Unconventional Applications of Financial Analysis Techniques

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Statement of Originality

This work has not previously been submitted for a degree or diploma in any university. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

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Abstract

Financial analysis and modelling are becoming increasingly relevant in modern finance. There is strong need for greater flexibility and wider coverage in the applications of trading, asset pricing and risk management, highlighted by the systemic collapse of financial institutions during the global financial crisis of 2007–08. Financial institutions that had aimed for profit maximisation now felt the need to constrain growth and use better modelling and risk management tools. There is also a sharp increase in the need to conceive and apply these models and tools in an innovative manner. This thesis presents studies in three different categories of analysis: the study of technical analysis and its use as an indicator for market risk and efficiency; the application of survivorship bias in a post-financial crisis environment and its effects on risk–reward structures of short to long term investment; and the opportunity for arbitrage by taking advantage of regulatory restrictions such as circuit breakers and price limits. This thesis studies three markets, the Australian, US, and Chinese Equity markets across three investigations respectively.

The first study explores a new explanation of why technical analysis still prevails despite evidence against it in the form of market efficiency. Rational investors should use technical analysis to benefit themselves. This study postulates that if abnormal excess return cannot be consistently generated, investors use technical analysis to reduce transaction costs and overall risk of trade. Connections can be drawn by exploring the links between common technical indicators and market efficiency proxies such as spread, liquidity and order book depth. The spread measures the implicit transaction cost as well as being an indicator of relative market efficiency. Market liquidity provides insight into how investors with large amounts of capital can potentially work their orders to minimise slippage. Order book depth explores the level of potential slippage relative to trading size experienced by these investors when choosing to operate with technical analysis as their trading signal.

The second study describes the application of the Black–Litterman model in a post-crisis scenario. In this scenario, general parametrics should fail due to irrational fear and overshooting of investor expectations. During these stressful times in the market, surviving firms are found to be financially sound or are saved via government or central bank interventions. These overreactions from the investors should be proxied by the return distribution of individual equities around the return of the market index (S&P500). Overperforming stocks should fare better in the medium to long run as investors are confident about these firms even during turmoil. Underperforming stocks should perform better in the short run as the market compensates for its overreaction once investors realise that these firms are cheap on a fundamental basis. Only the top and bottom quartiles are considered for view adjustments in the Black–Litterman model as these have the most significant shifts during the fall. In the final analysis, firm size and book to market ratios are controlled in a similar fashion as the Fama French three-factor model.

The last study investigates arbitrage opportunities in China. By taking advantage of Chinese circuit breaker regulations in the form of price limits on the Shanghai and Shenzhen Stock Exchanges, mispricing opportunities can be exploited via the convertible bonds market. Hedging exposures using the convertible bonds against their underlying equity when mispricing occurs demonstrates a significant return above the risk-free rate (10-year Chinese government bond yield) in an empirical context between 2010 and 2019.

These three studies show that non-traditional techniques and methods should be expanded in use, especially in the field of trading and risk management. There is strong evidence that technical analysis coincides with large increases in liquidity, and momentary increase in the level of market efficiency, hence reducing transaction costs and overall idiosyncratic risk when trading in equities. Adjusting weights on a market portfolio using the Black–Litterman model can yield substantially higher returns for lower downside risk during a post-financial crisis context based on the performance of sector stocks during the crash. Finally, significant returns above the risk-free rate can be obtained by arbitrageurs by taking advantage of regulatory inefficiencies in the Chinese market. Overall, these findings contribute towards the study of risk and return in the context of market microstructure, behavioural bias and modelling, and arbitrage via regulatory inefficiency.

Chapter 1: Introduction

1.1 Unconventional Application of Technical Analysis

The prevalent use of technical analysis in trading seems counterintuitive for those who believe in some form of market efficiency. Decades of market study show that it is improbable that a trader can consistently generate abnormal profit from past or stale information. Modern portfolio theory shows that the optimised method of balancing return against risk is by diversifying the portfolio, whereas technical analysis often takes the other extreme and involves concentrating in a few securities. Both mathematically and logically, the level of idiosyncratic risk taken by technical traders is greater than that of a market portfolio which, by definition, only contains systematic risk. While technical traders may outperform the market portfolio on any one trade, to do so consistently would be contradictory to the modern literature. The increased amount of risk would provide a suboptimal level of return versus the market index. If technical analysis can consistently generate greater returns, then it can be argued that the market is inefficient. Instead, the thesis proposes that technical analysis is not useful for generating abnormal returns but can have other uses such as reducing transaction costs. This reduction in transaction cost could be used to explain why there is a prevalent use of technical analysis whether traders use it consciously or not for this reason.

This thesis focuses on equity day traders and their interactions with the market. Other markets such as bond or commodities markets also use technical analysis. However, they are excluded from this thesis as they are heavily correlated with global demand and supply and hence have a strong relationship with policies and macroeconomic movement. The purpose of this thesis is not to study the predictive value of technical analysis against global macro trends. Rather, the purpose of this thesis is to provide a possible explanation on the prevalent use of technical analysis today. The term “day trader” refers to traders who mainly place speculative trades on the short to mid-term horizon (mainly on an intraday timescale). They differ from traditional investors in that they do not particularly care for the long term prospects (such as superannuation funds) of their holdings and instead focus on short to medium term returns.

This brings many technical traders. This is similar for equities where the recent rise in Contract for Difference (CFD) trading or margin trading has pushed equities towards the speculation end of the scale over investment.

Technical traders look for four distinct qualities when analysing potential trading opportunities: volume, price, time and magnitude. Logically, these four elements are important for all traders. The four qualities are ranked in order of importance to a technical trader. Volume mainly refers to on market traded volume. Trading is impossible if there is no volume and traders use on market transactions as a proxy to determine how liquid a stock is. It is used as a gauge mechanism so the traders can enter and exit the position with substantial size. It is ranked as the most important quality. Price refers to the price action and past patterns or signals. Price also includes the price range of the technical signal. Time refers to the timeframe at which the analyst observes the information or chart. Magnitude is the amount that price is expected move over some time period. The length of time of the price move is also the implied duration of the trade. For the purpose of this study, only the first three qualities are considered as there is no reason to predict holding period returns because the aim is to search for reductions in transaction cost (local minima of effective bid–ask spread) and not to anticipate abnormal returns.

To find the relationship between technical analysis and transaction costs, it is well-recognised that a reduction in transaction cost would increase a trader's profit, ceteris paribus. Hence, rather than exploiting inefficiencies in the market, technical trades can be argued to be exploiting periods of high efficiency and liquidity. This thesis does not aim to prove market efficiency, nor does it seek to disprove it. In Fama's (1970) efficient market hypothesis, the conditions he described to be necessary for a market to be efficient has been argued to not fully reflect reality. Specifically, Fama (1970) recognises that a market in which there are no transaction costs, all available information is free and readily available to all market participants, and market participants agree on the implications of current information, does not simulate conditions of real markets. This study also does not claim that technical analysis is only useful for reducing transaction cost and predicting critical points of higher than average liquidity. Furthermore, it does not claim that technical traders are aware of the reduction in transaction cost or increase in liquidity.

Technical analysis can be described as a group of strangers in a town all choosing a time and place to gather without any further information. A few may decide that the town hall at noon is a logical place to gather and head there voluntarily. If there are enough people heading to the town hall at noon, then the small mass of people heading there will attract further attention. Fung and Hsieh (2001) came to a similar conclusion by suggesting that technical traders often follow trends and momentum. Hence, these traders are mostly profit seeking and there are few signs that show they are aware of additional benefits[1]. This study looks to conclude that a lower transaction cost naturally occurs due to the nature of technical trading.

Furthermore, Sturm (2013) notes that both the efficient market hypothesis and technical analysis recognise that prices generally reflect all information about a stock. However, the efficient market hypothesis uses this recognition to argue that prices cannot be predicted, while technical analysis uses the same recognition to argue that prices reflect trends in investor sentiment that can be predicted.

The underlying theme of this research is that a trader can reduce transaction cost when trading at (or near) points that are technically critical (also known as technical signals)[2]. Both chart based as well as pattern based technical signals are investigated. The difference between the two is that a chart based signal arises from a type of overlay that may be in the same section as the price chart itself, or may be an addition. This research considers the most common types of moving average overlays used by technical analysts. Pattern based technical signals are more

[1] There are activities in the market where some trades actively seek to trade without aiming for profiting from market returns. This could be due to commission rebates, hedging reasons, regulatory mandates etc.

[2] Support and resistance signals include breakout strategies as they are also the same benchmarks from which breakouts are measured.

arbitrary and arise purely from "how the price action looks". As such, support and resistance levels are included in this research. However, it should be noted that there are multiple methods of finding support and resistance levels (as is with all types of technical indicators) and this study only examines one of many.

Outside of effective spread and traded volume at critical points (technical entries and exits), it is equally important to study the depth of the market. As the study focuses on the immediate trades around the technical points, it only takes the first 10 price steps on both the bid and offer respectively. Modelling the cumulative distribution of quoted depth shows the change in the first three moments relative to the general respective average moments of the entire dataset of its first derivation on both the bid and offer. The first four moments taken from the entire dataset are used as the sample standard against which moments taken from technically critical points are measured. The fourth moment is not required as the study is concerned about the immediate volume around the best bid and offer. How the liquidity is distributed at the tail ends is not the focus of this thesis study.

1.2 Survivorship Bias in a Post-Crisis Environment

Warren Buffet said, "you only find out who is swimming naked when the tide goes out" (Buffet, 2001). This is a reference to unsustainable growth and poor management practices that become apparent during and after periods of market stress. This study aims to find evidence for objective strategies that can generate significant excessive returns based on a post-crisis context. The main driver behind this significant alpha would be market overreaction. There is evidence of short-term momentum strategies and long run contrarian strategies in the equity space where investors construct portfolios based on previous performance of stocks.[3] However, trading these portfolios has its shortcomings. The investor either must pick one strategy or the

[3] Ample evidence can be found in DeBondt and Thaler (1985, 1987), Chopra, Lakonishok and Ritter (1992), Jegadeesh and Titman (1993), Chan, Jegadeesh and Lakonishok (1996), Richards (1997), Rouwenhorst (1998), Chan, Hameed and Tong (2000), Grundy and Martin (2001) and Jegadeesh and Titman (2001).

other (momentum or contrarian based on their investment duration needs) or needs to take into consideration hefty transaction costs and taxes if they wish to combine the two strategies. When comparing the strategies parametrically, several studies demonstrate similar results.[4] This study aims to find evidence for mean reversion in the short term, and evidence for a delayed response for momentum in the medium to long term. If this is found, then a portfolio can be constructed where the investor does not need to rebalance the weights throughout the holding period. This study helps minimise the need to switch portfolio positions via the Black–Litterman model, constructing weights that would allow a smooth transition between the short run and the long run by taking advantage of market overreactions that result from the bursting of a bubble.

Financial bubbles are recorded as early as the 18th century, starting with the infamous Mississippi bubble and the South Sea bubble (Mackay, 2012). Bubbles are very valuable for research as they demonstrate irrational behaviour in an otherwise rational market, as well as the ability to disrupt a market or an economy in general. Frehen, Goetzmann and Rouwenhorst (2013) investigate the role of innovation during the Mississippi, South Sea and Dutch Windhandel bubbles and find that it is one of the key drivers of market expectation. Similarly, when recounting the recent technology stock bubbles, both in the NASDAQ technology stock crash of 2000 and in the bitcoin price rally of 2017, the essence of innovation can be found behind the key selling points of the companies and products. All of them offer a new and disruptive way that can change the current market status quo or change the prevailing method of how things are done. On the other hand, regulation and market forces are also an undeniable aspect of bubbles. Ofek and Richardson (2003) explore the tech bubble from a regulatory perspective and conclude that the bubble was caused by restrictions on sales of new issues, and the crash by the information and supply shock following the lifting of constraints.

[4] Jegadeesh (1990), Pesaran and Timmermann (1995, 2000), Balvers, Wu and Gilliland (2000) and Balvers and Wu (2001).

When studying financial history, it seems that bubbles are an unavoidable phenomenon. As investors overindulge in one product or type of product, expectations become unjustified and prices become inflated. Attempts to predict and prevent financial crises are met with strong resistance from reality by irrational investors driven by fear or stop losses. An important feature in financial crises is a substantial increase in downside volatility. This is critical as there has yet to be any fear caused by a substantial increase in market price. Any fear of increase is always propelled by the fear of the drop that is to come when the market reverts to a rational level of operation. Hence this study does not attempt to predict or create preventive measures to mitigate financial bubbles or crises. This study aims to take advantage of oversold and mispriced securities in the aftermath of a collapse.

This study takes the corollary of Buffet's conjecture and suggests that not only do you discover which firm has the worst risk management and corporate governance, but also which has the best. In terms of equity, this refers to firms with strong fundamental backing, liquid and abundant cashflows, good management practices, and other indicators of strong corporate structure. Hansen and Wernerfelt (1989) studied firms' profitability by dissecting economic and organisational components and found that industrial selection and positioning, and managerial practices are both critical in affecting the profitability of a firm. On reflection, it should follow that this can be applied in a post-crisis scenario and the common characteristics of well managed firms with strong fundamentals could be pooled together to outperform the general market and other benchmarks in the short term. It is noteworthy that the study period in this thesis focuses on a time when the market is in distress, hence it does not contradict modern portfolio theory, nor does it offer any evidence against an efficient market.

Similar to Reinhart and Rogoff's (2014) study, this research studies systemic collapses rather than individual equity collapses. This study uses data from recent systemic collapses (Dot-Com Bubble and GFC) and uses the market index as a basic benchmark for the recovery periods. By using the returns of the market index as a benchmark, it considers companies that are delisted due to administration during the collapse and are an accurate measure of market conditions. However, this study does not delve deeply into how and why bubbles occur.

This research focuses on the secondary equity market. To qualify for this study, the market must be open for trading for at least one year both prior and post event, so there can be a comparison. The crash should also be recent enough to have had electronic trading. Due to change in the global and economic environment, studying the effects of the Dutch stock market collapse in 1720, coincidentally the same year the South Sea bubble occurred in England, would yield results that are hard to justify. With the evolution of politics, regulation and technology, original oversights and loopholes are considered. This allows for a case similar to how information is seen in market efficiency where one can assume that older loopholes should all be covered in more recent regulations and technologies. For example, short selling regulations and anti-market manipulation regulations were not as comprehensive back in the 18th century. Summers (2000) notes that recent financial innovations brought enormous potential to the fields of finance and trading, but at the same time the bubbles and crises are more extreme.

There are several key factors to consider when selecting the data. First, it is fundamental to define what a crash or a bubble is. Without a clear definition for financial bubbles and crises, it is impossible to determine when to apply the models proposed by this research. Furthermore, these distinctions are required to distinguish between a true bubble or crisis caused by over exuberance or irrationality among investors, and a natural pullback or profit taking behaviour from market participants. Second, to calculate recovery, there needs to be a point that can be referenced as the end of the collapse and the start of the recovery. This date should not be arbitrary and should not be a point that can only be selected in retrospect. Lastly, the collapse must be systemic and clearly distinguished as sector driven such as the dot-com bubble which was driven by technology stocks. Chapter 4 provides further details on these three factors.

1.3 Price Limits and Restrictions

Equity prices often exhibit large short-term price swings. To address this issue, regulators and exchanges implement circuit breakers based on volatility limits which can be points based or percentage movement based. The purpose of these is to limit the volatility of the market and to provide investors with more time to digest any incoming news that may impact the price of assets.

All circuit breakers limit trading for the purpose of either allowing more time for investors to integrate new information in their trading or to limit volatility of the asset or security. The most common of these are trading halts, in which as the name suggests, all trading activities on an asset stop when the trigger is hit. The trigger can often be a predetermined percentage or point movement. Trading is usually restored after some time. An example of this is the New York Stock Exchange's market wide trading halt. NYSE Rule 80B (that's now updated by the NYSE Rule 7.12) (NYSE, 2020) states:

> *"a circuit-breaker halt for a Level 1 (7%) or Level 2 (13%) decline in the S&P 500 Index occurring after 9:30 a.m. Eastern and up to and including 3:25 p.m. Eastern, or in the case of an early scheduled close, 12:25 p.m. Eastern, would result in a trading halt in all stocks for 15 minutes. If the S&P 500 Index declines by 20%, triggering a Level 3 circuit-breaker, at any time, trading would be halted for the remainder of the day."*

Price limits require all trading activities to be within a certain range. If the price action were to hit that limit, trading cannot go beyond it. However, if another trader were to trade in the opposite direction, and hence bring the price back within the price limit, it will be allowed. This is a simple tool to limit volatility in the market. A-shares in China, on the Shanghai and Shenzhen stock exchanges, use a ±10% price limit with varying degrees of success in lowering potential volatility. This is also the case in the main study of this research. Chapter 3, Section 4 of the Shanghai Stock Exchange Trading Rules notes:

*"3.4.13 The Exchange imposes the daily price limit on trading of stocks and mutual funds, with a daily price up/down limit of 10% for stocks and mutual funds and a daily price up/down limit of 5% for stocks under special treatment (ST shares or *ST shares).*

The price limit is calculated as follows: price limit = previous closing price × (1±price up/down limit percentage).

The calculation result shall be rounded to the tick size. The price limit does not apply to any of the following cases on the first trading day:

(1) IPO shares or closed-end funds;

(2) further issue;

(3) shares whose listing is resumed after suspension; or

(4) other cases as recognized by the Exchange.

The Exchange may adjust the daily price up/down limit upon the approval of the CSRC."

Hence for cases other than the four limits imposed above, a ±10% trading range is established for all A-shares for this study.

Other circuit breakers include transaction taxes, margin requirements, position limits and collars (Harris, 1997). These either increase the cost requirements for trading and reduce the incentives for traders to place trades, or they provide a hard limit and control the volume that traders can churn in a day. Regardless, these are all used by regulators and exchanges to provide further safeguards against unwanted market shocks.

Harris (1997) notes that both fortunately and unfortunately, there are no satisfactory answers on how well circuit breakers have performed. This is fortunate because the market in general dislikes volatility as it is the main measure of risk used, and unfortunate because without extreme volatility, we cannot test the effectiveness of the circuit breakers. This study seeks to expand the current empirical understanding of circuit breakers beyond trading halts.

Traditional trading halts are covered heavily in the literature both via mathematical models and empirical tests. However, there has been little evidence provided for these models and theories when the circuit breaker is a price limit.

There is evidence for the magnetic properties of price limits. The "magnet effect" is when the price action of an asset is close to a price limit, there is a pulling effect that acts on the price making it more likely to hit the circuit breaker, much like the pulling forces of a magnet. However, this effect only describes what happens in the short term, and the empirical evidence is supported by intraday data. Price limits are unlike trading halts that stop all trading when triggered. A price limit simply does not allow the price to move beyond a predetermined range. Hence it is unlikely that the asset is fairly priced at that point. The fair value of an asset is difficult to estimate, thus both an empirical and a mathematical approach are used in Chapter 5 to investigate this problem.

This study uses convertible bonds as a measure of equity price to determine the effects of price limits as there are no price limits for the convertible bond market in China. This opens opportunities for possible arbitrage opportunities, even under T+1 trading conditions for Chinese equity markets. Hedge Fund Research (Hedge Fund Research, 2008) conducted a study between 1990 and 2007 in American markets and concluded that, on average, an arbitrage strategy offered 10% growth year on year with an annualised (based on quarterly data) standard deviation of 5%. Overall, this offered a Sharpe ratio of 1.2, whereas the benchmark S&P500 index only demonstrated a Sharpe ratio of 0.4 over a similar time period. Since then, more complex and sophisticated strategies have been examined studies and are discussed in the literature review in Chapter 2.

1.4 Summary

The following chapters in this thesis provide insight into how traditional financial analysis and modelling techniques are used in unconventional circumstances. This introduction outlines the motivations and importance of each of the three studies. The thesis also aims to generate conclusive results, both academically and for industry practitioners, on traditional techniques in areas that have not been previously studied.

This thesis is organised as follows. Chapter 2 discusses literature on asset pricing, market efficiency proxies, arbitrage methods, modelling techniques, and other issues related to the methodology and research design of this thesis. Chapter 3 investigates the application of technical analysis outside of asset pricing. Chapter 4 discusses the applications of the Black–Litterman model and how to exploit market inefficiencies in a post-systemic crisis environment. Chapter 5 analyses the arbitrage opportunities in the Chinese equity market by exploiting regulatory restrictions. Each chapter discusses the data and sample, hypotheses and methodology, testing and empirical results, and implications. Chapter 6 concludes by highlighting the empirical evidence generated in this thesis. It explores possible avenues for both academics and industry practitioners to apply traditional financial analytical techniques in unconventional paradigms for the purposes of lowering market risk (liquidity and volatility).

Chapter 2: Literature Review

This chapter will seek to summarise the literature used in this thesis. It will be split into three sections, expanding on the works referenced in Chapters 3, 4, and 5 respectively. They will discuss previous works in the fields of technical analysis, market efficiency, Black Litterman Model, convertible bonds, price limits and circuit breakers, and arbitrage models.

2.1 Technical Analysis and Efficiency

This section aims to explore how technical analysis is used in application and studied by academics. This study aims to discover additional applications for technical analysis and how these applications can be expanded into new territories.

2.1.1 Technical Analysis in an Efficient Market

Taylor and Allen (1992) surveyed chief foreign exchange dealers in London in 1988 and found that over 90% placed weighting on technical analysis when trading. This is further skewed in the short run where dealers place heavier weightings on technical analysis over fundamental analysis. Furthermore, Brock, Lakonishok and LeBaron (1992) analysed 26 technical trading rules using 90 years of daily stock prices from the Dow Jones Industrial Average (1897 to 1987) and found that they all outperformed the market. There is further literature supporting the 'traditional' use of technical analysis as a predictor of price, but there is even more literature against it.[5]

Lo, Mamaysky and Wang (2000) explored the intricacies of 'charting' or technical analysis. They systematically grouped different types of shapes, patterns and indicators, and then further scrutinised the algorithmic aspect of these patterns using 31 years of American equity sample data. The results discovered evidence for practical applications for technical analysis, namely that patterns of historical return data can predict future price movements.

[5] For further details please refer to Blume, Easley and O'Hara (1994), Lui and Mole (1998), Fernandez-Rodriguez, Gonzalez-Martel and Sosvilla-Rivero (2000), Lee and Swaminathan (2000) and Neely and Weller (2001).

It is noteworthy that technical analysis remains a ‘numbers game’. By accepting what is the most probable action, the traders trade along what has been famously quoted by Jesse Livermore (2007) as the ‘direction of least resistance’. This eloquent method of justifying and recognising the intricacies of order clustering and market microstructure defines what the technical analysts have taken for granted. The rise of technical analysis within the foreign exchange market was first examined by Goodman (1979), but academics proved sceptical largely due to the influences of the efficient market hypothesis by Fama (1970), which states that all relevant information would have already been priced in and hence past data cannot obtain any abnormal returns.

The efficient market hypothesis suggests that the price movements of currency pairs on the foreign exchange market are at least weak form efficient. That is, all relevant past data has been computed within the current price and it cannot be used to generate any abnormal profits. Thus, the existence of technical analysis within the foreign exchange market would be considered irrational behaviour. Regardless of the reason a trader applies technical analysis, according to the efficient market hypothesis it will not generate any abnormal returns in the long run. However, given the existence of a major participant that does not aim to profit and has a significant impact on the market, namely central banks, then traders are able to generate abnormal returns with minimal risk in a consistent manner, thus giving credibility to technical analysis (Menkhoff and Taylor, 2007). The timing of these traders’ entry can be predicted with technical analysis and hence the risk of these trades is reduced via these signals. The central banks’ interventions and interactions with the foreign exchange market allow for the persistence of technical analysis to be rationalised.

Grossman and Stiglitz (1980) and Khanna and Palepu (2005) noted that the market cannot be fully efficient. Assuming that in real markets market efficiency holds true, then there would be no incentives to research and analyse information. Thus, there would be no information that goes into the market and the securities can no longer be priced by all the information as some would be missing. Therefore, there should be enough inefficiency in the market to at least incentivise and reward those who analyse information. Furthermore, Kavajecz and Odders-White (2004) found that technical analysis is widely used by almost all investment banks and trading firms in their trading decisions. The only plausible reason these firms would allocate resources towards technical analysis is if it generates sufficient returns to warrant its results.

A review of the Australian Securities Exchange (ASX Review, 2010) performed in 2010 and published in "Algorithmic Trading and Market Access Arrangements" states that:

> "*For example, some so-called 'momentum' algorithms have the potential to distort price discovery for a security. Within a multi-market operator environment, where liquidity has been fragmented and where maker-taker pricing encourages algorithms to 'chase' one another to receive incentives, the risk of price distortion increases significantly… The ASX Review concurred with ASIC's view that the need for the use of controls (such as 'circuit breakers') as a mechanism to limit the risk of significant price distortion should be assessed, noting that circuit breakers may themselves also introduce their own unintended risks or consequences."*

Any large movements in stock prices would result in the so called "Speeding Ticket" where the firm in question is placed into a halt so they can release information on the abnormal price movements. It also serves as time for traders and investors to digest any new information that may have arisen from or was caused by the price abnormality. This provides an interesting example where the market cannot process information and requires external aid to do so.

2.1.2 Market Efficiency against Uncertain Conditions and Regulation

Adding to the efficient market hypothesis, the random walk hypothesis also predicts market returns of equity to be stationary expressed as ARIMA (m, d, n) where d = 0. Hence when d ≠ 0, the market is inefficient and long term dependency equity data would find past information useful in improving the accuracy of return forecasts (Nagayasu, 2003). The nature of long term dependency or long memory in equity trading is in dispute. There is evidence against long range dependency: Lo (1991) used daily and monthly US equity return data between 1962 to 1987; Mills (1993) examined monthly UK stock returns between 1965 to 1990; and Cheung and Lai (1995) used monthly data of 18 countries on the Morgan Stanley Capital International indices between 1970 to 1992. These studies cover major markets in industrialised countries. On the contrary, there is also evidence in support of long range dependence in equity markets in industrialised countries as well: Cheung and Lai (1995) showed it also exists for Austria, Italy, Japan and Spain; McKenzie (2001) used monthly market returns on the Australian Stock Exchange (ASX) between 1876 to 1996; and there are similar results for other industrialised countries.

Despite the popularity of the efficient market hypothesis, there are problems as the level of market efficiency is difficult to measure. Lo (1991) proposed testing market efficiency within an equilibrium model that defines normal asset returns. Other difficulties exist as the efficiency of a market is also affected by the depth (liquidity) of the market and the maturity of its regulatory environment. Different regulatory environments dictate different reactions to shock within a localised system (market) and directly affect its aftermath. A common demonstration of differences in regulatory environment is how markets trade (by call or by continuous auction[6]) and how trading resumes after a halt.

The trading halt itself is a method of regulating the market. It is often used in anticipation of news. Trading halts are also used as a circuit breaker mechanism. The primary argument supporting circuit breakers (both price limits and trading halts) is that non-trading periods provide an opportunity for normal information transmission in times of market duress (Lee and Mullineaux, 1993). Proponents of circuit breakers claim that, during major price changes, there can be a breakdown in the transmission of information between the trading floor or the

[6] The main difference between a call market and a continuous auction market is that trading on a call market happens in discrete time periods whereas trading on a continuous auction market is ongoing. This means that a buy or sell order that crosses the spread on the latter would execute immediately in contrast to the former where buy and sell orders are batched and executed at a common price according to a predetermined set of rules at a predetermined point in time. In both markets, traders can place both limit and market orders.

electronic market and market participants. Therefore, "the primary function of a circuit breaker should be to reinform participants" (Greenwald and Stein, 1988, pg.17). Circuit breakers are placed as a measure against periods of potential volatility. When the depth of the market and the time to process information for market participants are insufficient, the market axiomatically cannot maintain efficiency. In other words, the mechanism of a circuit breaker is to maintain the integrity of the market by giving time for new information to be processed such that price discovery can take place and market efficiency can be restored without a period of high volatility that arises from information asymmetry. To clarify, the traditional function of a trading halt can be seen as twofold. First, it is used as a circuit breaker mechanism to halt periods of high volatility. As seen on the ASX, if there is a period of high price fluctuation, the market will impose a trading halt and request information from the company that may explain the reason behind the abnormal volatility. Such trading halts are usually intraday. Inter-day halts are often used in anticipation of a price sensitive announcement that has not been previously released or expected.

Price equilibrium obtained on the market is derived from the buying and selling pressures that are driven by information. When new information is processed in the market, traders observe the effects as changes in liquidity and price. When observing trading halts, price stability represents a major factor that needs to be considered. The call market method excels at price stability over the continuous auction market method as batching orders in discrete bundles eliminates the small fluctuations caused by the price moving between the bid–ask spread. As trading is done at a predetermined time period, the impact of orders with considerable volume also tends to be softened (Cohen and Schwartz, 2001). It also deals with information asymmetry as it asserts a delay on all market transactions.

Most markets use the continuous auction market method. This is because it can provide immediate execution and hence traders can expect a higher level of liquidity. It should be noted that both are often used within the same market including the ASX, London Stock Exchange (LSE) and New York Stock Exchange (NYSE). The combined use of the two mediates the trade-off between volatility and liquidity. Thus, these markets apply the call market method during periods of high volatility, such as during the open and close of the market, and when a stock is expected to resume trading (technically the same as the 'Open' of market trade), and then these markets switch to the continuous auction method for the remainder of the trading day. It should be noted that a higher volatility and variance at the open and close cannot be associated with the use of a call market method. Hong Kong and Tokyo are two exchanges that only use the continuous auction method (in 1998) but experience a greater price fluctuation on the open (Cheung and Ng, 1998). They suggest that the higher volatility during the open arises from the overnight period where new information is processed. In summary, trading halts are associated with highly informative news events. During the halt, the informed traders, or specialists, engage in a price discovery process using indicator quotes which converge toward the re-opening price. Opportunities for abnormal profits are insignificant before, during and after a halt (Lee, White, and Granger, 1993).

Frino, Lecce and Segara (2011) found halts increase both volume and price volatility on the ASX after the ASX resume trading. They also found that trading halts reduce market efficiency in the form of increased bid–ask spreads and reduced liquidity at the best-quotes in the immediate post-halt period. Hence, they concluded that trading halts do not improve market quality in markets that operate open electronic limit order books. Lucca and Moench (2011) also observed the Pre-Federal Open Market Committee (FOMC) announcement price drift. In anticipation of news events, leakage of private information can cause an observable impact on the pricing of equities. These changes, although observed in hindsight, saw excessive returns that can be made up to 24 hours prior to the announcements. They also observed similar phenomenon on other stock indices across the world. Trading volume and liquidity are observed to be different before and after the announcement. Frazzini and Lamont (2007) saw similar occurrences for individual equities in the US markets during the lead up to scheduled announcements.

2.1.3 Liquidity and Bid–Ask Spreads

Chakravarty and Sarkar (1999) performed a study on US corporate, municipal and government bonds between 1995 and 1997. (CAI) using a basic dataset of 450,000 daily insurance company bond transaction records from Capital Access International. The data contained records of transaction date, bond identification number, the total dollar value of the transaction, the number of contracts traded and whether the trade that occurred is a buy or a sell order of over 450,000 transactions by insurance companies spanning the corporate, municipal and government sectors. They found that liquidity showed direct correlation with the realised bid–ask spread of all three markets and that it is an important determinant as a gauge. Their results found that as trading volume increases, the realised bid–ask spread decreases.

Hasbrouck and Schwartz (1988) aimed to define liquidity and transaction costs in equity markets. They first noted that other factors such as market maker interventions, stale limit orders in the book, information arrivals and inaccurate price determinates from partial news adjustments also affect short term volatility. Hence these factors may dampen short run price volatility and can induce a negative execution cost. However, volatility itself will increase execution costs as it affects the spread and can cause inaccurate price discoveries (overshooting for example). The ratio of implied volatility against observed volatility was defined as the market efficiency coefficient. They found that the market efficiency coefficient and execution costs directly affect the level of liquidity and market movements.

Huberman and Halka (2001) studied time-varying systematic liquidity to explain systemic risk and return. They note that intuitively the cost of inventory, which would directly affect market liquidity, is influenced by the interest rates and the relative riskiness as perceived by other market participants. The adverse selection component of the spread is dependent on the proportion of informed and uninformed traders in the market. In the context of technical analysis, if we assume that there are only informed traders, then these traders would not trade at all. Short term liquidity is driven by uninformed noise traders (i.e., technical analysts) who try to discern future price movements based on non-fundamental information (Black, 1986).

2.1.4 Technical Analysis and Liquidity

Kavajecz and Odders-White (2004) stated that traditional academic wisdom and the investment industry are at odds because if the application of technical analysis is well founded then markets are inefficient in nature. Alternatively, if the efficient market hypothesis holds true, then substantial resources are being wasted. Hence, they proposed connections between technical analysis and liquidity provisions demonstrate clear evidence that technical analysis can be used to locate liquidity. However, as the results were shown in an aggregate manner, it does little to demonstrate the effects of technical support and resistance levels in locating liquidity for individual stocks. It is notable that volume can play other roles when used as a technical tool. This is not explored in detail in this study but proves the point that volume is the most important of the list of requirements of technical traders. Blume, Easley and O'Hara (1994) used a model where the only risk arises from the underlying information structure. In their model, technical analysis proved significant as current market statistics revealed some, but not all, information. As the underlying uncertainty within the model is not resolved in one period, residual information can be found in subsequent periods using only past information. Interestingly, volume provided information that is distinct from the information obtained from price. The volume captured important details regarding the quality of the traders' information. This may also help resolve some issues with the conundrum stated earlier.

2.2 Bubbles and Macroeconomics

2.2.1 Bubbles and Asset Mispricing

In studying bubbles and financial crises, Charles Mackay's *Extraordinary Popular Delusions and the Madness of Crowds* (2012) is commonly noted by both traders and academics. The first three chapters discussed three different economic bubbles: the South Sea bubble (1720), the Mississippi scheme (1718 - 1720), and Tulip mania (1635 – 1637). The concept of behavioural driven finance and irrational exuberance is documented and analysed clearly as early as 1840. There was no detailed description of the market structure at the time, but Mackay provided a clear insight into speculation among the early traders who bought shares and futures contracts for tulip bulbs. Mackay's analysis arises from a sociology perspective and deals with the intricacies of the changing perceptions during the bubbles. He explained in detail how traders' speculating is driven by their greed rather than market fundamentals. This propelled asset prices to great heights in a short amount of time, as well as the devastation caused after.

Sornette (2017) provided a new insight into bubbles in his book *Why Stock Markets Crash*. He proposed to use complexity theory, which states that complexity can be defined as things that are too much for a human mind to handle. When humans are met with cases or problems that are complex, they lose the ability for rational thinking. In the financial space, this creates room for asset mispricing and eventually causes bubbles and crashes in the stock market. He notes that there was unusually high correlation between world indices during the 1987 crash that may have arisen due to complexity (earlier works from Barro and Becker (1989), and White (1996) shows similar results). In the analysis of the dot-com bubble, Sornette applied the traditional dividend growth model as the basis of comparison and noted that traditional firms aim to generate profit and redistribute the earnings via dividends, whereas new era firms aim for extremely high growth and hence boost valuation that way. This creates complexity as the variations of asset pricing methods differ from company to company, and the application of these methods is also subjective. Thus, Sornette decided to analyse the crashes from a human or behavioural finance perspective. These common themes such as greed and irrational fear during a crisis cause feedback loops that further propagate any decline in prices as investors look back at previous disasters. This idea was incorporated in the theory of rational expectation bubbles (Johansen and Sornette, 1999; 2010).

Drees and Eckwert (2005) incorporated cognitive dissonance into their asset pricing model. Based on the studies of Festinger (1957) and Harmon-Jones and Mills (1999), Drees and Eckwert believe that cognitive dissonance can cause investors to avoid or discard information that is inconsistent with their beliefs. This is especially true in financial markets where information is complex and ambiguous. Hence the main cause of asset mispricing is the misevaluation of information by investors. In their model, investors have rational expectations ex ante, but once they have made a decision, their reactions to new information can be biased based on their investment decision.

From an analytical perspective, Scheinkman and Xiong (2003) offered a model to study bubbles generated from speculative trading. Overconfident agents show heterogeneous beliefs that exceed their current future valuation of an equity. This is propelled by their constant expectations that a future buyer will be willing to pay above market price and can hence justify the current purchase price that is above the valuation for future dividends. This proved consistent with the dot-com bubble and demonstrated that IPO underpricing and name changing strategies can be used by managers to exploit bubbles.

2.2.2 Efficient Market Hypothesis and Market Efficiency Anomalies

The concept of an efficient market has been prevalent in modern finance literature. Fama (1998) explored the relationship between an efficient market and market anomalies over the long run. He notes that the market's tendency to overreact cancels out its tendency to underreact to information over a long period of time. Furthermore, advances in technology further increase the level of market efficiency in the long run. Market anomalies are empirical results that can be categorised as either indicators of market inefficiency and inadequacies in the asset pricing model (Schwert, 2003). Fama also noted the inadequacies of asset pricing models in his 1998 paper. Banz (1981) noted that Sharpe's capital asset pricing model (1965) does not explain the variation in the returns of small market capitalisation stocks' returns. Thus, samples that are skewed towards specific parametrically categorised assets can always produce results that demonstrate the inadequacies of the models relative to the supposedly efficient market.

Fama (1998) argued further that models such as the Fama and French three-factor model (1993) cannot completely capture the average returns of stocks. This becomes a larger issue when it is tested over the long run. However, with a reasonable change in the model, the long run anomalies will disappear and hence these anomalies cannot be used as evidence against market efficiency. However, Latif, Heath and Rotenberry (2011) noted that behavioural finance can be used to explain the uncaptured information in the asset pricing models. They explored different types of market anomalies and explained them via behavioural tendencies and biases using the Fama French three-factor model.

Furthermore, Fama (1998) argued that anomalies can be calculated in different ways and the testings that were performed did not necessarily use the most prudent and suitable measures. Average abnormal returns (AAR) would provide different results from holding duration (buy and hold average return BHAR) or value weighted abnormal returns. This difference in calculation method would provide different outcomes, some of which would be sufficient 'evidence' for excessive abnormal return. However, this excessive return arises from the incorrect use of the metric itself. Hence the results should not be considered as valid when arguing against market efficiency. For example, studies using monthly return data should be conducted using AARs but this does not prove to be accurate for investors. A better measure would be to compound the daily returns into a monthly set of data or to use the BHAR as these would better represent how investors compute their returns.

The assumptions used by metrics that demonstrate abnormal returns should also be questioned. The capital asset pricing model (Lintner, 1965; Sharpe, 1964) assumes normality for the return distribution of the portfolio of stocks. Fama (1976, 1996) demonstrated that although this is an acceptable model in the short term, over the long run, the skewness of the distribution is an important element for investors who wish to model their returns.

Despite ample evidence for market efficiency and the discrediting of market anomaly studies, there are many studies that approach market inefficiencies and anomalies from different angles. Behavioural finance is a common source of hypotheses for testing market inefficiencies potentially explaining market anomalies (Thaler and Ganser, 2015). Thaler and Ganser states the inherent mispricing issues arise from the fact that economists assume that investors take the most rational option all the time. Investors should be self-serving, act only in their self-interest and always be rational. Hence the market should be an aggregate of such individuals described above. However, Thaler points out that in reality, humans often fail to optimise for multiple reasons. Factors that affect the end results of how investors look at asset pricing and the market in general include the difficulty of the problem, the lack of time, or some kind of inherent bias. These effects can also be seen in Mackay's works on the South Sea bubble, and Tulip mania. The underlying notion that humans are irrational at best under stressed circumstances is what causes asset mispricing and inefficiencies to occur in the market.

DeBondt, Muradoglu, Shefrin and Staikouras (2008) discuss the development of behavioural finance and how it evolved from the neoclassical finance paradigm in depth. The assumptions that human decisions (including investment and trading decisions) are affected by framing, bias and judgemental heuristics play a heavy role in explaining how the market works and aim to complete the picture of a cold and rational market. The view that the material taught in classical finance is correct but psychological obstacles may prevent the implementation also adds to the explanation of why mispricing occurs from a corporate finance perspective. Thaler (1999) noted that myopic loss aversion and the house money effect both cause sizable effects on the market and pricing of assets. The house money effect could boost up stock prices during bullish markets and cause overreaction from investors, whereas myopic loss aversion causes investors to sell down quickly during a crisis. Benartzi and Thaler (1995) noted that losses hurt around twice as much as gains feel good. Hence to mitigate further losses, investors sell down quickly in an irrational manner, which is why the price action of assets collapses in such a spectacular manner during the bursting of bubbles.

2.2.3 Mean Reversion and Momentum Effect

Mean reversion has been associated with long term investment and returns since 1985 when DeBondt and Thaler (1985, 1987) first demonstrated that contrarian and momentum investing can generate considerable excessive returns. Apart from DeBondt and Thaler, a large number of studies, such as Chopra, Lakonishok and Ritter (1992) and Richards (1997) showed that longing portfolios constructed of stocks that performed well and shorting portfolios constructed of stocks that performed poorly (mainly based on alphas) over a predetermined period a priori generated significant excess returns. However, there are also many studies, such as Jegadeesh and Titman (1993), Chan, Jegadeesh and Lakonishok (1996), Rouwenhorst (1998), Chan, Hameed and Tong (2000), Grundy and Martin (2001) and Jegadeesh and Titman (2001) that proved the opposite is true by shorting well performing stocks and longing poorly performing stocks. Balvers and Wu (2006) noted that these seemingly contradictory results do not actually conflict as they occur during different time periods. Contrarian strategies often work on a 3 to 5-year holding period, while taking into consideration an equal amount of time as a testing sample, whereas momentum strategies prove most successful on a 1, 3 and 12-month timeframe.

When observing equity markets, the risk–return property of equity far outweighs that of treasuries (Seigel and Thaler, 1997). Hence the equity premium puzzle is the mystery of why equity has such high reward relative to the amount of risk it requires. Under the assumptions of an efficient market, the risk or standard deviation of average returns between one period and another are independent. Furthermore, Poterba and Summers (1988) show that the standard deviation of stock returns would actually be lower than anticipated via the random walk model. Years with above average returns tend to be followed by those of lower than average returns and vice versa. Seigel and Thaler finds that the actual standard deviation of holding equity over 20 years is only 2.76%. This is substantially lower than any annualised return period's standard deviation. From a risk management perspective, this indicates that equity's mean reversion property should be considered by rational investors who are looking to optimise their return for risk ratio.

2.2.4 Black–Litterman Model and Applications

Fischer Black and Robert Litterman's paper "Global Portfolio Optimization" (1992) described a model built on the foundations of an efficient market and capital asset pricing model equilibrium. They extended the Markowitz model of mean-variance optimisation in a manner that avoids the many unrealistic consequences generated such as the high sensitivity to parameter changes, and highly skewed asset allocation weightings. In the Black–Litterman model when portfolio managers are faced with information that they believe has not been fully priced into the market, they may adjust their holdings of each portfolio component and change the weights based on the belief in how efficient the market is at the time and how much they trust their own newly obtained information. This creates a situation where managers accept that the market is always not efficient or at least not strong form in efficiency. This allows portfolio managers to engage under an efficient market paradigm with a prior distribution and new information (individual beliefs) to obtain the joint distribution. Jagannathan and Ma (2003) suggested that the presence of portfolio constraints and avoiding corner solutions in optimisation techniques allows the fund manager to achieve a better trade-off between specification error and sampling error similar to what can be achieved by statistical shrinkage techniques (Johansen, Sornette and Ledoit, 1999; Jorion, 1986).

In general, the Black–Litterman model can be split into several steps. According to Idzorek's *A Step-by-Step Guide to the Black–Litterman Model* (2007), the initial portfolio weighting should be based on the efficient frontier or the market allocation. This equates to the 'neutral point' or 'equilibrium' under the capital asset pricing model. This equilibrium is derived using the reverse optimisation process method where known information is used to obtain the vector of implied excess equilibrium returns. This is done by using the equation below:

$$\Pi = \lambda \Sigma w_{mkt} \qquad (2.1)$$

Where

Π is the implied excess equilibrium return vector (N x 1 vector)

λ is the risk aversion coefficient

Σ is the covariance matrix of excess returns for the assets in the portfolio (N x N matrix)

w_{mkt} is the weights of the assets as per market capitalisation.

The risk aversion coefficient describes the trade-off for investors between expected return for lower variance. In this process, a larger tolerance for risk (larger lambda) results in an increase in the estimated excess returns.

The full equation of the Black–Litterman formula is as below:

$$E[R] = [(\tau\Sigma)^{-1} + P'\Omega^{-1}P]^{-1}[(\tau\Sigma)^{-1}\Pi + P'\Omega^{-1}Q] \qquad (2.2)$$

Where

$E[R]$ is the posterior return vector (N x 1 vector)

τ is a scalar representing the confidence in the level of market efficiency

Σ is the covariance matrix of excess returns for the assets in the portfolio (N x N matrix)

P is a matrix that identifies the assets that incorporates the manager's views (K x N matrix where K is the number of views)

Π is the implied excess equilibrium return vector (N x 1 vector)

Q is the View Vector (K x 1 vector)

Ω is a diagonal covariance matrix that describes the error or uncertainty of each view (K x K matrix).

From here, we then incorporate the manager's views into the prior distribution. In this model, views can be defined as either 'absolute' or 'relative'. An absolute view would be described as "oil will yield a return of 15% in the coming year", whereas a relative view would be phrased as "oil will outperform gold by 15% in the coming year". A degree of certainty would then be allocated towards these views (the omega matrix in equation 2.2). There is a large degree of difference between the two. The former would indicate dedicated analysis on the asset while the latter has to recognise some sort of correlation between the two assets. However, this difference is observed in a practical sense when applied in the industry. For research purposes, it is difficult to describe anything in an absolute sense as it is difficult to obtain an objectively sound result for any method of asset pricing. Even if the methodology is correct, the justification for choosing that particular framework is also difficult to argue.

Beach and Orlov (2006) circumvented the issue with absolute views incorporated into the Black–Litterman model by using the Exponential GARCH-in-Mean model (EGARCH-M) to derive the views for their portfolio. In essence, they demonstrated an improvement on the a priori assumption (the capital asset pricing aspect of the model) and applied that as the view vector (Q in equation 2.2). The EGARCH-M model is used to provide views as well as confidence measures. For their regressors in the EGARCH-M(1,1) mean equation for excess returns, Dividend Yield (country specific), Inflation, Premium, Spread and Term are used.

In active portfolio management, the Black–Litterman framework is also used and has been found to generate unintended trades and risk taking (Silva, Lee and Pornrojnangkool, 2009). This issue arises from the mismatch between the optimisation problem used to incorporate the investor views and the optimisation problem used to generate the new weights for the final portfolio. If the two optimisation problems can be consistent, then by maximising the information ratio rather than the Sharpe ratio, any mismatch that would result in unwarranted trading can be avoided.

2.2.5 Equity Markets and Macroeconomics

The economy is positively correlated with equity markets. Fischer and Merton (1984) discussed the connections between macroeconomics and finance. Macroeconomics in general studies the allocation of resources between the household sector, the business sector and the government sector. Bilson, Brailsford and Hooper (2001) noted that macroeconomic variables can explain emerging stock market returns and used money supply, inflation, industrial production and exchange rates as the main factors of their multifactor model to proxy local factors to determine their explanatory power. They did not demonstrate any causality tests and hence no directional conclusions can be made on causation of factors and whether they influenced the stock market returns. A similar test was conducted by Tripathi and Seth (2014). They not only tested the explanatory power of each macroeconomic variable but also tested the causality of the relationships. They used inflation, interest rate and exchange rate as the factors to measure stock market performance of the Senex exchange (S&P Bombay Stock Exchange Sensitive Index). Causality was tested via the Granger Causality test and Johansen's Co-integration test. However, with a two-period lag, most economic variables are either bidirectional or it was the market return Granger causing the variables. It is noteworthy that the three factors selected by Tripathi and Seth are all correlated. Interest rate is correlated with both inflation and the exchange rate. This issue was not resolved in their study, such as via variance inflation factor testing, and no standardisation of factors was performed.

2.3 Price Limits and Arbitrage

2.3.1 Asset Return Distribution

Asset returns are assumed to provide a symmetrical return distribution such as the normal distribution (Engle, 1982). However, Harris, Coskun Küçüközmen and Yilmaz (2004) note that the use of symmetric distribution is inappropriate if the underlying return distribution shows levels of skewness. In the modern neoclassical finance literature, numerous models and applications depend on the correctness of a symmetric or normal distribution as a key element. For example, the Black–Scholes–Merton (BSM) option pricing model is a model that uses differential equations to solve for option prices with the underlying assumption that the returns of the underlying assets are normally distributed (Treynor and Black, 1973). This enables the volatility and risk-free rate to be parametrically defined in a known and constant manner against the underlying returns. In other fields, the Variance at Risk (VaR) model used in risk management relies on a normally distributed return to demonstrate the downside risk of an asset or portfolio. VaR parametrically defines the distribution function in order to create the estimation in the proper quantiles. The conditional distribution of portfolio returns and variance of the said distribution can be estimated using GARCH (Morgan, 1996). Hence it is notable that VaR is sensitive to skewness and kurtosis of the conditional distribution.

Much research on asymmetric parametric distributions has been conducted on exchange rate products. Panorska, Mittnik and Rachev (1995) used GARCH to model the conditional volatility with an asymmetric Paretian distribution. Putting the benefits of the high kurtosis and skewness aside, GARCH insists that multi-period returns must be drawn from the single period context, which was not supported by the empirical data. Furthermore, Lim, Lye, Martin and Martin (1998) used GARCH and E-GARCH models on intraday exchange rate returns data. Hansen (1994) used a GARCH model with a skewed Student-t distribution to model monthly exchange rates. However, these are all only effective in the short run as central limit theorem dictates that the conditional distributions will converge towards normality on an infinite time scale.

Harris, Coskun Küçüközmen and Yilmaz (2004) focused on the conditional distribution of equity returns and extended the theory to the fields of financial risk management, asset pricing and derivative pricing. Similar to the exchange rate asset pricing mentioned above, they used a skewed generalised-t (SGT) distribution and benchmarked its empirical performance against GARCH and E-GARCH models. The skewed generalised-t model showed a significant improvement of fit over the GARCH and E-GARCH models when measured against the US, UK, Japan, Canada, Germany and World equity market indices. Elyasiani and Mansur (1998) took a different direction and instead measured how outside factors such as interest rate and interest rate volatility can affect the return distribution of bank stocks. They used the GARCH-M model and determined that outside influence can affect the return distribution but did not measure its effects on the third and fourth moments. Anderson, Bollerslev, Diebold and Ebens (2001) found that the unconditional distributions of the variance and covariance of their sample were leptokurtic and highly skewed to the right. It is of interest that the scaled return distribution provided a Gaussian approximation.

From the above studies, a common conclusion of short term leptokurtic and skewed return conditional distributions can be found in the short term. The distribution itself is also receptive to external factor influences (Elyasiani and Mansur, 1998) which can define the shape of the distribution. Thus, it is reasonable to assume and test for the shape of the conditional return distribution of equity under the influence of price limits (Chen, Chiang and Hardle,2018).

2.3.2 The Magnet Effect and Spill Over Effect of Price Limits

Harris (1997) summarised the implementation of circuit breakers and price limits after the 1987 stock market crash. He concluded that, despite empirical evidence being unable to reach a common conclusion on the benefits of circuit breakers, exchanges and regulatory bodies are still willing to use them to conform to political pressures. He argues that due to the different possible interpretations of the data and results, empirical evidence does not give clear guidance on why circuit breakers and price limits are used by exchanges.

Subrahmanyam (1994) examined the effects of circuit breakers through mathematical models. Using a single market and a two-market situation, he examined the impact of circuit breakers in intertemporal and multimarket contexts. In the one market model, he showed that a circuit breaker may increase price variability and that when the price is close to the trigger for the circuit breaker volatility may increase causing the price to exceed that trigger. This is caused by traders suboptimally placing orders ahead of time to advance their trades before the circuit breaker is triggered. Ackert, Church and Jayaraman (2001) showed similar results in empirical testing. Their ANOVAs showed that both informed and uninformed traders increased trading prior to a trading halt.

The magnet effect is supported by empirical evidence. Cho, Russell, Tiao and Tsay (2002) demonstrated that on the Taiwan Stock Exchange there is a statistically significant tendency for prices to accelerate towards the upper and lower bounds of the price range as the price nears the bounds. They tested the effect using a generalised method of moments and fitted a GARCH(2,2) process that demonstrated serial correlations up to the third lag. They also showed that the support for the upper bound is more significant than that for the lower. This holds true even after controlling for momentum effects. Du, Liu and Rhee (2009) showed similar results in the Korea Stock Exchange.

Deb, Kalev and Marisetty (2010) took a different approach to the issue and investigated the benefits of exchanges using price limits with a game theoretic model. They found that when the cost of monitoring the market is high, price limit rules are beneficial. They also found that this is generally true empirically for 58 countries (including US and Chinese markets) in their study as the exchanges that use price limits are often those with a high cost of monitoring, and inefficiencies in legal and regulatory environments.

There is also evidence for the contrary. Abad and Pascual (2007) showed that the Spanish Stock Exchange demonstrates a repulsion force on prices as prices near the boundaries. However, it should be noted that the price limit regulations also differ in Spain. Unlike the thesis study in China, the Spanish Stock Exchange microstructure switches to a call auction once the price limit has been triggered. Furthermore, this halt will only last for 5 minutes. Prices show reversion tendencies when they do not hit the price limit, and slow down when approaching the limit for those that do trigger the limit. This implies that the switching mechanism employed does not induce traders to advance their trades ahead of the price filter.

There are also studies that demonstrate that the effect of price limits on market efficiency goes both ways. The overall effect depends on the direction of the price limit or circuit breaker. Zhang, Song, Shen and Zhang (2016) investigated the effects of price limits via a simulated stock exchange that trades with similar rules as the Shanghai and Shenzhen stock exchanges in China. A comparison between upper and lower price limits showed that general market efficiency will be lower using the proxy of slower price discovery for the upper limit. However, this is not true for the lower price limit. Chen, Qiao, Wang, Wang, Du and Stanley (2018) used Shenzhen stock exchange data to show daily price limits may lead to lower market efficiency. They explained the phenomenon as large investors buying on the days the stock price increases 10%, thus fulfilling the magnet effect of price limits. This causes a significant relationship with long run price reversals. If such patterns can be recognised in markets, then it is likely that investors can and should take advantage of this irrational behaviour.

This finding concurs with the findings of Zhang, Song, Shen and Zhang (2016) regarding the destructive market behaviour for upper price limits as the large volume entering the market immediately before the price hits the boundary delays the process of price discovery. They also compared regular stocks with special treatment stocks which are held at a 5% price limit range. They found causal relationships from market dynamics before and after the special treatment status was applied. Su and Fleisher (1997) studied the Chinese government's market liberalisation policies and concluded that they increased stock market volatility in China. They argue as the market is composed of rational and risk averse investors, the increase in volatility caused the investors to demand a higher risk premium. This in turn causes a higher cost of capital for the listed firms which slows economic development. Hence the price limit regulation can be seen as a function of minimising market volatility to decrease the cost of capital at the expense of market efficiency.

2.3.3 Price Discovery and Asset Pricing

How to fairly price an asset is an ongoing debate. There is a plethora of analysis and angles investigating how to derive an accurate and objective price. Anderson, Bollerslev, Diebold and Vega (2007) investigated real time response of US, German and British stock, bond and foreign exchange markets to macroeconomic news. They found that the inflows of unexpected information or news are linked to the price movements of stocks, bonds and foreign exchange products. Their studies concluded that different contexts would influence the market to integrate the same news (good or bad shocks to the market) in different ways. Bad news, for example, proved to have positive effects during expansionary periods. The expected negative effects were only true during recessions.

Asset pricing models come in many forms. From the basic dividend growth model to complex models derived from neural networks, each is used to analyse the objective price, or the 'fair market value', of an asset. Multifactor models and arbitrage pricing models derived from the efficient market hypothesis also serve as an important benchmark for many academic studies. However, behavioural finance argues that all prices are subjective in nature. Furthermore, the assumptions in an intertemporal capital asset pricing model seem farfetched. As described by Merton (1973)[7], the assumptions are mainly standard when analysing a perfect market. However, indivisibility, transactions costs and taxes do exist.

When considering the effects of price limits on price discovery, the concept (and degree) of market efficiency is unavoidable. The speed and effectiveness at which the price is adjusted to a 'fair market value' is a heavily researched field. Berstein's (1987) study demonstrated that market efficiency declines when circuit breakers and price limits are introduced into a market. Furthermore, Lee and Chung (1996) used the stock market crash of 1987 as the background for their analysis on the impact of price limits on market efficiency. Using data from the Korea Stock Exchange, they improved on Kodres' (1989, 1993) work which suggested, rather counterintuitively, that price limits have no effect on market efficiency. Lee and Chung found that price limits reduce market efficiency. They argue that the reduction in market efficiency is the trade-off for the reduction in volatility experienced in the markets where large information shocks arrive. All studies that found a reduction in market efficiency intuitively argued that it is at least partially due to how price limits restrict continuous trading and hence interrupt the price discovery process.

Chou, Huang and Yang (2013) explored another aspect of using price limits and how it affects asset pricing. They investigated the proposed effect of price limits and circuit breakers, which is to allow investors to 'cool off' and reassess the market conditions and any new information. They studied the limit-hit duration (the length of time that a security spent at the boundary of the price limit) on the Taiwan Stock Exchange and found that the price limits represent an implementation risk that impedes arbitrageurs from correcting potential mispricing. They found consistent, with their proposed hypothesis, that due to short sale restrictions, up limits

[7] Assumptions: All assets have limited liability; there are no transaction costs, taxes, or problems with indivisibilities of assets; there are a sufficient number of investors with comparable wealth levels so that each investor believes that they can buy and sell as much of an asset as they want at the market price; the capital market is always in equilibrium (no non-equilibrium trading); there exists an exchange market for borrowing and lending at the same interest rate; short sales of all assets with full use of the proceeds are allowed; and trading in assets takes place continually in time.

have a higher duration than down limits. This proved true for smaller capitalisation stocks that have higher idiosyncratic risk. Interestingly, they found that limit-hit durations are negatively correlated with various risk measures. This counterintuitive finding demonstrates that price limits aid in price discovery and assessing fair values of assets as they prevent larger than necessary transitory volatility that may exist due to non-fundamental behavioural forces.

2.3.4 Pricing Convertible Bonds and Arbitrage Strategies

Brennan and Schwartz (1980) note several characteristics of convertible bonds in their analysis. First, they have all the characteristics of ordinary bonds. Second, they have the characteristics of options. Third, they often rank lower than ordinary bonds. Lastly, they offer a lower coupon rate than ordinary bonds with similar characteristics except the convertible nature. The lower coupon rate is due to the nature of the security itself in which the potential for unlimited upside is priced into the original bond. It is the option-like component which allows for this.

Calamos' *Convertible Arbitrage: Insights and Techniques for Successful Hedging* (2011) suggested that traders prefer to use convertible arbitrage as it allows them to construct market neutral portfolios. Profits arise from market inefficiencies between the convertible asset and its underlying asset. Using these properties, it should be feasible to hedge out any excess volatility from the underlying equity by using convertible bonds. This will allow investors to generate potentially risk-free revenue by either exploiting any mispricing of the underlying and intrinsic value of the convertible bond or by using a strategy like a long run delta hedge style of investment and collapse the position at the expiry of the convertible bond. Traditional convertible bond strategies rely on a 'natural' scenario in which there is mispricing between the underlying equity and the derivative. This is true for almost all kinds of arbitrage. Risks associated with convertible bond arbitrage combine all elements of the equity, options and bond markets. Equity market risk, interest rate risk, credit risk, liquidity risk, legal provision and prospectus risk, currency risk and leverage risk are all possible pitfalls that investors have to manage. In general, investors who undertake this strategy prefer highly volatile stocks with high liquidity, high gamma and low equity risk (preferably low to no dividend payments).

The basic and simplest type of convertible arbitrage is to long the convertible bond and go short on the underlying security. As mentioned earlier, all risk would hopefully be hedged out, allowing the investors to take advantage of the mispricing that remains. Hence the amount of underlying equity to hedge becomes an important aspect of the equation. The number of shares sold should be a function of the conversion ratio, the delta and the gamma of the bond. However, the neutral hedge ratio should simply be the product of the conversion ratio and the delta.

Other methods of convertible bond arbitrage involve hedging the bond immediately after the issue. Marle and Verwijemern (2017) investigated this strategy and compared it to short term holding strategies like those mentioned above. They found that arbitrageurs who purchase the newly issued bonds have a relatively short holding period and tend to sell within a year after the purchase. Only 1.3% of the convertible bonds are held to expiry. This confirms the results of Brown, Grundy, and Lewis (2012) who argued that selling the convertible bonds while using a short holding period strategy will yield lower costs overall from financing. Agarwal, Fung, Loon and Naik (2006) noted the difficulty in obtaining data as convertible bonds are mostly over-the-counter transactions. Thus, convertible arbitrage hedge funds are used as a proxy to obtain the trading strategy information of arbitrageurs who provide liquidity to the convertible bond market. They tested three different styles of arbitrage: volatility, credit, and positive carry against US and Japanese convertible bonds between 1993 and 2002. From these strategies, supply and demand imbalance was used as a function to determine the profitability of arbitrage. This means that the arbitrage earned is the premium given for providing liquidity into the market.

2.3.5 Intrinsic Value of Convertible Bonds

To calculate the intrinsic value component, Chapter 5's study uses the evidence of Bakshi, Cao, Chen (1997). Their study on the Black–Scholes implied volatilities shows a relationship between the implied volatility of out-of-the-money calls and puts relative to their term to maturity. This is used to calculate the non-intrinsic value component of the option element of the convertible bond. Lau and Kwok (2004) aimed to calculate the options component of the convertible bond in a study of the optimal issuer's calling policy of convertible bonds or the 'delayed call phenomenon'. They noted that empirically, issuers do not call the convertible bonds as soon as the value exceeds the call price. Instead, they wait for a certain margin of profit before converting. They noted that there is a large time dependency with the price of the convertible bonds. This dependency can be negligible in the short run but shows that the critical conversion price will increase with time and that the convertible price function will diverge to infinite as time closes in on the coupon date. During the hard call protection period, the critical stock price will decline over time and rise slightly between each coupon period before declining further as time approaches maturity. Zimmermann (2016) detailed his evaluation of zero-dividend valuation models as structurally biased when applied in a convertible bond framework. As expected from a zero-dividend model, it was tested to induce a shortfall against dividend payments.

2.4 Summary

In summary, the study on technical analysis mainly deals with different indicators and a study of their performance relative to different benchmarks (generally market returns or buy and hold strategies). However, the volatility and timing element is rarely discussed. Chapter 3 aims to provide a new use for technical analysis in terms of lowering costs by predicting liquidity and market efficiency rather than generating profits.

The study on bubbles and economic crisis discussed the history of investor irrational behaviours and overreactions. The Black Litterman Model is used by fund managers and institutional traders to combine an efficient market with unique research while maintaining a diversified portfolio. Chapter 4 aims to combine the two by offering a robust method to exploit objective inefficiencies in the equity markets via market anomalies.

Price limits in the equity space was introduced to provide time for investors and traders to digest new information when the market is in a period of extreme volatility. The halt would allow the market to react rationally. However, as Chapter 5 will demonstrate, when the information proves that the market was not acting irrationally, this could be exploited in an arbitrage if any derivative products were not halted during this period.

Chapter 3: Unconventional Application of Technical Analysis

3.1 Introduction

The literature review in Chapter 2 discussed the evolution and use of technical analysis. The main application is in trading strategies that attempt to generate abnormal returns or alpha. The use of technical analysis in trading strategies is popular even though the concept of weak-form market efficiency suggests any past information should already be priced into current prices. Chapter 2 also discussed the links between technical analysis, liquidity and spread. The study presented in this chapter aims to provide additional understanding into why technical analysis is used, and how it could be used in ways that do not contradict the efficient market hypothesis.

The chapter has the following sections: Section 3.2 describes the data used, including the order book bid–ask spread measures, and provides the definition of technical trading rules considered; Section 3.3 presents the hypotheses and the methodology for the calculations; Section 3.4 discusses results and implications; and Section 3.5 concludes with a summary.

3.2 Data, Definition and Information

3.2.1 Data

The data is taken from TRTH (Refinitiv) and SIRCA and covers the top 200 ASX listed stocks from 2006 to 2015. This is the most used index for the ASX and is used heavily by funds, both as a portfolio and as a futures product. The ASX website states, "The S&P/ASX 200 Index (XJO) is recognised as the investable benchmark for the Australian equity market, it addresses the needs of investment managers to benchmark against a portfolio characterised by sufficient size and liquidity." (ASX, 2021) These 200 stocks represent a large portion of the ASX, although the proportion varies. In December 2016, the All Ords of the 500 largest companies was valued at AUD $1.76 trillion and the XJO of top 200 listed stocks on the ASX represented approximately 82% of the total market capitalisation out of a field of 2,215 stocks (1,969 domestic, 126 foreign/international).

Depth data is taken for 10 levels of both the bid and the offer (or ask) for each of the XJO component stocks. The price used for application of technical indicators is always the midpoint of the depth except for support and resistance levels. Support levels take the bid price, whereas resistance levels take the offer price as per the definitions of each term (see Section 2.1.3).

3.2.2 Definition and Information

Technical analysis relies on charting and pattern recognition of four elements: volume, price, time and space. This research does not include several techniques that are often used. The technique of observing a divergence between price action and indicators is commonly used in the industry as it is a graphical representation of a change in investor mindset as even though the price is getting higher, the momentum or trend looks less favourable. Other techniques include trend lines or channels where the price action of a security moves within a certain set of space defined by previous movements. In addition, there are many formations and patterns such as flags, head-and-shoulders and round tops that are all based on support, resistance and trend lines. These common techniques are not considered as they are subjective in nature and cannot be quantified meaningfully relative to the indicators used in this chapter. Hence, they cannot be defined objectively and may cause similar outcomes as when data mining.

Another more subjective indicator, Bollinger Bands, which uses mean reversion as a basis and believes that if the price strays too far from the average, in most cases two standard deviations, then it will pull back towards that mean, is not used because it is less common relative to the three techniques selected. To reiterate, the purpose of this research is not to find evidence that technical signals can predict future movements with any degree of success. Rather, it aims to find the existence of a relation between technical analysis and any possible reductions in trading cost that arise from an increase in liquidity or a decrease in effective spread.

The tick data is not considered when calculating the price level used for the technical analysis indicators. Rather than taking the tick data as the points for trades, this study aims to achieve a model where a trade can potentially occur at any point. Indicators will also not take the closing price of their respective time periods as per the norm for these kinds of studies. Instead, this research sets the critical points to be the best executable price, and it assumes that this price is at the midpoint of the spread. The midpoint price at any time will be assumed to the price where all executions can be filled. When the direction of the technical signal is determined, the model takes the volume on the bid or offer depending on whether the signal pushes for a buy or sell trade. Hence the simple moving average (SMA) and moving average convergence divergence (MACD) indicators will show a price that will differ slightly compared to that when derived from the closing price.

3.2.3 Moving Average Convergence Divergence (MACD)

MACD was created by Gerald Appel in the late 1970s. It is one of the most well-known and used indicators in technical analysis. This indicator has three exponential moving averages, two of which help to measure momentum in the security and one for short term guidance. The actual MACD is simply the difference between these two momentum indicator moving averages plotted against a centreline (given as the zero line). The MACD histogram is positive when the short term moving average is above the long term moving average. A positive MACD is defined to imply upward momentum or trend. The opposite is true when the short term moving average is below the long term moving average and the MACD is said to be negative. This suggests downward momentum or trend. Hence, when the MACD crosses over the zero line, mathematically it implies that a crossover between the short term and long term moving average occurred. For this research, the most common parameters are used. The moving average values are used in the calculation are the 26-day and 12-day exponential moving averages (Achelis and Stephen, 2000). The method to denote the indicator uses the three time parameters, in the form of MACD(x, y, z). As mentioned above, the parameters used will be MACD(12, 26, 9). These original settings were created for daily charts (as charting information in the 1970s was mainly daily charts) as the working week was six days. Hence the indicator represented two weeks, one month, and one and a half weeks. As it was the norm, it is still used across the time spectrum today. Different time periods can also use different indicators. A short term oscillation parameters such as the MACD(5, 35, 5) is a common setup for short term trading. However, the most common indicators are the main consideration for this study as it is the parameter setup used by the most traders to make decisions about buying and selling. The alpha for calculating the decay of the exponential moving average (EMA) is 2/(n+1), where n is the number of periods.

In constructing a MACD for any given stock or underlying security, the following is calculated:

(i) 12-day EMA of closing prices

(ii) 26-day EMA of closing prices

(iii) Subtract the longer EMA in (ii) from the shorter EMA in (i)

(iv) 9-day EMA of the MACD line obtained in (iii).

The crossing of the line is usually used to indicate a buy or sell signal. This indicates that a buy signal is generated when the MACD crosses above the signal line, while a sell signal occurs when the MACD crosses below the signal. The MACD is displayed as a subplot to the chart that runs continuous with the corresponding price in the sample dataset. The horizontal axis also represents time and a histogram is used to show convergence and divergence in the moving averages.

The shift in trend can be found by comparing fast EMAs with slow EMAs. This is because a fast EMA is more responsive to recent price movements, whereas the slow EMA will still be required to price in older information. This property also dictates that the MACD is a lagging indicator. Hence it was designed for trending stocks and is valued much less for stocks that are not trending or trade erratically. The trading rules of the MACD used in this research are:

- BUY after one period if MACD is above the signal line
- SELL after one period if MACD is below the signal line.

3.2.3 Support and Resistance Levels

In stock market technical analysis, support and resistance is a concept that the movement of the price of a security will tend to stop and reverse at certain predetermined price levels. These levels are denoted by multiple attempts of breakthrough of a price level without success. This study uses a method improving on the support and resistance formula in Kavajecz and Odders-White (2004). Trading data is broken down into 30-minute intervals and a support level is the lowest bid price that is attained at least twice during the preceding week (during the previous 60 half-hour observations as the ASX only has 6-hour trading days). Resistance levels take the opposite values. If levels are undefined over the past 60 hours, then the criteria are not met and there are no support or resistance levels for that time period.

Support is given by:

$$P_t^S = \begin{cases} \min(Bid_{t-w}, \ldots, Bid_t) \; provided \; P_t^S = Bid_i = Bid_j \; for \; some \; i,j \; in \; (t-w,t) \\ undefined \end{cases} \quad (3.1)$$

Resistance is given by:

$$P_t^R = \begin{cases} \max(Ask_{t-w}, \ldots, Ask_t) \; provided \; P_t^R = Ask_i = Ask_j \; for \; some \; i,j \; in \; (t-w,t) \\ undefined \end{cases} \quad (3.2)$$

The above are the equations used by Kavajecz and Odders-White (2004). The equations only search for the range maxima and minima within the last 120 periods (30-minute samples over a 60-hour period). The improvement made is the ability to search for and coalesce all maxima and minima within the previous 120 period timeframes. This study merges the price level of support and resistance. The logic is that by searching for a certain level, whether it is a peak or trough, determine its properties as support or resistance based on the relative positioning of the price. The equation is as follows:

$$P_t^{SR} = Mid_t \pm \alpha\sigma \quad (3.5)$$

To determine whether the sample close price at time t should trigger a support or resistance indication, the following procedure is required:

1. Take the previous 120 sample close prices (i.e. [t-120-1,t-1])
2. Identify all local extrema within that window

    a. Candidate close price is a local maxima if the first non-equal price at tc-1, tc-2, tc-3, ... is less than the current close price and the first non-equal price at tc+1, tc+2, tc+3, ... is less than the current close price. If the previous/next price is outside the window, then the candidate price is not an extremum
    b. Similar for local minima, except switch the comparison around
3. Take sample standard deviation over the window
4. If the price at t-1 falls within x$\pm\alpha\sigma$ (where x is one of the candidate prices) and the price at t falls outside x$\pm\alpha\sigma$, then if price at t-1 < price at t, consider it a buy, otherwise if price at t-1 > price at t, consider it a sell.

From a mathematical perspective, this captures all movements within the time period and can construct multiple support and resistance levels based on all maxima and minima within the range. Therefore, this equation, although simpler, is an improvement over the previous models. The trading rules of support and resistance levels used in this research are:

- BUY after one period if the price went above the critical price band (support)
- SELL after one period if the price went below the critical price band (resistance).

3.2.4 Simple Moving Average Crossovers

In trading, a simple moving average (SMA) is the unweighted mean of the previous n data or prices within a given time period. These prices are often taken from the open, high, low or closing price action of the given period. The period itself selected depends on the need of the trader or trading strategy, such as short, intermediate or long term. In technical analysis, moving average levels are often used as local support or resistance levels. Hence similar to support and resistance levels, in a falling market, it is seen as a support (price level hitting the moving average from above), whereas in a rising market, it is seen as a resistance (price level hitting the moving average from below).

The SMA is a lagging indicator. For data that does not follow mean reversion trends, the SMA lags by half the sample width. It also distributes the weightings evenly across all the periods in the sample and hence can yield results that change rapidly with new data coming in or old data phasing out. If a sample period has periodic fluctuation, applying a SMA with a similar period will cancel out all the variation within that period. This is rare, but is theoretically possible (Chou, 1975).

Another drawback of the SMA is also derived from the equal weighting it applies to data within its period. The data it derives from the sample period can result in an inverted result. Thus, there can be a case where a smoothed SMA shows a peak during a period where the data is showing a trough. Furthermore, it implies that occasionally there are times where the SMA is less smooth than the sample data. The SMA for period n at time T is defined as below:

$$SMA_{n,T} = \frac{1}{n}\sum_{i=T}^{T-n} x_i \quad , \qquad T = n, n+1, n+2, n+3 \ldots \qquad (3.3)$$

where “X” refers to the closing price at time i.

For the purpose of this study, the SMA takes on 30-minte time period blocks and uses 5 periods and 21 periods as the trading rule. Kavajecz and Odders-White (2004) applied a time period of 2.5 days for their short term SMA, and two weeks (10 days) for their long term SMA. However, this study aims to stay consistent with the time periods selected by the support and resistance level signals as it provides the same time scale when layering the signals to find constructive and destructive interferences. The periods are taken as they are widely used in the technical trading community, as 5 represents the number of trading days in a week (also known as the weekly average line), and 21 represents the average number of trading days in a month (also known as the monthly average line). Despite this study not being performed on the daily level, it is important to use what most traders are using to find the most accurate gauge of the effects of SMA crossover signals.

Crossover signals are found when two moving averages intersect. The trading rules of the SMA crossover used in this research are:

- BUY after one period when SMA(5) crosses over SMA(21) from below
- SELL after one period when SMA(5) crosses over SMA(21) from above.

3.4 Hypotheses and Methodology

3.4.1 Hypotheses Development

Generally, this study looks for increases in volume at technically significant signals. For bullish signals, there should be an increase in volume on the bid, and for bearish signals, there should be an increase in volume on the offer. If the technical signal proves right, then these additional volumes cause the price to move in the intended direction. This study improves on Kavajecz and Odders-White (2004) by using the MACD indicator as an additional indicator, as well as testing for the effects of aggregated technical signals. The Granger causality test is used to test whether the technical signals cause the increase in volume, or if there is simply a correlation with no certain causality. The results demonstrate that there is no clear causality.

H1-1: *At a technically critical point, an increase in the order book volume is expected.*

Many traders still use technical analysis today, despite evidence of market efficiency. Without concluding whether traders are correct or profitable, the assumption is that because of the role of technical signals, these traders contribute to abnormal liquidity relative to random samples in time. Should there be an observable increase in volume surrounding technically significant points, then it is fair to assume that there should be correlation between the two. Preethi and Santhi (2012) demonstrated the use of multiple artificial intelligence methods that are available in the industry today operating on a set of trading rules, most of which are based entirely on technical analysis. The most popular are neural networks, data mining and neuro-fuzzy systems. Regardless of the system used, they all use regression algorithms for testing.

To test for the abnormal increase in order book volume caused by technical indicators, this study runs a linear regression as below:

$$AbnormalVolume_{i,t} = \alpha + \beta ASV_{i,t} + \gamma Spread_{i,t} + \delta Depth_{i,t} + \theta NS_{i,t} + \varepsilon_{i,t} \quad (3.4)$$

where ASV is the absolute signal value; and NS is the number of signals. Any abnormal volume is defined as volume of the depth at the technical signal (technically one period after the technical signal itself) minus the average volume of that day. This abnormal volume can be either from the bid or offer (or both). In cases where the signal value is positive, it takes data from the bid as it demonstrates a buying technical entry. If the signal is negative, then it takes data from the offer. Should the signal be 0, then it would be from both. Regardless of which, the absolute value is taken for the regression as the side that is selected will always assume the positive. The signal value is defined on a signal by signal basis. A signal that suggests a buy is +1, whereas a bearish signal is -1. The case of 0 can arise when there are two signals of opposite directions within close proximity.

H1-2: *At a technically critical point, the effective bid–ask spread will be relatively lower than at other points.*

An increase in order book volume is expected to occur around technical signals. Blume, Easley and O'Hara (1994) and Kavajecz and Odders-White (2004) demonstrate that an increase in order book volume can be predicted by technical analysis. Hence, if an institution with a large book wished to exit or enter a position, it is better to place an order on the opposite side of the direction the technical indicator is showing (i.e. go short for bullish signals and go long for bearish signals). It is in their best interest to place their orders in the market at these points to benefit from the anticipated price move caused by those acting on the signal. This should reduce the market spread immediately around the technical signals as traders rush orders into the order book. Similar to H1-1, this study estimates a linear regression to test for correlation as below:

$$Abnormal\ Effective\ Spread_{i,t} = \alpha + \beta aMA_{i,t} + \gamma MACD_{i,t} + \delta SR_{i,t} + \varepsilon_{i,t} \quad (3.5)$$

where ASV is the absolute signal value; and NS is the number of signals. Abnormal Effective Spread is the negative of the difference between the spread at the point of the technical signal (once again it is actually one period after the technical signal itself) and the average effective spread of the day.

H1-3: *When there are multiple technical indicators at the same point or near the same point, there should be interference. The sum of the local indicators signal directions will determine the net direction of the signal.*

To simplify this concept, similarities and parallels are drawn between the volume and the effects of a technical signal with wave functions often seen in physics. Referring to simple harmonic wave functions there are constructive and destructive interferences based on the overlap of the wave functions. The exact outcome results from the properties of the wave functions. Two waves in the same function are constructive, whereas amplitudes in opposite directions create an overlapping result in destructive interference. The frequency also affects the outcome. In this particular case, the frequency can be matched with the number of bullish or bearish signals that come into play around a certain price level; the amplitude of a wave function can be seen as the associated increase in buy or sell volume around a technical signal. The other properties of a wave function should not be taken literally in this analogy.

As this study provides three different methods of providing technical signals, there are several outcomes that may arise from overlaps. The first and the simplest is just one technical signal. Then there may be two signals that overlap. These two may both indicate the same direction or opposite directions. In the first case, the expected result is an additive one similar to constructive interference. In the second, the expected result is a subtractive one, or destructive interference. Lastly, there are three signals all near a certain price point. This could cause a further six types of interference with combinations of bullish and bearish signals (bullish, bearish, bullish or bearish, bearish, bearish etc.).

Providing an example for expected outcomes, we first look at the second scenario as the third scenario of three signals can be interpreted as a combination of the outcomes of a double signal plus a single signal. If a certain bullish technical signal caused by a SMA crossover for a stock XYZ is to occur at $51.50, and there happened to be a support at $51.45, then according to the hypothesis, a trader should expect to see additional volume at those price levels. The increase in volume should also be greater than if the levels were simply a SMA crossover or just a support level. Logically speaking, the effect should not be purely additive as if a trader or investor believes in technical analysis, there is no reason they would only believe in one form or one particular indicator. This would 'cannibalise' the amount of volume from one indicator from the other. On the other hand, given the strength of multiple signals, the trader may become confident and increase their bet and place a larger order into the market. As there is no accurate method of predicting the precise increase in volume, this study aims to observe any increase above the greatest of the indicators.

The regression model below is used to predict the movements:

$$\delta V_{it} = \alpha + \beta_1 SMA_{it} + \beta_2 MACD_{it} + \beta_3 SR_{it} + \beta_4 Combined_{it} + \epsilon_{it} \qquad (3.6)$$

The left-hand side represents the abnormal volume by detecting a change in volume against the mean for a particular security *i* at time *t*. The right-hand side of the regression shows all three technical indicators as a factor for the change along with the covariance factors between all three technical indicators. This study is conducted twice, once for the buy side volume, and once for the sell side volume.

The second regression model that is used is below:

$$\delta ES_{it} = \alpha + \beta_1 aSMA_{it} + \beta_2 aMACD_{it} + \beta_3 aSR_{it} + \beta_4 Combined_{it} + \epsilon_{it} \qquad (3.7)$$

This is a similar regression as equation 3.6. Instead of an abnormal shift in volume in the order book, it attempts to identify the change in effective spread when measured against the three technical indicators. The signals are set as dummy variables rather than the [-1,1] discrete values that it can take to denote direction of the indicator trigger points.

3.2 Further Methodology

Testing for Continuous Trading

It is important to create a set of continuous trading data using the bid and offer data from the market. There is a total of 93 million data points when comparing the bid–offer 1-minute data sample to the normal data provided by the Morning Star databases which only provide approximately 71 million data points.

To determine when the market is open for continuous trading, this study uses a new model that uses the overlaps of prices to test whether the market is in a trading halt or in an active condition. This study takes TradeMatch (the ASX market) as the source market, meaning that all trading times use TradeMatch as the basis. The ASX has multiple phases during the open, with 5 different groups based on the first letter or number of the stock ticker. Specifically, the ASX defines it as below:

> *"Opening takes place at 10:00 am Sydney time and lasts for about 10 minutes. ASX Trade calculates opening prices during this phase. Securities open in five groups, according to the starting letter of their ASX code:*
>
> *Group 1 10:00:00 am +/- 15 secs 0-9 and A-B, e.g. ANZ, BHP*
>
> *Group 2 10:02:15 am +/- 15 secs C-F, e.g. CPU, FXJ*
>
> *Group 3 10:04:30 am +/- 15 secs G-M, e.g. GPT*
>
> *Group 4 10:06:45 am +/- 15 secs N-R, e.g. QAN*
>
> *Group 5 10:09:00 am +/- 15 secs S-Z, e.g. TLS*

The time is randomly generated by ASX Trade and occurs up to 15 seconds on either side of the times given above, e.g. group 1 may open at any time between 9:59:45 am and 10:00:15 am."

This problem is further complicated by the ASX having irregular announcements of irregular opening times. For example, on 15 September 2016, the ASX opened as below as it coincided with the last trading day of the S&P200 futures contract. However, this was not the case for other trading days that also coincided with futures contract expiries which open at:

- Equity Market Group 1 (A-B) OPEN at 10:00:00 ± 15 secs
- Equity Market Group 2 (C-F) OPEN at 10:04:00 ± 15 secs
- Equity Market Group 3 (G-M) OPEN at 10:08:00 ± 15 secs
- Equity Market Group 4 (N-R) OPEN at 10:12:00 ± 15 secs
- Equity Market Group 5 (S-Z) OPEN at 10:16:00 ± 15 secs

This stochastic opening time creates difficulties in collecting depth data in the most heavily traded timeframe of the market. Due to the nature of this research, previous methods such as only accounting for the data between 10:30 am and 4:00 pm will produce vastly different results. The prominent issue with defining times between 9:59:45 am (earliest possible opening time of the ASX) and 4:15 pm with non-staggered bid–ask prices as the opening price is that with the introduction of Chi-X, there is a possibility that the aggregated bid–ask between Chi-X and TradeMatch will be staggered. However, given that this study focuses on the most liquid stocks on the ASX, this issue will be quickly resolved by traders and algorithms seeking arbitrage. The closing price in this research is defined as the last shown traded price collected at 4:15 pm on every trading day.

Unit Root Problem

For technical resistance and support levels, as the series are specified in price, there is concern for the existence of unit roots. This becomes difficult as any spikes in the trend may cause problems with translating the data both within a series and between series. This study uses the

Dickey Fuller test to determine whether the unit root problem exists, and if it does, how heavily it affects the data series. On the other hand, due to the nature of the SMA and MACD indicators, they do not have a unit root and hence are exempt from the problem that technical support and resistance levels face. The test shows that there are no unit roots in the time series using a p-value < 1%.

This study uses a new method to determine the effect of changes in the order book. When observing the volume in the first 10 price steps, it can be considered as a probability distribution chart with each price step representing one decile and the volume representing how the probability is distributed. Using this analogy, this research examines the first three moments.

The change in the first moment, or the price weighted average of the depth, reflects the change in concentration of liquidity (depth) as information changes based on stale information. Stale information refers to information that is readily available to all market participants. This also describes how the market reacts to such a point and one can infer how market participants expect short term price movements around those points, regardless of accuracy.

The second moment refers to the how liquidity is distributed across those levels. Any differences between those around technically critical points and the sample standard reflects the degree at which participants react at those points. This shows the sensitivity of the participants and will aid analysts to determine under what conditions the market is more reactive to change for future studies.

The third moment shows how much of the liquidity is concentrated around the best bid and offer. This is important to further validate resistance levels. If around critical points volume tends to increase and concentrate around the best bid or offer, it could help to understand the expected direction of movements in the short term. For example, if the current spread of a security is $1.00 to $1.01, with one million shares on the bid at $1.00 and only 100,000 on the offer at $1.01, a trader is likely to expect that the price will have a higher probability of going up in the short term as it is easier for the price to move up rather than down with the same amount of money invested. Of course, this does not account for exceptional circumstances caused by the sudden arrival of new information such as news shocks. However, this effect is negligible for the large amounts of time series data in this study.

3.4 Results and Implications

3.4.1 Results

Figure 3.1 shows the normal dynamics of how volume is distributed when looking at the value of the average order book depth. As shown in Figure 3.2 there is a visually substantial increase in order book volume for equity for technical entry and exit signals over the time period of this study. There is an observable difference based on the average that is taken for all three technical signals. Overall results are presented in Table 3.1 and individual results are provided in the Appendix. The 10 years sample period between 2006 and 2015 represented the previous 10 full trading years and hence the most up-to-date data available. The 105 stocks represented all the stocks that remained in the ASX200 for the entirety of the sample period.

Table 3.1 1-minute and 30-minute summary statistics

Instruments	Return (bps)	Std.Dev (bps)	SMA signals	MACD signals	SR signals	Observations
1 minute	0.0430	18.8554	60,389.44	157,601.81	32,170.97	93,768,656
30 minutes	38.1120	440.5976	1852.35	4678.03	3321.74	3,195,575

The table describes the average of the 105 stocks on the ASX200 index composite and demonstrates their average returns and standard deviations, number of triggers for each respective technical signal, along with the number of total observations in the 1- and 30-minute time windows. Observations are averaged across equally weighted averages for each equity.

Firstly, the factor of reduction is in a linear scale as might be predicted. This is true for both the SMA crossover as well as the MACD signals. However, the approximate 30:1 does not hold true for the support and resistance band. As observed, there are a high number of SMA crossovers and MACD signals relative to the support and resistance levels in the 1-minute timeframe but not for the 30-minute timeframe. This is due to the noise of the 1-minute time windows that cannot be removed and hence results in a higher level of SMA crossovers. Furthermore, these noises cannot coalesce the support and resistance price levels into bands and thus it increases the overall number of triggers, whereas for the 30-minute time windows, with substantially less noise, the SMA crossover indicators and MACD signals experience a similar decrease in the 30:1 ratio. However, the combined price ranges of the 30-minute data will merge into a larger range and hence the reduction in signals will not be on a linear scale.

When observing the general liquidity in the depth of the order book, turnover is used as a method to standardise against different equity prices. Table 3.2 presents a summary.

Table 3.2 Summary order book depth statistics

Lvl 1 Bid	Lvl 1 Ask	Lvl 5 Bid	Lvl 5 Ask	Lvl 10 Bid	Lvl 10 Ask
$40,041	$41,809	$216,603	$211,925	$359,694	$352,336

The table describes the average of the 105 stocks on the ASX200 index composite and demonstrates their cumulative second by second tick weighted average value in the order book depth in the 1 and 30-minute time windows. Observations are averaged across equally weighted averages for each equity.

To help illustrate Table 3.2 shown above, Figure 3.1 below shows the value at each individual level of depth. The results show that the value of the order book on average stays consistent for the first 5 levels of depth. From there, it falls off linearly (until level 10) to around half the initial level. This effect is constant across both bid and ask depths. This effect also holds true at an individual stock level when averaged throughout the day without considering any effects of special news events.

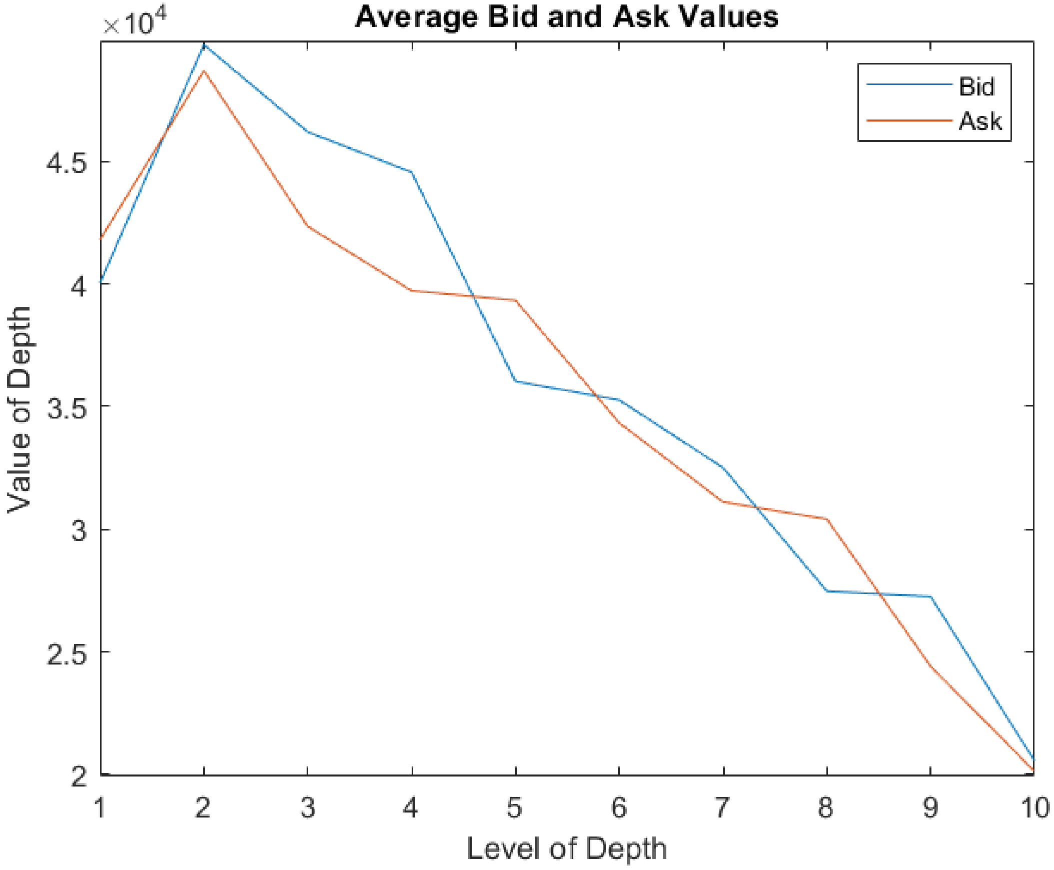


Figure 3.1 Average order book value

The figure describes the average dollar values of each price step in the depth of the 105 stocks on the ASX200 index composite. Observations are averaged across equally weighted averages for each instrument and demonstrate their cumulative second by second tick weighted average value in the order book depth.

Tables 3.3 – 3.5 below show the regression results (equations 3.4 – 3.7).

Table 3.3 Abnormal volume regression results

	Estimate	Std. Error	t-Stat	P-value
α	0.0979	0.0700	1.3989	0.1499
|signal|	1.7530	0.3359	5.2188	0
Spread	-3.0201	1.1640	-2.5945	0.01378
Depth	-9.8341	4.5450	-2.1637	0.0384
No. Signals	5.3870	1.3610	3.9581	0.0002

The table shows the linear relationship between the abnormal volume ahead of signals generated via technical indicators. It offers a cross-sectional look at how the volume (first three levels' value *of depth) changes relative to the spread and number of signals. If the signal is a sell, it observes the ask; if the signal is a buy, it observes the bid. The adjusted R squared is 0.0269.*

The results above present four different measures of how technical indicators could affect the level of market efficiency, reflected via liquidity and effective spread. Table 3.3 shows an abnormal shift in volume is highly correlated with when there are signals. The number of combined signals (in absolute terms) is positively correlated with the abnormal volume. Hence, when the number of technical points of interest is high, there should be more immediate volume. The spreads are lower in general as intuitively expected. The depth also has high positive correlations with the abnormal volume. The higher the cumulative depth, the lower the abnormal volume. The number of signals differs from the absolute signal in that it considers and sums up all the signal events locally. The explanatory power is low despite significant relationships as information is the key driver of change in volume rather than purely technical signals.

Table 3.4 Effective spreads regression results

	Estimate	**Std. Error**	**t-Stat**	**P-value**
α	0.0007	0.0360	0.0186	0.3989
SMA	-0.8300	0.7433	1.1166	0.2139
MACD	-0.4170	0.0858	-4.8630	0
SR	-0.6740	0.0238	-28.2837	0

The table shows the linear relationship between the abnormal volume ahead of signals generated via technical indicators. It offers a cross-sectional look at how the volume (first three levels' value of depth) changes relative to the spread and number of signals. If the signal is a sell, it observes the ask; if the signal is a buy, it observes the bid. The adjusted R squared is 0.0243.

Table 3.4 explains the relationship between spreads and the indicators. However, it seems that simple moving average crossovers do not generate any significant results. This could be due to the simplicity of the indicator itself. As it is adjustable and easily visually represented, there are infinite combinations of crossovers possible. However, MACD and support and resistance are much less open to any interpretation and are hence more objective, which caused a higher level of significance in the results. All signals are negatively correlated with the effective spreads. This is intuitive as immediately prior to the signal, volume increases (from previous results in Table 3.3) which would in turn decrease the effective spreads.

Table 3.5 Shift in volume and effective spreads regression results

	α	SMA	MACD	SR	Combined	adj. R^2
Shift in Volume	-0.0864*	0.4655*	0.3340**	2.0011***	2.4658***	0.0312
Shift in Spread	0.0671**	-0.3297**	-0.2122**	-1.1475**	-1.5348***	0.0256

Significance: * p<0.05, ** p<0.01, *** p<0.001

The table shows the linear relationship between the shift in volume and shift in spread prior and posterior to signal trigger events. The signals are variables for the three indicators used for this study, and a logit variable for the combined effect. If the signal is a sell, it observes the ask; if the signal is a buy, it observes the bid.

Table 3.5 describes the linear relationships between a shift in volume (between time t and t-1) and a shift in spread in respect to technical indicators and their combined values. The results are significant across the board at least at the 5% level. There is a consistent positive correlation between the shifts in volume and the indicators, and a consistent negative correlation between the shifts in spread and the indicators. It is noteworthy that the combined effects are more pronounced and have higher significance compared to the three individual indicators. The explanatory power remains low as there are many more contributing factors to spread and volume in the market microstructure.

Figure 3.2 below shows the shift in volume prior and posterior to signal events and Figure 3.3 below shows the shift in effective spread prior and posterior to signal events.

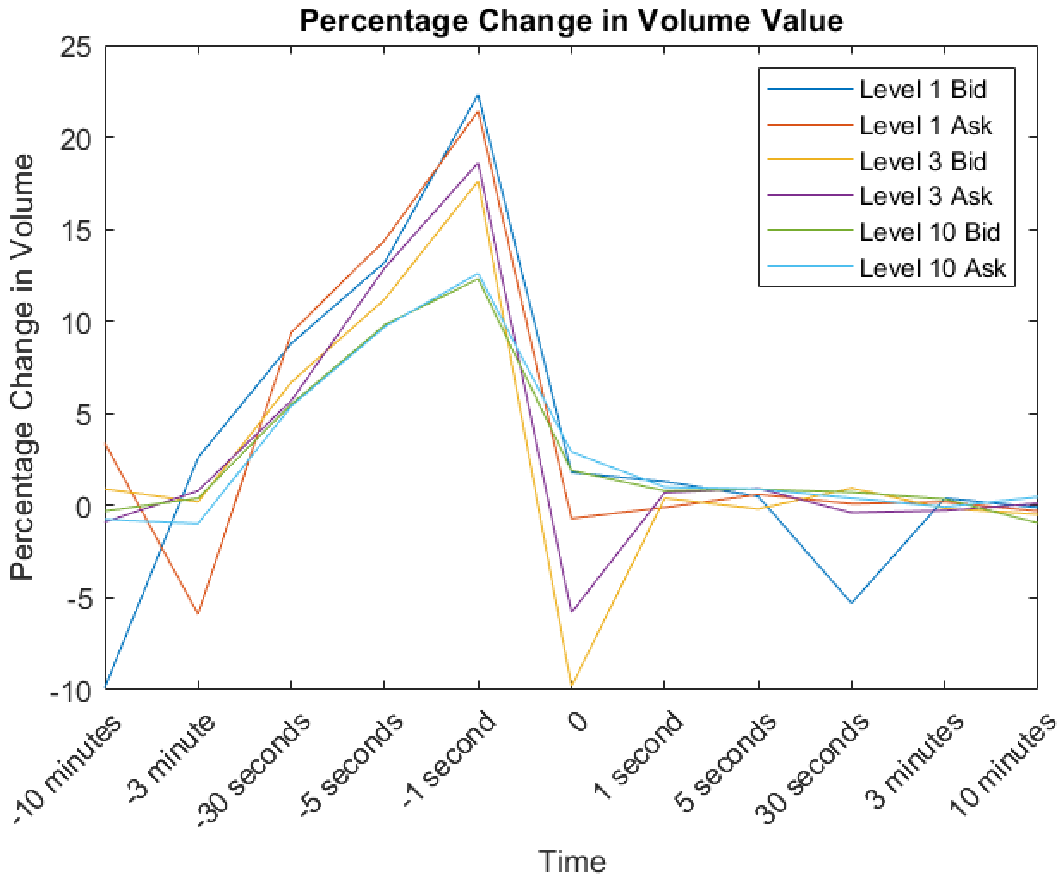


Figure 3.2 Shift in volume (by value)

The figure describes the average percentage change in dollar value of each price step in the depth of the 105 stocks on the ASX200 index composite. The levels in depth are cumulative. Observations are averaged across equally weighted averages for each instrument and demonstrate their cumulative second by second tick weighted average value in the order book depth.

Figure 3.2 shows an increase in cumulative volume across all the level tests (first level, first three levels, and all ten levels) immediately before the signal event. When the signal triggers and trades were executed, as intuitively expected, the volume decreases. The overall percentage change decreases as the level of depth increases, demonstrating that the majority of the volume shifts occur within the first few levels of depth. The volume generally starts to flow in 3 minutes prior to the trade with the maximum detected 1 second beforehand. The levels balance out around 30 seconds after the event.

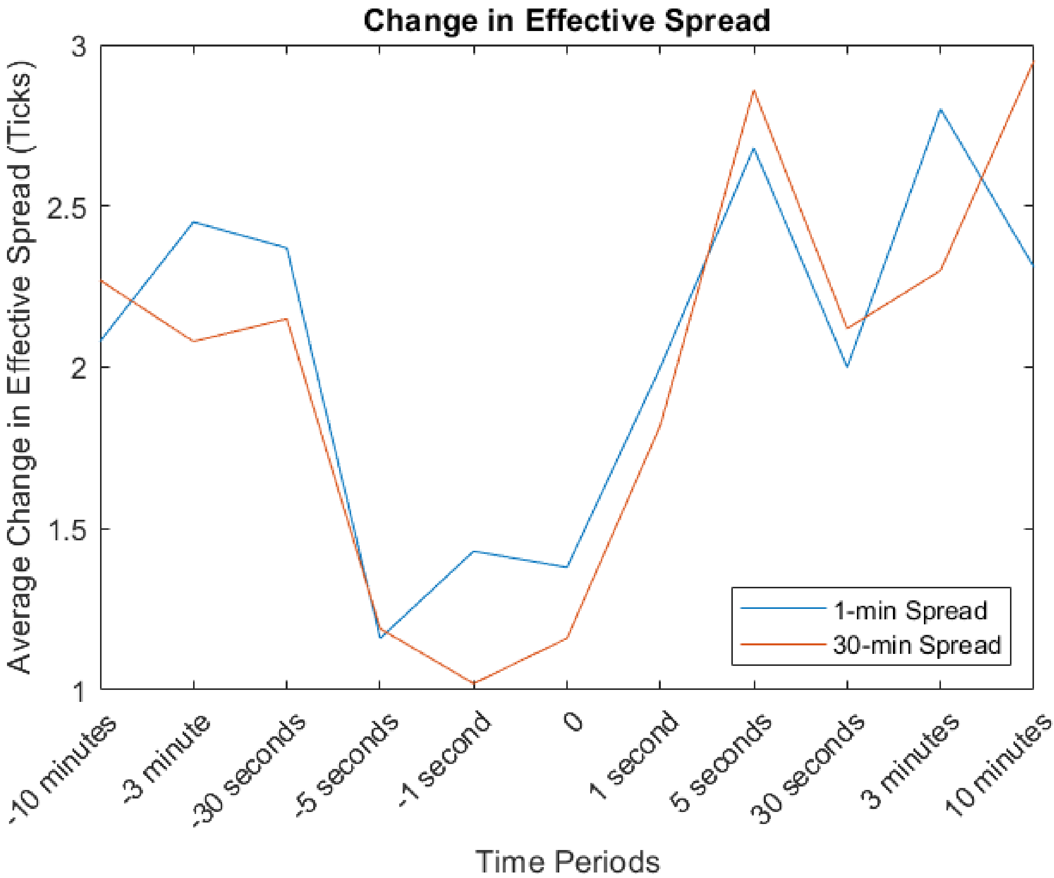


Figure 3.3 Shift in effective spread (in ticks)

The figure describes the change in effective spreads prior and posterior to the trade event (t = 0) where the signal occurs. The 1-minute and 30-minute lines each describe the signals generated in their respective sample time lengths.

Figure 3.3 shows that the effective spread drop as the time approaches the technical signal and increases after that. However, there seems to be a delayed effect that may result from any latencies caused by entering the order by operators manually only after the trigger occurs. To account for the size effect of stocks in the ASX, tick sizes were used to express the spread rather than cents as different prices have different minimum ticks.

3.4.2 Implications

This study aims to expand technical analysis beyond simply predicting price movements of securities. The industry applications are also significant. For any predicted increase in volume on the bid or offer, it is an opportunity for traders or trading strategies to enter positions at a reduced cost. This may prove interesting especially for those with large positions. Exiting a long trade at a relatively high point at buy signals to the market may incur a lower cost than if selling uniformly across a similar price range. As mentioned above, traders may already be doing so subconsciously, and this research merely documents this practice.

A more subtle application of this research is in market regulation and compliance. By using technical indicators and signals as an approximation for changes in volume, it is possible to anticipate different trading behaviour and patterns. This allows regulators and compliance managers to gain further insight into what could possibly be construed as market misconduct. As an example, if an alert is set for the percentage volume change in the first five price steps of the order book, then it is possible to adjust that percentage such that it would take into consideration whether the price action of the security has been affected by a technical signal. This can remove false positives from alert lists and reduce possible human error that may arise.

This study also introduced a new method to detect continuous trading for all markets that have auction based non-deterministic opening times. This is based on the staggered bid–ask prices during the auction phase. Should the stocks have high liquidity, any staggering of the bid–ask prices during continuous trading (which may be caused by having multiple exchanges) can be filtered out by having a minimum time allowance. This also resolves any issues with intraday trading halts or other unforeseeable market events.

3.5 Conclusion

In this study, tests were performed on three common technical indicators to analyse their uses in non-return-based outcomes, namely for their effects in detecting liquidity and periods of general increases in market efficiency. This may seem counterintuitive initially as technical analysis relies on lapses in market efficiency, but the results prove that the SMA, MACD and support and resistance indicators all proved useful in reducing transaction cost on both an intraday (1-minute indicator) and multiday level (30-minute indicator). This is especially true for trades of large volumes as shown in Figure 3.2, where volume shifts are large even at a cumulative 10 levels of depth. Furthermore, this study has shown that technical indicators can have constructive and destructive interferences, similar to sound waves or simple harmonic structures in physics. The results demonstrate that there is a significant relationship between liquidity and depth, and the number of technical analysis indicator triggers. The direction of the aggregate trigger affects the direction of the increase in liquidity in the order book.

It should be noted that data is missing for several time periods across the market due to the incompleteness of the data available at TRTH and SIRCA. There are also other data issues that required data cleaning such as timing issues where cancellations were pushed ahead of time which resulted in wrong orderings of the market flow. These technical difficulties were all resolved by interpolating data by filling in with the previous best correct values. Incorrect ordering of tick data was amended mainly manually by cross checking for time differences in timestamp data and trade or order flow data. The incorrect orderings were then changed such that time monotonically increased.

Chapter 4: When the Tide Wanes: A Study of Post-Systemic Collapse Portfolio Management

4.1 Introduction

This study aims to add to the literature of applications of the Black–Litterman model and derive objective measures for its parameters in a post-crisis market. The literature used in this study was discussed in Section 2.2. As mentioned, previous objective measures either come from the smoothing of returns or volatility. This study provides insight into a new line of thinking to exploit aspects of behavioural finance, such as market overreactions, and statistical phenomenon such as survivorship bias as the metric for investment. This study reports potential strategies that offers interesting results given the benefit of hindsight.

First, the effects of overreaction are measured against the market index. Section 4.2 discusses these in detail. Then the Black–Litterman model is applied to test for a portfolio which requires no re-adjustments that can exploit the short run and long run over-performance anomalies. Furthermore, the parameters for investor confidence and market efficiency in the current literature are unclear (Allaj, 2013). Hence, this study aims to provide a scenario in which these factors make little difference. This is undertaken across three different scenarios of market efficiency. The chapter is structured as follows: Section 4.2 details the data used and main hypotheses, Section 4.3 notes the methodology, Section 4.4 records the results and Section 4.5 discusses applications and concludes.

4.2 Data and Hypotheses

4.2.1 Data

There is no clear definition of what a bubble is in academia and literature. Even in the industry, investors define bubbles differently. Unfortunately, when selecting the data for a ‘bubble’, there needs to be a clear definition such that events can be studied in a quantitative manner. Hence not every collapse in the market can be included. Only events that receive enough public coverage and are widely believed by both industry and academia to be a bubble or a crisis are included. Therefore, this study analyses two recent events that represent the trend of financial crises: the dot-com bubble of the year 2000, and the global financial crisis of 2007-08

The S&P500 index hit a record high of 1,527.46 in March 2000. However, the dot-com bubble burst and in October 2002 the index ultimately reached as low as 800.58, down 47.59% from the peak. During the global financial crisis, the S&P500 index reached as high as 1,576.06 on October 2007. It reached a low of 666.92 on March 2009, down 57.49% from the peak. It is notable that the general index for both events fell by approximately half during the crisis, and both are generally accepted as bubbles[8]. For the entire sample period for the two events, the return statistics based on the adjusted closing prices are presented in Table 4.1.

Table 4.1 Summary statistics for S&P500 returns during study periods

	Mean (%)	Median (%)	Standard Deviation (%)	Minimum (%)	Maximum (%)	Observations
Dot-com PT	-0.109	0.078	2.621	-12.330	7.492	1,185
GFC PT	-0.084	0.180	3.584	-20.084	11.356	880
Dot-com Macro	-0.117	0.075	2.623	-12.330	7.492	1,180
GFC Macro	-0.075	0.056	3.446	-20.084	11.356	980

The table presents the descriptive summary for the dot-com bubble and the GFC for both scenarios used in this study. The summary is split between maximum peak to trough (PT) calculations and calculations of the drop returns based on macroeconomic indicators (Macro).

The variables are calculated based on the closing prices (of regular trading hours) and the results are daily. The number of observations is the number of days between the 'high' and the 'lows' calculated based on the absolute or macroeconomic indicator based.

4.2.2 Hypotheses

H4-1a: *Selecting a portfolio composed of equity that fell substantially less than the general sector will yield a stronger long-term return.*

[8] The GFC is technically a real estate bubble. However, it had severe consequences in the equity space, which will be explored in this study.

H4-1b: *Selecting a portfolio composed of equity that fell substantially more than the general sector will yield a stronger short-term return.*

This assumes that a company with a strong balance sheet, management and/or corporate structure will tend to not perform as poorly as the market in a time of crisis. During the expansion of the bubble, these firms rise to the top along with the market, but when the bubble bursts, these firms are considered as the more risk averse option by market participants.

In an extreme scenario, consider a listed company which only holds cash as an asset and has no liabilities or other capital structure intricacies that may affect its equity price. From this scenario, we can determine that outside of regular spending and revenue from productions, a decrease in general market sentiment should not affect the firm at all. The equity value, and hence the stock price under an efficient market, should always be equal to the value difference between asset and debt held by the firm. However, this is not the case in the real world. Furthermore, even stocks which hold a significant amount of cash, such as Apple Inc., are still affected by market sentiments. Hence this should be exploited when the market recovers.

The latter proposal may seem somewhat the opposite, however it only differs in market expectations. This is an application of the survivorship bias often discussed in behavioural finance. It should be viewed as an appropriation of the short-run mean reversion property of equity. The firm, having survived the systemic collapse, should also have a strong balance sheet, management and/or corporate structure relative to companies that went into administration or were delisted during the crisis. However, these stocks were evaluated to be riskier and hence sold off to a larger degree relative to the market by investors and traders. This adheres to the mean reversion property of equity valuation (Cecchetti, Lam, and Mark, 1988; Poterba and Summers, 1988). If there are no significant differences between the balance sheet and corporate structure of two firms, one of which dropped significantly during the crisis and the other which dropped less than the general market, it can be inferred that the difference in price movements between the two can be largely attributed to investors' behavioural differences. This behavioural difference is expected to have a noticeable impact on the return of the assets during the recovery period. This behavioural difference may be caused, for example, by the market participants' opinion and views on management quality (which may also have direct impact to prices).

H4-2: *The Black–Litterman portfolio which assigns heavier weights in the underperforming stocks and overperforming stocks will outperform the market without a need to change weighting allocations*

This hypothesises that in a portfolio managed by an investor, with views about both the short and long run, the portfolios can be combined simply by initialising the allocation of weights without the need to reallocate. This creates an objective standard to which all traders can operate and will be easier to manage on a holistic level. This is also a test for survivorship bias. If a trader can capture the information on survivorship bias before the market corrects itself, it should be viewed as a relatively safer option. It is certain that during a time of financial crisis, some listed companies will go into administration. This is especially true for those firms in a specific sector that is under stress. Like the concept of survival of the fittest, it stands to reason that in a post-crisis environment, the remaining listed companies should have an advantage over their fallen counterparts. These advantages may vary and include, but are not limited to, structure, size, management and strength of balance sheet. This study aims to find an application for survivorship bias during times of financial crisis to take advantage of the temporary market inefficiency that may occur during stressful periods. The adjustments made to the market portfolio will be based on the performance of the surviving stocks during the crash period.

4.3 Methodology

4.3.1 General Equations

General equations used in this study and applied throughout Chapter 4 and Chapter 5 are summarised below. This study uses discrete periodic returns:

$$r_{it} = \frac{P_{i,t}}{P_{i,t-1}} - 1 \qquad (4.1)$$

Variance of a portfolio is calculated as:

$$\sigma_P^2 = w'\Sigma w \qquad (4.2)$$

The Sharpe ratio is calculated as:

$$\theta_i = \frac{\overline{r_i} - r_f}{\sigma_i} \qquad (4.3)$$

The Sortino ratio is calculated as:

$$\phi_i = \frac{r_i - r_f}{Semidev_i} \qquad (4.4)$$

$$where\ semidev_i = \sqrt{\frac{1}{N}\sum_{r_i \leq \bar{r}}^{N}(r_i - \bar{r})^2} \quad (4.5)$$

4.3.2 Parameter Inputs

The risk aversion factor is calculated using historical data. Using the findings of Dimson, Marsh and Staunton (2002) who estimate the long term stock return between 1900 to 2000, a value of λ = 2.14 is obtained based on a risk premium of 6.2% and 17% volatility. τ is tested using τ = 0.01, τ = 0.05 and τ = 0.1 as recommended by Wai, Lee and Idzorek (2004). A higher level of τ means an increasing weighting towards the subjective views of the investor. It also represents the amount of distrust in the level of efficiency within the general market. Hence τ = 0 is not tested as then the portfolio will simply be a market capitalisation weighed composite. Blamont and Firoozye (2003) note that as τ represents the scalar, τ should be approximately 1 divided by the number of observations. Given each active portfolio has 125 stocks, the value of 0.01 is used for benchmark purposes in this study.

Investors' view of uncertainty is also a subjective matter and will change between different portfolio managers even if they use the same underlying theory. Hence, the investors' view of uncertainty is set on a sliding scale to test for the effects it has on the return of the portfolio. The lower the residual error, the lower the level of uncertainty in the views. As such, the quoted figures in the results all reflect zero uncertainty with a prudent level of market efficiency.

Investor views are purely based on a multiplier for the relative performance of stocks during the crash against the benchmark (S&P500 index). Only a one-to-one adjustment is made as any adjustments beyond this ratio of price increase against decrease may indicate an over or underperformance of greater than 100% relative to the benchmark. Hence the one-to-one multiplier acts as the highest level of risk that can be associated with the weighting distributions of the stocks, and acts as a prudent measure when adjusting for downside risk.

4.3.3 Bottom Picking

This study uses two different reference points as the entry level for the commencement of the portfolio strategy. The first point is the regular trading hours daily closing price of the absolute local bottom relative to the period after the drop in value of the general index. This represents the theoretical maximum that a passive investor would be able to earn if they purchased an index product at that time and serves as a benchmark. The second point is provided via a reversal of economic data. Upon the first positive CPI data (highest rating data on Bloomberg), the closing price of the same month is used as the entry level for the portfolio strategy (Bilson, Brailsford, and Hooper, 2001; Tripathi and Seth, 2014). This represents a practical application of the strategy and mimics a similar environment to what investors apply in industry. When observing the correlation of movements between macroeconomic leading indicators and equity markets, we find positive correlations such that we can assume that measuring CPI is a proxy for underlying strength of the economy as a signal for investors to buy. In this case, causality can be disregarded, and the focus is on the correlation aspect as purchase timing should be indifferent to investors due to the underlying economy and the market diverging (Tripathi and Seth, 2014).

A divergence between stock movement and economic indicator signifies that any movement beyond that point is an over or under reaction by the market. To simplify, only the headline figures are used for this study and any adjustments or information leakages are not considered. The deviation away from true value is then exploited by this model and an abnormal return should be available in the short run. This short run performance should then translate into a momentum effect that can carry into the long term. United States Consumer Price Index figures are used to judge the underlying inflation rate of the economy. To ensure that the stock market has fallen, the divergence in direction commences after the S&P500 falls outside the 95% price return confidence interval. Hence CPI data from the US Bureau of Labor Statistics from September 2008 onwards is considered for the test. Taking the monthly change in CPI data relative to the S&P500 index monthly returns measured the direction of co-movements of data. If one series is negative, while the other is positive, a divergence has occurred, and a buy signal is generated for this study. The monthly data of the S&P500 index is calculated using the closing data of the last day of each month from the set of daily data obtained prior.

4.3.4 Testing for Long Run Outperformance (13–24 months)

Over the long run, outperformance of the market should be associated with those stocks which overperformed during the fall. Other factors such as the semi-deviation of the stock during the fall is another indicator of the asset's downside risk. The log of the turnover acts as a proxy for the liquidity of the stocks. Finally, following Small minus Big and High minus Low proxies that Fama and French (1993) used for their three-factor model, the size and value effect are proxied directly via the natural log of the market capitalisation and the book to market ratio to assess the impact of the size effect and value effect of the portfolio.

The regression equation is estimated as:

$$r_P - r_M = \alpha_i + \beta R_i + \gamma SemiDev_i + \delta \ln(Turnover)_i + \theta \ln(MktCap)_i + \phi BMR_i + \varepsilon_i \qquad (4.6)$$

Where

$r_P - r_M$: the excessive return of the portfolio

R_i: the overperformance of asset i relative to the benchmark average

$SemiDev_i$: the semi-deviation of asset i

$Turnover_i$: the log of the turnover as a proxy for liquidity of asset *i*

BMR: Book to market ratio.

4.3.5 Testing for Short Run Outperformance (1–12 months)

The following regression analysis for the short run outperformance portfolio is estimated as:

$$r_P - r_M = \alpha_i + \beta(-R_i) + \gamma SemiDev_i + \delta \ln{(Turnover)_i} + \theta \ln(MktCap)_i + \phi BMR_i + \varepsilon_i \quad (4.7)$$

Where

$r_P - r_M$: the excessive return of the portfolio

R_i: the overperformance of asset *i* relative to the benchmark average

$SemiDev_i$: the semi-deviation of asset *i*

$Turnover_i$: the log of the turnover as a proxy for liquidity of asset *i*

BMR: Book to market ratio.

The short run cross-sectional regression analysis is the same as the long run. However, the expected results for the beta are negative as the results assume that stocks which underperform in the short term should recover at a faster rate due to the mean reversion properties of equity prices.

4.3.6 Constructing the Black–Litterman Portfolio

Stocks in the S&P500 index are split into quartiles based on their performance relative to the market. Those that performed extremely poorly and declared bankruptcy during the fall are excluded as investors cannot purchase those regardless. The weights of the top quartile will increase relative to their outperformance of the benchmark during the crash. The weights of the bottom quartile will also increase relative to their underperformance relative to the benchmark. The second and third quartile are not affected. Hence out of the 500 stocks, the top 125 and bottom 125 have their weights adjusted based on their performance statistics.

Similar to Da Silva, Lee, and Pornrojnangkool (2009), further analysis of the portfolio is required beyond the simple Sharpe ratio comparisons. For this study, instead of the information ratio which captures abnormal returns against idiosyncratic risk, the Sortino ratio is used to capture return versus downside risk via the semi-deviation. During the recovery period, a Sharpe ratio analysis considers any upside movements and volatility to be part of the overall risk. However, investors are concerned about losing money more than making money as demonstrated by the myopic loss aversion effect discussed previously.

As mentioned, for the main results based on τ = 0.01, tau is generally considered as the active risk which would asymptotically approach an upper bound as it increases (towards an undiversified portfolio). Hence the value represents a prudent level of risk is allocated towards the portfolio. The active risk is described as:

$$\sigma_A = \sqrt{w'_A \Sigma w_A} \qquad (4.8)$$

A similar cross-sectional regression analysis is conducted, using the following equation, with variables the same as previously described.

$$r_P - r_M = \alpha_i + \beta R_i + \gamma SemiDev_i + \delta \ln{(Turnover)_i} + \theta \ln(MktCap)_i + \phi BMR_i + \varepsilon_i \qquad (4.9)$$

4.4 Results

4.4.1 Summary for Portfolio Returns

The four tables below (Tables 4.2 – 4.5) summarise the general results for the returns and semi-deviation of the portfolios obtained. For both the dot-com bubble as well as the global financial crisis, using the absolute low of the crisis as measured by the S&P500 benchmark provides better returns for all portfolios in the periods following compared to the same portfolios when using CPI divergence figures as an entry point. This holds for both the long run as well as the short run portfolios. However, it should be noted that the bottom quartile outperforms the market index for the 3 months and 6 months consistently, while the top quartile outperforms the market for the 24 months consistently. This demonstrates a strong signal for outperformance over the short and long run periods. Further testing is conducted on the individual factors to determine drivers of the outperformance.

Table 4.2 From peak to trough of the dot-com bubble

	During Crash		3 months After		6 months After		12 months After		18 months After		24 months After	
	Return	**SemiDev**	**Return**	**SemiDev**	**Return**	**SemiDev**	**Return**	**SemiDev**	**Return**	**SemiDev**	**Return**	**SemiDev**
S&P500	-0.47587	0.02225	0.13491	0.01451	0.09777	0.01195	0.28638	0.01427	0.42623	0.01375	0.41335	0.01276
Top Quartile	0.1952	0.0507	0.2053	0.0688	0.2323	0.0747	0.0098	0.0839	0.0457	0.0253	0.3000	0.0196
2nd Quartile	0.1874	0.0478	0.1349	0.0809	0.1944	0.0572	-0.0415	0.0760	-0.0327	0.0421	0.1089	0.0754
3rd Quartile	-0.0973	0.0218	0.1905	0.0949	0.2862	0.0770	0.0189	0.0571	0.0250	0.0768	0.2763	0.0360
Bottom Quartile	-0.6136	0.0307	0.2814	0.0166	0.3558	0.0337	-0.0394	0.0229	0.0710	0.0432	0.4847	0.0563

This table reports the returns and semi-deviation of the S&P500 index, and the component stocks in quartile portfolios based on weight averaged results. These portfolios are tested for performance in the period during the crash, 3 months after, 6 months after, 12 months after, 18 months after and 24 months after the crash. The results are measured from the absolute peak of the S&P500 index to the absolute trough within the time period. The results in the table are combined from the dot-com bubble for the period 1 January 1999 to 31 December 2003.

Table 4.3 From peak to macroeconomic signal in the dot-com bubble

	During Crash		3 months After		6 months After		12 months After		18 months After		24 months After	
	Return	**SemiDev**	**Return**	**SemiDev**	**Return**	**SemiDev**	**Return**	**SemiDev**	**Return**	**SemiDev**	**Return**	**SemiDev**
S&P500	-0.4583	0.0224	0.0581	0.0079	0.0437	0.0115	0.2048	0.0133	0.3393	0.0135	0.3417	0.0127
Top Quartile	0.1762	0.0407	0.1881	0.0413	0.2000	0.0265	0.0095	0.0231	0.0428	0.0249	0.2634	0.0206
2nd Quartile	0.1664	0.0426	0.1151	0.0303	0.1723	0.0601	-0.0390	0.0134	-0.0290	0.0136	0.0939	0.0593
3rd Quartile	-0.0850	0.0093	0.1768	0.0372	0.2767	0.0862	0.0173	0.0175	0.0217	0.0864	0.2420	0.0340
Bottom Quartile	-0.5535	0.0696	0.2575	0.0354	0.3120	0.0836	-0.0381	0.0568	0.0664	0.0753	0.4435	0.0741

This table reports the returns and semi-deviation of the S&P500 index, and the component stocks in quartile portfolios based on weight averaged results. These portfolios are tested for performance in the period during the crash, 3 months after, 6 months after, 12 months after, 18 months after and 24 months after the crash. The results are measured from the absolute peak of the S&P500 index to the absolute trough within the time period. The results in the table are combined from the dot-com bubble for the period 1 January 1999 to 31 December 2003.

Table 4.4 From peak to trough in the global financial crisis

	During Crash		3 months After		6 months After		12 months After		18 months After		24 months After	
	Return	**SemiDev**	**Return**	**SemiDev**	**Return**	**SemiDev**	**Return**	**SemiDev**	**Return**	**SemiDev**	**Return**	**SemiDev**
S&P500	-0.5624	0.0340	0.3757	0.0324	0.4873	0.0232	0.6663	0.0185	0.6163	0.0188	0.9653	0.0189
Top Quartile	0.1642	0.0762	0.1461	0.0752	0.1399	0.0936	0.4020	0.0927	0.8687	0.0901	1.2903	0.0339
2nd Quartile	0.1038	0.0547	0.1187	0.0649	0.1645	0.0758	0.3580	0.0456	0.7012	0.0841	0.8377	0.0580
3rd Quartile	-0.3718	0.0370	0.1175	0.0320	0.1784	0.0189	0.3672	0.0611	0.3786	0.0849	0.4096	0.0630
Bottom Quartile	-0.8679	0.1490	0.1136	0.0989	0.1400	0.0602	0.4727	0.0930	0.4519	0.0496	0.5732	0.0145

This table reports the returns and semi-deviation of the S&P500 index, and the component stocks in quartile portfolios based on weight averaged results. These portfolios are tested for performance in the period during the crash, 3 months after, 6 months after, 12 months after, 18 months after and 24 months after the crash. The results are measured from the absolute peak of the S&P500 index to the absolute trough within the time period. The results in the table are combined from the global financial crisis for the period 1 January 2007 to 31 December 2011.

Table 4.5 From peak to macroeconomic signal in the global financial crisis

	During Crash		3 months After		6 months After		12 months After		18 months After		24 months After	
	Return	**SemiDev**	**Return**	**SemiDev**	**Return**	**SemiDev**	**Return**	**SemiDev**	**Return**	**SemiDev**	**Return**	**SemiDev**
S&P500	-0.4371	0.0328	0.2188	0.0110	0.3024	0.0123	0.2262	0.0181	0.4463	0.0169	0.5286	0.0151
Top Quartile	0.1562	0.0722	0.1417	0.0703	0.1272	0.0824	0.3586	0.0848	0.8340	0.0808	1.1084	0.0289
2nd Quartile	0.0953	0.0473	0.1083	0.0620	0.1505	0.0677	0.3140	0.0397	0.6395	0.0781	0.7765	0.0549
3rd Quartile	-0.3250	0.0320	0.1067	0.0306	0.1552	0.0170	0.3455	0.0553	0.3498	0.0800	0.3957	0.0602
Bottom Quartile	-0.7820	0.1337	0.1078	0.0883	0.1253	0.0569	0.4264	0.0859	0.3859	0.0469	0.5147	0.0124

This table reports the returns and semi-deviation of the S&P500 index, and the component stocks in quartile portfolios based on weight averaged results. These portfolios are tested for performance in the period during the crash, 3 months after, 6 months after, 12 months after, 18 months after and 24 months after the crash. The results are measured from the absolute peak of the S&P500 index to the absolute trough within the time period. The results in the table are combined from the global financial crisis for the period 1 January 2007 to 31 December 2011.

4.4.2 Results for Short Term Contrarian Outperformance

Over the relatively short term periods, the 3-month, 6-month and 12-month portfolio returns of the 125 underperforming stocks all show conclusive results regarding outperformance relative to the benchmark. The results are presented in Table 4.6 using the benchmark index and in Table 4.7 using macroeconomic factors as the entry condition.

Table 4.6 Peak to trough short run regression results

	α	R_i	SemiDev	Turnover	MktCap	BMR	adj. R^2
Dot-com 3m	-0.0373***	0.2332***	-1.0518**	9.8448*	-2.4658***	3.2195***	0.6092
Dot-com 6m	-0.0184***	1.6035**	-0.4692**	7.2812**	-2.2012***	3.4075**	0.6506
Dot-com 12m	-0.0654***	1.5261***	-1.8770**	7.1201*	-1.3928***	3.5754**	0.6184
GFC 3m	0.0152**	1.9215***	-0.3268**	7.9289**	-2.5216**	1.1765***	0.6425
GFC 6m	0.0279***	1.4899***	-0.9040**	9.1738***	-1.5049***	4.2231*	0.6711
GFC 12m	0.0671***	1.7571**	-0.5368**	7.0471**	-1.9725**	2.2789**	0.7292

Significance: * $p<0.05$, ** $p<0.01$, *** $p<0.001$

The table shows the linear relationship between the short term portfolio constructed against the price returns prior to the absolute low, the liquidity factor (in terms of turnover), size effect (log of market capitalisation), and book to market ratio.

The results demonstrated a statistically significant relationship between all abnormal returns generated using this strategy relative to their price movements prior to the collapse. This shows that the abnormal drop during the fall of the market also recovered at a faster rate after the event. Furthermore, it can be observed that there is a positive correlation with liquidity. The higher the liquidity, the higher the abnormal returns generated. Smaller stocks also seemed to perform better. The results are consistent between the absolute low and the low generated via the CPI indicator. The results for the peak to trough tend to be similar between the 6-month and the 12-month periods when compared to the 3-month study period. However, this effect is observed on a lesser scale for the macroeconomic factor. This could indicate that there is a lagging effect of returns even after the benchmark index hits the bottom.

Table 4.7 Peak to macroeconomic short run regression results

	α	R_i	SemiDev	Turnover	MktCap	BMR	adj. R^2
Dot-com 3m	0.0396**	1.6509***	-0.2891**	8.2114**	-1.835***	2.0368***	0.5404
Dot-com 6m	0.0816***	1.5909**	-3.0682**	9.7578***	-1.0261**	2.1494***	0.4673
Dot-com 12m	-0.0604***	0.6759**	-2.4100*	7.2335*	-1.2615*	1.8018**	0.7132
GFC 3m	0.0122***	0.7714***	-0.3062**	7.3502**	-1.7664***	3.0729**	0.6434
GFC 6m	-0.0405***	1.2606**	-1.1867**	9.945***	-1.4594**	1.3633***	0.6713
GFC 12m	-0.0513***	1.3080***	-2.3642*	9.6964***	-1.9279***	1.8826***	0.6572

Significance: * p<0.05, ** p<0.01, *** p<0.001

The table shows the linear relationship between the short term portfolio constructed against the price returns prior to the low indicated by a divergence between macroeconomic factors and the market, the liquidity factor (in terms of turnover), size effect (log of market capitalisation), and book to market ratio.

4.4.3 Results for Long Term Momentum Outperformance

The long term returns over both the 18-month and 24-month periods of the overperforming portfolio of 125 stocks yields positive abnormal returns against the market index. Over the long term periods, 18-month and 24-month portfolio returns of the 125 overperforming stocks are presented in Table 4.8 using the benchmark index and in Table 4.9 using macroeconomic factors as the entry condition.

Table 4.8 Peak to trough long run regression results

	α	R_i	SemiDev	Turnover	MktCap	BMR	adj. R^2
Dot-com 18m	0.064***	1.4708**	-0.9472**	6.3879**	-1.9808***	3.3678***	0.728
Dot-com 24m	-0.0963***	1.4496***	-1.95489**	6.5929**	-2.8816***	1.2386***	0.7177
GFC 18m	0.1325***	0.7361***	-3.1535**	6.659***	-1.8689***	2.8226***	0.6716
GFC 24m	0.0075***	1.7308***	-0.02775**	8.5656**	-1.9751***	1.3416***	0.6741

Significance: * p<0.05, ** p<0.01, *** p<0.001

The table shows the linear relationship between the long term abnormal returns of the long term portfolio constructed against the price returns prior to the absolute low, the liquidity factor (in terms of turnover), size effect (log of market capitalisation), and book to market ratio.

Table 4.9 Peak to macroeconomics long run regression results

	α	R_i	SemiDev	Turnover	MktCap	BMR	adj. R^2
Dot-com 18m	0.144***	1.3661***	-0.3024***	9.2685	-2.7716**	2.5812**	0.7264
Dot-com 24m	0.1065***	1.1774***	-2.2472***	8.3014*	-1.8527***	1.1227***	0.7436
GFC 18m	-0.026**	0.7591***	-0.1872**	9.9486**	-2.3877**	1.5085***	0.7187
GFC 24m	0.0386***	1.7152***	-1.1889***	9.3332*	-1.1313**	3.1912***	0.7973

Significance: * $p<0.05$, ** $p<0.01$, *** $p<0.001$

The table shows the linear relationship between the abnormal returns of the long term portfolio constructed against the price returns prior to the low indicated by a divergence between macroeconomic factors and the market, the liquidity factor (in terms of turnover), size effect (log of market capitalisation), and book to market ratio.

Once again, the results demonstrated a statistically significant relationship between all abnormal returns generated using this strategy. The results demonstrate that stocks which outperformed the benchmark average perform better at the longer scale. Apart from the difference in returns calculation when compared to the short term analysis, all other factors demonstrate similar levels of significance. The effects observed here do not have any noticeable differences between the two testing methods (peak to trough, and peak to indicator). This could be because all short term effects are negligible at these time scales. The lack of noticeable differences would indicate that the long term strategy is not as dependent on entry timing as the short term strategy. However, the difference between testing periods still exists similar to the short term studies. The explanatory power of the models is higher than the short term studies, indicating that the long term effects are stronger. Better performing equity that survives the initial collapse tends to recover better, perhaps due to more adequate capital relative to their worse performing counterparts.

4.4.4 Results for Black–Litterman Model Outperformance

On average, between the two events (dot-com bubble and GFC), with a tau of 0.01, and a one-to-one weighting allocation for the investor views, the Black–Litterman portfolio returns 13.22% above the market index in a 24-month period after entry (where entry is the day after diverging macroeconomic event news). Results for other tau values are presented in Figure 4.1. The cross-sectional regression analysis shows similar results for both the benchmark test as well as the macroeconomic indicator signal test. The regression results are presented in Tables 4.10 and 4.11.

Table 4.10 Peak to trough Black–Litterman regression results

	α	R_i	SemiDev	Turnover	MktCap	BMR	adj. R^2
Dot-com 3m	-0.0528**	0.1113***	-0.5261**	9.2913*	-1.439***	4.657***	0.4548
Dot-com 6m	-0.074***	1.3799***	-0.427**	9.4921**	-2.701**	2.485***	0.5522
Dot-com 12m	0.0926*	1.3114***	-0.2341***	6.0569***	-1.709***	4.828***	0.4326
Dot-com 18m	-0.0812*	0.784***	-0.3319	9.1916*	-2.606***	3.942***	0.4988
Dot-com 24m	0.1056**	1.4095***	-0.1344**	7.8417*	-1.418***	1.7717***	0.5599
GFC 3m	0.047**	0.3659***	-0.9174**	9.4247	-2.176***	5.6857**	0.6491
GFC 6m	0.1397**	1.792***	-0.6681**	8.3987***	-1.492**	4.7714**	0.6878
GFC 12m	0.0028**	0.4392***	-0.1016**	7.4156*	-1.24***	3.2859*	0.4574
GFC 18m	-0.0336***	1.6059**	-0.3089**	9.2431*	-1.209***	4.8142**	0.4597
GFC 24m	0.0685*	0.2352***	-0.6205**	7.3388**	-1.112***	4.3285***	0.5237

Significance: * p<0.05, ** p<0.01, *** p<0.001

The above regression shows the Black–Litterman model portfolio in terms of the benchmark test for both the dot-com bubble and the global financial crisis across all five tested time periods. There is a high level of significance in almost every aspect.

Table 4.11 Peak to macroeconomics Black–Litterman regression results

	α	R_i	SemiDev	Turnover	MktCap	BMR	adj. R^2
Dot-com 3m	0.1268**	1.6042***	-0.1483**	7.443*	-1.2684***	5.7142***	0.4698
Dot-com 6m	0.1099**	1.8223**	-0.2504**	7.5978*	-2.8734***	4.2571***	0.4537
Dot-com 12m	-0.0211***	0.8995*	-0.0095*	6.9205*	-1.132**	6.1571**	0.6182
Dot-com 18m	-0.0716**	1.3862**	-0.1320**	8.8428*	-1.0332**	4.7285***	0.4351
Dot-com 24m	0.0058*	0.4814***	-0.0018***	7.6922*	-1.081***	2.2714***	0.7061
GFC 3m	-0.1023*	1.6889***	-0.0265**	7.6156*	-2.6965**	2.8428*	0.5678
GFC 6m	-0.1091**	0.557*	-0.3924**	7.3433*	-1.765***	4.8142**	0.7013
GFC 12m	-0.0569**	0.6174***	-0.0224**	7.3904*	-1.7198***	1.6142***	0.4308
GFC 18m	-0.0487***	1.9505***	-0.0166**	8.4578*	-2.067***	3.1233**	0.6096
GFC 24m	0.0016***	1.052*	-0.0004***	8.7702*	-1.092***	3.4285***	0.6039

Significance: * p<0.05, ** p<0.01, *** p<0.001

The above regression shows the Black–Litterman model portfolio in terms of the macroeconomic signal test for both the dot-com bubble and the global financial crisis across all five tested time periods. There is a high level of significance in almost every aspect.

As investors' uncertainty increases, the variance of their views increases, with the aggregated uncertainty in investor views expressed through Ω. The x-axis in Figure 4.1 shows the uncertainty in investor views. The higher the standard deviation, the higher the deviance. This in conjunction with the level of market efficiency that is assumed through the tau value influences the final portfolio differently, mainly through the explicit weight allocations. As seen in Figure 4.1, the level of outperformance increases as market efficiency decrease (Allaj, 2013). Furthermore, the higher the level of certainty investors have in their views (in this case of the hypothesis), the higher the returns. However, when the level of uncertainty is sufficiently high, the model's weight allocation towards investor views decreases significantly which results in the performance of the portfolios converging as sigma increases, regardless of the level of market efficiency.

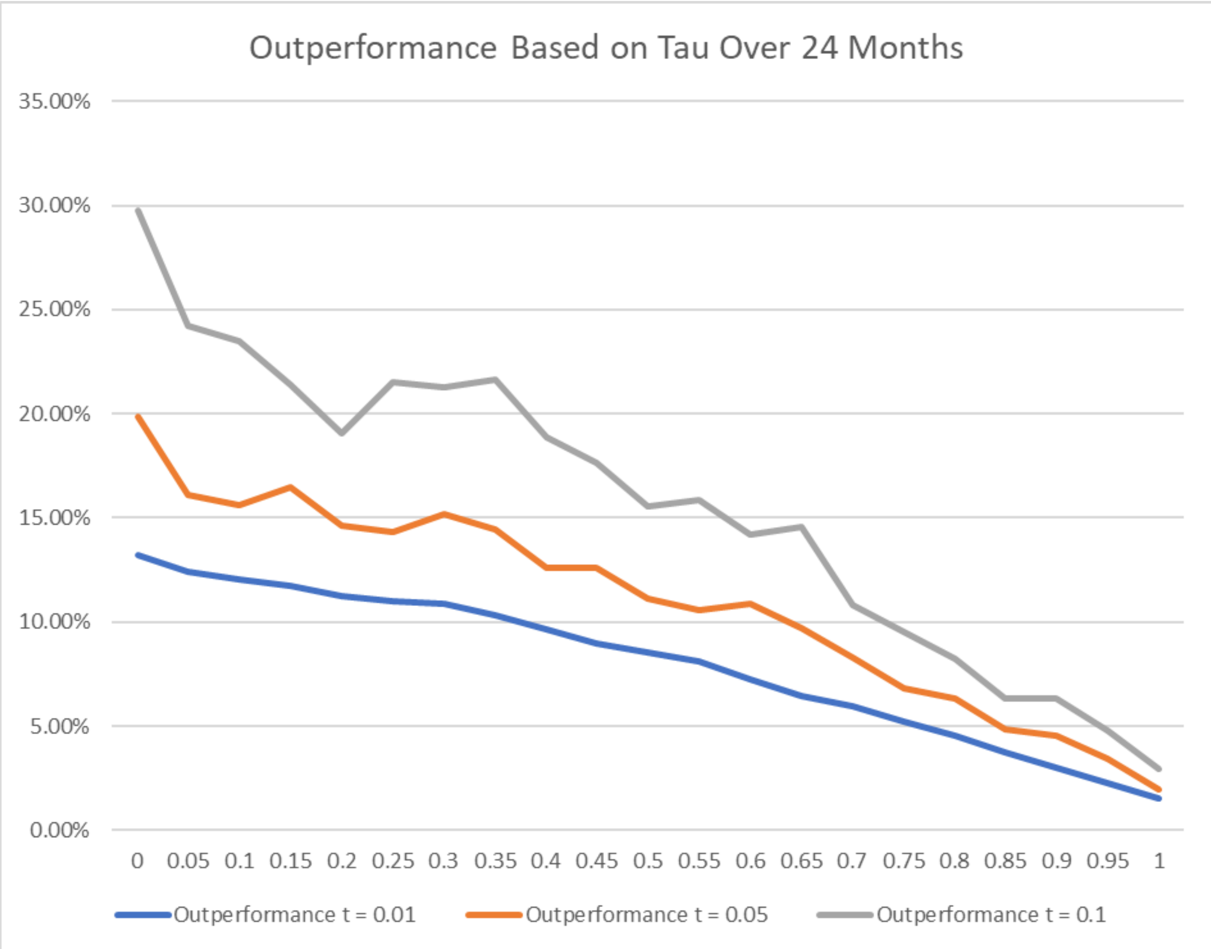


Figure 4.1 One-to-one performance view adjustment Black–Litterman portfolio returns

The figure shows the results of the Black–Litterman portfolio's outperformance against the S&P500 index benchmark returns over the same time period for different levels of expectation in tau. The higher the tau value, the higher the risk investors are willing to undertake. However, as demonstrated, even a tau of 0.05 may result in a non-monotonic line when measured against the level of confidence (sigma) of the investor view (omega).

A high level of correlation is evident across all factors over all time periods. To adjust for the market capitalisation and the book to market ratio effects of each composite stock, log of market capitalisation and book to market ratio factors are taken (Fama and French, 1992). The adjusted explanatory powers are sufficiently high across all time periods and show no significant difference between the benchmark test and the macroeconomic signal entry test. There is also a sizable difference between the adjusted R-squared value for this portfolio relative to the market weight adjusted quartile portfolios earlier. The decrease in explanatory power arises from the increase in stocks that do not offer any additional benefits other than diversification of total risk. However, as the assessment of return is based on downside risk, the explanatory power is expected to decrease. Furthermore, as expected, the performance factors all demonstrate a positive correlation, while the downside risk factors all correlate negatively. This means that the relative over and underperformance of the composite stocks is used as a measure of overperformance during the recovery period. Furthermore, the Sortino ratio is used to assess the risk of the portfolio immediately after executing the purchase. As the outperformance is measured relative to the S&P500 index, it demonstrates that the portfolio generated contains lower downside risk relative to the market during the recovery period.

For tables 4.6 to 4.11, negative alphas are observed in many results with high levels of significance. This indicates that other influential risk factors have not been included in this study that may affect the performance of the constructed portfolios. Managerial styles and performance could be one such factor. A difference in management performance could be tested as key factors in future studies.

Special Note: September 11 Attack and the Dot-Com Bubble Recovery

The September 11 terrorist attack on the World Trade Centre in New York City in 2001 yielded only a temporary shock to the market. The effect of the attack was a 14.8% drop in the S&P500 index for the week of 11 September, which recovered within 2 weeks by 30 September. As the attack was during a period of downturn, it is difficult to attribute the effect of any losses from the attack towards any results in the recovery period. Thus, any concluding remarks disregard the impact of this event.

4.5 Conclusion

This chapter demonstrates that excess returns can be generated by exploiting violations of market efficiency during periods of abnormal market stress. It aims to provide insight into anomalies that arise from the efficient market hypothesis, such as momentum and long term reversal effects. This study does not claim that the strategies used are always effective in active portfolio management. Instead, it could be applied in risk management to anticipate possible pitfalls in the short lapse of market efficiency. Using daily data from the S&P500 component stocks, and measuring them against various indices during volatile periods, it also demonstrates how to maximise risk–return in different post-crisis scenarios, thereby minimising market risk. If implemented as an active trading strategy, additional dynamic portfolio management strategies are advised, and more sophisticated econometric methodologies should be employed. It should also be noted that there is a limit to liquidity in the general market, and any trading strategies that are large enough to severely affect the microstructure should avoid using this as a risk management tool or trading guideline. Price and market impact were not considered in this thesis and should be assessed in future studies.

It is demonstrated that a portfolio can outperform the market in the short term with a consistent strategy of asset allocation in a long only portfolio. Furthermore, this study shows that using economic indicators as a sign of recovery during a post-crisis scenario is an effective method of bottom picking for portfolio managers. When examining the individual components of a portfolio comprised only of index assets, idiosyncratic risk market overreaction plays a major role in outperforming the market benchmark. The companies that experienced the largest percentage drops but did not fall out of the index performed the best in the 6-month and 12-month recovery periods. This holds when using the absolute low as well as economic indicators as a sign of entry. Over longer terms, it appears that market sentiment is towards companies that are perceived as more reliable or resilient, and hence fall the least, and perform better. However, this only holds after excluding equity from traditional defensive sectors (such as utilities, healthcare, and consumer staples). In terms of volatility, there is little difference between stocks in the same time periods before and after the collapse. However, when only considering the semi-deviation, it is shown that there are less downside movements for underperforming equity during the recovery period.

Finally, the results suggest that a portfolio manager could maximise return for downside risk by manipulating the exposure in a long only portfolio in a post-crisis environment. It also demonstrates that the long run reversion effect occurs on a faster time scale in a post-crisis scenario, with the usual time period of 3 to 5 years shortening to approximately 12 months. This could be due to the abundance of investors buying what they perceive as cheaper stocks, and inadvertently taking advantage of the overreaction that occurred. This suggests that although the reversion may cause similar effects, the underlying reasons for the effects are different. This conclusion is further justified by the selection of economic indicators for the entry point as any divergence among equity performance and the indicators signify further overreactions and hence further mispricing.

This study does not take into consideration transaction costs and taxes. Furthermore, it is mainly for funds, or those with sufficient capital, that can buy a large range of stocks across an entire market. This particular property makes it difficult for those with little capital to execute the strategy. As large amounts of capital enter the market, especially in a period of poor liquidity such as after a recent crash, transaction costs that arise from a lack of liquidity due to lower market depth should also be considered in further studies to assess the feasibility of the portfolio in a trading scenario. This is especially true as the commonality of liquidity is a serious issue during the recovery period after a crash.

Chapter 5: Circuit Breaking the Market: Arbitraging Regulatory Restrictions

5.1 Introduction

This chapter studies traditional arbitrage strategies and applies them to scenarios where market inefficiencies are artificially created by regulatory environments. These inefficiencies are demonstrated by mispricing between assets and their respective derivative products, in this case, equities and convertible bonds. In China, most equities are bound by a trading price limit, while their convertible bonds are not. This means that when new information arrives, the market reacts differently as the equity market is restricted from trading once the limit is reached. To advance current understanding, this study focuses on the distribution of maximum price range of stocks and how this affects propensity to generate risk-free returns. The literature relevant to this chapter was discussed in Section 2.3. In this chapter, Section 5.2 describes the data and model used, Section 5.3 discusses the hypotheses and the methodology, Section 5.4 analyses the results, and Section 5.5 provides a summary and concludes.

5.2 Data and Model

Daily open, high, low, close (OHLC) price data is collected from Bloomberg for the Shanghai Shenzhen China Composite 300 component stocks (CSI300) over a 7-year period between 1 January 2012 and 31 December 2018. The data is aggregated to find the largest intraday price range by finding the maximum of the absolute value between the previous day's closing price and the current day's high and low. The corresponding 197 convertible bonds (full set) are observed over the same sample period. The individual properties of each are reported in the Appendix (Table A.7). This data sample period is selected based on all available data across the set in Bloomberg at the time of study.

Convertible bonds are embedded with properties that affect the bond's price or conversion limits based on the valuation of the bond. The value of the bond itself depends on the underlying stock price movements and the parameters of the conversion terms. From issue, the buyer of a

Chinese convertible bond takes on the risk of price movements and hence gambles for an upside as time progresses. The issuer, on the other hand, wishes for the lowest possible conversion price when the buyers wish to exercise the bonds' call option. Hence the convertible bond itself must not be priced lower than the conversion value. If this does not hold true, then investors would immediately convert bonds into stocks and make a profit. Thus, call provisions are placed by issuers. For example, the call provision of the China Everbright Bank Co. Ltd states:

> *"In 30 consecutive trading days, the closing stock price is not less than 130% of the conversion price in 15 trading days. The firm has the option to call the bond at the face value of the bond plus the current accrued interest."*

This is logical as the call price in the above scenario would be lower than that of the conversion value, and hence the firm would call the bonds. When the bond is called, the holders must elect to convert the bonds into stocks, and the value of the convertible bond must be the convertible value. There are four convertible bonds that hold the 'convertible/call' maturity type as opposed to the usual 'convertible'. The main distinction is that 'convertible/call' types, also known as callable bonds, is the party that can legally enforce the conversion of the bond. The issuing firm decides when to call the 'convertible/call' bonds and provide a window of time where such actions should be taken. The regular 'convertible' bonds have the bond holders decide when to convert the bond.

5.2.1 Data Summary

Table A.7 in the Appendix presents the precise data of the convertible bonds and their conversion and issue prices. A summary of the data is shown in Table 5.1.

Table 5.1 Convertible bond summary

	Observations	Mean Coupon	Standard Deviation Coupon	Mean Difference	Standard Deviation Difference
Convertible Bonds	197	0.7467	0.901	2.97665	6.394501

Table 5.1 shows the average and standard deviation of 197 convertible securities over the study period between 1 January 2012 and 31 December 2018. The 'Mean Difference' and 'Standard Deviation Difference' are derived from the difference between the issue price of the convertible bond and the conversion price at the time of the study.

The summary shows that, on average, the convertible bonds decrease in value relative to the conversion price at issuance over the time period examined in this study as the mean difference is positive. There is a notable impact from this decrease in value which is accounted for in the calculations via the options element of the convertible bond.

5.2.2 The Model

The proposed model converts the value of convertible bonds at time t with maturity T into the equity component (by valuing it as an option of the underlying stock) and the standard bond component with similar characteristics as the convertible bond (Carayannopolous and Kalimipalli, 2003).

$$P_{CB}(t) = B_{CB}(t) + O_{CB}(t) \qquad (5.1)$$

Where P is the price of the convertible bond, B is the bond pricing aspect, and O is the imbedded options aspect.

By treating a convertible bond as a combination of a basic bond with coupon C that expires at time T; and a call (or put for put convertibles) option with strike price X that has the same expiry, an arbitrage can be obtained by assessing the value of the bond and option individually. The option is broken down into the intrinsic value and time value. The focus is on the intrinsic value of the bond. The focus is a simple one period discrete price action and hence using the binomial model is a better fit than traditional models such as the Black–Scholes–Merton model (Calamos, 2003). However, as the prices are all given, there is no need to calculate the option value; only the intrinsic value component needs to be derived. Furthermore, as the study is a one period analysis of price movements, the time value of the option component is assumed to be constant when the hedge is being held overnight. The intrinsic value is calculated as:

$$Intrinsic\ Value_{CB}(t) = \max\{0, X - S_t\} \qquad (5.2)$$

As seen, the intrinsic value is simply defined as the greater of values between zero and the difference between the strike price and the underlying stock price at time t.

5.2.3 The Arbitrage Process

When executing an arbitrage trade in Chinese markets, a trader may take advantage of the price limits that could prevent information from flowing in an effective manner and execute a long short strategy in the markets. Given a large institutional trader who has a book of the underlying market (CSI component stocks and their respective convertible bonds), the trader should purchase the stock when it hits the upper price range limit, and simultaneously short sell the corresponding convertible bond. Similarly, when the stock hits the lower price range limit, the trader should short sell the stock and purchase the corresponding convertible bond. This simple strategy forms the basis of the arbitrage trading. The initial assessment is performed under a perfect market paradigm. Tax and transaction costs, and liquidity analysis, are conducted separately.

In live trading environments, if a stock hits the upper price limit, it is improbable that a buyer can purchase at that price as it would involve another market participant selling down. It would also be impossible for a trader to buy up as the price has already triggered the trading limit. For a trading strategy to be risk free, and therefore be an arbitrage, the buying and selling of the stock must be simultaneous and occur immediately before the price hits the price limit. This requires mispricing to occur prior to the triggering of the price limit and for the breaker to be triggered by the trader.

Compared to traditional arbitrage models for convertible bonds, the details involved in real trading prove more difficult to overcome. Hence the only realistic assumption in this study is the T+1 trading limit that China imposes on the equity market. This also simplifies the model immensely as it only requires the calculation of a one period discrete return distribution to be made and many continuous time and stochastic assumptions can be ignored.

5.3 Hypothesis and Testing

H5-1*: The maximum price action movement range of stocks should be bimodal to reflect the difference between market sentiments with the anti-mode near zero.*

Rather than investigating the daily return distribution, it is more meaningful to gain insight into the maximum price movement range of equity trading under a price limit paradigm. This means that when measuring the movement of convertible bonds, it is insufficient to use a normal distribution when pricing the risk and return. This is because only the extremities are of interest when conducting the arbitrage strategy.

The kurtosis of the distribution should be leptokurtic and thus also demonstrate the propensity to hit the trigger of the price limit like the magnet effect. This implies that the magnet effect and spill over effect are detected simply by observing the tail end distributions of extreme movements. This also allows traders to detect whether arbitrage opportunities exist in the market as if price limits reduce volatility and information loss to a high degree, then there should be no observable increase in the tail ends. As the price limit circuit breaker triggers at 10% but maintains the ability for market participants to continue trading if they do not exceed the 10% mark, this allows us to capture every stock that has been in a price limit trigger event even if only for a fraction of a moment. The formula used is as below:

$$S(t+1) = \left(\frac{|H_{t+1}|}{C_t} > \frac{|L_{t+1}|}{C_t} \rightarrow \frac{H_{t+1}}{C_t}\right) \vee \left(\frac{|H_{t+1}|}{C_t} < \frac{|L_{t+1}|}{C_t} \rightarrow \frac{L_{t+1}}{C_t}\right) \tag{5.3}$$

Where

S_{t+1}: The stock price for time t+1

H_{t+1}: The intraday high price for time t+1

L_{t+1}: The intraday low price for time t+1

C_t : The closing price for time t.

Hence the function describes the largest absolute price range in any given day. The third and fourth moments are calculated as:

$$Skewness = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{r_i - \bar{r}}{\sigma}\right)^3 \qquad (5.4)$$

$$Kurtosis = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{r_i - \bar{r}}{\sigma}\right)^4 \qquad (5.5)$$

Where

r_i : i-th observation

$\bar{r}$: the mean

σ : the standard deviation

N : the number of observations.

H5-2*: The long–short convertible bond arbitrage strategy should yield an abnormal positive return.*

Convertible bonds demonstrate properties of both bonds and options (Carayannopolous and Kalimipalli, 2003). Hence price movements when beyond the 'strike price' should be similar to a call option. Theoretically, the price should follow equation 5.1.

Using this, a delta hedging strategy can be used to generate an arbitrage when mispricing occurs due to price limit restrictions on the underlying stock. The expected result should be that the risk-free returns generated by the arbitrage strategy should yield a higher return than the risk-free rate as investors could otherwise simply invest in the risk-free product. Hence the results could be reflected as below:

$$CA(i) = \left(r_{CB_i} - r_{S_i}\right) - r_f > 0 \qquad (5.7)$$

The equation shows that the return generated from the convertible bond arbitrage strategy for asset *i* should be greater than the risk-free rate. Furthermore, the relations of the arbitrage returns can be shown in the regression equation below:

$$CA = \alpha + \beta_1(|\sigma_S - \sigma_{CB}|) + \beta_2\kappa_S + \beta_3R_M + \beta_4R_{CBM} + \beta_5\Delta_{CB} + \beta_6\Gamma_{CB} + \beta_7\ln(Turnover_S + Turnover_{CB}) + \epsilon \quad (5.8)$$

Where

σ_s: standard deviation of the underlying stock's distribution

σ_{CB}: standard deviation of the convertible bond's distribution

κ_S: kurtosis of the underlying stock's distribution of price extremities

R_M: market premium (CSI300)

R_{CB}: mean China convertible bond index premium

Δ_{CB}: delta of the convertible bond's distribution

Γ_{CB}: gamma of the underlying stock's distribution of price extremities

r_f: risk free returns.

The propensity to hit the tail end of the bimodal distribution should be proportional to the amount that the arbitrage strategy could earn. It indicates that the price limits are actively preventing the process of price discovery. Convertible bonds that are not subjected to the price limit restrictions would provide the basis of the arbitrage if liquidity is present for such trade. It also postulates that the higher the relative difference is between the volatility of the underlying equity and the volatility of the convertible bond, the more likely convertible arbitrage exists. The third and fourth factors are standardised against their mean returns to remove the issue of multicollinearity of data. As the price movement of convertible bonds is highly dependent on the underlying stocks, it should follow that the convertible bond index should closely follow the equity index. Furthermore, a variance inflation factors (VIF) test is also applied to check for any collinearity among factors after the regression is estimated.

An increase in liquidity, gamma and volatility will promote the ability for arbitrageurs to profit from this trading strategy. An increase in liquidity should increase the likelihood for arbitrage. This may seem counterintuitive, but any increase in liquidity would mean that there should be an accurate pricing for the convertible bond products while the underlying equity is restricted by the price range of the trading limits. As mentioned by Calamos (2003), investors have several criteria when assessing whether the situation is suitable for a convertible arbitrage strategy. Liquidity, transaction costs, volatility and gamma are all key variables that investors should consider. Equation 5.8 is used to assess these variables and determine their effects on the return of the long–short equity convertible bond arbitrage strategy.

The logic of the trading strategy can be summarised as below in just two steps assuming that liquidity and short selling allocations are met:

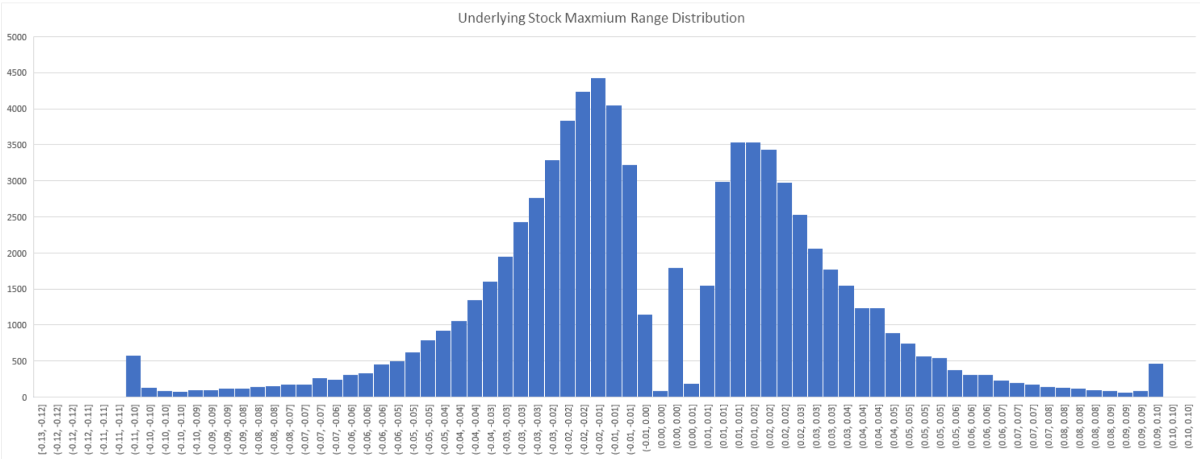
1. If a stock hit the price limit, check for price movement of convertible bond
2. If convertible bond pricing does not reflect a similar magnitude price shift as the underlying stock, then the 'pair trade' takes place where the trader buys the 'undervalued' and sells the 'overvalued' asset

This benefits from the price limit as changes in pricing from the underlying equity can only move in one direction. Furthermore, the magnet effect is likely to cause the pricing discrepancies while possible spill over volatility hopefully remains in the convertible bond pricing.

5.4 Results

Initial assessment of the data shows a bimodal distribution of the daily min–max price range. There is an observable sharp increase at the tail ends (10% and –10%) which supports previous evidence and literature. An initial visual assessment shows obvious results (Figure 5.1). Mathematically, to test for the abnormal increase in the tail end, the distribution is observed as two overlapping normal distributions. Hence the bimodal distribution acts normally when considering the tail ends. The increase in concentration at the extremities outweighs the cumulative density of the tail ends of a Gaussian distribution, thus proving the leptokurtic property of the daily extreme return distribution.

Figure 5.1 Min–Max return distribution of CSI300



The figure shows the distribution of all maximum price movements of underlying stocks of convertible bonds on the Shanghai and Shenzhen Stock Exchange.

Pearson (1916) shows that for any bimodal distribution, if the difference between the kurtosis and the square of the skewness is greater than one, it can be split into two normal distributions provided that $b_2 - b_1 \geq 1$. Hence in this case, we can observe that the tail-end price return distributions allow for statistical arbitrage to occur. Table 5.2 presents summary statistics.

Table 5.2 Summary statistics of maximum range distribution

	Observations	Mean	Standard Deviation	Skewness	Kurtosis
Bimodal Distribution	92,800	-0.0028	0.0331	-0.0691	3.5817
Left Distribution	59,364	-0.0266	0.0203	-1.7386	6.5875
Right Distribution	33,436	0.0276	0.0181	1.5968	5.7806

The distributions show that the bimodal distribution could be observed as a combination of two normal distributions. Hence the kurtosis and tail-end price return behaviour could be applied in a statistical arbitrage that takes advantage of such regulatory difference.

5.4.1 Strategy Results

Using a strategy that takes advantage of the magnet effect (Ackert et al., 2001), where the price is purposefully pushed towards the price limit, the investor assumes a buy or sell on the underlying stock depending on its relative distance to the price limits, and the opposite direction trade is hedged using a convertible bond. The second strategy is when the inherent mispricing is greater than 10% when comparing the intrinsic value element of a convertible relative to its underlying counterpart, a long–short strategy can be used. By taking the rule of buying the cheaper of the two and selling the more expensive, the summary for the trades is in Table 5.3.

Table 5.3 Convertible arbitrage strategy return summary

	Observations	Mean	Standard Deviation	Min	Max
Strategy 1 CA(i)	398	0.036042	0.020056	0.01	0.0691
Strategy 2 CA(i)	136	0.011454	0.006921	0.01	0.0233

The table summarises the returns for executing strategies 1 and 2. Strategy 1 describes the outcomes of the strategy that takes advantage of the magnet effect. Strategy 2 describes the outcomes of the strategy that only enters a position if the price limit has been triggered and an even larger move occurs on the convertible bond.

The results demonstrates that both strategies make an abnormal return. The mean return demonstrates the return over the risk-free rate that each trade generates. While there are small variations in the returns generated, this was caused by different levels of mispricing in the convertible bonds and no drawdowns were observed. From the result statistics, this study concludes that strategy 1 generates a greater return by taking advantage of the magnet effect of price limits (Chen, Gao, Jiang, and Xiong, 2018). Large investors purposefully push up the price, resulting in a higher return for arbitrageurs. There is also a fault with the second strategy where it relies on the intrinsic value of the convertible bond to exceed the underlying stock by a further 10% (in either direction depending on the long or short of the underlying stock). This means a 20% move in one day which is quite rare, with only 136 observations across 7 years.

However, this strategy is easily automated via algorithms should there be sufficient liquidity for borrowing and lending of bonds and/or stocks.

5.4.2 The Intrinsic Value of Convertible Bonds and Mispricing

When the face value of the convertible bond is removed from the price, only the options component remains. This is further split into the intrinsic or underlying value of the option, and its time value. The intrinsic value is found once standardised against the number of stocks callable for each bond. The assumption is that in the short run, the time value component will not change (on an intraday level). Results of the OLS regression analysis of convertible arbitrage strategies when combining the two strategies are presented in Table 5.4.

As predicted, there is highly significant correlation among the difference of volatility of the underlying stock against its convertible bond counterpart, along with the kurtosis of the stock's maximum price movements. As is well studied, volatility increases the pricing of options (apparent in the Black–Scholes–Merton option pricing model, for example) and hence increases the likelihood of arbitrage opportunities when the underlying stock return is being limited by price limits. The largely leptokurtic nature of the underlying stocks' maximum daily price range means that when calculating the price of the convertible bond (which assumes a normal distribution of returns), statistical arbitrage will exist. It is interesting that the convertible risk premium does not show significant results, while the market risk premium of 6.95% demonstrates extremely positive results.

Table 5.4 Convertible arbitrage combined strategy regression results

	Coefficients	Standard Error	t Stat	P-value
Intercept	-5.4073	0.4835	-11.1820	6E-20
Risk Deviance	0.3145	0.0729	4.3113	3.51E-05
Kurtosis	1.4611	0.1952	7.4826	1.77E-11
Market Risk Premium	0.0695	0.0132	5.2736	6.59E-07
Convertible Risk Premium	1.2559	0.8653	1.4514	0.1495
Delta	0.2256	0.1175	1.9200	0.0574
Gamma	-0.5332	0.0529	-10.0705	2.26E-17
Liquidity	-0.0645	0.0413	-1.5585	0.1219

The table describes the OLS regression statistics for the convertible arbitrage. The adjusted R square statistic is 64.69% and the F-probability is 0 (4 significant figures).

Against expectations, the liquidity factor shows a negative correlation (Calamos, 2003). This can largely be explained by how liquidity promotes a higher rate of market efficiency and hence should demonstrate arbitrage opportunities becoming apparent only in low liquidity circumstances. However, this result does not yield significance (even at the 10% level) and should only be used as a reference. It is also interesting to note that the delta coefficient is positive, while the convertible arbitrage strategy's relationship with the gamma of the convertible bonds is negative. This means that there should be an upper limit to the level of market overreaction as the amount of return obtainable from the arbitrage will begin to drop as the option component of the convertible bond moves further in-the-money or out-of-the-money.

Observations of the individual OLS regressions for each strategy are presented in Table 5.5. As the table demonstrates, the key elements and significance all somewhat match the combined results.

Table 5.5 Convertible arbitrage strategy individual regression results

	α	$\lvert\sigma_{CB}-\sigma_S\rvert$	κ	R_M	R_{CB}	Δ	Γ	Liq	$adj.R^2$
Strategy 1	-4.71***	0.553***	1.881***	0.015**	2.331**	0.345*	-0.736***	-0.123	0.698
	(-7.33)	(3.94)	(6.65)	(2.01)	(1.99)	(1.70)	(-12.1)	(-1.60)	
Strategy 2	-5.05***	0.135**	1.116***	0.123***	1.34	0.119**	-0.387***	-0.055	0.577
	(-8.62)	(2.11)	(8.14)	(6.83)	(0.44)	(1.99)	(-9.56)	(-1.33)	

Significance: * p<0.05, ** p<0.01, *** p<0.001

This table describes the OLS regression statistics for the convertible arbitrage. Strategy 1 is where the trader takes advantage of the magnet effect of price limits. Strategy 2 takes advantage of the tail-end mispricing caused by the price limit. Figures in parentheses are the t-statistics of each corresponding factor. The factors are the difference between volatility, kurtosis, risk premium of the equity and convertible bond market, delta and gamma of the convertible bond, and the liquidity.

The results show that both strategies are significantly affected by the difference between the volatility of the convertible bond and underlying stock. This is an intuitive result as the theoretical price of the convertible bond assumes a normally distributed return series of the underlying stock. The higher the difference in volatility, the more likely these strategies will make an abnormal return. The normal distribution pricing method also leads to the significant correlation with the kurtosis. The difference in tail-end distribution of return is caused by the price limits boundaries in the underlying equity but not the convertible bond. This causes cases where information is incorporated into the pricing of the convertible bond earlier than the equity. Thus, a statistical arbitrage[9] could be generated. The negative alpha values in both Tables 5.4 and 5.5 indicate a loss after adjusting for risk factors. This demonstrates that there are other factors that affects the arbitrage returns unaccounted for in this thesis that should be evaluated in further studies.

The risk premiums of the market return and the convertible bond market return showed less significance in general, with the convertible bond premium showing no significance for strategy 2. Furthermore, the coefficients show that the performance of the arbitrage is more likely to be correlated with how well the convertible bond market does rather than the underlying equity market. Similarly, the delta and gamma also showed low values. Lastly, the liquidity does not seem to demonstrate any significant effects in either strategy. The explanatory power of the strategies is sufficiently high to pursue further studies once the liquidity and borrowing constraint can be resolved.

5.4.3 Robustness Check

As the convertible bond prices are derived from the underlying stock prices, there is a potential for multicollinearity within the factors for the market premium of the stock market and the market premium of the convertible bond market. An analysis of the variance inflation factors

[9] Statistical arbitrage differs from true arbitrage in that their profits are not guaranteed. They can be defined by an econometrics where the profit is to be made in a market neutral portfolio.

(VIF) was conducted to test for multicollinearity. This method ensures that the explanatory power remains unchanged while preventing erroneous results in the p-values. To solve the issue of multicollinearity, all factors are standardised by deducting the mean values of each respective factor. The VIF results after standardising against the respective means are presented in Table 5.6. The results are considered as acceptable as the Mean VIF is under the value of 5.

Table 5.6 Variance inflation factors

	VIF	***1/VIF***
Risk Deviance	1.14	0.8772
Kurtosis	2.47	0.4049
Market Risk Premium	3.62	0.2762
Convertible Risk Premium	3.55	0.2817
Delta	1.57	0.6369
Gamma	1.11	0.9009
Liquidity	2.63	0.3802
Mean VIF	***2.2986***	

The variance inflation factor (VIF) is a test for collinearity factors. If there is a high level of collinearity, any regression results that use the factors together cannot be said to be robust. The results show that multicollinearity is not an issue among the factors as they are all below 5.

5.5 Summary

This study provides a workable strategy for convertible arbitrageurs to take advantage of mispricing caused by market regulations in China. A role of price limits in the equity space is postulated to be able to create enough mispricing relative to the convertible bond market to allow such arbitrage to exist. By analysing the maximum movements of the underlying stock, this study enables investors to predict the propensity of a stock hitting the price limit. The propensity to hit price limits also correlates positively with the arbitrage opportunities and risk-free returns generated. The results show that there is an opportunity for arbitrage when investors seek opportunities in the convertible bond market to take advantage of the price limit trading restrictions on the underlying stock exchange in local Chinese markets.

The results presented demonstrate that mispricing that occurs due to the spill over effect of the price limit can be used in two different strategies. The first requires the convertible bond price movements to lead the underlying equity movement while the second requires the convertible bond price movements to lag the underlying equity. By splitting the convertible bond into a basic bond component and a call option component (as put convertibles are not considered in this study), the intrinsic value of each option component is calculated. As the underlying equity of the convertible securities are the largest in China, over the short term, any credit risk and default risk is assumed to be zero. By calculating the intrinsic value of the call option component, any apparent mispricing is obtained and used by arbitrageurs for their profit.

The first strategy involves trading with the intraday magnet effect of the underlying security by buying up or selling down toward the price limit while simultaneously trading in the opposite direction for the convertible security. This relies on simultaneous execution of trades to exploit the mispricing. The second strategy involves the convertible bond's option component's intrinsic value moving more than 20% (i.e. 2 days' worth of maximum movement). This means that the arbitrageur can potentially buy or sell the convertible bond today and collapse the position the next day with the underlying and create a delta hedge strategy to eliminate the underlying volatility. This strategy also applies when the underlying hits the price limit first and the intrinsic value of the convertible bond does not move by 10%. The first strategy demonstrates an ability to earn an average of 3.60% above risk-free returns (based on Chinese 10-year government bond yields), whereas the second strategy yields an average of 1.15% return above risk-free rates. However, it should be noted that the second strategy is more common than the first.

This study documents these arbitrage opportunities and demonstrates how convertible securities in emerging markets behave in an environment that restricts the maximum movements of securities. It also documents potential loopholes in the market microstructure when applying circuit breakers (price limits in particular) in one market without any restrictions in their derivative counterparts. Strong evidence of arbitrage opportunity is presented in this study. A variety of robustness checks for controlling potential endogeneity of the trading strategies yields similar results. It should be noted that security borrowing and lending facilities in China does exist but are difficult to access for retail traders. Facilities outside of China also offers this product (CIMB for example offers lending on the CSI300 but none of their clients currently employ this strategy). Liquidity data of convertible bonds should also be investigated in further studies that aims to verify this strategy. Other areas of interest are the structural mispricing in the bond-equity markets and how these mispricing may arise from regulatory effects.

Chapter 6: Conclusion

This study examines new uses for traditional financial analysis techniques. As market turmoil increases in modern times so does the need for innovation in techniques for analysis. It also calls for traditional analysis or modelling techniques to be used in new areas as the market evolves. As the techniques discussed in this thesis is all studied and tested by both industry and academia, these techniques can be applied swiftly in new contexts and situations.

In Chapter 2, the literature review provided links between different subjects and established the gaps in research for the thesis to study. The first section reviewed links for order book depth, liquidity and current applications of technical analysis. Furthermore, it established the context of an efficient market and thus the framework of how technical analysis can exist under such a market. It demonstrated via the scopes of changes in the limit order book how technical analysis can be used to anticipate changes in liquidity and market microstructure.

The second element of the literature review described the correlation between the equity space and macroeconomic factors. It linked evidence of using macroeconomic indicators as a leading indicator for equity performance with evidence for generating abnormal returns by assuming market inefficiencies surrounding times of financial crisis. The Black–Litterman model is used to generate the portfolio that would combine short run and long run effects such that the portfolio would minimise costs associated with changing the portfolio structure.

The final element of the literature review discussed arbitrage opportunities by exploiting regulatory differences between the equity and convertible bond market in the Chinese market. It explored the use of convertible bonds and the increase in liquidity in recent years in the Chinese market. Furthermore, it investigated different price range limits in stock markets and their effectiveness in reducing volatility at the cost of market efficiency. It described how this may cause an increase in inefficiency which is a possible source of arbitrage.

Chapter 3 demonstrated the use of technical analysis as a tool to reduce transaction costs in the market. Arguments that technical analysis cannot generate excess return and therefore remains useless in an efficient market rely on the idea that it can only be used as an asset pricing technique. Technical analysis does not necessarily need to generate abnormal return to be useful. As shown in this thesis, it can be used to predict non-price related movements that may not generate return but provide additional value to trading. Linking the relationships between technical analysis and liquidity, and liquidity and transaction costs, helps to explain why there is a prevalent use of technical analysis despite the consensus within academia that the market is efficient in one form or another. Informed traders would not cross the spread. Hence the market relies on uninformed traders that cause noise for liquidity. A large number of noise traders use technical signals to make trading decisions. This change in liquidity and trading volume around certain technical points would be reflected in the limit order book and create additional buying or selling pressure which can be exploited by funds.

Chapter 4 examined constructed portfolios created to maximise risk adjusted returns during the post-systemic collapse recovery periods. Focusing on market anomalies such as survivorship bias, long run reversal effect and short run mean reversion, this study demonstrated the role of market forces in a post-systemic collapse market environment. Using the Black–Litterman model to calculate short-term and long-term return periods on US equities, this study finds that firms which survived the systemic shocks generated a higher return against the same period a priori. It is also possible to construct the portfolio based on the stocks' performances during the collapse event period in an objective fashion. This study provides insight into market efficiency anomalies and understanding of market efficiency when markets are under stress. This study also provides new insight into diversification of two strategies with different holding periods into one portfolio. This further diversifies the risk, which can be seen in the low Sortino ratio. It also halves transaction costs and reduces any errors or risks associated with changing asset structures in portfolios. More systemic collapses could also be investigated.

Finally, Chapter 5 determined the role of price limits in asset pricing by comparing stocks in China with their convertible bond counterparts. By exploring A-shares on the Shanghai and Shenzhen Stock Exchange in China where a 10% volatility price limit is enforced for all stocks, this study provided empirical evidence for the effectiveness of price limits on price discovery through their ability to reduce volatility. This study demonstrated that arbitrageurs can earn up to 3.60% return over the 10-year Chinese government bond yield in this market discounting for transaction costs and taxes. One potential improvement of this work is to incorporate realistic transaction costs and taxes to check whether it would yield similar results in reality. Further studies using similar methods in other emerging markets with similar setups as China could also be compared and thus different microstructural elements that arise from different regulatory environments can be included which will facilitate estimating arbitrage opportunities in different markets.

Further studies can be undertaken on technical analysis and how it affects market microstructure by observing non-price determinant technical price predictors for Chapter 3. However, it should be noted that a metric such as order book imbalance was not included in this study as it would be an endogenous variable as it is defined by the microstructure of the limit order book at any time. An extension to Chapter 4 is to expand on the entry of the portfolio position. The current entry relies on the divergence in the difference of macroeconomic data and equity returns. There are other possible signals, such as government or reserve bank interventions, or average broker sentiments and consensus across different banks and analysts. Strong buying from large funds or other 'informed' market participants could also be considered, although these would require proprietary data. Lastly, Chapter 5 can be extended by finding similar markets to replicate the results. Given the price range limit and in a similar context, other regulatory controls can be introduced to measure whether they are exogenous factors that would affect the returns of the arbitrage. Furthermore, proprietary data could be included to detect how transaction costs, cost of borrowing and cost of carry would affect returns.

References

Abad, D. and Pascual, R., 2007. On the magnet effect of price limits. *European Financial Management*, *13*(5), pp.833-852.

Ackert, L.F., Church, B. and Jayaraman, N., 2001. An experimental study of circuit breakers: The effects of mandated market closures and temporary halts on market behavior. *Journal of Financial Markets*, *4*(2), pp.185-208.

Agarwal, V., Fung, W.H., Loon, Y.C. and Naik, N.Y., 2011. Risk and return in convertible arbitrage: Evidence from the convertible bond market. *Journal of Empirical Finance*, *18*(2), pp.175-194.

Agarwal, V., Fung, W.H., Loon, Y.C. and Naik, N.Y., 2011. Risk and return in convertible arbitrage: Evidence from the convertible bond market. *Journal of Empirical Finance*, 18(2), pp.175-194.

Allaj, E., 2013. The Black–Litterman model: a consistent estimation of the parameter tau. *Financial Markets and Portfolio Management*, 27(2), pp.217-251.

Allen, F., Litov, L. and Mei, J., 2006. Large investors, price manipulation, and limits to arbitrage: An anatomy of market corners. *Review of Finance*, *10*(4), pp.645-693.

Andersen, L.B. and Buffum, D., 2002. Calibration and implementation of convertible bond models. *Available at SSRN 355308*.

Andersen, T.G., Benzoni, L. and Lund, J., 2002. An empirical investigation of continuous-time equity return models. *The Journal of Finance*, *57*(3), pp.1239-1284.

Andersen, T.G., Bollerslev, T., Diebold, F.X. and Ebens, H., 2001. The distribution of realized stock return volatility. *Journal of Financial Economics*, 61(1), pp.43-76.

Andersen, T.G., Bollerslev, T., Diebold, F.X. and Vega, C., 2007. Real-time price discovery in global stock, bond and foreign exchange markets. *Journal of International Economics*, 73(2), pp.251-277.

Asness, C.S., Berger, A. and Palazzolo, C., 2009. The limits of convertible bond arbitrage: Evidence from the recent crash. *Insights into the Global Financial Crisis*, pp.110-123.

Australian Securities Exchange. (n.d.). Capitalisation indices. [online] Available at: https://www2.asx.com.au/investors/learn-about-our-investment-solutions/indices/types/capitalisation-indices#:~:text=The%20S%26P%2FASX%20200%20Index [Accessed 13 Aug. 2021].

Bakshi, G., Cao, C. and Chen, Z., 1997. Empirical performance of alternative option pricing models. *The Journal of Finance*, 52(5), pp.2003-2049.

Balvers, R., Wu, Y. and Gilliland, E., 2000. Mean reversion across national stock markets and parametric contrarian investment strategies. *The Journal of Finance*, 55(2), pp.745-772.

Balvers, R.J. and Wu, Y., 2006. Momentum and mean reversion across national equity markets. *Journal of Empirical Finance*, 13(1), pp.24-48.

Banz, R.W., 1981. The relationship between return and market value of common stocks. *Journal of Financial Economics*, 9(1), pp.3-18.

Barro, R.J. and Becker, G.S., 1989. Fertility choice in a model of economic growth. *Econometrica: Journal of the Econometric Society,* pp.481-501.

Beach, S.L. and Orlov, A.G., 2007. An application of the Black–Litterman model with EGARCH-M-derived views for international portfolio management. *Financial Markets and Portfolio Management*, 21(2), pp.147-166.

Benartzi, S. and Thaler, R.H., 1995. Myopic loss aversion and the equity premium puzzle. *The Quarterly Journal of Economics*, 110(1), pp.73-92.

Bernstein, P.L., 1987. Liquidity, stock markets, and market makers. *Financial Management*, pp.54-62.

Bielecki, T.R., Crépey, S., Jeanblanc, M. and Rutkowski, M., 2008. Arbitrage pricing of defaultable game options with applications to convertible bonds. *Quantitative Finance*, *8*(8), pp.795-810.

Bilson, C.M., Brailsford, T.J. and Hooper, V.J., 2001. Selecting macroeconomic variables as explanatory factors of emerging stock market returns. *Pacific-Basin Finance Journal*, *9*(4), pp.401-426.

Black, F., 1986. Noise. *The journal of finance*, *41*(3), pp.528-543.

Black, F. and Litterman, R., 1992. Global portfolio optimization. *Financial Analysts Journal*, 48(5), pp.28-43.

Blume, L., Easley, D. and O'Hhara, M., 1994. Market statistics and technical analysis: The role of volume. *The Journal of Finance*, 49(1), pp.153-181.

Brennan, M.J. and Schwartz, E.S., 1980. Analyzing convertible bonds. *Journal of Financial and Quantitative Aanalysis*, *15*(4), pp.907-929.

Brock, W., Lakonishok, J. and LeBaron, B., 1992. Simple technical trading rules and the stochastic properties of stock returns. *The Journal of Finance*, 47(5), pp.1731-1764.

Brown, S.J., Grundy, B.D., Lewis, C.M. and Verwijmeren, P., 2012. Convertibles and hedge funds as distributors of equity exposure. *The Review of Financial Studies*, 25(10), pp.3077-3112.

Calamos, N.P., 2011. *Convertible arbitrage: insights and techniques for successful hedging* (Vol. 177). John Wiley & Sons.

Carayannopoulos, P. and Kalimipalli, M., 2003. Convertible bond prices and inherent biases. *The Journal of Fixed Income*, *13*(3), pp.64-73.

Cecchetti, S.G., Lam, P.S. and Mark, N.C., 1988. Mean reversion in equilibrium asset prices (No. w2762). *National Bureau of Economic Research*.

Chakravarty, S. and Sarkar, A., 1999. Liquidity in US fixed income markets: A comparison of the bid-ask spread in corporate, government and municipal bond markets. FRB of New York Staff Report, (73).

Chan, K., Hameed, A. and Tong, W., 2000. Profitability of momentum strategies in the international equity markets. *Journal of Financial and Quantitative Analysis*, pp.153-172.

Chen, C.Y.H., Chiang, T.C. and Härdle, W.K., 2018. Downside risk and stock returns in the G7 countries: An empirical analysis of their long-run and short-run dynamics. *Journal of Banking & Finance*, 93, pp.21-32.

Chen, L., Qiao, Z., Wang, M., Wang, C., Du, R. and Stanley, H.E., 2018. Which artificial intelligence algorithm better predicts the Chinese stock market?. *IEEE Access*, 6, pp.48625-48633.

Chen, T., Gao, Z., He, J., Jiang, W. and Xiong, W., 2019. Daily price limits and destructive market behavior. *Journal of Econometrics*, 208(1), pp.249-264.

Cheung, Y.W. and Lai, K.S., 1995. A search for long memory in international stock market returns. *Journal of International Money and Finance*, 14(4), pp.597-615.

Cheung, Y.W. and Ng, L.K., 1998. International evidence on the stock market and aggregate economic activity. *Journal of Empirical Finance*, 5(3), pp.281-296.

Chien, M.S., Lee, C.C., Hu, T.C. and Hu, H.T., 2015. Dynamic Asian stock market convergence: Evidence from dynamic cointegration analysis among China and ASEAN-5. Economic Modelling, 51, pp.84-98.

Cho, D.D., Russell, J., Tiao, G.C. and Tsay, R., 2003. The magnet effect of price limits: evidence from high-frequency data on Taiwan Stock Exchange. *Journal of Empirical Finance*, *10*(1-2), pp.133-168.

Chopra, N., Lakonishok, J. and Ritter, J.R., 1992. Measuring abnormal performance: do stocks overreact?. *Journal of Financial Economics*, 31(2), pp.235-268.

Chordia, T., Roll, R. and Subrahmanyam, A., 2008. Liquidity and market efficiency. *Journal of Financial Economics*, *87*(2), pp.249-268.

Chou, P.H., Chou, R.K., Ko, K.C. and Chao, C.Y., 2013. What affects the cool-off duration under price limits?. *Pacific-Basin Finance Journal*, *24*, pp.256-278.

Chou, P.H., Huang, T.Y. and Yang, H.J., 2013. Arbitrage risk and the turnover anomaly. *Journal of Banking & Finance*, 37(11), pp.4172-4182.

Cohen, K.J. and Schwartz, R.A., 1989. An electronic call market: its design and desirability. The Challenge of Information Technology for the Securities Markets: Liquidity, Volatility, and Global Trading, pp.15-58.

Cohen, K.J. and Schwartz, R.A., 2001. An electronic call market: Its design and desirability. In *The electronic call auction: Market mechanism and trading* (pp. 55-85). Springer, Boston, MA.

Curran, E., 2017. The magnet effect of price limits on the Shanghai Stock Exchange and the impact of the Shanghai-Hong Kong connect.

Da Silva, A.S., Lee, W. and Pornrojnangkool, B., 2009. The Black–Litterman model for active portfolio management. *The Journal of Portfolio Management*, 35(2), pp.61-70.

Danthine, J.P., Donaldson, J.B. and Siconolfi, P., 2005. Distribution risk and equity returns.

Davis, M. and Lischka, F.R., 2002. Convertible bonds with market risk and credit risk. *AMS IP Studies in Advanced Mathematics*, *26*, pp.45-58.

De Bondt, W.F. and Thaler, R., 1985. Does the stock market overreact?. *The Journal of Finance*, 40(3), pp.793-805.

De Bondt, W.F. and Thaler, R.H., 1987. Further evidence on investor overreaction and stock market seasonality. *The Journal of Finance*, 42(3), pp.557-581.

De Bondt, W.F., Muradoglu, Y.G., Shefrin, H. and Staikouras, S.K., 2008. Behavioral finance: Quo vadis?. *Journal of Applied Finance* (Formerly Financial Practice and Education), 18(2).

De Jong, A., Dutordoir, M. and Verwijmeren, P., 2011. Why do convertible issuers simultaneously repurchase stock? An arbitrage-based explanation. *Journal of Financial Economics*, *100*(1), pp.113-129.

Deb, S.S., Kalev, P.S. and Marisetty, V.B., 2010. Are price limits really bad for equity markets?. *Journal of Banking & Finance*, 34(10), pp.2462-2471.

Drees, B. and Eckwert, B., 2005. Asset mispricing due to cognitive dissonance.
Elyasiani, E. and Mansur, I., 1998. Sensitivity of the bank stock returns distribution to changes in the level and volatility of interest rate: A GARCH-M model. *Journal of Banking & Finance*, 22(5), pp.535-563.

Engle, R.F., 1982. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica: Journal of the Econometric Society*, pp.987-1007.

Exchange, A.S., 2010. Algorithmic trading and market access arrangements. *ASX Review*.

Fabozzi, F.J., Liu, J. and Switzer, L.N., 2008. Market efficiency and returns from convertible bond hedging and arbitrage strategies. *The Journal of Alternative Investments*, *11*(3), pp.37-64.

Fama, E.F. and French, K.R., 1993. Common risk factors in the returns on stocks and bonds. Journal of.

Fama, E.F. and French, K.R., 1996. Multifactor explanations of asset pricing anomalies. *The Journal of Finance*, 51(1), pp.55-84.

Fama, E.F., 1970. Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, 25(2), pp.383-417.

Fama, E.F., 1970. Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, 25(2), pp.383-417.

Fama, E.F., 1976. Inflation uncertainty and expected returns on treasury bills. *Journal of political economy*, 84(3), pp.427-448.

Fama, E.F., 1976. Inflation uncertainty and expected returns on treasury bills. *Journal of Political Economy*, 84(3), pp.427-448.

Fama, E.F., 1996. Multifactor portfolio efficiency and multifactor asset pricing. Journal of financial and quantitative analysis, 31(4), pp.441-465.

Fama, E.F., 1998. Market efficiency, long-term returns, and behavioral finance. *Journal of financial economics*, 49(3), pp.283-306.

Fernandez-Rodrıguez, F., Gonzalez-Martel, C. and Sosvilla-Rivero, S., 2000. On the profitability of technical trading rules based on artificial neural networks:: Evidence from the Madrid stock market. *Economics Letters*, 69(1), pp.89-94.

Festinger, L., Irle, M. and Möntmann, V., 1978. Theorie der kognitiven Dissonanz (p. 16). Bern: Huber.

Fischer, S. and Merton, R.C., 1984. Macroeconomics and finance: The role of the stock market (No. w1291). National Bureau of Economic Research.

Frazzini, A. and Lamont, O.A., 2007. The earnings announcement premium and trading volume. NBER working paper, (w13090).

Frehen, R.G., Goetzmann, W.N. and Rouwenhorst, K.G., 2013. New evidence on the first financial bubble. *Journal of Financial Economics*, 108(3), pp.585-607.

Frino, A., Lecce, S. and Segara, R., 2011. The impact of trading halts on liquidity and price volatility: Evidence from the Australian Stock Exchange. *Pacific-Basin Finance Journal*, 19(3), pp.298-307.

Fung, W. and Hsieh, D.A., 2001. The risk in hedge fund strategies: Theory and evidence from trend followers. *The Review of Financial Studies*, 14(2), pp.313-341.

Goodman, L.A., 1979. Simple models for the analysis of association in cross-classifications having ordered categories. *Journal of the American Statistical Association*, 74(367), pp.537-552.

Greenwald, B.C. and Stein, J., 1988. The task force report: The reasoning behind the recommendations. *Journal of Economic Perspectives*, 2(3), pp.3-23.

Grossman, S.J. and Stiglitz, J.E., 1980. On the impossibility of informationally efficient markets. *The American Economic Review*, 70(3), pp.393-408.

Grundy, B.D. and Martin, J.S.M., 2001. Understanding the nature of the risks and the source of the rewards to momentum investing. *The Review of Financial Studies*, 14(1), pp.29-78.

Hansen, B.E., 1994. Autoregressive conditional density estimation. *International Economic Review,* pp.705-730.

Hansen, G.S. and Wernerfelt, B., 1989. Determinants of firm performance: The relative importance of economic and organizational factors. *Strategic Management Journal*, 10(5), pp.399-411.

Harmon-Jones, E.E. and Mills, J.E., 1999. Cognitive dissonance: Progress on a pivotal theory in social psychology. In Scientific Conferences Program, 1997, U Texas, Arlington, TX, US; This volume is based on papers presented at a 2-day conference at the University of Texas at Arlington, winter 1997.. American Psychological Association.

Harris, L., 1998. Circuit breakers and program trading limits: What have we learned. *Brookings-Wharton papers on financial services,* 63.

Harris, R.D., Coskun Küçüközmen, C. and Yilmaz, F., 2004. Skewness in the conditional distribution of daily equity returns. *Applied Financial Economics*, 14(3), pp.195-202.

Hasbrouck, J. and Schwartz, R.A., 1988. Liquidity and execution costs in equity markets. *Journal of Portfolio Management*, 14(3), p.10.

Hedge Fund Research, 2008, Global Hedge Fund Industry Report [online] https://www.hfr.com/hfr-industry-reports [Accessed 18 Jul. 2018]

Hirshleifer, D., 2001. Investor psychology and asset pricing. *The Journal of Finance*, 56(4), pp.1533-1597.

Huberman, G. and Halka, D., 2001. Systematic liquidity. *Journal of Financial Research*, 24(2), pp.161-178.

Hung, M.W. and Wang, J.Y., 2002. Pricing convertible bonds subject to default risk. *The Jjournal of Derivatives*, 10(2), pp.75-87.

Hutchinson, M.C., 2006. *Convertible arbitrage: risk, return and performance* (Doctoral dissertation, Dublin City University).

Idzorek, T., 2007. A step-by-step guide to the Black-Litterman model: Incorporating user-specified confidence levels. In *Forecasting expected returns in the financial markets* (pp. 17-38). Academic Press.

Jagannathan, R. and Ma, T., 2003. Risk reduction in large portfolios: Why imposing the wrong constraints helps. *The Journal of Finance*, 58(4), pp.1651-1683.

Jegadeesh, N. and Titman, S., 2001. Profitability of momentum strategies: An evaluation of alternative explanations. *The Journal of Finance*, 56(2), pp.699-720.

Jegadeesh, N., 1990. Evidence of predictable behavior of security returns. *The Journal of finance*, *45*(3), pp.881-898.

Jegadeesh, N., 1990. Evidence of predictable behavior of security returns. *The Journal of Finance*, *45*(3), pp.881-898.

Johansen, A. and Sornette, D., 2010. Shocks, crashes and bubbles in financial markets. *Brussels Economic Review*, 53(2), pp.201-253.

Johansen, A., Sornette, D. and Ledoit, O., 1999. Predicting financial crashes using discrete scale invariance. *arXiv preprint cond-mat/9903321*.

Jorion, P., 1986. Bayes-Stein estimation for portfolio analysis. *Journal of Financial and Quantitative Analysis*, pp.279-292.

Kavajecz, K.A. and Odders-White, E.R., 2004. Technical analysis and liquidity provision. *Review of Financial Studies*, 17(4), pp.1043-1071.

Khanna, T., Palepu, K.G. and Sinha, J., 2005. Strategies that fit emerging markets. *Harvard Business Review*, *83*(6), pp.4-19.

Kodres, L.E., 1989. Tests of unbiasedness in foreign exchange futures markets: The effects of low volume in the nearby futures contract and price limits.

Kodres, L.E., 1993. Tests of unbiasedness in the foreign exchange futures markets: An examination of price limits and conditional heteroscedasticity. *Journal of Business*, pp.463-490.

Latif, Q.S., Heath, S.K. and Rotenberry, J.T., 2012. How avian nest site selection responds to predation risk: testing an 'adaptive peak hypothesis'. *Journal of Animal Ecology*, 81(1), pp.127-138.

Lee, C.M. and Swaminathan, B., 2000. Price momentum and trading volume. *The Journal of Finance*, 55(5), pp.2017-2069.

Lee, S.B. and Chung, J.S., 1996. Price limits and stock market efficiency. *Journal of Business Finance & Accounting*, *23*(4), pp.585-601.
Lee, S.W. and Mullineaux, D.J., 2004. Monitoring, financial distress, and the structure of commercial lending syndicates. *Financial management*, pp.107-130.

Lee, T.H., White, H. and Granger, C.W., 1993. Testing for neglected nonlinearity in time series models: A comparison of neural network methods and alternative tests. *Journal of Econometrics*, 56(3), pp.269-290.

Lejeune, M.A., 2011. A VaR Black–Litterman model for the construction of absolute return fund-of-funds. *Quantitative Finance*, *11*(10), pp.1489-1501.

Lim, G.C., Lye, J.N., Martin, G.M. and Martin, V.L., 1998. The distribution of exchange rate returns and the pricing of currency options. *Journal of International Economics*, 45(2), pp.351-368.

Lintner, J., 1965. Security prices, risk, and maximal gains from diversification. *The Journal of Finance*, 20(4), pp.587-615.

Liu, J. and Switzer, L.N., 2010. Liquidity risk, firm risk, and issue risk premium effects on the abnormal returns to new issues of convertible bonds. *International Journal of Business*, 15(3), p.333.

Livermore, J. and Smitten, R., 2007. *How To Trade In Stocks*. New York: McGraw-Hill.
Lo, A.W., 1991, Long-term memory in stock market prices, *Econometrica* 59, 1279-1313

Lo, A.W., Mamaysky, H. and Wang, J., 2000. Foundations of technical analysis: Computational algorithms, statistical inference, and empirical implementation. The *Journal of Finance*, 55(4), pp.1705-1765.

Loncarski, I., Horst, J.T. and Veld, C., 2006. Convertible Debt Issues and Convertible Arbitrage-issue Characteristics, Underpricing and Short sales. *University of Stirling, Working paper*.

Loncarski, I., Ter Horst, J. and Veld, C., 2009. The rise and demise of the convertible arbitrage strategy. *Financial Analysts Journal*, *65*(5), pp.35-50.

Lucca, D.O. and Moench, E., 2015. The pre-FOMC announcement drift. *The Journal of Finance*, 70(1), pp.329-371.

Lui, Y.H. and Mole, D., 1998. The use of fundamental and technical analyses by foreign exchange dealers: Hong Kong evidence. *Journal of International Money and Finance*, 17(3), pp.535-545.

Luo, X. and Zhang, J., 2019. Pricing Chinese Convertible Bonds with Default Intensity by Monte Carlo Method. *Discrete Dynamics in Nature and Society*, *2019*.

Mackay, C., 2012. *Extraordinary popular delusions and the madness of crowds*. Simon and Schuster.

Mancini-Griffoli, T. and Ranaldo, A., 2011. Limits to arbitrage during the crisis: funding liquidity constraints and covered interest parity. *Available at SSRN 1569504*.

McKenzie, M.D., 2001. Non-periodic Australian sStock mMarket cCycles: Evidence from rRescaled rRange aAnalysis. *Economic Record*, 77(239), pp.393-406.

Menkhoff, L. and Taylor, M.P., 2007. The obstinate passion of foreign exchange professionals: technical analysis. *Journal of Economic Literature*, 45(4), pp.936-972.

Merton, R.C., 1973. Theory of rational option pricing. T*he Bell Journal of Economics and Mmanagement Sscience,* pp.141-183.

Mills, T.C., 1993. Is there long-term memory in UK stock returns?. *Applied Financial Economics*, 3(4), pp.303-306.

Mitchell, M. and Pulvino, T., 2012. Arbitrage crashes and the speed of capital. *Journal of Financial Economics*, *104*(3), pp.469-490.

Morgan, J.P., 1997. Creditmetrics-technical document. JP Morgan, New York.

Nagayasu, J., 2003. The Efficiency of the Japanese Equity Market (No. 03/142). International Monetary Fund.
Neely, C.J. and Weller, P.A., 2001. Predicting Exchange Rate Volatility: Genetic Programming vs. GARCH and Risk Metrics™. Federal Reserve Bank of St. Louis Working Paper Series, (2001-009).

Neely, C.J. and Weller, P.A., 2001. Technical analysis and central bank intervention. *Journal of International Money and Finance*, 20(7), pp.949-970.

New York Stock Exchange, 2020, Market-Wide Circuit Breakers FAQ [online] Available at: https://www.nyse.com/publicdocs/nyse/NYSE_MWCB_FAQ.pdf [Accessed 25 Nov. 2020].

Ofek, E. and Richardson, M., 2003. Dotcom mania: The rise and fall of internet stock prices. *The Journal of Finance*, 58(3), pp.1113-1137.

Panorska, A.K., Mittnik, S. and Rachev, S.T., 1995. Stable GARCH models for financial time series. *Applied Mathematics Letters*, 8(5), pp.33-37.

Pearson, K., 1916. IX. Mathematical contributions to the theory of evolution.—XIX. Second supplement to a memoir on skew variation. Philosophical Transactions of the Royal Society of London. Series A, Containing Papers of a Mathematical or Physical Character, 216(538-548), pp.429-457.

Pesaran, M.H. and Timmermann, A., 1995. Predictability of stock returns: Robustness and economic significance. *The Journal of Finance*, 50(4), pp.1201-1228.

Pesaran, M.H. and Timmermann, A., 2007. Selection of estimation window in the presence of breaks. *Journal of Econometrics*, 137(1), pp.134-161.

Poterba, J.M. and Summers, L.H., 1988. Mean reversion in stock prices: Evidence and implications. *Journal of Financial Economics*, 22(1), pp.27-59.

Reinhart, C.M. and Rogoff, K.S., 2014. Recovery from financial crises: Evidence from 100 episodes. *American Economic Review*, 104(5), pp.50-55.

Richards, A.J., 1997. Winner-loser reversals in national stock market indices: Can they be explained?. *The Journal of Finance*, 52(5), pp.2129-2144.

Rouwenhorst, K.G., 1998. International momentum strategies. The *Journal of Finance*, 53(1), pp.267-284.

Scheinkman, J.A. and Xiong, W., 2003. Overconfidence and speculative bubbles. *Journal of Political Economy*, 111(6), pp.1183-1220.

Schwert, G.W., 2003. Anomalies and market efficiency. *Handbook of the Economics of Finance*, 1, pp.939-974.

Sharpe, W.F., 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, 19(3), pp.425-442.

Sharpe, W.F., 1965. Risk-aversion in the stock market: Some empirical evidence. *The Journal of Finance*, 20(3), pp.416-422.

Shleifer, A., 2000. *Inefficient markets: An introduction to behavioural finance*. OUP Oxford.
Siegel, J.J. and Thaler, R.H., 1997. Anomalies: The equity premium puzzle. *Journal of Economic Perspectives*, 11(1), pp.191-200.

Sornette, D., 2017. *Why stock markets crash: critical events in complex financial systems* (Vol. 49). Princeton University Press.

Stöckl, T., 2014. Price efficiency and trading behavior in limit order markets with competing insiders. *Experimental Economics*, 17(2), pp.314-334.

Sturm, R.R., 2013. Market Efficiency and Technical Analysis: Can they Coexist?. *Research in Applied Economics*, 5(3), p.1.

Su, D. and Fleisher, B.M., 1998. Risk, return and regulation in Chinese stock markets. *Journal of Economics and Business*, 50(3), pp.239-256.

Subrahmanyam, A., 1994. Circuit breakers and market volatility: A theoretical perspective. *The Journal of Finance*, 49(1), pp.237-254.

Summers, L.H., 2000. International financial crises: causes, prevention, and cures. *American Economic Review*, 90(2), pp.1-16.

Takahashi, A., Kobayashi, T. and Nakagawa, N., 2001. Pricing convertible bonds with default risk. *The Journal of Fixed Income*, *11*(3), pp.20-29.

Taylor, M.P. and Allen, H., 1992. The use of technical analysis in the foreign exchange market. *Journal of international Money and Finance*, 11(3), pp.304-314.

Thaler, R.H. and Ganser, L.J., 2015. *Misbehaving: The making of behavioral economics*. New York: WW Norton.

Thaler, R.H., 1999. Mental accounting matters. *Journal of Behavioral decision making*, 12(3), pp.183-206.

Thaler, R.H., 1999. Mental accounting matters. *Journal of Behavioral Decision Making*, 12(3), pp.183-206.

Treynor, J.L. and Black, F., 1973. How to use security analysis to improve portfolio selection. *The Journal of Business*, 46(1), pp.66-86.

Tripathi, V. and Seth, R., 2014. Stock market performance and macroeconomic factors: the study of Indian equity market. *Global Business Review*, 15(2), pp.291-316.

Warren Buffet (2001) Berkshire Hathaway Inc. 2001 Chairman's Letter, Available at: https://www.berkshirehathaway.com/2001ar/2001letter.html (Accessed: 17 Apr 2017).

White, E.N., 1996. *Stock market crashes and speculative manias*. Edward Elgar Publishing.
Yan Du, D., Liu, Q. and Rhee, S.G., 2009. An analysis of the magnet effect under price limits. *International Review of Finance*, *9*(1-2), pp.83-110.

Yang, J., Bessler, D.A. and Leatham, D.J., 2001. Asset storability and price discovery in commodity futures markets: a new look. *Journal of Futures Markets: Futures, Options, and Other Derivative Products*, *21*(3), pp.279-300.

Zhang, Y., Song, W., Shen, D. and Zhang, W., 2016. Market reaction to internet news: Information diffusion and price pressure. *Economic Modelling*, 56, pp.43-49.

Appendix

Table A.1 Individual stock summary and alert triggers (30 minutes)

INSTRUMENTS	RETURN	STD.DEV	SMA	MACD	SR	OBSERVATIONS
AAC	-0.00000599	0.00780103	2142	5751	3436	32013
ABC	0.00002793	0.00662362	2011	5254	3858	32250
ABP	0.00002270	0.01274517	2354	6434	2937	31730
ALL	-0.00000525	0.00737252	1942	4848	3813	32234
ALU	0.00014733	0.01799214	1253	3195	1734	20936
AMC	0.00002042	0.00508394	1922	4882	4028	32230
AMP	-0.00000880	0.00500849	1876	4658	3917	32253
ANN	0.00001369	0.00574049	2058	5042	3489	32231
ANZ	-0.00000058	0.00486894	1850	4398	3479	32224
APA	0.00002424	0.00578692	2181	5636	3716	32063
API	-0.00001266	0.01112014	2124	6161	2669	31155
APN	-0.00006222	0.00969664	2218	5992	3423	32135
ASX	0.00000759	0.00482415	1906	4674	3573	32212
AWC	-0.00005431	0.00835106	1769	4480	3737	32173
BEN	-0.00000863	0.00583770	1950	4840	3713	32182
BHP	-0.00000941	0.00567896	1792	4000	3310	32248
BKL	0.00008277	0.00660743	1975	5045	2739	30122
BKW	0.00000711	0.00621483	2019	5417	3235	30527
BLD	-0.00000858	0.00643421	1947	4837	3937	32235
BOQ	-0.00000583	0.00560962	1806	4757	3657	32161
BPT	-0.00001278	0.00873608	1888	5030	3558	31914
BSL	-0.00000393	0.01322644	1802	4782	3768	32039
BWP	0.00001770	0.00627327	2325	6235	3202	32185
CBA	0.00001816	0.00445419	1700	4288	3311	30906
CCL	0.00000421	0.00473684	1860	4626	3495	30972
CCP	0.00002548	0.01202247	1785	4563	3236	30191
CGF	0.00002353	0.00824245	1821	4589	3725	30951
CMW	0.00001006	0.00868913	2243	6709	2163	29875
COH	0.00002600	0.00541893	1854	4428	3223	30973
CPU	0.00001202	0.00571788	1936	4616	3484	30971
CSL	0.00002838	0.00745019	1714	4091	3248	30818
CSR	-0.00000163	0.00933536	1836	4676	3725	30769
CTX	0.00001812	0.00642875	1853	4344	3250	30965
DMP	0.00010221	0.00761733	1756	4464	2706	28109
DOW	-0.00002018	0.00792684	1848	4510	3672	30879
DUE	-0.00000327	0.00622568	2051	5829	3077	30588
FBU	0.00000014	0.00540216	1814	4422	3667	30590
FLT	0.00004731	0.00742533	1857	4605	3265	30921
FMG	-0.00002460	0.01675966	1677	4043	3321	30578
FPH	0.00003898	0.00707211	1426	3752	2361	24431
FXJ	-0.00004986	0.00752437	1865	4865	3523	30930
GNC	-0.00001176	0.00707190	1921	4849	3463	30560

GPT	0.00000692	0.01199186	1930	5102	3442	30789
GUD	-0.00000263	0.00668645	1964	4957	3629	30934
HVN	0.00001526	0.00647141	1807	4753	3786	30964
IAG	0.00000088	0.00519716	1926	4780	3736	30930
IFL	0.00000720	0.00843090	1983	4859	3651	30936
IGO	0.00001651	0.01052119	1772	4464	3690	30866
ILU	-0.00000577	0.00800984	1771	4288	3515	30907
IOF	0.00003744	0.01139649	1990	5662	2977	30751
IPL	-0.00005477	0.02018758	1731	4416	3720	30762
IRE	0.00003054	0.00647982	1986	4998	3547	30934
IVC	0.00003609	0.00557209	2050	5122	3686	30974
JBH	0.00005721	0.00696606	1874	4430	3398	30969
JHX	0.00002257	0.00749576	1826	4518	3410	30963
LLC	-0.00000099	0.00587149	1897	4302	3537	30813
MGR	-0.00002442	0.00762431	1903	4860	3546	30847
MMS	0.00006204	0.00878811	1675	4346	2845	28360
MND	0.00001261	0.00806313	1804	4674	3390	30931
MTS	-0.00003036	0.00544361	1978	5142	3527	30932
NAB	-0.00000669	0.00504996	1752	4266	3290	30866
NCM	-0.00001217	0.00751643	1619	3783	3154	30891
NST	0.00014018	0.02090331	1327	3217	2090	22819
NUF	-0.00001410	0.00753493	1822	4626	3536	30813
NWS	-0.00000877	0.00634550	1667	3954	3008	30429
ORG	-0.00001255	0.00587867	1846	4346	3435	30671
ORI	-0.00000923	0.00600526	1845	4400	3291	30924
OSH	0.00001926	0.00673302	1775	4250	3577	30874
PMV	0.00005225	0.00688213	1646	4240	2876	26445
PPT	-0.00001429	0.00699865	1806	4610	3304	30966
PRY	-0.00003700	0.00680662	1945	4787	3694	30754
QAN	0.00000032	0.00664773	1778	4520	3573	30760
QBE	-0.00001884	0.00601959	1765	4245	3316	30900
REA	0.00010041	0.01360774	1855	4814	3107	30027
RHC	0.00006014	0.00527474	1983	4675	3444	30950
RIO	-0.00001556	0.00714526	1686	3826	3025	30912
RMD	0.00001146	0.00708242	1722	4545	3498	30964
RRL	0.00010420	0.01950067	1890	4742	2714	29744
RSG	-0.00002521	0.01385137	1809	4634	3430	30157
SBM	0.00005125	0.01849043	1861	4985	2906	30686
SEK	0.00005339	0.00711608	1833	4527	3437	30951
SFR	0.00013640	0.01767581	1647	4060	2905	27731
SGM	-0.00002262	0.00777711	1838	4484	3346	30944
SGP	-0.00001344	0.00647045	1897	4805	3902	30919
SHL	0.00000777	0.00515695	1930	4550	3420	30932
SIP	-0.00003519	0.00914080	1910	5312	3127	30587
SKC	0.00000085	0.00679645	1686	4376	2775	26407
SKT	-0.00001778	0.00732789	848	2078	1589	14826
SRX	0.00009268	0.01065285	1887	4381	2825	28825
STO	-0.00003628	0.00700634	1720	4200	3308	30732

SUL	0.00003749	0.00830079	1960	4896	3442	30289
SUN	-0.00001684	0.00612380	1868	4178	3413	30775
TAH	-0.00004169	0.00687255	2044	5042	3744	30857
TCL	0.00001740	0.00492849	2002	4838	3714	30809
TGR	0.00003868	0.00821843	2004	5332	3343	30265
TLS	0.00000968	0.00377746	1710	4690	3567	30955
TNE	0.00007299	0.00870862	2050	5232	2615	29348
TTS	0.00000548	0.00534771	2003	5309	3304	30942
WBC	0.00000940	0.00474223	1778	4170	3314	30904
WEB	0.00009219	0.01166891	1882	5260	3085	30093
WES	0.00000371	0.00480047	1788	4406	3200	30547
WOR	-0.00002702	0.00811005	1805	4319	3299	30871
WOW	0.00000886	0.00391102	1800	4350	3339	30954
WPL	-0.00001358	0.00547877	1761	4216	3180	30888
WSA	0.00000418	0.00990138	1653	4427	3447	30681

The table describes the 105 stocks on the ASX200 index composite and demonstrates their respective average returns and standard deviations, number of triggers for each respective technical signal, and the number of total observations for each respective stock.

Table A.2 Individual stock summary and alert triggers (1 minute)

INSTRUMENTS	RETURN	STD.DEV	SMA	MACD	SR	OBSERVATIONS
AAC	-0.000000211	0.001992	49701	129312	21158	923585
ABC	0.000000937	0.001917	73539	197083	28328	930270
ABP	0.000000787	0.003671	64960	168664	18801	915745
ALL	-0.000000192	0.001819	70059	183186	38714	929511
ALU	0.000005132	0.003443	16086	41788	8582	601035
AMC	0.000000704	0.001258	71877	193623	39962	929522
AMP	-0.000000301	0.001364	80301	230651	36421	930208
ANN	0.000000482	0.001308	64668	158460	44392	929465
ANZ	-0.000000019	0.000997	60757	156163	44859	929216
APA	0.000000854	0.001652	71957	191035	30788	924767
API	-0.000000446	0.002769	36129	92283	15052	899171
APN	-0.000002157	0.002814	62942	161772	23927	926938
ASX	0.000000262	0.001011	62333	150963	43127	928978
AWC	-0.000001880	0.002261	80057	223198	32489	927917
BEN	-0.000000305	0.001312	66163	170426	43090	928335
BHP	-0.000000324	0.001107	59592	147393	41646	930081
BKL	0.000002872	0.001346	19048	48102	12502	868994
BKW	0.000000246	0.001355	36781	89033	23996	880557
BLD	-0.000000294	0.001621	72480	195074	38684	929694
BOQ	-0.000000212	0.001259	64919	164497	43431	927643
BPT	-0.000000454	0.002649	76590	207090	24580	920612
BSL	-0.000000128	0.003236	77585	212923	35713	923985
BWP	0.000000611	0.001848	69116	182203	21481	928427
CBA	0.000000612	0.000898	59628	145536	40653	921816
CCL	0.000000148	0.001122	68108	181274	42683	923766
CCP	0.000000860	0.002237	35931	90807	23729	895000
CGF	0.000000802	0.002059	69620	186224	35321	923250
CMW	0.000000339	0.002168	40572	104428	10536	885851
COH	0.000000872	0.001122	61937	146850	39346	923819
CPU	0.000000398	0.001286	65747	168269	44472	923868
CSL	0.000000950	0.001431	61925	151137	41313	919200
CSR	-0.000000058	0.002275	80681	220859	27652	917815
CTX	0.000000605	0.001352	62437	152291	44054	923499
DMP	0.000003471	0.001562	27019	67817	18752	827570
DOW	-0.000000671	0.001857	68308	179584	38698	920817
DUE	-0.000000101	0.001922	80656	218149	20626	912196
FBU	0.000000005	0.001269	47556	127021	29130	908600
FLT	0.000001586	0.001587	59971	144949	40742	922239
FMG	-0.000000833	0.003324	64594	181078	40135	911799
FPH	0.000001347	0.001437	13442	35616	8474	713480
FXJ	-0.000001669	0.002531	85578	235388	23308	922426
GNC	-0.000000397	0.001554	55582	146474	32629	904125
GPT	0.000000231	0.003176	86835	244845	25623	913062
GUD	-0.000000089	0.0016	59816	149414	37888	917373

HVN	0.000000518	0.001828	76900	209108	29085	918290
IAG	0.000000032	0.001586	82697	233115	31405	917318
IFL	0.000000244	0.002046	59948	152559	37719	917403
IGO	0.000000557	0.002409	58496	149548	38804	915306
ILU	-0.000000196	0.00184	63676	162705	39632	916542
IOF	0.000001262	0.003302	81685	218574	20434	912030
IPL	-0.000001851	0.003964	73866	204860	32680	911881
IRE	0.000001032	0.001543	61370	149852	40049	917252
IVC	0.000001217	0.00138	59107	148551	36258	918472
JBH	0.000001931	0.001463	60909	151308	43160	918516
JHX	0.000000757	0.001733	64223	163165	42678	918258
LLC	-0.000000047	0.001339	64933	165683	44764	913602
MGR	-0.000000824	0.002144	83800	231818	27575	914711
MMS	0.000002110	0.001808	35501	87399	25593	834037
MND	0.000000430	0.001667	57904	139339	41084	917111
MTS	-0.000001023	0.001614	83269	232763	26194	917501
NAB	-0.000000231	0.001019	59456	148622	42718	910175
NCM	-0.000000397	0.001484	59638	148152	43205	910861
NST	0.000004798	0.004111	30923	83116	15314	666695
NUF	-0.000000478	0.001689	63334	163240	38725	908535
NWS	-0.000000298	0.001292	64908	162817	39942	897289
ORG	-0.000000430	0.001296	64027	165046	43527	903886
ORI	-0.000000310	0.001309	62248	150888	44055	911931
OSH	0.000000656	0.001592	69097	187516	37808	910125
PMV	0.000001784	0.001601	42141	105390	25932	774613
PPT	-0.000000485	0.001567	60163	143793	38923	913134
PRY	-0.000001248	0.00166	65978	178584	30554	905758
QAN	0.000000008	0.002	85443	240275	26089	906761
QBE	-0.000000643	0.001561	62348	160118	45420	911238
REA	0.000003436	0.002643	39216	96834	26200	880794
RHC	0.000002043	0.001225	61979	150363	41323	912705
RIO	-0.000000527	0.001359	56686	135955	38141	911138
RMD	0.000000391	0.001691	76177	206011	26983	913041
RRL	0.000003497	0.003934	40719	107803	23157	873433
RSG	-0.000000865	0.00345	52794	138700	24119	888605
SBM	0.000001806	0.005213	58936	153410	19283	898332
SEK	0.000001856	0.001684	63272	162434	39415	906178
SFR	0.000004678	0.003429	40152	101050	28243	808504
SGM	-0.000000779	0.001627	61616	148767	43153	905975
SGP	-0.000000462	0.001727	80130	224512	32200	905226
SHL	0.000000263	0.00117	64221	160293	44599	905608
SIP	-0.000001202	0.003016	72617	191189	17243	895432
SKC	0.000000026	0.001563	23797	63258	12375	764375
SKT	-0.000000617	0.001545	18866	50992	9791	427260
SRX	0.000003187	0.002113	28543	71075	19477	838101
STO	-0.000001237	0.001481	62337	162450	44351	899186
SUL	0.000001284	0.001756	45155	113951	29058	884109
SUN	-0.000000575	0.001336	64712	174772	43541	901146

TAH	-0.000001432	0.001637	78143	209625	34385	903269
TCL	0.000000599	0.001332	77095	210277	33009	902035
TGR	0.000001325	0.001913	38727	101383	19333	883562
TLS	0.000000331	0.00159	107619	311251	22189	906236
TNE	0.000002509	0.00196	26432	68672	13942	853752
TTS	0.000000191	0.001873	88319	243055	21123	905916
WBC	0.000000323	0.000963	59668	150927	43383	904777
WEB	0.000003160	0.002426	31550	80020	16637	877967
WES	0.000000125	0.000976	60078	149813	41415	894524
WOR	-0.000000922	0.001608	60666	146424	42477	903589
WOW	0.000000299	0.000848	62870	161163	44078	906161
WPL	-0.000000461	0.001082	59748	145848	40752	904343
WSA	0.000000149	0.002188	56480	145077	35764	897919

The table describes the 105 stocks on the ASX200 index composite and demonstrates their respective average returns and standard deviations, number of triggers for each respective technical signal, and the number of total observations for each respective stock.

For the limitation of active risk relative to tau:

$$\sigma_A = \sqrt{w_A \Sigma w'_A} \qquad \text{(A.1)}$$

$$= \frac{\tau}{\lambda}\sqrt{(Q - P\Pi)'(\tau P \Sigma P')^{-1} P \Sigma P' (\tau P \Sigma P' + \Omega)^{-1}(Q - P\Pi)}$$

Hence, active risk is a non-linear monotonically increasing function relative to tau is:

$$\sigma_A^{MAX} = \lim_{\tau \to \infty} \sigma_A = \left(\frac{1}{\lambda}\right)\sqrt{(Q - P\Pi)'(P \Sigma P')^{-1}(Q - P\Pi)} \qquad \text{(A.2)}$$

Equation A.1 is used as a method to provide a close form solution for the market risk of the active portfolio. This active risk will be based on the Black Litterman result itself adjusted with respect to τ and λ (i.e. it incorporates the investor's risk aversion and anticipated level of market efficiency). Equation A.2 is the limit equation that demonstrates what happens when τ becomes large. It demonstrates a scenario where Ω does not influence the perceived market volatility.

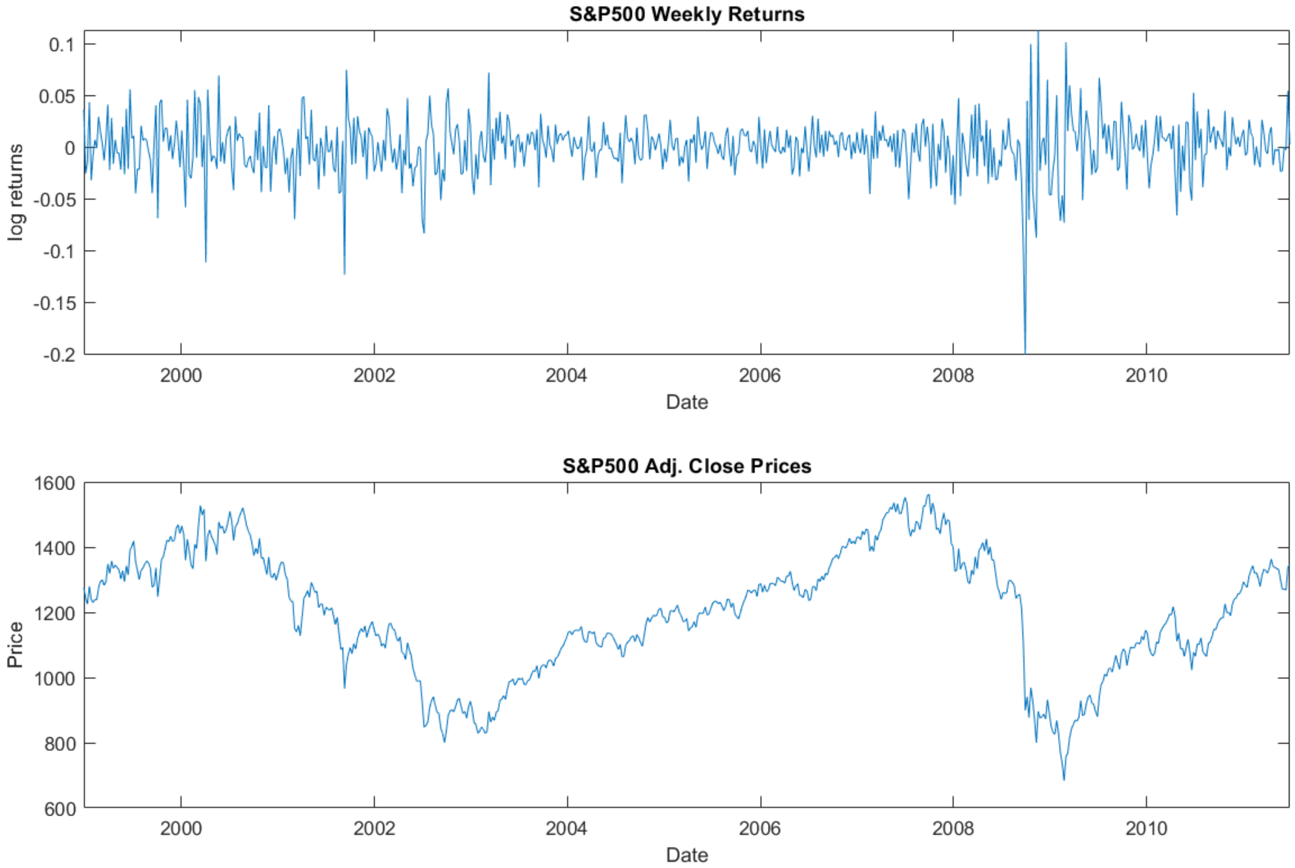


Figure A.1 S&P 500 weekly returns time series and adjusted closing price time series

The above regression shows the Black–Litterman model portfolio in terms of the macroeconomic signal test for both the dot-com bubble and the global financial crisis across all five tested time periods. There is a high level of significance in almost every aspect.

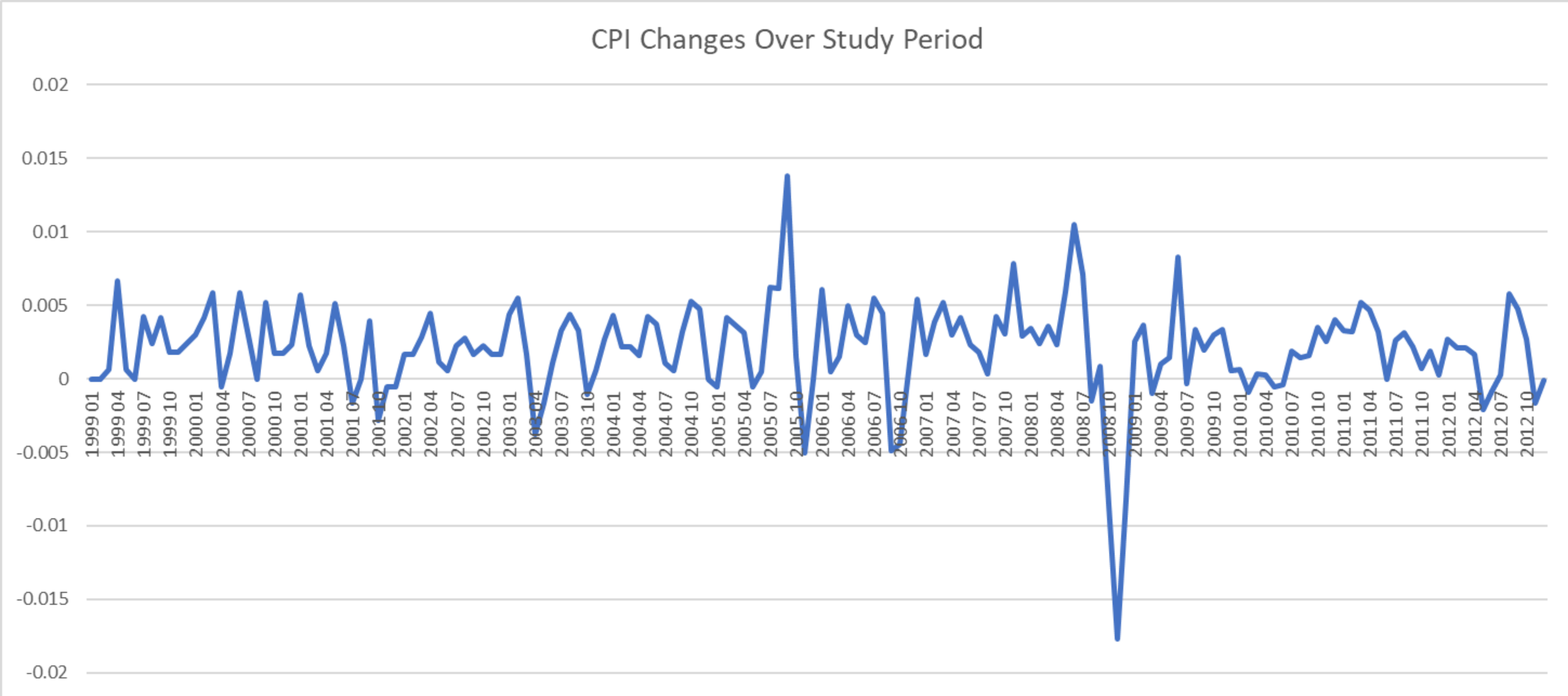


Figure A.2 US CPI time series

The above regression shows the Black–Litterman model portfolio in terms of the macroeconomic signal test for both the dot-com bubble and the global financial crisis across all five tested time periods. There is a high level of significance in almost every aspect.

Table A.3 Black–Litterman cross-sectional regression results (tau = 0.05)

	α	R_i	SemiDev	Turnover	MktCap	BMR	adj. R^2
Dot-com 3m	0.0419***	0.815***	0.019693**	6.3783*	-1.796***	6.0142***	0.5296
Dot-com 6m	0.0366***	0.2344***	0.01464**	7.7697****	-2.673***	5.8857***	0.5926
Dot-com 12m	-0.0027***	1.1275**	0.0006*	7.7703**	-2.362***	3.5285***	0.5905
Dot-com 18m	0.0417***	0.0313***	0.0174**	8.8747**	-2.536***	3.5857***	0.5527
Dot-com 24m	-0.001**	0.3774***	0.0004***	6.2214*	-1.464***	4.3285***	0.6077
GFC 3m	-0.1044**	0.9296***	0.0267**	6.8378**	-1.534***	4.4***	0.7102
GFC 6m	0.0572*	0.8046***	0.018304**	9.262***	-2.376***	5.6285***	0.5211
GFC 12m	0.1466***	0.5504**	0.0485**	9.6681**	-1.215***	2.7428***	0.5459
GFC 18m	0.0204***	0.9555***	0.01***	8.9021**	-2.094***	4.6714***	0.4417
GFC 24m	-0.1086***	0.708***	0.0308**	6.1157**	-1.725***	5.4428***	0.7016

Significance: * p<0.05, ** p<0.01, *** p<0.001

$$r_P - r_M = \alpha_i + \beta R_i + \gamma SemiDev_i + \delta \ln(Turnover)_i + \theta \ln(MktCap)_i + \phi BMR_i + \varepsilon_i$$

The above regression shows the Black–Litterman model portfolio in terms of the macroeconomic signal test for both the dot-com bubble and the global financial crisis across all five tested time periods. There is a high level of significance in almost every aspect.

Table A.4 Black–Litterman portfolio peak to macroeconomics cross-sectional regression results (tau = 0.05)

	α	$\mathbf{R_i}$	**SemiDev**	**Turnover**	**MktCap**	**BMR**	**adj. $\mathbf{R^2}$**
Dot-com 3m	-0.0683**	0.3698***	-0.7513**	7.2335**	-1.336***	1.7934***	0.4285
Dot-com 6m	0.0854**	1.0034***	-2.5363**	8.6405*	-2.224**	3.7385**	0.6996
Dot-com 12m	-0.0694***	0.2336**	-1.5823***	8.9063*	-2.755*	1.7551***	0.4267
Dot-com 18m	-0.0267*	1.8796**	-0.3898**	8.7329**	-1.188**	3.9827***	0.7222
Dot-com 24m	0.0655***	1.4418***	-1.9519**	7.6514***	-1.947**	3.8224*	0.4309
GFC 3m	-0.0844**	1.8696***	-0.2532**	8.414***	-1.598**	3.4574**	0.5284
GFC 6m	0.1118***	0.8352*	-4.1925**	9.2617**	-2.559**	3.1708***	0.5451
GFC 12m	0.1448***	1.7943*	-1.36112**	9.5358***	-2.325***	3.7743***	0.6885
GFC 18m	-0.0432***	1.9267***	-0.3931**	9.6442*	-1.924***	2.9488***	0.6964
GFC 24m	-0.0217***	0.2941**	-0.4708**	7.6891***	-1.704**	3.0946***	0.5644

Significance: * p<0.05, ** p<0.01, *** p<0.001

$$r_P - r_M = \alpha_i + \beta R_i + \gamma SemiDev_i + \delta \ln\,(Turnover)_i + \theta \ln(MktCap)_i + \phi BMR_i + \varepsilon_i$$

The above regression shows the Black–Litterman model portfolio in terms of the macroeconomic signal test for both the dot-com bubble and the global financial crisis across all five tested time periods. There is a high level of significance in almost every aspect.

Table A.5 Black–Litterman portfolio cross-sectional regression results (tau = 0.1)

	α	$\mathbf{R_i}$	**SemiDev**	**Turnover**	**MktCap**	**BMR**	**adj. $\mathbf{R^2}$**
Dot-com 3m	0.0328**	1.6102***	-0.4198***	9.2803*	-1.363***	4.0472***	0.6211
Dot-com 6m	0.0167***	0.406***	-0.3129***	8.5582*	-1.108***	3.2144***	0.5201
Dot-com 12m	0.0696**	0.8252**	-2.56824**	6.0848**	-1.9905*	2.7157**	0.4368
Dot-com 18m	-0.0718***	1.5785**	-1.9386***	6.9509***	-1.2492**	3.1911***	0.6969
Dot-com 24m	0.1471***	1.3285***	-4.98669**	6.8635*	-2.2959***	2.662***	0.5746
GFC 3m	0.0151***	0.5636**	-0.1208***	6.0304**	-1.5359**	2.1863***	0.6725
GFC 6m	0.1421**	0.9632***	-3.73723**	7.1933**	-2.8515***	2.7795***	0.7234
GFC 12m	-0.1037***	0.9272***	-1.64883**	6.3253**	-1.2945**	2.1919***	0.4453
GFC 18m	0.0652***	0.2287**	-1.6039***	7.1316***	-1.064***	2.54***	0.4692
GFC 24m	0.0184***	0.3804***	-0.0589***	7.3917***	-2.5569***	3.8738***	0.4952

Significance: * p<0.05, ** p<0.01, *** p<0.001

$$r_P - r_M = \alpha_i + \beta R_i + \gamma SemiDev_i + \delta \ln{(Turnover)_i} + \theta \ln(MktCap)_i + \phi BMR_i + \varepsilon_i$$

The above regression shows the Black–Litterman model portfolio in terms of the macroeconomic signal test for both the dot-com bubble and the global financial crisis across all five tested time periods. There is a high level of significance in almost every aspect.

Table A.6 Black–Litterman portfolio peak to macroeconomics cross-sectional regression results (tau = 0.1)

	α	R_i	SemiDev	Turnover	MktCap	BMR	adj. R^2
Dot-com 3m	-0.1132**	0.6057**	-3.7922**	6.2846***	-1.4228***	3.7419***	0.7112
Dot-com 6m	0.1214*	1.2766*	-0.0242**	9.9935**	-2.8012***	3.2612***	0.5087
Dot-com 12m	0.111***	0.8519**	-0.0888**	6.5072*	-2.5005***	2.2038**	0.5391
Dot-com 18m	-0.0106***	1.9161***	-0.1473***	9.2115***	-1.6646***	4.1307*	0.7234
Dot-com 24m	0.0576***	1.805**	-2.2348**	8.6072***	-1.7528**	2.2046***	0.5712
GFC 3m	-0.0145***	1.3685*	-0.0551**	8.6337**	-1.8186***	3.2428***	0.5447
GFC 6m	-0.0696***	0.2066***	-0.8492**	7.9858***	-1.7471***	3.7091**	0.5273
GFC 12m	0.1131*	0.0467**	-2.5221**	7.4471***	-1.3054***	3.733**	0.5900
GFC 18m	0.1162**	1.3688***	-3.9154**	6.7817***	-2.1053***	3.9538***	0.6529
GFC 24m	0.0712***	0.0986***	-0.7902**	7.8451**	-2.6466**	1.5584***	0.4379

Significance: * p<0.05, ** p<0.01, *** p<0.001

$$r_P - r_M = \alpha_i + \beta R_i + \gamma SemiDev_i + \delta \ln(Turnover)_i + \theta \ln(MktCap)_i + \phi BMR_i + \varepsilon_i$$

The above regression shows the Black–Litterman Model portfolio in terms of the macroeconomic signal test for both the dot-com bubble and the global financial crisis across all five tested time periods. There is a high level of significance in almost every aspect.

Table A.7 Summary for convertible bonds on the Shanghai and Shenzhen Stock Exchange

ISSUER NAME	CPN	MATURITY	MATURITY TYPE	CONVERSION PRICE	CONV PX AT ISS	UNDERLYING STOCK
PING AN BANK CO LTD	0.2	21-Jan-25	CONV/CALL	11.63	11.77	000001 CH Equity
CHINA THREE GORGES CORP	0.5	09-Apr-24	CONVERTIBLE	18.12	18.8	600900 CH Equity
LONGI GREEN ENERGY TECHNOLOGY CO LTD	0.5	02-Nov-23	CONVERTIBLE	18.66	32.35	601012 CH Equity
CHINA NATIONAL PETROLEUM CORP	1	13-Jul-22	CONVERTIBLE	8.54	9	601857 CH Equity
SHANGHAI ELECTRIC GROUP CO LTD	1.5	02-Feb-21	CONVERTIBLE	5.13	10.72	601727 CH Equity
SHENZHEN H&T INTELLIGENT CONTROL CO LTD	0.4	04-Jun-25	CONVERTIBLE	9.09	9.09	002402 CH Equity
SHENZHEN SUNTAK CIRCUIT TECHNOLOGY CO LTD	0.5	15-Dec-23	CONVERTIBLE	14.76	30.93	002815 CH Equity
SHANGHAI GUOSHENG GROUP CO LTD	1	05-Nov-21	CONVERTIBLE	6.25	10.52	600170 CH Equity
HAN'S LASER TECHNOLOGY INDUSTRY GROUP CO LTD	0.4	06-Feb-24	CONVERTIBLE	52.3	52.7	002008 CH Equity
CHINA CITIC BANK CORP LTD	0.3	04-Mar-25	CONVERTIBLE	7.22	7.45	601998 CH Equity
BANK OF NINGBO CO LTD	0.4	05-Dec-23	CONV/CALL	17.7	18.45	002142 CH Equity
CHINA BAOWU STEEL GROUP CORP LTD	1	24-Nov-20	CONVERTIBLE	9.05	10	600019 CH Equity
VENUSTECH GROUP INC	0.4	27-Mar-25	CONVERTIBLE	28.29	28.33	002439 CH Equity
TONGWEI CO LTD	0.5	18-Mar-25	CONVERTIBLE	12.28	12.44	600438 CH Equity
CHINA NATIONAL PETROLEUM CORP	1.4	01-Feb-23	CONVERTIBLE	8.98	9.38	601857 CH Equity
DASHENLIN PHARMACEUTICAL GROUP CO LTD	0.3	03-Apr-25	CONVERTIBLE	36.5	48.05	603233 CH Equity
CHINA EVERBRIGHT BANK CO LTD	1	17-Mar-23	CONVERTIBLE	3.97	4.36	601818 CH Equity
BANK OF JIANGSU CO LTD	0.2	14-Mar-25	CONVERTIBLE	7.56	7.9	600919 CH Equity
AUTOBIO DIAGNOSTICS CO LTD	0.3	28-Jun-25	CONVERTIBLE	64.11	64.11	603658 CH Equity
SHANGHAI STATE-OWNED ASSETS OPERATION CO LTD	1.7	08-Dec-20	CONVERTIBLE	35.66	39.88	601601 CH Equity
JUHUA GROUP CORP	1	04-Sep-20	CONVERTIBLE	10.07	13.49	600160 CH Equity
LENS TECHNOLOGY CO LTD	0.5	08-Dec-23	CONVERTIBLE	10.44	36.59	300433 CH Equity
CHINA NATIONAL NUCLEAR POWER CO LTD	0.2	15-Apr-25	CONVERTIBLE	6.2	6.32	601985 CH Equity
ZHEJIANG CRYSTAL-OPTECH CO LTD	0.5	17-Nov-23	CONVERTIBLE	12.23	29.9	002273 CH Equity
SHANDONG HI-SPEED GROUP CO LTD	1.7	24-Apr-22	CONVERTIBLE	10	10	600350 CH Equity
YTO EXPRESS GROUP CO LTD	0.5	20-Nov-24	CONVERTIBLE	10.73	10.89	600233 CH Equity
SHANYING INTERNATIONAL HOLDING CO LTD	0.4	21-Nov-24	CONVERTIBLE	3.34	3.34	600567 CH Equity
BLUEFOCUS INTELLIGENT COMMUNICATIONS GROUP CO LTD	1.5	18-Dec-21	CONVERTIBLE	4.28	4.28	300058 CH Equity
CHINA MERCHANTS EXPRESSWAY NETWORK & TECHNOLOGY HOLDINGS CO LTD	0.1	22-Mar-25	CONVERTIBLE	9.34	9.34	001965 CH Equity
JIANGSU ZHONGTIAN TECHNOLOGY CO LTD	0.4	28-Feb-25	CONVERTIBLE	10.19	10.29	600522 CH Equity
GUOTAI JUNAN SECURITIES CO LTD	1	07-Jul-23	CONVERTIBLE	19.4	19.4	601211 CH Equity
BEIJING ORIENTAL YUHONG WATERPROOF TECHNOLOGY CO LTD	1	25-Sep-23	CONVERTIBLE	22.33	38.48	002271 CH Equity

UNILUMIN GROUP CO LTD	0.8	07-Nov-24	CONVERTIBLE	7.82	9.45	300232 CH Equity
WUHU TOKEN SCIENCE CO LTD	0.4	18-Mar-25	CONVERTIBLE	6.25	6.38	300088 CH Equity
AISINO CORP	1.5	12-Jun-21	CONVERTIBLE	42.38	86.61	600271 CH Equity
JUEWEI FOOD CO LTD	0.4	11-Mar-25	CONV/CALL	28.51	40.52	603517 CH Equity
SHENZHEN ASIANTIME INTERNATIONAL CONSTRUCTION CO LTD	0.5	17-Apr-25	CONVERTIBLE	14.8	17.49	002811 CH Equity
AVIC JONHON OPTRONIC TECHNOLOGY CO LTD	0.5	05-Nov-24	CONVERTIBLE	30.87	40.26	002179 CH Equity
GUANGZHOU AUTOMOBILE GROUP CO LTD	1.5	22-Jan-22	CONVERTIBLE	14.41	21.99	601238 CH Equity
JIANGSU ETERN CO LTD	0.4	16-Apr-25	CONVERTIBLE	6.35	6.5	600105 CH Equity
LAOBAIXING PHARMACY CHAIN JSC	0.2	29-Mar-24	CONVERTIBLE	60.09	60.59	603883 CH Equity
TONGKUN GROUP CO LTD	0.3	19-Nov-24	CONVERTIBLE	12.51	12.63	601233 CH Equity
CHINA NATIONAL CHEMICAL ENGINEERING GROUP CORP LTD	0.9	24-Apr-23	CONVERTIBLE	7.54	7.75	601117 CH Equity
NANJING HANRUI COBALT CO LTD	0.3	20-Nov-24	CONVERTIBLE	57.49	81.49	300618 CH Equity
CHINA AVIONICS SYSTEMS CO LTD	0.5	25-Dec-23	CONVERTIBLE	14.18	14.29	600372 CH Equity
JIANGSU ZHANGJIAGANG RURAL COMMERCIAL BANK CO LTD	0.6	12-Nov-24	CONVERTIBLE	5.91	6.06	002839 CH Equity
HENGTONG OPTIC-ELECTRIC CO LTD	0.3	19-Mar-25	CONVERTIBLE	21.64	21.79	600487 CH Equity
UTOUR GROUP CO LTD	0.5	01-Dec-23	CONVERTIBLE	7.92	11.12	002707 CH Equity
WONDERS INFORMATION CO LTD	0.4	04-Mar-25	CONVERTIBLE	13.6	13.62	300168 CH Equity
SKYWORTH DIGITAL CO LTD	0.4	15-Apr-25	CONVERTIBLE	11.49	11.56	000810 CH Equity
CHINA NUCLEAR ENGINEERING CORP LTD	0.2	08-Apr-25	CONVERTIBLE	9.87	9.93	601611 CH Equity
GANFENG LITHIUM CO LTD	0.5	21-Dec-23	CONVERTIBLE	42.58	71.89	002460 CH Equity
HENAN QING SHUI YUAN TECHNOLOGY CO LTD	0.6	19-Jun-25	CONVERTIBLE	11.95	11.95	300437 CH Equity
HUBEI KAILONG CHEMICAL GROUP CO LTD	0.5	21-Dec-24	CONVERTIBLE	6.77	6.97	002783 CH Equity
SHANDONG SUN PAPER INDUSTRY JSC LTD	0.5	22-Dec-22	CONVERTIBLE	8.65	8.85	002078 CH Equity
JASON FURNITURE HANGZHOU CO LTD	0.6	12-Sep-24	CONVERTIBLE	36.57	52.2	603816 CH Equity
JILIN AODONG PHARMACEUTICAL GROUP CO LTD	0.4	13-Mar-24	CONVERTIBLE	20.62	21.12	000623 CH Equity
GUANGDONG HIGHSUN GROUP CO LTD	1.5	08-Jun-22	CONVERTIBLE	3.01	5.26	000861 CH Equity
SHENZHEN JINXINNONG TECHNOLOGY CO LTD	0.6	09-Mar-24	CONVERTIBLE	9.62	9.72	002548 CH Equity
SHENZHEN ZHONGZHUANG CONSTRUCTION GROUP CO LTD	0.4	26-Mar-25	CONVERTIBLE	6.19	6.24	002822 CH Equity
SHANDONG LINGLONG TYRE CO LTD	0.5	01-Mar-23	CONVERTIBLE	18.55	19.1	601966 CH Equity
BEIJING SDL TECHNOLOGY CO LTD	0.5	27-Dec-23	CONVERTIBLE	8.93	13.35	002658 CH Equity
ZHEJIANG YATAI PHARMACEUTICAL CO LTD	0.3	02-Apr-25	CONVERTIBLE	16.25	16.3	002370 CH Equity
TIBET HUAYU MINING CO LTD	0.3	14-Jun-25	CONVERTIBLE	10.17	10.17	601020 CH Equity
SANLUX CO LTD	0.5	08-Jun-24	CONVERTIBLE	5.83	7.38	002224 CH Equity
XINJIANG YILITE INDUSTRY CO LTD	0.5	15-Mar-25	CONVERTIBLE	17.25	17.6	600197 CH Equity
JIANGSU DINGSHENG NEW ENERGY MATERIALS CO LTD	0.4	09-Apr-25	CONVERTIBLE	15.28	20.8	603876 CH Equity
DAWNING INFORMATION INDUSTRY CO LTD	0.6	06-Aug-24	CONVERTIBLE	36.53	51.28	603019 CH Equity

JIANGSU LINYANG ENERGY CO LTD	1	27-Oct-23	CONVERTIBLE	8.76	8.8	601222 CH Equity
SHANGHAI ENVIRONMENT GROUP CO LTD	0.2	18-Jun-25	CONVERTIBLE	10.44	10.44	601200 CH Equity
SANHUA HOLDING GROUP CO LTD	6	25-Sep-20	CONVERTIBLE	18.49998	18.49998	002050 CH Equity
SHENZHEN TOPBAND CO LTD	0.4	07-Mar-25	CONVERTIBLE	5.64	5.64	002139 CH Equity
GUANGZHOU SHIYUAN ELECTRONIC TECHNOLOGY CO LTD	0.4	11-Mar-25	CONVERTIBLE	75.72	76.25	002841 CH Equity
TECON BIOLOGY CO LTD	0.5	22-Dec-23	CONVERTIBLE	8.15	8.25	002100 CH Equity
QIANHE CONDIMENT AND FOOD CO LTD	0.5	20-Jun-24	CONVERTIBLE	18.31	18.31	603027 CH Equity
V-GRASS FASHION CO LTD	0.5	24-Jan-25	CONVERTIBLE	10.52	14.96	603518 CH Equity
JOINTOWN PHARMACEUTICAL GROUP CO LTD	0.8	15-Jan-22	CONVERTIBLE	18.32	18.78	600998 CH Equity
ZHEJIANG SHUANGHUAN DRIVELINE CO LTD	0.5	25-Dec-23	CONVERTIBLE	9.93	10.07	002472 CH Equity
CHONGQING ZAISHENG TECHNOLOGY CORP LTD	0.6	19-Jun-24	CONVERTIBLE	8.59	11.32	603601 CH Equity
XINFENGMING GROUP CO LTD	0.5	26-Apr-24	CONVERTIBLE	16.83	23.74	603225 CH Equity
HAN'S HOLDINGS GROUP LTD	1	28-Mar-22	CONVERTIBLE	48.45	48.45	002008 CH Equity
CHINA COMMUNICATIONS CONSTRUCTION GROUP LTD	1	10-Nov-20	CONVERTIBLE	16.06	16.06	601800 CH Equity
HLA CORP LTD	0.5	12-Jul-24	CONVERTIBLE	12.02	12.4	600398 CH Equity
GUIZHOU BROADCASTING & TV INFORMATION NETWORK CO LTD	0.5	05-Mar-25	CONVERTIBLE	8.04	8.13	600996 CH Equity
ANHUI ZHONGDING SEALING PARTS CO LTD	0.5	08-Mar-25	CONVERTIBLE	11.79	11.99	000887 CH Equity
JIANGXI FUSHINE PHARMACEUTICAL CO LTD	0.6	01-Mar-25	CONVERTIBLE	14.93	18.05	300497 CH Equity
CHANGJIANG SECURITIES CO LTD	0.4	12-Mar-24	CONVERTIBLE	7.45	7.6	000783 CH Equity
JIANGSU JIANGYIN RURAL COMMERCIAL BANK CO LTD	0.5	26-Jan-24	CONVERTIBLE	4.68	9.16	002807 CH Equity
JIANGSU PHOENIX PUBLISHING & MEDIA GROUP CO LTD	1	31-Oct-21	CONVERTIBLE	14.8	16	601928 CH Equity
JIANGSU CHANGQING AGROCHEMICAL CO LTD	0.5	27-Feb-25	CONVERTIBLE	7.41	11.41	002391 CH Equity
GUANGDONG WENCAN DIE CASTING CO LTD	0.5	10-Jun-25	CONVERTIBLE	19.93	19.93	603348 CH Equity
CHONGQING PHARSCIN PHARMACEUTICAL CO LTD	0.5	24-Jun-25	CONVERTIBLE	18.08	18.11	002907 CH Equity
AVIC ELECTROMECHANICAL SYSTEMS CO LTD	0.5	27-Aug-24	CONVERTIBLE	7.63	7.66	002013 CH Equity
ZHESHANG SECURITIES CO LTD	0.2	12-Mar-25	CONVERTIBLE	12.46	12.53	601878 CH Equity
BEIJING JOIN-CHEER SOFTWARE CO LTD	1	08-Jun-23	CONVERTIBLE	9.48	12.97	002279 CH Equity
SHENZHEN SENIOR TECHNOLOGY MATERIAL CO LTD	0.5	07-Mar-24	CONVERTIBLE	27.49	27.99	300568 CH Equity
ANHUI JINHE INDUSTRIAL CO LTD	1	01-Nov-23	CONVERTIBLE	22.96	23.92	002597 CH Equity
TKD SCIENCE AND TECHNOLOGY CO LTD	0.6	15-Dec-23	CONVERTIBLE	17.9	25.41	603738 CH Equity
JIANGXI FANGDA IRON & STEEL GROUP CO LTD	2	29-Apr-22	CONVERTIBLE	15.7	15.7	600507 CH Equity
CAMEL GROUP CO LTD	1	24-Mar-23	CONVERTIBLE	13.44	16.78	601311 CH Equity
ZHE JIANG TAIHUA NEW MATERIAL CO LTD	0.4	17-Dec-24	CONVERTIBLE	8.11	11.56	603055 CH Equity
ZHEJIANG JINFEI KAIDA WHEEL CO LTD	0.6	28-Feb-25	CONVERTIBLE	6.78	6.8	002863 CH Equity
FUJIAN FUNENG CO LTD	0.4	07-Dec-24	CONVERTIBLE	8.48	8.69	600483 CH Equity
LIER CHEMICAL CO LTD	0.6	17-Oct-24	CONVERTIBLE	18.62	18.82	002258 CH Equity

XINYU IRON & STEEL GROUP CO LTD	0.5	18-Apr-22	CONVERTIBLE	6.3	6.55	600782 CH Equity
HENAN MINGTAI AL INDUSTRIAL CO LTD	0.4	10-Apr-25	CONVERTIBLE	11.3	11.49	601677 CH Equity
SHANGHAI SHYNDEC PHARMACEUTICAL CO LTD	0.2	01-Apr-25	CONVERTIBLE	9.99	10.09	600420 CH Equity
BROTHER ENTERPRISES HOLDING CO LTD	0.5	28-Nov-23	CONVERTIBLE	5.35	18.17	002562 CH Equity
HARBIN VITI ELECTRONICS CO LTD	0.6	20-Jul-23	CONVERTIBLE	4.85	5.92	603023 CH Equity
SHENZHEN SDG INFORMATION CO LTD	0.4	16-Nov-23	CONVERTIBLE	5.61	6.78	000070 CH Equity
PCI-SUNTEK TECHNOLOGY CO LTD	0.4	19-Dec-24	CONVERTIBLE	7.89	7.95	600728 CH Equity
YIXINTANG PHARMACEUTICAL GROUP CO LTD	0.3	19-Apr-25	CONVERTIBLE	27.28	27.28	002727 CH Equity
GUANGDONG VTR BIO-TECH CO LTD	0.4	20-Dec-24	CONVERTIBLE	8.35	8.41	300381 CH Equity
BLUEDON INFORMATION SECURITY TECHNOLOGY CO LTD	0.6	13-Aug-24	CONVERTIBLE	5.79	7.89	300297 CH Equity
LEO GROUP CO LTD	0.5	22-Mar-24	CONVERTIBLE	1.72	2.76	002131 CH Equity
MOON ENVIRONMENT TECHNOLOGY CO LTD	0.4	14-Jan-25	CONVERTIBLE	5.47	5.52	000811 CH Equity
BEYONDSOFT CORP	0.5	05-Mar-25	CONVERTIBLE	8.81	8.9	002649 CH Equity
CHONGQING SOKON INDUSTRY GROUP CO LTD	1	06-Nov-23	CONVERTIBLE	17.12	17.12	601127 CH Equity
GUANGDONG SHENGLU TELECOMMUNICATION TECH CO LTD	0.7	17-Jul-24	CONVERTIBLE	6.85	6.88	002446 CH Equity
JISHI MEDIA CO LTD	0.5	27-Dec-23	CONVERTIBLE	2.95	2.95	601929 CH Equity
JIANGSU SUZHOU RURAL COMMERCIAL BANK CO LTD	0.8	02-Aug-24	CONVERTIBLE	5.67	6.34	603323 CH Equity
HUBEI JUMPCAN PHARMACEUTICAL CO LTD	0.5	13-Nov-22	CONVERTIBLE	38.81	41.04	600566 CH Equity
JIANGSU XINQUAN AUTOMOTIVE TRIM CO LTD	0.5	04-Jun-24	CONVERTIBLE	18.89	25.34	603179 CH Equity
LINGNAN ECO&CULTURE-TOURISM CO LTD	0.5	14-Aug-24	CONVERTIBLE	5.92	10.7	002717 CH Equity
SHENZHEN HONGTAO GROUP CO LTD	1.5	29-Jul-22	CONVERTIBLE	9.97	10.28	002325 CH Equity
XIAMEN ITG GROUP CORP LTD	1.4	05-Jan-22	CONVERTIBLE	7.42	9.03	600755 CH Equity
HUNAN AIHUA GROUP CO LTD	0.5	02-Mar-24	CONVERTIBLE	21.43	21.43	603989 CH Equity
ANHUI SIERTE FERTILIZER INDUSTRY LTD CO	0.4	08-Apr-25	CONVERTIBLE	6.15	6.25	002538 CH Equity
ZHEJIANG DOYIN PUMP INDUSTRY CO LTD	0.6	02-Aug-24	CONVERTIBLE	6.55	13.47	002793 CH Equity
KUNSHAN KERSEN SCIENCE & TECHNOLOGY CO LTD	0.5	16-Nov-24	CONVERTIBLE	8.7	8.95	603626 CH Equity
WUXI RURAL COMMERCIAL BANK CO LTD	0.5	30-Jan-24	CONVERTIBLE	6.7	8.9	600908 CH Equity
INNER MONGOLIA MENGDIAN HUANENG THERMAL POWER CORP LTD	0.6	22-Dec-23	CONVERTIBLE	2.82	2.95	600863 CH Equity
ZHEJIANG WEIMING ENVIRONMENT PROTECTION CO LTD	0.4	10-Dec-24	CONVERTIBLE	17.47	23.92	603568 CH Equity
GUANGDONG LIANTAI ENVIRONMENTAL PROTECTION CO LTD	0.3	23-Jan-25	CONVERTIBLE	8.72	12.31	603797 CH Equity
HEALTHCARE CO LTD	0.7	08-Nov-24	CONVERTIBLE	14.28	19.03	603313 CH Equity
HANGZHOU CABLE CO LTD	0.5	06-Mar-24	CONVERTIBLE	7.24	7.29	603618 CH Equity
GUANGDONG GUANGHUA SCI-TECH CO LTD	0.5	14-Dec-24	CONVERTIBLE	12.72	17.03	002741 CH Equity
JOLYWOOD SUZHOU SUNWATT CO LTD	0.5	25-Feb-25	CONVERTIBLE	13.29	20.41	300393 CH Equity
SHENZHEN GLORY MEDICAL CO LTD	0.4	14-Feb-25	CONVERTIBLE	4.89	4.94	002551 CH Equity

CHANGSHA DIALINE NEW MATERIAL SCI & TECH CO LTD	0.4	21-Mar-24	CONVERTIBLE	24.9	24.9	300700 CH Equity
SHAANXI BROADCAST & TV NETWORK INTERMEDIARY GROUP CO LTD	0.6	27-Jun-24	CONVERTIBLE	6.9	6.91	600831 CH Equity
YANTAI CHINA PET FOODS CO LTD	0.4	15-Feb-25	CONVERTIBLE	22.28	37.97	002891 CH Equity
SHENZHEN TECHAND ECOLOGY & ENVIRONMENT CO LTD	0.5	18-Dec-23	CONVERTIBLE	3.98	12.39	300197 CH Equity
BEIJING GEOENVIRON ENGINEERING & TECHNOLOGY INC	0.6	26-Jul-24	CONVERTIBLE	9.33	9.38	603588 CH Equity
ORIENT INTERNATIONAL ENTERPRISE LTD	1.5	26-Mar-22	CONVERTIBLE	8.63	8.63	600909 CH Equity
TIANSHUI ZHONGXING BIO-TECHNOLOGY CO LTD	0.6	13-Dec-23	CONVERTIBLE	11.54	11.74	002772 CH Equity
SUNRESIN NEW MATERIALS CO LTD	0.5	11-Jun-25	CONVERTIBLE	29.58	29.59	300487 CH Equity
YANKUANG GROUP CO LTD	2.7	25-Sep-20	CONVERTIBLE	14.10002	14.10002	600188 CH Equity
HAINAN DRINDA AUTOMOTIVE TRIM CO LTD	0.6	10-Dec-24	CONVERTIBLE	21.66	21.74	002865 CH Equity
ZHEJIANG ASIA-PACIFIC MECHANICAL & ELECTRONIC CO LTD	0.5	04-Dec-23	CONVERTIBLE	10.44	10.44	002284 CH Equity
ZHEJIANG GRANDWALL ELECTRIC SCIENCE&TECHNOLOGY CO LTD	0.5	01-Mar-25	CONVERTIBLE	24.03	24.18	603897 CH Equity
ANHUI ZHONGHUAN ENVIRONMENTAL PROTECTION TECHNOLOGY CO LTD	0.5	10-Jun-24	CONVERTIBLE	12.31	12.31	300692 CH Equity
CHINA SHIPBUILDING INDUSTRY CORP NO 725 RESEARCH INSTITUTE	0.9	13-Dec-20	CONVERTIBLE	26.95999	26.95999	300003 CH Equity
ANHUI XINHUA DISTRIBUTION GROUP HOLDING CO LTD	1	23-Jun-21	CONVERTIBLE	15.38	16.5	601801 CH Equity
ZHEJIANG HUATONG PHARMACEUTICAL CO LTD	0.6	14-Jun-24	CONVERTIBLE	11.45001	11.45	002758 CH Equity
FUXIN DARE AUTOMOTIVE PARTS CO LTD	0.8	18-Jul-24	CONVERTIBLE	34.66	35.26	300473 CH Equity
ZHEJIANG THREE STARS NEW MATERIALS CO LTD	0.4	31-May-25	CONVERTIBLE	19.75	19.75	603578 CH Equity
ZHEJIANG DAFENG INDUSTRY CO LTD	0.4	27-Mar-25	CONVERTIBLE	16.76	16.88	603081 CH Equity
TIANJIN KEYVIA ELECTRIC CO LTD	0.6	27-Jul-23	CONVERTIBLE	8.15	8.15	300407 CH Equity
SUZHOU HYCAN HOLDINGS CO LTD	0.5	27-Nov-24	CONVERTIBLE	7.52	7.58	002787 CH Equity
ZHEBAO MEDIA HOLDING GROUP CO LTD	1	17-Aug-22	CONVERTIBLE	24.18	25	600633 CH Equity
NINGBO XUSHENG AUTO TECHNOLOGY CO LTD	0.4	22-Nov-24	CONVERTIBLE	29.6	29.86	603305 CH Equity
ZHEJIANG JIULI HI-TECH METALS CO LTD	1	08-Nov-23	CONVERTIBLE	7.92	7.92	002318 CH Equity
WUHAN JINGCE ELECTRONIC GROUP CO LTD	0.5	29-Mar-25	CONVERTIBLE	50.25	75.88	300567 CH Equity
BEIJING CHANGJIU LOGISTICS CORP	0.8	07-Nov-24	CONVERTIBLE	11.99	11.99	603569 CH Equity
DER FUTURE SCIENCE & TECHNOLOGY HOLDING GROUP CO LTD	0.5	03-Apr-25	CONVERTIBLE	8.67	8.74	002631 CH Equity
CHINA SHIPBUILDING INDUSTRY CO LTD	1	04-Jun-18	CONVERTIBLE	4.74001	6.05	601989 CH Equity
TSINGHUA HOLDINGS CORP LTD	1	26-Oct-18	CONVERTIBLE	16.7	16.88	600109 CH Equity
SHANGHAI STEP ELECTRIC CORP	1	06-Nov-23	CONVERTIBLE	7.45	7.45	002527 CH Equity
JIANGNAN MOULD AND PLASTIC TECHNOLOGY CO LTD	1	02-Jun-23	CONVERTIBLE	7.59	8	000700 CH Equity
HUBEI BROADCASTING & TELEVISION INFORMATION NETWORK CO LTD	0.8	28-Jun-24	CONVERTIBLE	7.92	10.16	000665 CH Equity
QIJING MACHINERY CO LTD	0.4	14-Dec-24	CONVERTIBLE	14.56	14.76	603677 CH Equity

ANHUI GUOZHEN ENVIRONMENT PROTECTION TECHNOLOGY JSC LTD	0.5	24-Nov-23	CONVERTIBLE	8.6	21.04	300388 CH Equity
SHANXI YONGDONG CHEMISTRY INDUSTRY CO LTD	1	16-Apr-23	CONVERTIBLE	12.64	30.77	002753 CH Equity
GUANGZHOU DEVOTION THERMAL TECHNOLOGY CO LTD	0.4	20-Mar-25	CONVERTIBLE	7.19	7.39	300335 CH Equity
JIANGSU HUIFENG BIO AGRICULTURE CO LTD	1.3	21-Apr-22	CONVERTIBLE	7.71	29.7	002496 CH Equity
SICHUAN YAHUA INDUSTRIAL GROUP CO LTD	0.4	16-Apr-25	CONVERTIBLE	8.96	8.98	002497 CH Equity
FUJIAN HAIXIA ENVIRONMENTAL PROTECTION GROUP CO LTD	0.4	02-Apr-25	CONVERTIBLE	7.75	7.8	603817 CH Equity
SHANTOU WANSHUN NEW MATERIAL GROUP CO LTD	0.6	20-Jul-24	CONVERTIBLE	5.36	6.47	300057 CH Equity
CHINA BAOWU STEEL GROUP CORP LTD	1.5	10-Dec-17	CONVERTIBLE	42.30996	43.28	601336 CH Equity
SHANDONG DAYE CO LTD	0.4	09-May-24	CONVERTIBLE	12.56	12.56	603278 CH Equity
SHENZHEN KAIZHONG PRECISION TECHNOLOGY CO LTD	0.6	30-Jul-24	CONVERTIBLE	13.01	13.25	002823 CH Equity
GUANGDONG DOWSTONE TECHNOLOGY CO LTD	0.7	28-Dec-23	CONVERTIBLE	15.2	45.21	300409 CH Equity
TEYI PHARMACEUTICAL GROUP CO LTD	0.5	06-Dec-23	CONVERTIBLE	16.1	20.2	002728 CH Equity
FUJIAN TIANMA SCIENCE & TECHNOLOGY GROUP CO LTD	0.6	17-Apr-24	CONV/CALL	7.32	11.04	603668 CH Equity
NINGBO HENGHE MOULD CO LTD	0.8	26-Jul-24	CONVERTIBLE	9.26	9.26	300539 CH Equity
CHINA ZHONGHUA GEOTECHNICAL ENGINEERING GROUP CO LTD	0.5	15-Mar-24	CONVERTIBLE	8.01	8.05	002542 CH Equity
BAOTOU IRON AND STEEL GROUP CO LTD	1.3	27-Sep-19	CONVERTIBLE	17.06001	17.06001	600111 CH Equity
ZHEJIANG JIAAO ENPROTECH STOCK CO LTD	1	10-Nov-23	CONVERTIBLE	45.03999	45.48	603822 CH Equity
JIANGSU AUCKSUN CO LTD	1.6	22-Jan-22	CONVERTIBLE	9.26	9.44	002245 CH Equity
GUANGXI BOSSCO ENVIRONMENTAL PROTECTION TECHNOLOGY CO LTD	0.6	05-Jul-24	CONVERTIBLE	12.38	12.38	300422 CH Equity
SHUANGLIANG ECO-ENERGY SYSTEMS CO LTD	1.7	04-May-15	CONVERTIBLE	12.58	21.11	600481 CH Equity
BEIJING TOURISM GROUP CO LTD	0.095	23-Dec-18	CONVERTIBLE	18.40001	18.55	600258 CH Equity
JUHUA GROUP CORP	0	24-Apr-22	CONVERTIBLE	10.68	10.68	600160 CH Equity
MARKOR INVESTMENT GROUP CO LTD	4.5	08-Dec-18	CONVERTIBLE	19.69	20	600337 CH Equity
SHENZHEN BAOAN BAOLILAI INDUSTRIAL CO LTD	10	19-Nov-16	CONVERTIBLE	23.23998	23.23998	000008 CH Equity
CENTRAL CHINA PUBLISHING & MEDIA INVESTMENT HOLDING GROUP CO LTD	1.8	24-Dec-23	CONVERTIBLE	9.71	10.05	000719 CH Equity

The above table shows the list of convertible bonds that were active between January 2012 and December 2018 along with their properties. The underlying securities are laid out as Bloomberg Ticker Codes. All values are denominated in Chinese Yuan (CNY).