)	(.004)	(.004)	(.003)

** p< 0.10, ** p< 0.05, *** p< 0.01*

The Chinese stock markets are almost for every period significant at a p-value of 0.01, only for the period between 2000 to 2006 no significant result is obtained. The highest abnormal returns and therefore the highest inefficiencies are measured in the first and last periods. Groenewold et al. (2004) found evidence for the first-period inefficiency at such levels as well. Lim et al. (2008) gave the Asian crisis as an argument for the inefficient market, creating a chaotic financial environment. The last two periods are after the state-owned enterprise reform, which should deliver a more efficient stock market (Chong et al., 2012) generates significant results as well at the same levels as before the reformation. The Chinese stock markets are highly significantly inefficient. Qi et al. (2000) already warned for this, since the Chinese stock market has a weak correlation between returns and outstanding equity in tradable state-owned enterprises, causing an insufficient change of efficiency.

Regarding the results of table 5.7, all the hypotheses are approved or rejected, starting with the low-volatility effect. The first hypothesis stating that the low-volatility effect leads to an overall higher abnormal return in China than in the US stock markets is approved. However, the low-volatility effect is solely driven by the last period of 2012 to 2018. The hypothesis, that the momentum effect leads to an overall higher abnormal return in China than in the US stock markets is approved as well. Although, the momentum effect is based on the short-term reversal effect and the 6-2 months formation period. The other formation period models were not efficient regarding the GRS-test.

The third hypothesis, the contrarian effect leads to an overall higher abnormal return in China than in the US stock markets is approved concerning table 5.7. However, no significant results for 2000 till 2006. The last hypothesis, stating that the liquidity effect leads to an overall higher abnormal return in China than in the US stock market is rejected. No significant results are found in the whole sample, only from 2006 to 2011, a significant result is obtained.

Table 5.7 shows differences in abnormal returns between Chinese stock markets and US stock markets. The differences are measured by Chinese returns minus US returns. All effects are tested against the FF5. Only efficient models are used regarding the GRS-test. The short-term reversal effect is included in the momentum effect with the opposite sign.

	'94-'99	**'00-'05**	**'06-'11**	**'12-'17**	**Full**
Low-volatility effect	.023*	-.005	.009	.010***	.008***
	(.012)	(.005)	(.017)	(.002)	(.002)
Momentum effect	.017***	.006	.019***	.022***	.020***
	(.002)	(.004)	(.002)	(.007)	(.006)
Contrarian effect	.008***	.002	.021***	.028***	.017***
	(.002)	(.003)	(-.001)	(.001)	(.001)
Liquidity effect	.000	.001	.011**	.001	.004
	(.007)	(.007)	(.005)	(.004)	(.003)
All effects	.015*	.005	.011***	.015***	.013***
	(.008)	(.013)	(.003)	(.004)	(.004)

** p< 0.10, ** p< 0.05, *** p< 0.01*

Next up is the analysis of all effects, a significant difference is found between the Chinese and US stock market regarding the full sample, meaning that the Chinese stock markets are indeed more inefficient than the US stock markets. This is in line with the three approved hypotheses and confirms the existing literature about the more regulated Chinese stock markets versus the more liberal US stock markets. There are many reasons for this significant difference, starting with the phase of the markets, the Chinese are emerging stock markets and the US are mature stock markets. Besides, the lack of management of the Chinese stock markets against the adequate management of the US stock markets is highlighted by Yang (2020).

Furthermore, the different stock types cause a lack of liquidity, leading to inefficiency (Tabak, 2004). However, the liquidity effect does not present a significant difference, because the US is exposed at the same levels to the liquidity effect, regarding table 5.5. The high US liquidity is caused by the overestimation of illiquid stocks, because of loss-aversion (Tversky and Kahneman, 1991). Last, the paper of Chang (2021) states that the daily limit and the many non-tradable shares owned by the government cause inefficiencies as well in the Chinese stock markets.

In table 5.7 only one complete period shows insignificant results, videlicet 2000 to 2006. Merely, both countries have efficient stock markets in this period, referring to table 5.6. Lim et al. (2008) explain that the efficiency of Asian stock markets is the reaction to the Asian crisis, which was just before the second period, causing inefficiency at the markets. For the US markets it is slightly different, because from 2000 to 2006 the highest abnormal returns are measured of the whole sample however, it is insignificant. The still efficient market is in line with Seth and Sharma (2015) arguing that the efficiency of the US stock market did not get affected by the dot-com bubble and burst of 1998 to 2000.

The significant difference of the full sample is mostly caused by the two latest periods, so from 2006 to 2018. The US stock markets do not deliver extremely low abnormal returns therefore, the effect is mainly driven by the higher inefficient Chinese stock markets. This has not been researched a lot, because of the fairly new data however, Malafeyev et al. (2019) did find inefficient emerging Asian markets as well. Their results were not quite serious as in table 5.6, although they argue that the inefficiency is caused by the Chinese crisis in 2015, causing an unstable financial environment.

CHAPTER 6 Conclusion & Discussion

The paper analyses the efficiency of the US and Chinese stock markets and if differences between the stock markets arise based on trading strategies. In the literature, a prevalent view of whether the US and Chinese stock markets are inefficient does not appear. In combination with the contained Chinese stock market, causing inefficiencies (Chang, 2021), the following research question has been formulated: *Are the Chinese stock markets more inefficient than the US stock markets and which trading strategy can exploit these potential inefficiencies?* The efficiency of a stock market is often tested through the use of trading strategies. In this paper, four trading strategies have been executed, exploiting the low-volatility effect, momentum effect, contrarian effect and liquidity effect.

The data sample used for research starts in January 1991 until December 2020 and is divided into four periods to analyse whether the effect is concentrated or scattered. The trading strategies are portfolio-based executed within ten portfolios contingent on a characteristic of a trading strategy (return, volatility and liquidity). The utmost portfolios are used to create a riskless long-short strategy, based on the different strategies a trader would go long in the highest portfolio and short in the lowest portfolio or vice versa using one of the characteristics of the trading strategies (volatility, liquidity or return). In an efficient stock market, such a trading strategy would not generate abnormal returns. Abnormal return is only abnormal when it is robust against factor models, which capture risk (Malkiel, 1983). This research uses three factor models: CAPM, FF3 and FF5 to conclude whether abnormal returns are significantly present. The trading strategies are all separately tested on the Chinese and the US stock markets and with these outcomes, it is possible to make a one-on-one comparison for the different stock changes based on a set of definitions in the same period.

First, the GRS-test is performed on all the factor models for every trading strategy. Almost all models are efficient and as such their results are interpretable. However, the momentum effect models using a formation period of 12 until 2 and 12 until 7 are not interpretable for the Chinese stock markets. All in all, the data sample shows that the Chinese stock markets are more inefficient than the US stock markets in line with Chang (2021). He concludes that the non-tradable shares and the daily limit are the main reason for this. Other researchers like Yang (2020) see a lack of management at the Chinese stock markets. In addition, the Chinese stock markets are less liquid due to the different stock types causing inefficiency (Tabak, 2004).

The different periods show only a significant difference in abnormal returns from 2006 to 2018, caused by higher inefficiency in the Chinese stock markets especially in the last timeframe. Malafeyev et al. (2019) come to the same conclusion and root it back to the Chinese crisis in 2015 as clarification, causing unstable financial markets. Remarkable are the results of efficiency in the US stock markets. The last period, from 2012 to 2018, is the only period that shows significant abnormal returns in contrast to many researchers like, Caporale et al. (2019) and Imran et al., (2020). They conclude a decreasing trend in the efficiency of US stock markets. Besides a notable result for the period from 2000 to 2006, which is the only period not showing inefficient results for both stock markets. The US and Chinese stock markets were in the years before respectively exposed to the dot-com bubble and the Asian crisis. Afterwards, the stock markets were not interrupted by major shocks translating into efficient stock markets.

The results of the abnormal returns and inefficiencies are exposed by the executed trading strategies. The low-volatility effect and the contrarian effect show significant abnormal returns in both countries and significantly higher abnormal returns in Chinese stock markets than in the US stock markets. The momentum effect does find significant results for the Chinese stock markets, but not for the US stock market. Therefore, a significant difference between the US and Chinese stock markets is not surprising. The liquidity effect generates significant results as well for both stock markets, though the difference between the US and Chinese stock markets is not significant. All in all, three trading strategies are generating higher significant abnormal returns in Chinese stock markets than in US stock markets. They show higher inefficiency in Chinese stock markets than in the US. The trading strategies are low-volatility effect, momentum effect and contrarian effect.

This research has several limitations, which could be used as avenues for further research. The first serious limitation is that the trading strategies could be proxying other known or unknown risk factors. Robustness tests are already executed with the CAPM, FF3 and FF5. However, other less common factor models were not used like, the q^5-factor model (Hou et al., 2018). They found for example, that the expected growth factor incorporated in the q^5-factor model largely explains the liquidity effect, which is significant in the analyses of this paper. Furthermore, the low-volatility effect could be captured by the betting-against-beta factor found by Frazzini and Pedersen (2014).

Besides, the cost side of trading can be a limitation. In this research, the focus is on the potential revenue side for a trader, without taking any costs into account. For example, the transaction costs could be different for stock markets and stocks on their own. Small low-priced stocks can have relatively higher transaction costs than average stock size (Falkenstein, 1996). Besides transaction costs, the costs of shorting are not taken into account, which is relevant as well (Ofek et al., 2004). Shorting in stocks is more expensive than taking a long position, because of the extra risk taken to which brokers are exposed Besides some positions are not able to short. Taking trading costs into account could be a valuable next step in the field of research.

Another interesting avenue for further research is the adaptive market hypothesis. Lo (2005) proposed this alternative theory next to the efficient market hypothesis of Fama (1970). The adaptive market hypothesis reconciles the efficient market hypothesis with behavioural alternatives. These alternatives were already found by, for example, Kahneman and Tversky (1982) stating that people do not act in line with the Bayes' rule, one of the underlying theories for the existence of most trading effects researched in this paper. Such behavioural biases in finance are consistent with the model of Lo (2005), where individuals can make mistakes however, they are capable to adapt and learn their behaviour appropriately. Evidence in favour of the adaptive market hypothesis is found by Urquhart and Hudson (2013) for the USA, UK and Japan stock markets from 2000 to 2009, whereas Todea et al. (2009) found it for several Asian countries including the Chinese stock markets.

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