Information Asymmetry and Performance of Technical Analysis During Times of Crises in Scandinavian Markets

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Abstract

This thesis investigates the probability of informed trading (PIN) during crisis periods across the Norwegian, Swedish, and Danish stock exchanges. The focus is on the financial crisis of 2008, the COVID-19 pandemic, and the Russia-Ukraine war. Utilizing the framework of Hung and Lai (2022), this study examines the effectiveness of the technical analysis indicators Moving Average Crossover (MAC) and Moving Average Convergence Divergence (MACD) conducted on the Oslo Stock Exchange. The crises are sectioned into pre-, during, and post-crisis periods, estimating PIN for each phase on the separate exchanges to identify patterns across the different markets. Our results indicate a higher probability of informed trading during the financial crises compared to the health or geopolitical crises, with various PIN values observed among the Scandinavian markets. Furthermore, we investigate the performance of technical analysis during periods of varying information asymmetry. The findings suggest that using a MAC strategy before and during a financial crisis outperforms a Buy-and-Hold (BH) strategy. However, there are no significant outperformance measures for the health and geopolitical crises. The thesis contributes to the understanding of market behavior during uncertainties in financial markets, highlighting the information asymmetry in disruptive time periods. Despite having limitations, the research paves the way for future research to refine our findings and explore further market contexts.

Keywords: PIN, Crises, Financial Markets, Technical Analysis

JEL Classification: D82, G01, G14, G40, G41

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Chapter 1

Introduction

Financial markets are complex and influenced by a multitude of factors, ranging from economic indicators to global events. Amidst these crises, whether financial, health-related, or geopolitical, pose significant challenges. Taking a further look into how these crises impact trading behavior and market dynamics is crucial for both researchers and investors. This thesis uses the framework of Hung and Lai (2022), to investigate the probability of informed trading (PIN) across the Norwegian, Swedish, and Danish Stock Exchanges, during three major crises: the financial crisis of 2008, the COVID-19 pandemic, and the Russia-Ukraine war. We further look into the effectiveness of technical analysis indicators, Moving Average Crossover (MAC) and Moving Average Convergence Divergence (MACD), on Oslo Stock Exchange (OSE) during times characterized by high probabilities for informed trading.

In our research the crises has been sectioned into three periods, pre-, during, and post-crisis. The PIN is then calculated on each phase to investigate for similarities or patterns across different exchanges. Duarte and Young (2009), Hung and Lai (2022), and Yan and Zhang (2012), all have worked on the PIN framework of Easley et al. (1996), where they have found some limitations to the original framework. Some of these limitations are the algorithm of Lee and Ready (1991), firm size, and systematic order-flow shocks. Larger market capitalization (cap) firms will have lower PIN, due to financial institutions analyzing and posting their interpretations of news regarding bigger companies. Information is essential for traders to understand capital markets. However, traders access and utilize information differently. While measuring how traders may be informed or uninformed is complicated, there are models developed to estimate the PIN. The PIN estimation works as a proxy for information asymmetry in the respective markets. Researchers such as J. Bai et al. (2016) and Marshall and Cahan (2005), questions if financial market prices have become more informative and efficient. On the other hand, other researchers like Blume et al. (1994), Duarte and Young (2009), Easley and O'Hara (1992), Easley et al. (1996), Hung and Lai (2022), and Yan and Zhang (2012), imply in their studies that there are information asymmetry in financial markets, and some indicate that this can be exploited using technical analysis.

The secondary objective is to explore whether technical analysis can enhance profits during these crises. Technical analysis depend on historical prices and volume data, Brock et al. (1992), Chong and Ng (2008), Cowles (1933), Han et al. (2013), and Teixeira and de Oliveira (2010) studied this concept and concluded that this trading approach generates higher profits than a Buy-and-Hold (BH) strategy. The theory has sceptics, Bodie et al. (2021), Fama (1970), and Samuelson (1965), all state that it will not be possible to predict the price movements, based on historical data. These sceptics are mainly supporters of the efficient market hypothesis.

Fang et al. (2023) wrote a paper, investigating the short-, medium- and long-term risk spillover caused by COVID-19 across financial markets. They found that this crisis raised the risk of short-term stock and other commodity investments. The medium and long term showed evidence of a significant risk spillover across financial markets. This spillover correlated significantly with the increase in investor panic and irrational behavior. Research by C. Bai et al. (2023), looked into the challenge of analyzing the market due to lack of insight into the health crisis, and the abrupt societal changes. Izzeldin et al. (2023) conducted a study analyzing the European and global stock markets response to the Russian invasion of Ukraine. The study compare the war response against the COVID-19 pandemic and the financial crisis of 2008. The results show that the stock markets respond most rapidly to the geopolitical crisis, and the intensity of the post-invasion period is noticeably smaller than both the COVID-19 crisis and the financial crisis. Their results also show that there was an instantaneous reaction of the global stock markets to the invasion, implying that investors were prepared and reacted quickly. This was a notable difference compared to the two other crises, where there was a lagged response.

This research contributes to the field of finance by increasing our understanding of market behavior during crises. It offers awareness into how financial markets respond to different types of crises, providing information on potential strategies for future crises. Our findings indicate that the three different crises had varied impact on OSE, Stockholm Stock Exchange

(SSE), and Copenhagen Stock Exchange (CSE). Notably, the most significant PINs was exhibited in the financial crisis, implying that institutional investors had superior knowledge compared to uninformed investors. Out of the technical analysis indicators, only MAC indicate significant results pre and during the financial crisis on OSE. The significant findings, exhibited better returns using a MAC strategy compared to the BH strategy.

The reminder of our thesis will consist of chapter 2, which provides a clear description of the different crisis types and the background. Furthermore, chapter 3 presents the underlying literature for our research problem. While chapter 4 gives a explanation of our data gathering process, and a description of the collected data. Chapter 5 explains the research methodology used in our thesis. Moreover, chapter 6 presents our results by utilizing plots and tables. In chapter 7, we further discuss our findings. Lastly, chapter 8 concludes the thesis with a summary of our findings, and suggestions for future research.

Chapter 2

Crises

2.1 Financial Crises

A financial crisis occurs when financial obligations and/or assets drop significantly. As a result of this, businesses have trouble meeting their financial obligation, and financial institutions face shortages of cash or other convertible assets. The importance of temporary liquidities during rapid build up of external debt is highlighted by Radelet et al. (1998) and Chang and Velasco (2001).

In 1929, a major financial crisis known as The Great Depression began, significantly impacting global economies. The Federal Service System tracked change in status for all United States operating banks from 1929 to 1933. Richardson (2007) studied chronological patterns in aggregate series from the data collected by the Federal Service System in this time period. The findings were that it was illiquidity and solvency that were the substantial source of distress for the banks. The heightened distress correlated with the increase of illiquidity, started the initial bank panics. These factors led to an increase in unemployment and a lower financial stability for both businesses and people. National crises can affect the global financial market, underlying the globalization and interconnected nature of modern economies.

Foster and Magdoff (2009) argue that the financial crisis of 2008 was a precipitated by a combination of low lending standards, misuse of collateralized debt obligations and insufficient regulation of the financial institutions. These occurrences tend to trigger panic selling and lack of confidence in the financial systems, which amplifies the dropping of market prices.

Both of these crises show that the illiquidity and solvency is one of the main problems, indicating that the lending practices are driven by speculation and regulatory failures. Financial institutions often cease to function or operate under severe legal constraints when decisive actions are taken. When these institutions do not work properly, it is unrealistic to expect the financial markets to remain efficient. In theory, market equilibria may no longer exist due to this lack of market efficiency. In our research, we have decided to focus only on the financial crisis of 2008.

2.2 Health Crises

A health crisis is defined as a significant public health event, that crosses international borders affecting a large number of people. There is clear evidence of the different health crises affecting people's lives, economy and well being. Kelly (2011) describes it as an epidemic or pandemic that impacts societies and economies. Some of the different pandemics we have experienced include SARS, where Siu and Wong (2004) state that the pandemic started in the Chinese province of Guangdong at the end of 2002. By 2003 it had spread across 29 countries and 3 regions, infecting thousands of people and accumulating approximately 916 deaths.

Another devastating health crisis was the Spanish Flu, reining from 1918 to 1920. According to Barro et al. (2020), it was estimated to affect millions world wide and resulting in the deaths of around 40 million people. Karlsson et al. (2014) and Del Angel et al. (2023) are some of the few that have done research on the economical impact of the Spanish flu. With both studies indicating that the Spanish flu had a negative economic impact. Their studies were based on different markets and regions, with one study based in Sweden and the other in U.S. Karlsson et al. focusing on the general economic conditions and well-being, and Del Angel et al. study stock returns in the U.S.

This research will take a look at the most recent health crisis that started in late 2019, named COVID-19, originating from Wuhan, China. This health crisis was identified as a global pandemic in March 2020 (World Health Organization, 2020b). There is a large amount of research done in recent years, and how COVID-19 has affected the global markets. For example, Ullah et al. (2023) used quantile regression to study the nexus between COVID-19 and market volatility of global markets. Their results show that any increase in COVID-19 positively caused volatility in the market. The financial markets will not be affected during a health crisis, such as for a financial crisis. The environment in which the institutions operate will be affected, but the financial institutions themselves will continue to function.

2.3 Geopolitical Crises

Caldara and Iacoviello (2022) describes a geopolitical risk as "the threat, occurrence, and escalation of adverse event concerning war, terrorism and any tension between states and political factors that impact the peace process in international relations". These crises often impact not only the countries involved but also global peace, security, and economic stability. Similar to health crises, financial institutions are likely to remain unaffected during geopolitical crises and continue to function.

Currently, Europe is witnessing the war between Ukraine and Russia. According to Jonathan Masters (2024), Western analysts look at the invasion initiated by Russia as a resentment towards NATO and their influence on former Soviet regions. Putin and other Russian leaders alleged the US and NATO to violate pledges made in the early 1990s. U et al. (2024) check the impact of the Russia-Ukraine war has had on volatility spillovers. According to their research, the war impacted the spillover to other markets. The restrictions was one of the main factors causing this, with Russian banks losing access to Society for Worldwide Interbank Financial Telecommunications (SWIFT). They also found that the spillovers is correlated with the Ruble at the start of the war, but this diminishes when investors realize that the war is likely to persist over a longer period.

The second war is between Israel and Palestine. An article Jonas Iversen (2024) posted on the United Nations web page, explains how the war in Gaza is a conflict that has been ongoing for decades with a 58 year occupation, but in October 2023 Hamas militants killed over 1.100 Israelis. Israels military reaction to this, has resulted in over 30.000 killed Palestinians. Actions like this affects the political, economical, military and social aspects of especially the nations involved, but also other nations.

This research will further investigate the reproductions of such geopolitical crisis, focusing on the financial impact of the Russia-Ukraine conflict and the information asymmetry it might create in financial markets.

Chapter 3

Literature Review

3.1 Market Efficiency

The financial industry has expanded, financial markets have seen more an increase in liquidity, and there has been advancement in information technology. J. Bai et al. (2016) question if financial markets prices have become more informative. They study the informativeness of predicting future cash flows based on current market prices using annual data from 1960 to 2014. During this period, they find that price informativeness has improved over longer time horizons, specifically three to five years. They observed an informativeness increase of 60% over a three-year horizon and 80% over a five-year horizon from 1960 to 2014. Their study shows evidence supporting the hypothesis that the increase in informativeness reflects greater revelatory price efficiencies. Indicating that the markets are more informative and therefore more efficient at capital allocation.

Lo (2004) developed a tailored concept of Adaptive Market Hypothesis (AMH), against the background of doubts that the efficient market theory was an all-or-none concept. The AMH reconciles behavioral alternatives by applying the principles of evolution; competition, adaptation, and natural selection. Rodriguez et al. (2014) use the framework by Lo, to study the deviation of the random walk behavior over time. Rodriguez et al. states that the market efficiency varies over different time scales from weeks to years. Their results showed that interday and intraday returns are more serially correlated than overnight returns, meaning that how past price changes relate to future price changes differs based on the time frame considered.

3.2 Information Asymmetry

Capital markets are dictated by information. While investors trade based on information, others trade with no information. Easley and O'Hara (1992) developed PIN to measure information heterogeneity in the market. Easley et al. (1996) present the probability of informed trading as a proxy for information asymmetry. This measurement is based on the probability that trades are based on information, or not based on any information.

Coller and Yohn (1997) examines the ask-bid spread related to quarterly earnings forecasts to determine the motivations behind these forecasts and their impact on information asymmetry. A higher spread generally indicates greater uncertainty. The study finds that within nine days of a forecast release, the spread decreases significantly, suggesting enhanced clarity and reduced information asymmetry. Consequently, the study concludes that market efficiency improves with the reduction in information asymmetry. Furthermore, Blume et al. (1994) investigates the effectiveness of technical analysis within environments characterized by information asymmetry. The study finds that technical analysis is effective when prior information on a security is not precise, and market data is of high-quality. Moreover, the paper puts forward that small-cap stocks are more affected by private information, making technical analysis based on private data more likely to succeed for these securities.

3.3 Behavioral Finance Perspective

Researchers within behavioral finance look at technical analysis and the profitability of this method of investing as a result of security prices being affected by human errors. Researchers like Daniel et al. (1998) state that investors are overconfident in the private signals they obtain. The authors think this is a result of biased self-attribution and that it might lead to positive autocorrelation of returns in the short term and negative correlation in the long term. Investigating investor sentiment might reveal further price distortions, a topic that Shleifer and Vishny (1997) explore in their study on the limits of arbitrage. De Long et al. (1990) imply that the presence of noisy trader risks will further increase the risk for rational traders, making them less likely to correct price trends. There are other factors like conservatism which Barberis et al. (1998) takes a look at and Bikhchandani et al. (1992) herding research might also contribute to price trends.

3.4 Probability of Informed Trading

Information asymmetry in markets may be hard to measure. Easley et al. (1996) developed a measurement for informational trades in the market. There have been several extensions to the framework in recent times. Duarte and Young (2009) added the assumption of the market witnessing unexpected symmetric order flows. AdjPIN is defined as the ratio of expected informed orders in total expected order flow. In this study, they estimate PIN based on intra day data from the Institute of the Study of Securities Markets (1983-1992) and the New York Stock Exchange (NYSE) Trade and Quote (1993-2005) database. From these databases, the full sample include all stocks on NYSE and American Stock Exchange (AMEX). After calculating the PIN for these two exchanges, the percentiles of 95, 50, and 5, have PIN estimations of 0.51, 0.20, and 0.10, respectively. While the AdjPIN was 0.37, 0.17, and 0.08, in the same percentiles.

Moreover, Yan and Zhang (2012) develop an algorithm to overcome the estimation bias caused by boundary solutions. Furthermore, they use the likelihood functions EHO factorization by Easley et al. (2010), and the LK factorization by Lin and Ke (2011). The findings shows that the EHO factorization shows downwards bias, while the LK factorization shows a high frequency of boundary solutions. As a result, a new algorithm is developed using the LK factorization.

While the PIN is considered a robust proxy for measuring prevalence of informed trades, it has its critics. According to Jackson (2013), PIN estimations can fail for firms with high trading volumes due to computational issues such as over/under-flow. Jackson suggests scaling the largest trade count to between 800 and 1000 to ensure accurate PIN estimation for large, liquid firms, an approach that will become increasingly important as trading rates continue to rise. Yan and Zhang (2014) provide evidence supporting the PIN-return relationship, addressing estimation biases and improving the quality of quarterly PIN estimations. Their Fama-MacBeth cross-sectional regressions demonstrate stronger evidence for a positive PIN-return relationship, which remains robust against January, liquidity, and momentum effects. Additionally, Boehmer et al. (2007) critiques the PIN estimation first developed by Easley et al. (1996), highlighting that trade classification algorithms often inaccurately infer buyer- and seller-initiated trades, resulting in downward-biased PIN estimations. They recommend a data-based adjustment procedure to mitigate this misclassification bias. Kubota and Takehara (2009) investigate whether the variables related to PIN estimations by Easley et al. (1996), help explain the daily price discovery process in an electronically order-driven market of the Tokyo Stock Exchange from 1996 to 2005. In their computations of the PIN estimations, they found the mean, median, and standard deviation, 0.189, 0.187, and 0.063, respectively. These results are close to the results found by Easley et al., which look at the NYSE from 1983 to 1998. Easley et al. (1996) found a mean of 0.191 with standard deviation 0.057. The results regarding mean and standard deviation are surprisingly close, regarding the two different markets and time periods.

3.5 Technical Analysis

3.5.1 Moving Averages

There has been a long dispute regarding the profitability and predictive powers of technical analysis. Brock et al. (1992) used simple technical analysis indicators on the Dow Jones index from 1897 to 1986. The results gave strong support for strategies based on technical analysis. Furthermore, studies such as Chong and Ng (2008), Teixeira and de Oliveira (2010), and Han et al. (2013) conclude that using technical analysis can generate greater profits than the BH strategy. While these studies utilize different technical analysis tools to generate higher profits, we can see evidence that there are some predictive powers in these technical analysis strategies. Additionally, Hsu et al. (2010) tests the predictive power of technical analysis in growth and emerging markets. The study finds significant evidence of predictive power in these markets when applying technical analysis. Y. Zhu and Zhou (2009) provide a theoretical justification for investors to use the Moving Average (MA) rule in a standard asset allocation problem. Their study shows, when stock returns are predictable, technical analysis, enhances the effectiveness of widely applied allocation strategies. A combination of the fixed allocation rules when integrated with technical analysis, can surpass the performance of the prior-dependent optimal learning model when the prior is not too informative, when uncertainty exits about predictability. Chong and Ng (2008) and Chong et al. (2014) tests MACD on 60 years of data on the London Stock Exchange. Chong and Ng (2008) found that the MACD (12,26,10) strategy outperformed the BH strategy on the London Stock Exchange. On the other hand, Chong et al. (2014) revisit the study, and tests three different MACD strategies on the five different exchanges. When revisiting at a later time, there is no significant evidence that MACD will beat the BH strategy consistently, where some results outperform BH, and vice versa.

Blume et al. (1994) take a further look at the potential effectiveness of technical analysis when information asymmetries are present. The authors suggest a scenario where both the mean and the variances of price signals are unpredictable. In such circumstances, investors should be able to enhance their expected utilities by utilizing historical prices to estimate future prices. In certain conditions, the study suggest that technical analysis could prove to be particularly beneficial. For instance, employing technical analysis when there is a lack of precise prior information about a security and market data contain valuable insight, will make technical analysis more advantageous. In addition, they state that specific securities, like small-cap stocks or stocks with less market attention, are more susceptible to the influence of private information compared to public information. Technical analysis strategies with more private information are more likely to be successful in these cases.

Hung and Lai (2022) examine the conjunction of Blume et al. (1994)'s work empirically. The paper construct portfolios from NYSE and AMEX based on their PIN. They compare the profitability of the different portfolios that are based on different levels of PIN. The technical analysis strategy they are testing is MA, with MA 10, 20 and 50 days. The results show that portfolios with a high PIN will produce abnormal returns, when using an MA strategy compared to a BH strategy. The results still persist after employing the Fama French five-factor model created by Fama and French (2015) which capture size, value, profitability and investment patterns.

Scepticism Towards Technical Analysis

There is also scepticism around technical analysis, these sceptics are mainly supporters for the efficient market hypothesis. They assume that it is not possible to expect profits using past prices as shown by Samuelson (1965) and Fama (1970). Bodie et al. (2021) arguments that using technical analysis will lead to failure. Furthermore, they assume that investors are more than capable of identifying patterns and trade on technical analysis signals, and with competition in the market, the abnormal returns will be equal to zero. Studies such as H. Zhu et al. (2015), Chen et al. (2009), and Chuang et al. (2024) share the conclusions that although technical analysis may generate higher profitability, the high frequent trading, results in high transaction costs that eliminate the profits. Moreover, the work of Marshall and Cahan (2005) applies technical analysis strategies to the New Zealand market as it has signs of market inefficiency. The study concludes that technical analysis is no longer profitable as markets may be efficient.

3.6 Firm Size

Earlier research has studied how firm size impacts technical analysis, Aslan et al. (2011) find evidence of consistency with high information risk firms being smaller, having larger cash holdings, being more heavily held by insiders, being more heavily traded by institutions, and belonging to more volatile industries. The most important influence found in their data, was of the firm size. Smaller firms have higher PIN's, indicating that information structure of small firms may differ from larger firms. To investigate these size effects further, they ran their estimating equation separately for the firm sizes, the smallest 50% and the largest 50%. For the small firms, the size is somewhat less important than the first sample. On the other hand, large firms have an even greater negative effect, amplifying their results that information-based trading is a higher risk for small firms.

Shynkevich (2012a) find that technical analysis work better for small-cap portfolios than large-cap tech firms. Their results show that several tech industries and a number of small-cap sector portfolios produce superior performance. This is after adjusting for data snooping bias, but before transaction cost. After adjusting for both, only small-cap companies have a grater success when applying technical analysis. In the other study by Shynkevich (2012b), examines the return predictability along two dimension, value/growth and size. The use of daily returns allows for evaluation of the historical effectiveness if a set of active investment strategies are applied to portfolios consisting of small and large cap stocks. Where they find that smaller market cap companies produce better predictability in returns compared to larger market cap companies. Han et al. (2013) show that using MA rules is effective regarding market cap. The evidence show that smaller market cap portfolios, perform significantly better than larger market cap portfolios. When the portfolio returns are compared, both beat the market return with 10, 20, 50, 100 and 200 MA rules.

Chapter 4

Data

4.1 Data Gathering

4.1.1 Application Programming Interface

The data has been provided by Saxo Bank which is a Danish bank. They provide a range of investment instruments, where we have used stocks as our instrument for this research. The process behind retrieving historical stock prices for Norwegian, Swedish and Danish stocks starts at Saxo Bank. They provide the opportunity to access their Application Programming Interface (API) for free by registering as a customer. The service is called Open API which can be found under their Developer Portal.

After becoming a costumer, a user-ID will be created which gives you the credentials to log in to the Developer Portal. When you have gained access to their Developer Portal, the next step will be to create a simulation application which can access OpenAPI in the DEMO environment. In addition to this, there will be a need to request a live app, which can access the OpenAPI in the live environment.

After creating the two applications, the applications will allow access to their brokerage web page called SaxoTraderGo. Once this connection is created, we used Python to extract the historical prices. Since we do not need live data, we used the client API KEY and SECRET KEY provided through the simulation application. In the application the authorization endpoint and token endpoint are provided; these two endpoints are the same for everyone using the simulation application.

The next step of collecting the data is to write code in Python which can extract the historical prices. In the Python code, a redirect URL is provided, which also has been implemented in the simulation application created in the Developer Portal. This redirect URL will provide you with the opportunity to log on to the simulation application through the script in Python, by running the code then typing the redirect url in a browser. In Python, the API KEY and SECRET KEY are provided to connect to the correct application and user id.

After the data is collected from the API, the code in Python transforms the data into Comma-Separated Values (CSV) files. The CSV files have Close, High, Interest, Low, Open, Time and Volume as headers. Since we use the algorithm of Lee and Ready (1991), we exclude the headers Interest, Open and Volume. After rearranging the headers we keep, the output of the data is sorted by Time, Close, High, Low when we implement it into R.

Stock Selection

After fetching the data using the OpenAPI provided by Saxo Bank, we end up with 30 different CSV files, one for each stock fetched from the three different exchanges. We construct three portfolios of 10 stocks each, based on which exchange they are listed on. We have fetched the data for 10 Norwegian stocks listed and traded on OSE, 10 Swedish stocks listed and traded on SSE and 10 Danish stocks listed and traded on CSE. The companies are listed in table 4.1.

OSE - Norwegian	**SSE - Swedish**	**CSE - Danish**
DNB Bank ASA *(9,24%)*	ABB Ltd *(10,75%)*	A.P. Møller - Mærsk A A/S *(2,49%)*
Equinor ASA *(27,16%)*	AstraZeneca PLC *(26,70%)*	Carlsberg B A/S *(2,06%)*
Mowi ASA *(3,07%)*	Atlas Copco AB ser. A *(9,66%)*	Coloplast B *(2,93%)*
Norsk Hydro *(3,99%)*	ASSA ABLOY AB ser. B *(3,54%)*	Danske Bank A/S *(2,50%)*
Orkla ASA ASA *(2,48%)*	Hexagon AB ser. B *(3,38%)*	Demant A/S *(1,09%)*
Stolt-Nielsen ASA *(0,92%)*	Hennes & Mauritz AB *(2,79%)*	DSV A/S *(3,26%)*
Storebrand ASA *(1,49%)*	Investor AB ser. A *(8,83%)*	Genmab A/S *(1,99%)*
Telenor ASA *(5,25%)*	Sandvik AB *(3,03%)*	Novo Nordisk B *(61,12%)*
Tomra Systems ASA *(1,25%)*	Skandinaviska Enskilda Banken ser. A *(3,14%)*	Tryg A/S *(1,35%)*
Yara International ASA *(2,44%)*	Volvo AB ser. A *(5,90%)*	Vestas Wind Systems A/S *(2,96%)*

Table 4.1: This Table Provides an Overview of the Portfolios of OSE, SSE, and CSE. Companies are Listed Alphabetically Along with Their Respective Market Capitalization.

4.1.2 Rationale for Data Selection

The data we have chosen to use includes 10 stocks from each of the three Scandinavian exchanges. The reason we chose these stocks is because of the availability of intraday historical data down to 15 minutes data points. These specific companies have this data all the way back to 2007 and further. Since the first crisis we are testing is the financial crisis in 2008, we only need data from the start of 2007 and no further back in time. These companies are also the largest companies on their respective exchanges based on market capitalization that have accessible data back to 2007 through the API.

4.1.3 Time Intervals

When we are looking at the different crisis situations we have sectioned the three crises into pre-, during- and post-crisis. After earlier research done by Aslan et al. (2011) and Yan and Zhang (2012), they use quarterly time intervals when calculating the PIN. Yan and Zhang use nearly 80.000 stock-quarters in their research. Since we do not have the opportunity to use that many quarters, we will use 12-month intervals to represent the different stages of the financial crisis, and 10 months for the health- and geopolitical crisis. When we define the 'during crisis' period, it will start from the month when, in our cases, the financial crisis was officially declared, when World Health Organization (WHO) officially declared COVID-19 a Public health Emergency of International Concern and when Russia invaded Ukraine. We have chosen these time intervals based on economic, political, and market behavioral changes. Table 4.2 gives a clear overview of our time intervals used in our thesis.

Time Intervals Overview						
	Pre-Crisis		During-Crisis		Post-Crisis	
Crisis Type	Start	End	Start	End	Start	End
Financial	2007-09-15	2008-09-15	2008-09-15	2009-09-15	2009-09-15	2010-09-15
Health	2019-03-30	2020-01-29	2020-01-30	2020-11-29	2020-11-30	2021-09-29
Geopolitical	2021-04-24	2022-02-23	2022-02-24	2022-12-23	2022-12-24	2023-10-23

Table 4.2: Overview of Time Intervals for Each Crisis Type.

Financial Crisis

We define the pre-crisis interval for the financial crisis from September 15, 2007, to September 15, 2008. According to Kosová and Enz (2012) the financial crisis commenced September 15, 2008. Consequently, we have decided to use 12 months prior this date to construct the pre-crisis period. The interval during the crisis are from September 15, 2008, to September 15, 2009. This is marked by the collapse of Lehman Brothers, which shocked and significantly impacted the financial markets, as documented by Kosová and Enz. Lastly, the post period spans from September 15, 2009, to September 15, 2010. Brem et al. (2020), Cheema et al. (2022) and Fan et al. (2022) states that from June 2009 the market dynamics started to shift, signaling the end of the financial crisis. Since the time intervals for the financial crisis are 12 months, we have decided to start the time period for the post period immediately after interval during the crisis ends.

Health Crisis

For the health crisis, we define the pre-crisis interval from March 30, 2019, to January 30, 2020, a full 10 months before the designated crisis period. The during-crisis interval is from January 30, 2020 to October 30, 2020. The start date is based on WHO declaring COVID-19 as a Public health Emergency of International Concern, following recommendations of the Emergency Committee, (World Health Organization, 2020a). The post-crisis period runs from October 30, 2020, to August 30, 2021, which spans 10 months following the end of our designated crisis period

Geopolitical Crisis

For the geopolitical crisis, the pre-crisis interval is defined from April 24, 2022, to February 24, 2022. This timeline is based on when Russia initiated their first move over Ukraine's borders, making the onset of the invasion, as stated by U et al. (2024), Mishra et al. (2024), Urak et al. (2024). The during-crisis interval covers February 24, 2022, to December 24, 2022, the first 10 months of the conflict. Finally, the post-crisis period extends from December 24, 2022, to October 24, 2023, covering the 10 months following the during-crisis phase.

4.2 Visualization of Price Evolution under Crises

Figures 4.1, 4.2 and 4.3 shows historical prices for the financial, health, and geopolitical crisis time periods. The prices are computed by the equally weighted portfolio of 10 stocks from each stock exchange, which has been illustrated in Table 4.1. The plots represent an overview of the price change before, during, and after the different crises. This gives a better understanding of the reaction of the different markets.

4.2.1 Financial Crisis

Figure 4.1, which represents the financial crisis, has price data from the start of 2007 until the start of 2010. Even though the financial crisis started on the 25th of September when Lehman Brothers went bankrupt as stated earlier in the paper, there is clear evidence that the market had reacted before this event. For both SSE and CSE, the exchanges started to gradually decline in price already at the end of 2007. OSE, on the other hand, had a significant decrease from the summer in 2008.

For all three exchanges, the negative trend reversed in the first quarter of 2009, and they gradually started to recover, but the recovery did not reach back to the pre-crisis prices until after 2010. Some of the main differences for the three exchanges are the government and the central banks monetary policies, as a response to reduce the financial impact.

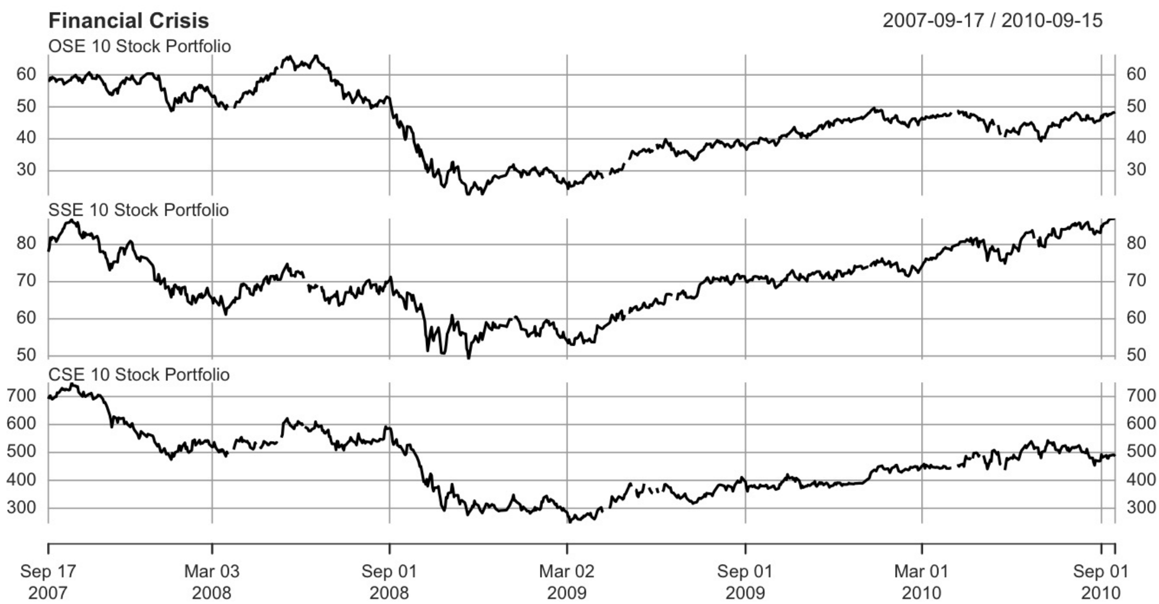


Figure 4.1: Financial Crisis Indices Price Data

4.2.2 Health Crisis

The pattern of the price during the health crisis period in Figure 4.2, is almost identical for the three exchanges. This shows a clear period during which the crisis affected the financial markets form the start of 2019 to the second quarter in 2021. This was when WHO declared the crisis a pandemic at the start of March 2020 (World Health Organization, 2020b). It took approximately the same time for the exchanges to reach the bottom by the end of the month. The reversal of the price also occurred at the same time, with the recovery following the same pattern for all the exchanges.

Interestingly, for both SSE and CSE constitutes pharmaceutical and biotech companies make up a large portion of the exchanges. With AstraZeneca PLC account for 26,7% of the entire SSE, and CSE having Novo Nordisk and Genmab, constituting 61,12% and 1,99% of CSE, respectively. Even though almost two thirds of CSE's market capitalization consist of the pharmaceutical sector, the two companies does not produce anything significantly regarding COVID-19 vaccines or similar pharmaceuticals. AstraZeneca PLC, on the other hand, was one of the companies that produced the vaccines against COVID-19, and in December 2020, their vaccines was authorized for emergency supply in the UK, (AstraZeneca, 2020). Although AstraZeneca PLC have produced vaccines since 2020, and their market capitalization have more than doubled. It does not show any evidence of impacting the SSE significantly.

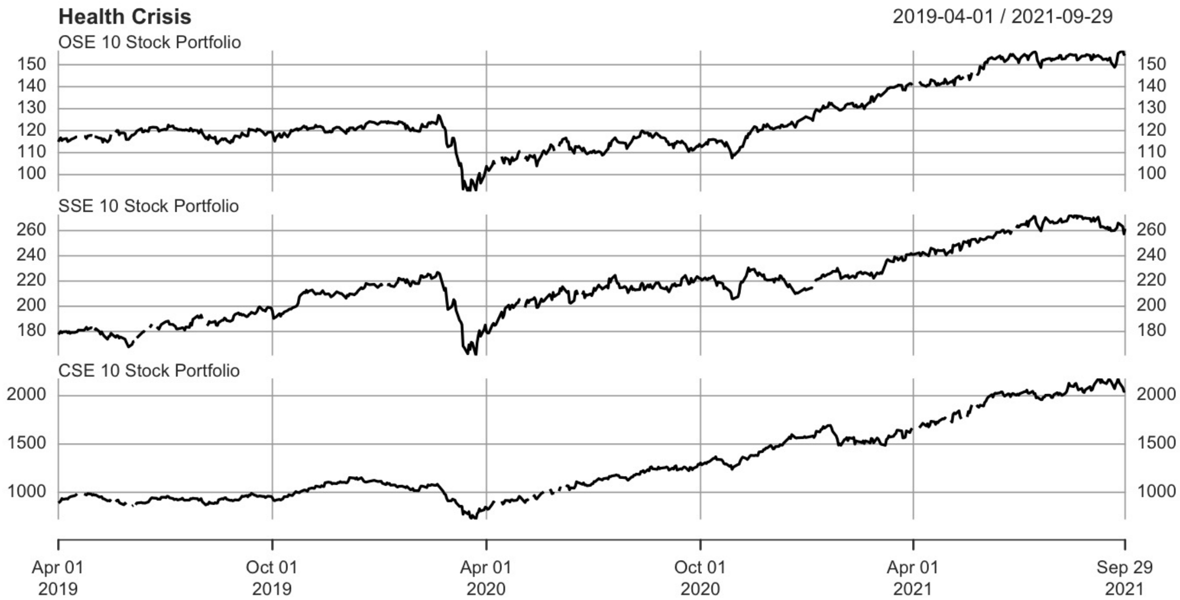


Figure 4.2: Health Crisis Indices Price Data

4.2.3 Geopolitical Crisis

Finally, the geopolitical crisis in Figure 4.3. The price plots for SSE and CSE show a somewhat similar pattern at the turn of the year 2021, declining in price. There was a lot of uncertainty at the start of 2022 in Europe, due to the tension between Russia and Ukraine. Investors wondering what effect and impact a potential war would have on Europe.

OSE, on the other hand, had a gradually increase in price from the first to the third quarter of 2022. This can be explained by the fact that OSE is composed of several oil and gas companies, which make up a large part of the entire exchange. Equinor from Table 4.1 constitutes 27,16%, and two other oil comapnies, Aker BP and Vår Energi which does not have data back to 2007, constitutes of approximately 5,35% and 2,81%, respectively, of the entire exchange at this time. The sanctions towards Russia and their oil and gas industry caused the companies within this sector to increase their revenues drastically during the first two quarters of 2022. The scarcity of oil and gas caused the prices to increase with between 60-70% from December 2021 to March 2022. Evidence from the research by Katsampoxakis et al. (2022), found that when OSE in a high volatility trend, the stocks on the exchange have a higher correlation with Brent Crude Oil compared to OSE's volatility being steady. This could help explain the difference of price movements for OSE compared to SSE and CSE.

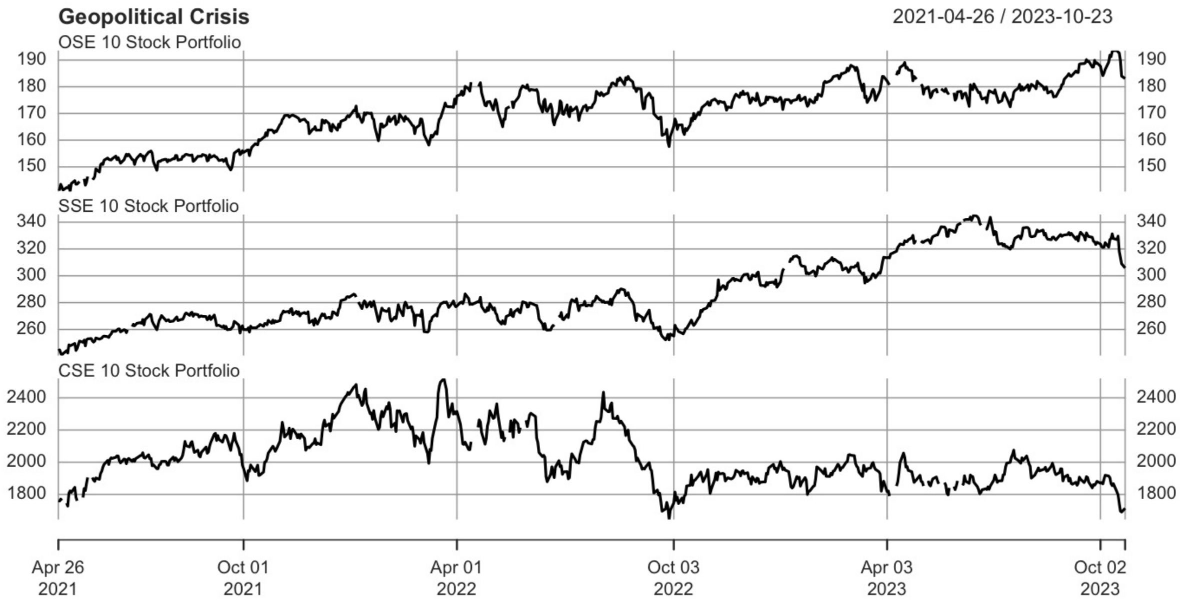


Figure 4.3: Geopolitical Crisis Indices Price Data

4.3 Data for the Technical Analysis

For our technical analysis, we will use historical daily stock data derived from Yahoo Finance. Moreover, we will use the adjusted close prices to compute the total returns (TOT) for the portfolio, and close prices to compute the capital gain returns (CAP). While for the risk-free (RF) interest, we use data from Odegaard (2021) website[1]. The risk-free interest is estimated by using forward looking interbank rates (NIBOR). Table 4.3 presents a summarized overview of the descriptive statistics for returns of the 10 Stock in the OSE portfolio. We divide the

[1]Asset Pricing Data by Bernt Arne Ødegaard: https://ba-odegaard.no/financial_data/ose_asset_pricing_data/index.html

descriptive statistics in 3 periods, where each period represents a crisis type. The crisis periods starts and ends with our defined crisis time periods from Table 4.2.

Crisis Analysis Across Different Phases									
	Financial Crisis			Health Crisis			Geopolitical Crisis		
Statistics	TOT	CAP	RF	TOT	CAP	RF	TOT	CAP	RF
Mean (%)	-0.11	-0.12	0.01	0.03	0.02	0.00	-0.04	-0.06	0.01
St.Dev (%)	2.37	2.36	0.01	1.27	1.36	0.00	1.07	1.22	0.01
Minimum (%)	-11.14	-11.07	0.01	-9.84	-10.24	0.00	-6.38	-8.23	0.00
Maximum (%)	8.34	8.23	0.03	4.80	5.95	0.01	3.03	2.86	0.02
Skewness	-0.66	-0.65	0.28	-0.87	-0.73	0.62	-0.90	-1.18	0.33
Excess Kurtosis	2.82	2.79	-1.60	7.65	6.95	-1.21	3.70	5.65	-1.35
Jarque-Bera	302	296	90	1603	1315	78	446	986	60
p-value	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**

Table 4.3: Descriptive statistics for our 10 stock portfolio from Oslo Stock Exchange separated in financial, health, and geopolitical crisis periods. *TOT* denotes the total return, *CAP* denotes the capital gain return, and *RF* denotes the risk-free return. *Jarque-Bera* represents the statistics in the normality test and the p-value connected to the test are reported below. Bold p-values are significant at the 5% level.

Table 4.3 shows that the TOT and CAP had a negative mean return during the financial and geopolitical crisis period. Conversely, the health crisis period reported marginally positive mean returns. The standard deviation indicates that the financial crisis period exhibits more variations in the returns. Furthermore, our descriptive statistics shows that the TOT and CAP for all crises have negative skewness, indicating that the distribution is skewed to the left. On the other hand, the RF for all crises have positive skewness, indicating that the distribution is skewed to the right. This suggests that there are more extreme negative returns compared to positive returns for TOT and CAP, while there are more extreme positive returns compared to negative returns for the RF. Moreover, the excess kurtosis for the TOT and CAP for all crises are positive, indicating heavier tails and a sharper peak compared to a normal distribution. Conversely, the excess kurtosis for RF shows negative values for all crises, indicating lighter tails and a flatter peak than a normal distribution. Correspondingly, the performed Jarque-Bera test rejects the null hypothesis of normally distributed returns in each crisis period.

Chapter 5

Methodology

5.1 Classifying Trading Data

We need to classify our high-frequency data into buyer-initiated and seller-initiated trades. There are different algorithms and literature regarding this topic. We will utilize the algorithm developed by Lee and Ready (1991) which uses the tick test technique to determine the direction of a trade. The algorithm uses the transaction price relative to the mid-point of the bid and ask quote at the time of the transaction. If the transaction price is higher (lower) than the mid-point, the algorithm classifies the trade as a buyer-initiated (seller-initiated) trade. When the transaction price is equal to the mid-point, the trade will be classified by using the tick test. This test will check if the transaction price is higher (lower) than the previous transaction price, to determine if the trade is classified as a buyer-initiated (seller-initiated) trade. Furthermore, Ellis et al. (2000) found that Lee and Ready´s algorithm classified 81.05% correctly.

5.2 PIN Estimation

We will utilize the PIN to measure the information asymmetry. More precisely, we will follow Yan and Zhang (2012) algorithm which is using the LK factorization by Lin and Ke (2011). The model outlines that on any given day t, the likelihood of observing any number of buy initiated trades B_t and the number of sell initiated trades S_t is given by the following:

$$L(\theta \mid B_t, S_t) = \Pi_{t=1}^{T} l(\theta \mid B_t, S_t), \tag{5.1}$$

Where

$$
\begin{aligned}
L(\theta \mid B_t, S_t) =&(1-\alpha)e^{\epsilon_b}\frac{\epsilon_b^{B_t}}{B_t!}e^{\epsilon_s}\frac{\epsilon_s^{S_t}}{S_t!} + \alpha\delta e^{-\epsilon_b}\frac{\epsilon_b^{B_t}}{B_t!}e^{-(\mu+\epsilon_s)}\frac{(\mu+\epsilon_s)^{S_t}}{S_t!} \\
&+ \alpha(1-\delta)e^{-(\mu+\epsilon_b)}\frac{(\mu+\epsilon_b)^{B_t}}{B_t!}\frac{\epsilon_s^{S_t}}{S_t!}
\end{aligned}
\tag{5.2}
$$

The set of parameters $\Theta = (\alpha, \delta, \epsilon_b, \epsilon_s, \mu)$ characterizes the trading dynamics for each day. Where, α represents the probability of an informational event occurring, and $1-\alpha$ representing the probability of no event. Furthermore, the parameter δ gives the probability of bad news, and conversely, $1-\delta$ giving the probability of good news for the security. While these informational events occur or not, uninformed traders will submit buy orders following the arrival rate ϵ_b and submit sell orders following the arrival rate ϵ_s. Lastly, given an informational event, informed traders will submit buy or sell orders at the daily arrival rate of μ. The PIN is then defined as the rate of informed trades divided by the rate of total trades given by the following formula:

$$
PIN = \frac{\alpha\mu}{\alpha\mu + \epsilon_b + \epsilon_s} \tag{5.3}
$$

To illustrate the connection of the parameters, we will use the following tree diagram:

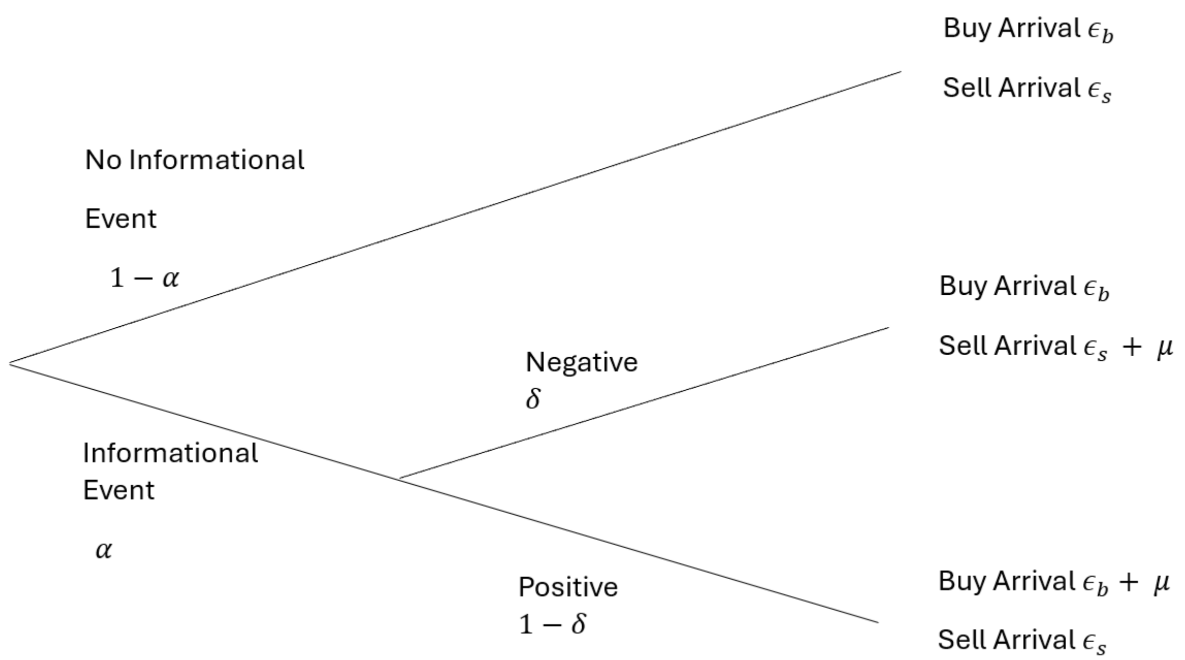


Figure 5.1: Tree Diagram of PIN Model. Reproduced from (Hung & Lai, 2022)

Figure 5.1 provides a clear and intuitive representation of the PIN Model. Given no informational event, the arrival rates of buy and sell will be noise trades. While when a informational event occur, we can observe that the arrival rate of informed traders are introduced based on the good or bad news.

5.3 Technical Analysis

5.3.1 Moving Averages

The MA is the average price of a commodity over a specific period. This indicator is visualised by a line following the price, and the lines movement is smoother than the charted price movement. The prices in the selected time interval of the MA are equally weighted, giving the most recent price the same influence of the MA line as the first price in the interval. Using the computation of the MA presented by Zakamulin (2016), whereas he used monthly data and we use daily data. The moving average $MA_t(L)$ is given by the following formula:

$$MA_t(L) = \frac{P_t + P_{t-1} + \cdots + P_{t-k+1}}{L}. \tag{5.4}$$

Where P_t is the price of the asset at the current time period t, with P_{t-1} being the price of the asset at the previous time period and P_{t-k+1} representing the price k periods before t. The k value is determined so the total numbers of terms are equal to L, the length of the MA window.

Exponential Moving Average (EMA) is based on historical prices. It is similar to the MA, the difference is how the prices are weighted. In the MA as explained in the previous prargraph, all the prices are equally weighted in calculating the average price. The EMA on the other hand, have a greater weighting on the recent price movement and less on the earliest price. The EMA formula is given by:

$$EMA_t = \alpha \times P_t + (1 - \alpha) \times EMA_{t-1} \tag{5.5}$$

Where EMA_t is the exponential moving average at time t. P_t is the price at time t and α is the smoothing factor, which determines the weight given to the most recent price. The α is calculated with the formula in Equation (5.6) where n is the number of periods.

$$\alpha = \frac{2}{n+1} \tag{5.6}$$

5.3.2 MA Strategies

For our research, we will utilize two different trading strategies based on moving averages. Traders want to buy a risky asset when the price is low, and sell when the price is high. Furthermore, to minimize the losses, traders should sell before a downward trend. The MA strategies are commonly used for this purpose, and alternates between investing in a risky asset, and a risk-free asset. We determine the time for buying or selling the risky asset by generating buy and sell signals with our trading strategies. When the trading strategy generates a buy signal, we either buy or keep our investment in the risky asset. Conversely, when a sell signal is generated we either invest in, or continue our investment in the risk-free asset. The process for generating these signals follows two steps. Firstly, we use historical data to compute the indicators. Secondly, we utilize these indicators to generate the buy and sell signals. There are an array of different trading strategies regarding technical analysis. For our research we will use the moving average strategies, MAC and MACD.

Moving Average Crossover

The MAC strategy uses two MA with different lengths to generate buy or sell signals. When the shorter MA crosses above the longer MA, a buy signal is generated. On the other hand, when the shorter MA crosses below the longer MA, a sell signal is generated. The formula for the MAC indicator is given by:

$$\text{Indicator}_t^{MAC(s,l)} = MAC_t(s,l) = MA_t(s) - MA_t(l) \tag{5.7}$$

Where s represent the short MA window size, and l represents the long MA window size. The formula clearly shows the relation between the shorter MA and the longer MA.

Moving Average Convergence/Divergence

Appel (1979) introduced the MACD technical indicator and is widely used in technical analysis. This strategy uses a combination of three different EMAs. Firstly, two EMAs are used to calculate the MAC indicator as the following formula:

$$MAC_t(s,l) = EMA_t(s) - EMA_t(l) \tag{5.8}$$

This MAC strategy, as previously mentioned, generates signals based on whether the shorter MA is above or below the longer MA. Moreover, Appel (2005) argues that the MAC can generate false signals, and suggests the use of a smoothed MAC to confirm the indicator signals. This gives us the MACD indicator which is given by the following:

$$\text{Indicator}_t^{MACD(s,l,f)} = MAC_t(s,l) - EMA_t\left(f, MAC(s,l)\right) \tag{5.9}$$

We introduce the notion f which represents the final window size. The indicator will generate signals in relation to the price trend. More specifically, the indicator utilize the convergence and divergence of the short MA and long MA.

5.3.3 Trading Signals

The MAC and MACD has the common purpose of generating a sell or buy signal. Whereas a buy signal tells us that we will invest or keep investing in the risky asset, and conversely, a sell signal tells us to invest or keep investing in a risk-free asset. We can formulate how these trading signals are being generated at time $t+1$ by the following formula:

$$\text{Signal}_{t+1} = \begin{cases} \text{Buy}, & \text{if Indicator}_t > 0, \\ \text{Sell}, & \text{if Indicator}_t \leq 0. \end{cases} \tag{5.10}$$

In the article by Zakamulin (2016), an additional condition is added. This condition stipulates that whenever the investor holds no position in the portfolios, the cash reserve are to be invested in a risk-free asset. The equation for r_{t+1} is given by:

$$r_{t+1} = \begin{cases} R_{t+1} & \text{if } (\text{Signal}_{t+1} = \text{Buy}) \text{ and } (\text{Signal}_t = \text{Buy}), \\ R_{t+1} - \tau & \text{if } (\text{Signal}_{t+1} = \text{Buy}) \text{ and } (\text{Signal}_t = \text{Sell}), \\ r_{f,t+1} & \text{if } (\text{Signal}_{t+1} = \text{Sell}) \text{ and } (\text{Signal}_t = \text{Sell}), \\ r_{f,t+1} - \tau & \text{if } (\text{Signal}_{t+1} = \text{Sell}) \text{ and } (\text{Signal}_t = \text{Buy}). \end{cases} \tag{5.11}$$

Where r_{t+1} represents the return on the asset at time $t+1$, and $(R_1, R_2, ..., R_T)$ denotes the daily portfolio returns on the investments. The series $(r_{f,t1}, r_{f,t2}, ..., r_{f,tT})$ represents the risk-free return. Equation 5.11 assumes that there are no transaction costs related to the risk-free assets. However, transactions related to the buying and selling of the portfolio incur costs and are denoted by τ. Zakamulin (2016) uses 50 basis points as the price of the transaction costs, the same as Glabadanidis (2015) used in his empirical study. We assume that the one-way transaction cost amounts to 8 basis points (0.08%), that is, $\tau = 0.0008$. This is based on the transaction price at Saxo Bank from Table 5.1.

5.4 Transaction Costs

Transaction cost are expenses incurred by an investor during the stock purchasing process. The specific transaction costs referred to in this paper is solely brokerage fees, which is a fixed fee per trade or volume based. We use Saxo Bank's prices in Table 5.1, as our benchmark for the transaction cost in the calculations. The reasoning behind our choice of benchmark, is their wide range of instruments. They offer all stocks listed on OSE, SSE and CSE, but also plenty other exchanges. This benchmark can therefore be used by others calculating MA on the same or other exchanges. Saxo Bank's prices for the three Scandinavian exchanges are the same. Minimum price of 10 kroner in their respective currency, or 0.08% of the total purchasing, if the price exceeds the minimum price.

Exchange	**Price**
Norway	0.08% (min. 10 NOK)
Sweden	0.08% (min. 10 SEK)
Denmark	0.08% (min. 10 DKK)

Table 5.1: Transaction cost Saxo Bank

5.5 Back Test Strategies

In our thesis, we will utilize a commonly used test to evaluate the performance of our strategies. The test we will use is back-test, also known as a in-sample test. The back-test simulates the strategies over a given historical time period. We do not utilize the back-test to select the best strategy, but simply to simulate the pre-decided strategies on our historical data. Furthermore, the back test uses the mean excess return as the performance measurement.

5.6 Statistical Outperformance Test

5.6.1 Outperformance Hypothesis

The estimated performance measures for the moving average and buy-and-hold strategy can be denoted by $\widehat{\boldsymbol{PM}}_{\mathrm{MA}}$ and $\widehat{\boldsymbol{PM}}_{\mathrm{BH}}$ respectively. Moreover, we simply subtract the performance of the BH strategy from the performance measure of the MA strategy. The formula for the outperformance measure is given by:

$$\widehat{\Delta} = \widehat{\boldsymbol{PM}}_{\text{MA}} - \widehat{\boldsymbol{PM}}_{\text{BH}}.$$

Furthermore, as $\{r_t^e\}$ and $\{R_t\}$ are series of observations of two random variables, as a result of this, the estimator $\widehat{\Delta}$ is again a random variable and may give $\widehat{\Delta} > 0$ by chance (Zakamulin, 2017). We will have to use a statistical test to ensure that the $\widehat{\Delta}$ is significantly greater than zero. Furthermore, the alternative and null hypothesis for the real outperformance (denoted by Δ) is given by:

$$H_0 : \Delta \leq 0 \quad \text{versus} \quad H_A : \Delta > 0. \tag{5.12}$$

5.6.2 Bootstrapping Test

There are various methods for assessing the statistically significance of results, primarily classified into parametric and non-parametric tests. Parametric tests depends on assumptions such as normal distribution in the data and no serial dependence, which financial data often does not hold true. As observed in our data, the non-normal distribution and heteroscedasticity makes it clear that the assumptions does not hold. As a result, we can not use parametric tests for the purpose of this thesis. On the other hand, non-parametric tests does not rely on assumptions such as the parametric tests. Given our dataset, the non-parametric tests is preferable for our thesis. We will use the bootstrap technique introduced by Efron (1979). This involves drawing random samples with replacement from the time series data. For our analysis, the paired excess returns are $\{r_t^e\}$ and $\{R_t^e\}$, where $t = 1, 2, \ldots, T$. We draw N bootstrap resamples $t^b = \{s_1^b, s_2^b, \ldots, s_T^b\}$, with each index s_i^b randomly selected with replacement from $\{1, 2, \ldots, T\}$. Each resample t^b generates pseudo-time series $\{r_{t^b}^e\}$ and $\{R_{t^b}^e\}$. This method maintains the correlation structure between the two original data series since each pair $(r_{s_i^b}^e, R_{s_i^b}^e)$ (for $i = 1, \ldots, T$) is sampled simultaneously. We then calculate the difference between the estimated performance measures $\widehat{\Delta}^b$ for each pseudo-time series. Repeating this N times constructs the bootstrap distribution of $\widehat{\Delta}$. To test the hypothesis from Equation (5.12), we count how often $\widehat{\Delta}^b$ is less than zero. The p-value is estimated by $\frac{n}{N}$, where n is the number of negative values.

5.7 R Programming

In our thesis we have utilized the programming software R with the tool Rstudio for our analyses. We have used specialized packages for the purpose of PIN estimation and technical analysis. The following sections will provide a brief overview and explanation of the packages used.

5.7.1 PIN Estimation Program

We have used the packages "PINstimation" and "InfoTrad" which has the functions we need for our analysis. The "PINstimation" package is designed for estimating, the probability of informed trading through the most established estimation methods in the literature (Ghachem & Ersan, 2022). For our analysis, we will use this package to classify the buyer- and seller-initiated trades. The function "aggregate_trades" uses our data with the variables time, price, bid, and ask to output a dataframe with 2 vectors of buy trades(b) and sell trades(s). The "InfoTrad" package provides users with a wide range of options to overcome problems such as floating-point-exception (FPE) and boundary solutions when estimating the PIN. To overcome the bias created by FPE, the package provides the numerical factorization by Lin and Ke (2011). Moreover, to overcome the boundary solution problem, the package provides the YZ algorithm by Yan and Zhang (2012) to estimate the PIN. These packages gives a useful toolkit for PIN estimation in R. The visualization of the results were created with packages from the Comprehensive R Archive Network (CRAN).

5.7.2 Technical Analysis Program

We have utilized the R package "matiming" from the book by Zakamulin (2017) for our technical analysis. Firstly, the package provides us with the function "sim.mac.strategy" and "sim.macd.strategy" which simulates the MAC and MACD strategy returns. Secondly, the function "back.test" provides us the necessary tools to back test our moving average strategies, while also considering a buy-and-hold strategy. Lastly, the function "descriptive.statistics" computes the summary statistics for both the moving average strategy and the buy-and-hold strategy. Furthermore, this function also runs the outperformance test by the bootstrapping method. This package gives us a versatile and effective toolkit to conduct our technical analysis.

Chapter 6

Results

In this chapter we will present our results generated from the analysis. Firstly, we will provide our estimated PIN values derived from a 3 x 3 x 3 structured analysis framework. We have utilized three different stock exchanges, three different crisis types, and three different sub-periods for each crisis type. To provide a effective illustration of the trend and relationship in the PIN values, we utilize bar plots as our visualization tool. The purposed bar plots has been chosen because of its simplicity and effectiveness of comparing varying values over different sub-periods. Secondly, provide a deeper understanding of the results, we visualize the estimated parameters in a structured table. This structured visualization of the data is effective as it organises the data and supports direct comparisons over different crisis periods and sub-periods.

Lastly, we will present our technical analysis results. The technical analysis results are separated into MAC and MACD strategies. We provide performance measures in tables, with the following p-value for our statistical outperformance test.

6.1 PIN Estimation Plots

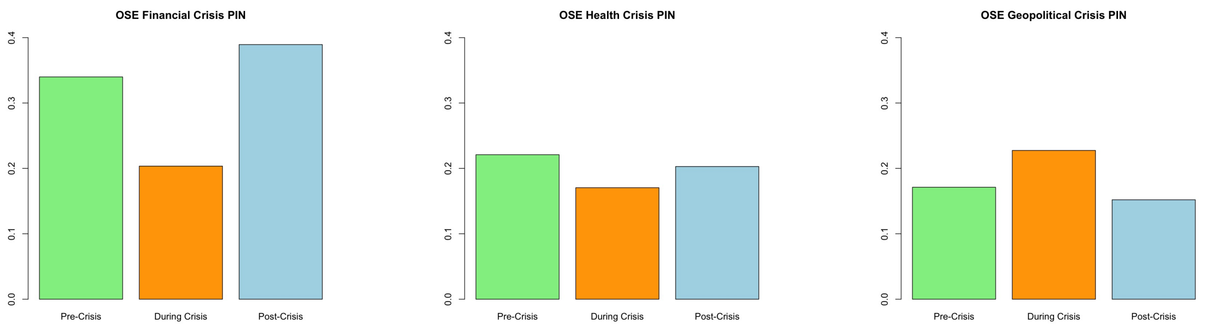
6.1.1 Oslo Stock Exchange

Firstly, we will examine the bar plots for the OSE. Figure 6.1 reports the average PIN values for for the given periods in each crisis type.

Furthermore, Figure 6.1a reports the average PIN values for each crisis period during the financial crisis. The pre-crisis period reports a average PIN value of 3.40. Conversely, the during crisis period reports a significantly lower average PIN value of 2.04. Interestingly, the post-crisis period reports a significantly higher average PIN value of 3.89. The financial crisis period shows a clear pattern of average PIN values going from high, to lower, and back to the highest recorded average PIN value for all three periods.

Figure 6.1b reports the average PIN values for each crisis period during the health crisis. The pre-crisis period reports a average PIN value of 2.21. The during crisis period on the other hand, reports a similar but lower average PIN value of 1.7. Lastly, the post-crisis period reports a similar but higher average PIN value of 2.03.

Figure 6.1c reports the average PIN values for each crisis period during the geopolitical crisis. The pre-crisis period reports a average PIN value of 1.72. We can observe a higher average PIN value for the during crisis period of 2.28. However, the average PIN value for the post-crisis period reverses back to a value of 1.53.



(a) Financial Crisis PIN (b) Health Crisis PIN (c) Geopolitical Crisis PIN

Figure 6.1: PIN Plots for Oslo Stock Exchange

Figure 6.1 shows clear patterns for each crisis type. Particularly, the financial crisis results is showing significant changes in average PIN values. Likewise, the health crisis results are showing the same pattern, but not as significantly. Whereas the geopolitical crisis is showing a reversed pattern of higher PIN value during the crisis, and lower in the pre- and post-crisis periods.

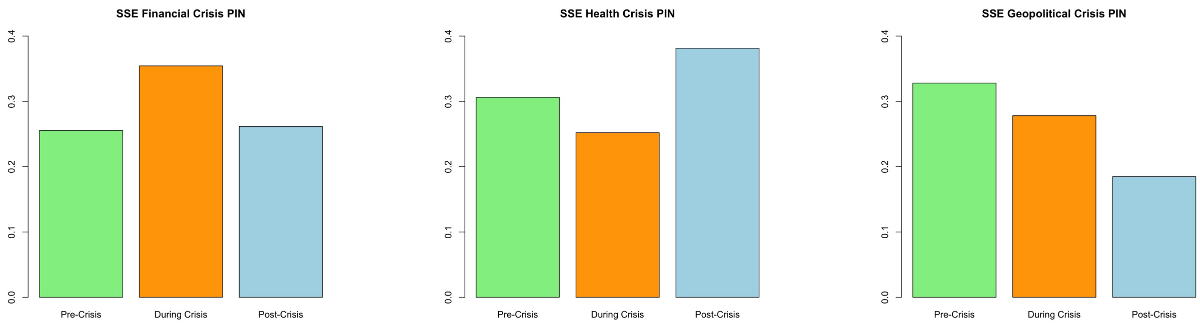
6.1.2 Stockholm Stock Exchange

Figure 6.2 reports the average PIN values for the financial crisis, health crisis, and the geopolitical crisis on the SSE. More precisely, it illustrated the average PIN values for the pre-, during, and post-crisis periods for each crisis type.

Figure 6.2a reports the average PIN values for the financial crisis. We can observe a pre-crisis value of 2.56. Conversely, the during crisis period reports a higher value of 3.55. Lastly, the post-crisis period value reverses back to a value of 2.62 which is similar to the pre-crisis period value.

Figure 6.2b reports the average PIN values for the health crisis. The pre-crisis period reports a value of 3.06. However, the during crisis period is reporting a slightly lower value of 2.53. Interestingly, the post-crisis period reports a significantly higher value of 3.82 which is the highest value for all periods in the health crisis.

Figure 6.2c reports the average PIN values for the geopolitical crisis. The pre-crisis period reports a value of 3.28. By contrast, the during crisis period reports a lower value of 2.78. Lastly, the post-crisis period reports a significantly lower value of 1.85, which is the lowest value of the periods in the geopolitical crisis.



(a) Financial Crisis PIN (b) Health Crisis PIN (c) Geopolitical Crisis PIN

Figure 6.2: PIN Plots for Stockholm Stock Exchange

Figure 6.2 shows different patterns for each of the crisis types. Firstly, we can observe a higher PIN value during the financial crisis, with similar PIN values in the pre- and post-crisis. Secondly, we can observe a lower PIN value during the health crisis, with higher PIN values in the pre- and post-crisis periods. Lastly, the health crisis shows a declining pattern of PIN values, where the pre-crisis values is the highest, and post-crisis values the lowest.

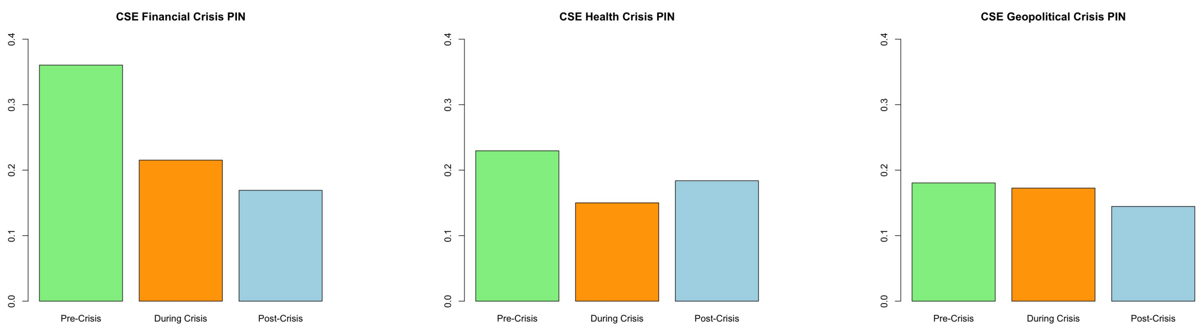
6.1.3 Copenhagen Stock Exchange

Figure 6.2 reports the average PIN values for the financial crisis, health crisis, and the geopolitical crisis on the CSE. More precisely, it illustrated the average PIN values for the pre-, during, and post-crisis periods for each crisis type.

Figure 6.3a shows the average PIN values for the financial crisis. The pre-crisis period reports a significantly high value of 3.61. Conversely, the during crisis period is showing a lower value of 2.16. Interestingly, the post-crisis period is showing the lowest value of 1.69.

Figure 6.3b shows the average PIN values for the health crisis. The pre-crisis period reports the highest value of 2.30. On the other hand, the during crisis period reports a lower value of 1.50. Lastly, the post-crisis period reports a slightly higher value of 1.85.

Figure 6.3c shows the average PIN values for the geopolitical crisis. The pre-crisis period reports a value of 1.81. Similarly, the during crisis period reports a value of 1.73. Lastly, the post-crisis period reports a slightly lower value of 1.44.



(a) Financial Crisis PIN (b) Health Crisis PIN (c) Geopolitical Crisis PIN

Figure 6.3: PIN Plots for Copenhagen Stock Exchange

Figure 6.3 shows different patterns across the different crisis types. The highest PIN value is reported in the pre-crisis of the financial crisis. The health crisis shows a pattern of a lower PIN value in the during crisis period, but not a significant pattern.

6.2 Model Parameters

6.2.1 Oslo Stock Exchange

Table 6.1 reports the model parameters for OSE for all crisis types and sub-periods. The probability of an informational event (α) is high, but some veriation is observed. The financial crisis had a slightly lower probability of an informational event occurring. While the α is high, we can observe different probabilities that the information is bad (δ) or good

$(1-\delta)$ news. Interestingly, we can observe lower probability of bad news in the pre-crisis and during crisis periods of the geopolitical crisis. While the health post-crisis period has a higher probability of bad news. Furthermore, we can observe that the financial crisis exhibit a high fluctuation. The arrival rate of informational trades (μ) is high before and after the financial crisis, while it is significantly lower during the crisis. This implies that there are less trades during the crisis period based on informational events. We can observe the same, but not as distinct pattern for the health crisis. On the other hand, geopolitical crisis period shows a reversed pattern of informed based trades. This suggests that there are more information based trades during a geopolitical crisis. Additionally, we have to consider the noise traders. We can observe a lower level of (ϵ_b) in the pre- and post periods of the financial crisis, and higher arrival rate of uninformed trades (ϵ_s) in the crisis period. This suggests that during the financial crisis, the market experienced a higher arrival rate of uninformed trades.

Oslo Stock Exchange

	Financial Crisis			Health Crisis			Geopolitical Crisis		
	Pre	During	Post	Pre	During	Post	Pre	During	Post
α	1.00	0.93	0.94	0.96	0.96	0.96	0.96	1.00	1.00
δ	0.44	0.46	0.39	0.62	0.52	0.72	0.25	0.32	0.57
μ	10.37	5.38	14.64	5.55	3.63	5.55	3.60	5.20	3.44
ϵ_b	8.91	13.11	7.11	12.27	12.83	13.32	11.84	11.00	13.82
ϵ_s	10.44	14.02	10.56	11.34	12.46	10.23	13.79	13.43	12.46

Table 6.1: PIN Model Parameters Across Different Crises for a Portfolio of Stocks on the Oslo Stock Exchange.

6.2.2 Stockholm Stock Exchange

Table 6.2 report the model parameters for SSE with all crisis types and sub-periods. As the results for OSE showed, we can observe high values of α through out all the sub-periods, except the pre-geopolitical crisis. Nevertheless, the probability of an informational event to occur during all periods is high. While these informational events are highly likely to occur, we also have to evaluate whether the information is characterized as good or bad news by checking the δ values. We can observe a high probability of bad news (δ) during and post financial crisis with 80% and 86% probability respectively. Likewise, as we would expect, the probability of the informational event to be bad is 74% during the geopolitical crisis. On the other hand, we can observe a high probability of good news $(1-\delta)$ post-health crisis and pre-geopolitical crisis with 90% and 84% respectively. Furthermore, the daily arrival rate of trades by informed traders (μ) is fluctuating between each sub-period. For the financial crisis we can observe a significantly high value of 15.53 during the crisis, while the pre- and post-crisis periods exhibit lower values at 7.20 and 9.27 respectively. Conversely, the health crisis shows a lower μ during the crisis rather then pre- or post-crisis. This suggests that there are more informed trades during the financial crisis than the health crisis. Additionally, the arrival of uninformed buy trades (ϵ_b) and uninformed sell trades (ϵ_s) is showing interesting results. We can observe ϵ_b in the post-crisis period of both the financial and geopolitical crisis. On the contrary, the post-crisis period of the health crisis shows the lowest ϵ_b value. This result suggests that the noise traders buying more in the post-crisis periods of financial and geopolitical crisis, rather then the health crisis. Moreover, we can observe a significantly low ϵ_s during the financial crisis at 3.78, while the the financial post-crisis and geopolitical during crisis periods also exhibits lower values at 8.42 and 8.86 respectively. Interestingly, these results suggests that during crises, uninformed traders submit less sell orders.

Stockholm Stock Exchange

	Financial Crisis			Health Crisis			Geopolitical Crisis		
	Pre	During	Post	Pre	During	Post	Pre	During	Post
α	0.99	0.99	0.99	0.99	1.00	1.00	0.93	1.00	1.00
δ	0.44	0.80	0.86	0.34	0.38	0.10	0.16	0.74	0.62
μ	7.20	15.53	9.27	9.44	7.01	11.40	9.94	10.24	6.50
ϵ_b	12.06	13.71	15.35	10.43	11.21	6.90	8.23	14.66	16.51
ϵ_s	13.49	3.78	8.42	13.79	15.45	15.41	15.54	8.86	10.71

Table 6.2: PIN Model Parameters Across Different Crises for a Portfolio of Stocks on the Stockholm Stock Exchange.

6.2.3 Copenhagen Stock Exchange

Table 6.3 report the model parameters for CSE with all crisis types and sub-periods. The results for the probability of an information event to occur (α) follows the OSE and SSE results previously mentioned. Moreover, the probability of these information events to be bad news (δ) is highest in the financial and geopolitical post-crisis periods. Furthermore, the arrival rate of informed trades μ is highest in the financial pre-crisis period. However, all other sub-periods exhibit low μ values, suggesting that there are low values of informed trades for CSE. We do not observe significant differences - neither across crisis nor across time periods for uninformed buy trades (ϵ_b). On the other hand, uninformed sell trades (ϵ_s) shows a significantly low value for the financial pre-crisis period. This results suggests that there are more information based trades, while there are less noise traders selling in the financial pre-crisis period.

	Financial Crisis			Health Crisis			Geopolitical Crisis		
	Pre	During	Post	Pre	During	Post	Pre	During	Post
α	0.99	1.00	1.00	0.96	1.00	1.00	1.00	1.00	1.00
δ	0.68	0.47	0.77	0.39	0.51	0.54	0.65	0.67	0.81
μ	14.09	5.55	4.24	5.78	3.28	4.38	4.43	4.20	3.39
ϵ_b	11.15	13.22	15.05	11.93	14.39	13.20	14.79	15.15	15.64
ϵ_s	6.21	12.89	12.31	14.18	14.31	14.41	12.78	12.64	12.96

Copenhagen Stock Exchange

Table 6.3: Model Parameters Across Different Crises for a Portfolio of Stocks on the Copenhagen Stock Exchange.

6.3 Technical Analysis Results

6.3.1 BH vs. MAC Strategy

Financial Crisis

Table 6.4 report the performance metrics for a BH strategy and a MAC strategy across three different periods of the financial crisis. The results for the mean returns are negative in the

Financial Crisis Performance Metrics

	Pre		During		Post	
	BH	MAC	BH	MAC	BH	MAC
Mean returns %	-1.00	0.28	-2.36	0.56	1.29	0.43
Std. deviation %	5.40	2.71	9.83	1.71	7.44	3.84
Skewness	-0.36	-0.69	-0.58	0.44	-0.12	0.24
Kurtosis	0.49	6.72	1.63	18.16	1.69	3.98
Average drawdown %	4.24	3.32	27.47	2.97	5.48	3.39
Sharpe	-0.23	0.01	-0.26	0.20	0.16	0.08
p-value		**0.05**		**0.01**		0.68

Table 6.4: Analysis of Financial Performance Over Three Periods for BH and MAC Strategies During the Financial Crisis. The p-value refer to the ordinary bootstrap test. Bold p-values indicate significance at the 5% level.

first two periods for BH, where MAC is outperforming BH with positive returns. Both strategies achieve positive returns post-crisis, with BH achieving a mean return of 1.29% compared to MAC returns of 0.43%. Interpreting the standard deviation, which indicates the volatility of the strategies, BH has a higher risk in all three periods. This shows that the MAC strategy, guided by its systematic rules, reduces the chances of risk. The skewness is negative in all scenarios for BH, and only pre-period for MAC, indicating that there are more frequent extreme negative returns than positive ones for BH. For kurtosis, on the other hand, the difference is more significant. In all three periods, BH has a lower kurtosis than

MAC. The highest kurtosis for BH is 1.69, and 18.16 for MAC. This indicates that MAC has a higher risk of extreme return events, regardless of the period. Looking at the drawdown metric, MAC has lower drawdowns than the BH in every scenario, which reinforces the results given by the standard deviation. The Sharpe ratios show that BH have poor risk-adjusted returns in the first two periods. The p-values show significance in MAC outperforming the BH for the first two periods, we fail to reject H_0 in these two periods, with values of 0.05, and 0.01, respectively. Meanwhile, we reject the H_0 in the last period, since the p-value is 0.68.

Health Crisis

Table 6.5 exhibits the performance metrics for a BH strategy and an MAC strategy during the health crisis periods. BH produces a higher mean return than MAC for the first two

Health Crisis Performance Metrics

	Pre		During		Post	
	BH	MAC	BH	MAC	BH	MAC
Mean returns %	0.23	-0.07	-0.02	-0.09	0.22	0.28
Std. deviation %	2.99	2.61	4.58	1.82	4.60	2.21
Skewness	-0.36	-0.52	-0.97	-0.30	-0.98	0.03
Kurtosis	0.97	2.69	6.81	6.19	6.76	2.51
Average drawdown %	3.67	5.37	4.50	2.67	4.40	1.80
Sharpe	0.06	-0.05	-0.01	-0.07	0.05	0.13
p-value		0.90		0.61		0.34

Table 6.5: Analysis of Financial Performance Over Three Periods for BH and MAC Strategies During the Health Crisis. The p-value is from the ordinary bootstrap test. Bold p-values indicate significance at the 5% level.

periods, with almost similar returns post-crisis, with MAC slightly higher. In the post-crisis period, MAC exhibits positive returns for the first and only time during the health crisis. The standard deviation follows the same pattern as in Figure 6.4, where the MAC strategy has a lower risk than the BH strategy for all periods. The negative skewness for both strategies in all scenarios except MAC post-crisis, indicates that all a higher likelihood of negative returns. The BH strategy appears more susceptible to extreme market movements during and post crisis, while the MAC strategy, on the other hand, shows a better ability to stabilize post-crisis. The average drawdowns measures the average decline from a peak to a though the investment's value before a new peak is achieved. In this instance, MAC has a declining drawdown throughout the periods, while BH increase after the first period, and stabilize at approximately the same level for the remaining periods. Looking at the Sharpe ratios, the risk-adjusted returns are barely positive for half of the output, and slightly negative for the other half. In neither of the periods under the health crisis, is there significant evidence of MAC outperforming BH, the H_0 is therefore rejected in all three cases, with p-values of 0.90, 0.61, and 0.34, respectively.

Geopolitical Crisis

Table 6.6 presents the performance metrics for BH and MAC strategies for pre- and during the geopolitical crisis. Post-period of the crisis does not have any values, since there was no buy-signal in the MAC strategy. Therefore, the back-test will not simulate any results as the strategy only invests in the risk-free interest. For the pre-crisis, the BH outperforms MAC

Geopolitical Crisis Performance Metrics

	Pre		During		Post	
	BH	MAC	BH	MAC	BH	MAC
Mean returns %	0.50	0.23	-0.42	0.17	N/A	N/A
Std. deviation %	3.18	2.73	3.60	2.12	N/A	N/A
Skewness	-0.26	-0.33	-0.70	-0.72	N/A	N/A
Kurtosis	0.74	1.62	1.75	5.66	N/A	N/A
Average drawdown %	2.07	1.93	2.71	1.80	N/A	N/A
Sharpe	0.15	0.08	-0.13	0.06	N/A	N/A
p-value		0.80		0.11		N/A

Table 6.6: Analysis of Financial Performance Over Three Periods for BH and MAC Strategies During the Geopolitical Crisis. The p-value is from the ordinary bootstrap test. Bold p-values indicate significance at the 5% level.

in terms of mean return. However, this trend is reversed during the crisis. Moreover, the standard deviation follows the same pattern as the two other crisis metrics, with MAC having lower standard deviations than BH. The skewness for the two strategies and periods, are all negative with an increase in the during-period, indicating that the extreme observations are higher during the crisis. The kurtosis for the periods in both strategies increases during the crisis, with MAC having a significant transition from 1.62 to 5.66. Furthermore, the average drawdown has similar values for the different strategies across the different periods. Checking the Sharpe ratio, only BH during the crisis exhibits a negative value, however beating MAC in the pre-period. Interestingly, the p-value for the two periods is the same as the health crisis, and the H_0 is rejected. None of the two have significant evidence of MAC outperforming the BH strategy.

6.3.2 MACD vs BH Strategy

Financial Crisis

Table 6.7 reports the performance metrics for a BH strategy and a MACD strategy across three different periods of the financial crisis. The mean returns for both strategies are negative in the pre-crisis and during-crisis periods, with the MACD strategy outperforming BH in terms of smaller losses. However, in the post-crisis period, both strategies show positive mean returns, with the BH strategy outperforming the MACD strategy. The standard deviation, which indicates the volatility associated with each strategy, shows consistently higher volatility for the BH strategy across all periods. The skewness values, indicating the asymmetry of return distributions, show that returns are negatively skewed in all periods except for a slight positive skewness in the MACD strategy in the pre-crisis period. The kurtosis values reveal that the MACD strategy exhibits higher kurtosis in all periods, suggesting a higher risk of extreme returns compared to the BH strategy. Average drawdown percentages are notably higher during the crisis period, peaking at 27.47% for BH and 9.49% for MACD, compared to much lower values in the pre- and post-crisis periods. The Sharpe ratio is negative for both strategies during the crisis, indicating poor risk-adjusted returns, but turns positive in the post-crisis period, especially for the BH strategy. The p-values for the results are 0.21 for the pre-crisis period, 0.12 for the during-crisis period, and 0.69 for the post-crisis period, which suggests that the results are not significant and the H_0 is rejected. Showing no evidence of the MACD strategy producing superior returns compared to the BH strategy.

Financial Crisis Performance Metrics

	Pre		During		Post	
	BH	MACD	BH	MACD	BH	MACD
Mean returns %	-1.00	-0.14	-2.36	-0.53	1.29	0.54
Std. deviation %	5.40	3.32	9.83	6.64	7.44	5.29
Skewness	-0.36	0.03	-0.58	-1.06	-0.12	-0.38
Kurtosis	0.49	2.62	1.63	6.88	1.69	5.96
Average drawdown %	4.24	2.84	27.47	9.49	5.48	6.08
Sharpe	-0.23	-0.12	-0.26	-0.11	0.16	0.08
p-value		0.21		0.12		0.69

Table 6.7: Analysis of Financial Performance Over Three Periods for BH and MACD Strategies During the Financial Crisis. The p-value is from the ordinary bootstrap test. Bold p-values indicate significance at the 5% level.

Health Crisis

Table 6.8 presents the performance metrics for a BH strategy and a MACD strategy across three different periods of the health crisis. In contrast to the earlier data, the mean returns

Health Crisis Performance Metrics

	Pre		During		Post	
	BH	MACD	BH	MACD	BH	MACD
Mean returns %	0.23	-0.58	-0.02	-0.17	0.22	0.15
Std. deviation %	2.99	1.93	4.58	2.74	4.60	2.89
Skewness	-0.36	-0.91	-0.97	0.11	-0.98	0.10
Kurtosis	0.97	6.18	6.81	8.81	6.76	7.14
Average drawdown %	3.67	18.81	4.50	9.27	4.40	3.04
Sharpe	0.06	-0.32	-0.01	-0.08	0.05	0.05
p-value		1.00		0.65		0.50

Table 6.8: Analysis of Financial Performance Over Three Periods for BH and MACD Strategies During the Health Crisis. The p-value is from the ordinary bootstrap test. Bold p-values indicate significance at the 5% level.

indicate that the BH strategy has a slight advantage in the pre- and post-crisis periods, while both strategies face reduced returns during the crisis, with the MACD strategy experiencing more significant losses. The standard deviation consistently shows higher volatility for the BH strategy across all periods. This suggests that the MACD strategy holds a lower risk profile. Skewness values, indicating the asymmetry of return distributions, are negative for BH in all periods and for MACD in the pre-crisis period, turning positive only for MACD during and after the crisis. Kurtosis values are notably high for both strategies across all periods but are consistently higher for the MACD strategy, indicating higher occurrence of extreme returns than the BH strategy. This is particularly evident during and after the crisis with kurtosis values peaking at 8.81 for MACD. Average drawdown percentages reflect notable fluctuations, with MACD experiencing a severe drawdown in the pre-crisis peaking at 18.81% period compared to BH peaking at 3.67%. During the crisis, both strategies experience increased drawdowns, but MACD's peak less severely than in the pre-crisis period. Post-crisis, drawdowns for MACD decrease, reflecting improved stability. The Sharpe ratio, a measure of risk-adjusted returns, shows a slight edge or parity in the post-crisis period for both strategies but reflects poor performance during the crisis. Lastly, the p-values for the results are 1.00 for the pre-crisis period, 0.65 for the during-crisis period, and 0.50 for the post-crisis period, which suggests that the results are not significant and the H_0 is rejected. Showing no evidence of the MACD strategy being superior to the BH strategy.

Geopolitical Crisis

Table 6.9 provides performance metrics for BH and MACD strategies during different phases of the geopolitical crisis. In the pre-crisis period, BH achieves a higher mean return compared

Geopolitical Crisis Performance Metrics

	Pre		During		Post	
	BH	MACD	BH	MACD	BH	MACD
Mean returns %	0.50	0.19	-0.42	0.07	-0.59	-0.01
Std. deviation %	3.18	2.14	3.60	2.26	3.48	2.10
Skewness	-0.26	0.16	-0.70	-0.34	-0.86	-0.11
Kurtosis	0.74	4.39	1.75	3.72	3.23	3.01
Average drawdown %	2.07	2.29	2.71	2.70	4.49	2.59
Sharpe	0.15	0.09	-0.13	0.01	-0.20	-0.06
p-value		0.69		0.21		0.17

Table 6.9: Analysis of Financial Performance Over Three Periods for BH and MACD Strategies During the Geopolitical Crisis. The p-value is from the ordinary bootstrap test. Bold p-values indicate significance at the 5% level.

to the MACD. During the crisis, the roles reverse with MACD posting a slight positive return of 0.07%, while BH experiences a negative return of -0.42%. In the post-crisis period, both strategies show negative returns, though MACD shows reduced losses.The standard deviation is consistently lower for MACD in all periods compared to BH. This suggests that MACD maintained lower volatility across these periods. The skewness is only positive for MACD in the pre-crisis period, while all other values show negative skewness, indicating a leftward tail in return distributions. Kurtosis is higher for MACD, especially in the pre-crisis period at 4.39, suggesting a higher probability of extreme returns. Drawdown percentages shows a closer performance in the crisis period, while in the post-crisis, BH faces a significantly higher average drawdown of 4.49% compared to MACD's 2.59%. Sharpe ratios reflect more favorable risk-adjusted returns for MACD during the crisis and less negative post-crisis compared to BH's Sharpe ratio during and post-crisis. P-values remain high with 0.69 in the pre-crisis, 0.21 in the during crisis, and 0.17 in the post-crisis period, the H_0 is therefore rejected, and the MACD strategy is not superior to the BH strategy.

Chapter 7

Discussion

The primary aim for this study can be derived into two parts. Firstly, we investigate if there are a higher probability of informed trades in times of different crises, based on three financial markets in Scandinavia. Our results indicate that the prevalence of informed trades is higher when a financial crisis occurs, indicating higher information asymmetry, compared to a health or geopolitical crisis. Notably, the pattern of the PIN differs for SSE. Secondly, we want to evaluate the performance of technical analysis in periods exhibiting different levels of information asymmetry. More specifically, we utilize two moving average strategies, MAC and MACD, which are directly compared to a BH strategy. Our results indicates that a MAC strategy could outperform a BH strategy in the period before and during a financial crisis. For the other crises, the performance of both MA strategies does not show significant evidence of outperforming the BH strategy.

Building on the summary of our findings, it is essential to further investigate their implications. The observation from the PIN estimations, display both similarities and differences. Furthermore, patterns need to be carefully analysed. OSE and CSE have almost identical PIN during the health crisis, implying similar information asymmetry. SSE and CSE have the same pattern in the PIN for the geopolitical crisis. The main difference is for the financial crisis, where all three markets has different patterns and values, exhibiting no significant form for similarities. This can be an indication on the financial institutions often cease to function or operate under severe legal constraints when financial crises occur, due to the lack of market efficiency. Interestingly, the PIN estimations, for OSE in all except pre and post financial crisis, and CSE in all except pre financial crisis, are quite similar. The PIN estimations in our study are close to the median PIN estimations in the research of Duarte and Young (2009), Easley et al. (1996), and Kubota and Takehara (2009).

Secondly, we examine if the technical analysis indicator MAC outperforms the BH strategy. The results indicate that MAC outperform BH in the first two periods of the financial crisis, where the results are significant. This further strengthens the findings of Hung and Lai (2022), that a MA strategy will outperform BH in periods of higher PIN estimations. The MAC strategy has lower volatility in both of the first periods of the financial crisis, implying that technical analysis reduce investment risk. For all the other scenarios of the MAC strategy, even though they are not significant, the returns are negative twice, 0.07% and 0.09%. With this knowledge, using a MA strategy, can help an investor reduce the risk by implementing technical analysis.

Furthermore, our studies are based on the 10 largest firms with available data, in regard of market cap on their respective exchanges. According to former studies by Aslan et al. (2011) and Shynkevich (2012a, 2012b), firms with smaller market cap are more likely to see better performance from technical analysis compared to those with larger market cap. This should be considered when interpreting the results. Implications regarding increased probability of informed trading during financial crises suggest heightened market sensitivity and potential of significant market movements. The effectiveness of the MAC strategy during a financial crisis implies that technical analysis can be a useful tool for investors looking to navigate volatile markets.

This study has limitation which can be viewed from several perspectives, including selection of stocks, data quality and coverage, methodology, and validity of the results. The methodology based on the algorithm created by Lee and Ready (1991), although it is widely used, it only provides an accuracy of 81.05% of classifying buy and sell trades based on the bid and ask spread. Having an inaccuracy of 18.95% could lead to a proportion of misclassified trades, leading to a potential skewness in the PIN estimation. The use of transaction data would be a more representative measure of numbers of trades executed. Only limiting ourselves to one algorithm, limits the robustness of our findings, as newer methods for identifying initial trades might be more accurate. Regarding limitations of the results, the use of different markets introduces variation in market structure, regulations, economic conditions, and crisis measures. These factors could possibly change the price dynamics for the different exchanges, making the comparisons problematic and less robust. By focusing the study to focus specifically on crises might limit the applicability of the findings to other types of market disruptions that is not a direct consequence of the current crisis. These market disruptions could amplify the signals of informed trades, which could give a false indication on the investors behaviors. Additionally, focusing solely on the Scandinavian markets might limit the generalizability to other financial markets. The Scandinavian exchanges are affected by other global markets, which might imply that adding a wider range of portfolios, would produce other estimations and open for other interpretations. Two of the time intervals overlaps, the post-crisis period for the health crisis and the pre-crisis period for the geopolitical crisis. This overlap presents a challenge in isolating the effects of each crisis. The trading behavior or market dynamics for these two periods, might be influenced by lingering effects of the COVID-19 pandemic or emerging disturbance of the geopolitical tensions.

Future Research

Future research could benefit from using extended periods for estimating PIN. Previous research often use multiple quarters of data to estimate PIN, this study only uses interval of 10 to 12 months, potentially missing out on longer-term trends. This study uses 15 minutes intraday data to estimate the frequency of trades during a day, while the optimal would be one minute intraday data. This would yield a more precise estimate of initial trades, as calculated in Equation (5.1). Another area for future research is the construction of more diversified portfolios. The portfolios in this study has limitations in the selection of stocks, constructed by only 10 stocks in each portfolio. Using small sample sizes does not accurately represent the overall market behavior. We have chosen to weight the stocks in the portfolios equally, this does not represent their actual weighing on their respective exchanges. Furthermore, our selection of large cap firms based on the availability, does not account for mid- and small-cap firms that is part of the exchange. Where future work could include this aspect of the exchanges, as these often exhibits higher volatility and are more sensitive to news events. This is based on Aslan et al. (2011) and Hung and Lai (2022) statements, explaining that smaller cap firms have higher PIN estimations. A greater variation in market cap firms would provide more significant PIN estimations during different periods.

Chapter 8

Conclusion

The main goal of our thesis was to contribute to existing literature regarding the probability of informed trading, in the context of crises that impact global markets. Furthermore, testing if technical analysis can help produce higher returns compared to a buy-and-hold investment approach before, during, and after the various types of crises.

In summary, this study has provided valuable insight into market information asymmetry, with the probability of informed trading during crises across different Scandinavian markets. The results reveal higher probability of informed trading during a financial crisis, compared to a health- or geopolitical crisis, highlighting the sensitivity of markets to economic disruptions. Furthermore, the technical analysis strategy based on Moving Average Crossover have been proven to gain higher returns on the Oslo Stock Exchange before and during the financial crisis, compared to a Buy-and-Hold strategy.

While this study provides valuable insight to financial markets during crises, it also has limitations within a part of the methodology's algorithm, the different governments' crisis measures, frequency of the data, and firm size. Where future research could delve deeper into extended periods when estimating PIN values for the different crises periods, to check if other intervals give varied estimations. While also creating more diversified portfolios with a greater spread of large to small market cap companies.

While our thesis has explored the Scandinavian market, future research might explore other markets. Furthermore, other crises may be included in future work to better understand the information asymmetry in different crises. Additionally, future research my implement other technical analysis strategies, including other strategies than moving averages. Particularly, utilizing the PIN estimation with other strategies should be further explored to fully understand how technical analysis may perform in times of information asymmetry.

In conclusion, this research highlights the probability of informed trading during financial crises and the potential superiority of technical analysis over the Buy-and-Hold strategy, paving the way for future research to refine these findings and broaden their relevancy.

Bibliography

Appel, G. (1979). *The moving average convergence-divergence trading method advanced version*. Scientific Investment Systems Incorporated. https://books.google.no/books?id=8DUxtAEACAAJ

Appel, G. (2005). *Technical analysis: Power tools for active investors*. Financial Times/Prentice Hall. https://books.google.no/books?id=RFYIAAAACAAJ

Aslan, H., Easley, D., Hvidkjaer, S., & O'Hara, M. (2011). The characteristics of informed trading: Implications for asset pricing. *Journal of Empirical Finance*, *18*(5), 782–801. https://doi.org/https://doi.org/10.1016/j.jempfin.2011.08.001

AstraZeneca. (2020). Astrazeneca's covid-19 vaccine authorised for emergency supply in the uk [Accessed: 2023-05-10]. Retrieved May 10, 2023, from https://www.astrazeneca.com/media-centre/press-releases/2020/astrazenecas-covid-19-vaccine-authorised-in-uk.html

Bai, C., Duan, Y., Fan, X., & Tang, S. (2023). Financial market sentiment and stock return during the covid-19 pandemic. *Finance Research Letters*, *54*, 103709. https://doi.org/https://doi.org/10.1016/j.frl.2023.103709

Bai, J., Philippon, T., & Savov, A. (2016). Have financial markets become more informative? *Journal of Financial Economics*, *122*(3), 625–654. https://doi.org/https://doi.org/10.1016/j.jfineco.2016.08.005

Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment1we are grateful to the nsf for financial support, and to oliver blanchard, alon brav, john campbell (a referee), john cochrane, edward glaeser, j.b. heaton, danny kahneman, david laibson, owen lamont, drazen prelec, jay ritter (a referee), ken singleton, dick thaler, an anonymous referee, and the editor, bill schwert, for comments.1. *Journal of Financial Economics*, *49*(3), 307–343. https://doi.org/https://doi.org/10.1016/S0304-405X(98)00027-0

Barro, R. J., Ursúa, J. F., & Weng, J. (2020). *The coronavirus and the great influenza pandemic: Lessons from the "spanish flu" for the coronavirus's potential effects on *mortality and economic activity* (Working Paper No. 26866). National Bureau of Economic Research. https://doi.org/10.3386/w26866

Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy*, *100*(5), 992–1026. https://doi.org/10.1086/261849

Blume, L., Easley, D., & O'Hara, M. (1994). Market statistics and technical analysis: The role of volume. *The Journal of Finance*, *49*(1), 153–181. Retrieved April 9, 2024, from http://www.jstor.org/stable/2329139

Bodie, Z., Kane, A., & Marcus, A. J. (2021). *Investments* (12th) [Accessed on [insert date here]]. McGraw-Hill. http://elibrary.gci.edu.np/bitstream/123456789/706/1/BM-802%20Investments%2C%20by%20Bodie%20Z.%2C%20Kane%20A.%2C%20Marcus%20A.J..pdf

Boehmer, E., Grammig, J., & Theissen, E. (2007). Estimating the probability of informed trading—does trade misclassification matter? *Journal of Financial Markets*, *10*(1), 26–47. https://doi.org/https://doi.org/10.1016/j.finmar.2006.07.002

Brem, A., Nylund, P., & Viardot, E. (2020). The impact of the 2008 financial crisis on innovation: A dominant design perspective. *Journal of Business Research*, *110*, 360–369. https://doi.org/https://doi.org/10.1016/j.jbusres.2020.01.048

Brock, W., Lakonishok, J., & LeBaron, B. (1992). Simple technical trading rules and the stochastic properties of stock returns. *The Journal of Finance*, *47*(5), 1731–1764. Retrieved March 14, 2024, from http://www.jstor.org/stable/2328994

Caldara, D., & Iacoviello, M. (2022). Measuring geopolitical risk. *American Economic Review*, *112*(4), 1194–1225. https://doi.org/10.1257/aer.20191823

Chang, R., & Velasco, A. (2001). A Model of Financial Crises in Emerging Markets*. *The Quarterly Journal of Economics*, *116*(2), 489–517. https://doi.org/10.1162/003355301511444087

Cheema, M. A., Faff, R., & Szulczyk, K. R. (2022). The 2008 global financial crisis and covid-19 pandemic: How safe are the safe haven assets? *International Review of Financial Analysis*, *83*, 102316. https://doi.org/https://doi.org/10.1016/j.irfa.2022.102316

Chen, C.-W., Huang, C.-S., & Lai, H.-W. (2009). The impact of data snooping on the testing of technical analysis: An empirical study of asian stock markets. *Journal of Asian Economics*, *20*(5), 580–591. https://doi.org/https://doi.org/10.1016/j.asieco.2009.07.008

Chong, T. T.-L., & Ng, W.-K. (2008). Technical analysis and the london stock exchange: Testing the macd and rsi rules using the ft30. *Applied Economics Letters*, *15*(14), 1111–1114. https://doi.org/10.1080/13504850600993598

Chong, T. T.-L., Ng, W.-K., & Liew, V. K.-S. (2014). Revisiting the performance of macd and rsi oscillators. *Journal of Risk and Financial Management*, *7*(1), 1–12. https://doi.org/10.3390/jrfm7010001

Chuang, O.-C., Chuang, H.-C., Wang, Z., & Xu, J. (2024). Profitability of technical trading rules in the chinese stock market. *Pacific-Basin Finance Journal*, *84*, 102278. https://doi.org/https://doi.org/10.1016/j.pacfin.2024.102278

Coller, M., & Yohn, T. L. (1997). Management forecasts and information asymmetry: An examination of bid-ask spreads. *Journal of Accounting Research*, *35*(2), 181–191. Retrieved May 11, 2024, from http://www.jstor.org/stable/2491359

Cowles, A. (1933). Can stock market forecasters forecast? *Econometrica*, *1*, 309–324. Retrieved February 25, 2024, from http://www.jstor.org/stable/1907042

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under- and overreactions. *The Journal of Finance*, *53*(6), 1839–1885. https://doi.org/https://doi.org/10.1111/0022-1082.00077

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise trader risk in financial markets. *Journal of Political Economy*, *98*(4), 703–738. https://doi.org/10.1086/261703

Del Angel, M., Fohlin, C., & Weidenmier, M. D. (2023). Stock returns and the spanish flu, 1918–1920. *Explorations in Economic History*, *90*, 101543. https://doi.org/https://doi.org/10.1016/j.eeh.2023.101543

Duarte, J., & Young, L. (2009). Why is pin priced? *Journal of Financial Economics*, *91*(2), 119–138. https://doi.org/https://doi.org/10.1016/j.jfineco.2007.10.008

Easley, D., Hvidkjaer, S., & O'Hara, M. (2010). Factoring information into returns. *Journal of Financial and Quantitative Analysis*, *45*(2), 293–309. https://doi.org/10.1017/S0022109010000074

Easley, D., Kiefer, N. M., O'Hara, M., & Paperman, J. B. (1996). Liquidity, information, and infrequently traded stocks. *The Journal of Finance*, *51*(4), 1405–1436. https://doi.org/https://doi.org/10.1111/j.1540-6261.1996.tb04074.x

Easley, D., & O'Hara, M. (1992). Time and the process of security price adjustment. *The Journal of Finance*, *47*(2), 577–605. https://doi.org/https://doi.org/10.1111/j.1540-6261.1992.tb04402.x

Efron, B. (1979). Bootstrap Methods: Another Look at the Jackknife. *The Annals of Statistics*, *7*(1), 1–26. https://doi.org/10.1214/aos/1176344552

Ellis, K., Michaely, R., & O'Hara, M. (2000). The accuracy of trade classification rules: Evidence from nasdaq. *The Journal of Financial and Quantitative Analysis*, *35*(4), 529–551. Retrieved April 12, 2024, from http://www.jstor.org/stable/2676254

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, *25*(2), 383–417. Retrieved April 9, 2024, from http://www.jstor.org/stable/2325486

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, *116*(1), 1–22. https://doi.org/https://doi.org/10.1016/j.jfineco.2014.10.010

Fan, Z., Paseka, A., Qi, Z., & Zhang, Q. (2022). Currency carry trade: The decline in performance after the 2008 global financial crisis. *Journal of International Financial Markets, Institutions and Money*, *76*, 101460. https://doi.org/https://doi.org/10.1016/j.intfin.2021.101460

Fang, Y., Shao, Z., & Zhao, Y. (2023). Risk spillovers in global financial markets: Evidence from the covid-19 crisis. *International Review of Economics Finance*, *83*, 821–840. https://doi.org/https://doi.org/10.1016/j.iref.2022.10.016

Foster, J. B., & Magdoff, F. (2009). *The great financial crisis : Causes and consequences*. Monthly Review Press.

Ghachem, M., & Ersan, O. (2022). Pinstimation: An r package for estimating models of probability of informed trading. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4117946

Glabadanidis, P. (2015). Market timing with moving averages. *International Review of Finance*, *15*(3), 387–425. https://doi.org/https://doi.org/10.1111/irfi.12052

Han, Y., Yang, K., & Zhou, G. (2013). A new anomaly: The cross-sectional profitability of technical analysis. *The Journal of Financial and Quantitative Analysis*, *48*(5), 1433–1461. Retrieved February 27, 2024, from http://www.jstor.org/stable/43303847

Hsu, P.-H., Hsu, Y.-C., & Kuan, C.-M. (2010). Testing the predictive ability of technical analysis using a new stepwise test without data snooping bias [Cited by: 102; All Open Access, Green Open Access]. *Journal of Empirical Finance*, *17*(3), 471–484. https://doi.org/10.1016/j.jempfin.2010.01.001

Hung, C., & Lai, H.-N. (2022). Information asymmetry and the profitability of technical analysis. *Journal of Banking Finance*, *134*, 106347. https://doi.org/https://doi.org/10.1016/j.jbankfin.2021.106347

Izzeldin, M., Muradoğlu, Y. G., Pappas, V., Petropoulou, A., & Sivaprasad, S. (2023). The impact of the russian-ukrainian war on global financial markets. *International Review of Financial Analysis*, *87*, 102598. https://doi.org/https://doi.org/10.1016/j.irfa.2023.102598

Jackson, D. (2013). Estimating pin for firms with high levels of trading. *Journal of Empirical Finance*, *24*, 116–120. https://doi.org/https://doi.org/10.1016/j.jempfin.2013.10.001

Jonas Iversen. (2024). *Konflikter: Palestina* [Accessed on: April 5, 2024]. https://fn.no/konflikter/palestina

Jonathan Masters. (2024). *Ukraine Conflict at the Crossroads of Europe and Russia* [Accessed on: April 5, 2024]. https://www.cfr.org/backgrounder/ukraine-conflict-crossroads-europe-and-russia#chapter-title-0-1

Karlsson, M., Nilsson, T., & Pichler, S. (2014). The impact of the 1918 spanish flu epidemic on economic performance in sweden: An investigation into the consequences of an extraordinary mortality shock. *Journal of Health Economics*, *36*, 1–19. https://doi.org/https://doi.org/10.1016/j.jhealeco.2014.03.005

Katsampoxakis, I., Christopoulos, A., Kalantonis, P., & Nastas, V. (2022). Crude oil price shocks and european stock markets during the covid-19 period. *Energies*, *15*(11). https://doi.org/10.3390/en15114090

Kelly, H. (2011). The classical definition of a pandemic is not elusive. *Bulletin of the World Health Organization*, *89*(7), 540–541. https://doi.org/10.2471/BLT.11.088815

Kosová, R., & Enz, C. A. (2012). The terrorist attacks of 9/11 and the financial crisis of 2008: The impact of external shocks on u.s. hotel performance. *Cornell Hospitality Quarterly*, *53*(4), 308–325. https://doi.org/10.1177/1938965512457021

Kubota, K., & Takehara, H. (2009). Information based trade, the pin variable, and portfolio style differences: Evidence from tokyo stock exchange firms. *Pacific-Basin Finance Journal*, *17*(3), 319–337. https://doi.org/https://doi.org/10.1016/j.pacfin.2008.06.001

Lee, C. M. C., & Ready, M. J. (1991). Inferring trade direction from intraday data. *The Journal of Finance*, *46*(2), 733–746. https://doi.org/https://doi.org/10.1111/j.1540-6261.1991.tb02683.x

Lin, H.-W. W., & Ke, W.-C. (2011). A computing bias in estimating the probability of informed trading. *Journal of Financial Markets*, *14*(4), 625–640. https://doi.org/https://doi.org/10.1016/j.finmar.2011.03.001

Lo, A. W. (2004). The adaptive markets hypothesis: Market efficiency from an evolutionary perspective [30th Anniversary Issue]. *The Journal of Portfolio Management*, *30*, 15–29. https://doi.org/10.3905/jpm.2004.442611

Marshall, B. R., & Cahan, R. H. (2005). Is technical analysis profitable on a stock market which has characteristics that suggest it may be inefficient? *Research in International Business and Finance*, *19*(3), 384–398. https://doi.org/https://doi.org/10.1016/j.ribaf.2005.05.001

Mishra, A. K., Ansari, Y., Bansal, R., & Maurya, P. K. (2024). Regional and periodic asymmetries in the effect of russia-ukraine war on global stock markets. *Heliyon*, *10*(7), e28362. https://doi.org/https://doi.org/10.1016/j.heliyon.2024.e28362

Odegaard, B. A. (2021). *Empirics of the Oslo Stock Exchange. Basic, descriptive, results 1980-2020* (UiS Working Papers in Economics and Finance No. 2021/3). University of Stavanger. https://ba-odegaard.no/wps/empirics_ose_basics/empirics_ose_basics_2021_03.pdf

OpenAI. (2024). Chatgpt (version gpt-4) [large language model]. https://chat.openai.com/

Radelet, S., Sachs, J. D., Cooper, R. N., & Bosworth, B. P. (1998). The east asian financial crisis: Diagnosis, remedies, prospects. *Brookings Papers on Economic Activity*, *1998*(1), 1–90. Retrieved April 30, 2024, from http://www.jstor.org/stable/2534670

Richardson, G. (2007). Categories and causes of bank distress during the great depression, 1929–1933: The illiquidity versus insolvency debate revisited. *Explorations in Economic History*, *44*(4), 588–607. https://doi.org/https://doi.org/10.1016/j.eeh.2007.01.001

Rodriguez, E., Aguilar-Cornejo, M., Femat, R., & Alvarez-Ramirez, J. (2014). Us stock market efficiency over weekly, monthly, quarterly and yearly time scales. *Physica A: Statistical Mechanics and its Applications*, *413*, 554–564. https://doi.org/https://doi.org/10.1016/j.physa.2014.07.036

Samuelson, P. A. (1965). Proof that properly anticipated prices fluctuate randomly. In *The world scientific handbook of futures markets* (pp. 25–38). https://doi.org/10.1142/9789814566926_0002

Shleifer, A., & Vishny, R. W. (1997). The limits of arbitrage. *The Journal of Finance*, *52*(1), 35–55. https://doi.org/https://doi.org/10.1111/j.1540-6261.1997.tb03807.x

Shynkevich, A. (2012a). Performance of technical analysis in growth and small cap segments of the us equity market. *Journal of Banking Finance*, *36*(1), 193–208. https://doi.org/https://doi.org/10.1016/j.jbankfin.2011.07.001

Shynkevich, A. (2012b). Short-term predictability of equity returns along two style dimensions. *Journal of Empirical Finance*, *19*(5), 675–685. https://doi.org/https://doi.org/10.1016/j.jempfin.2012.07.003

Siu, A., & Wong, Y. C. R. (2004). Economic impact of sars: The case of hong kong. *Asian Economic Papers*, *3*(1), 62–83. https://doi.org/10.1162/1535351041747996

Teixeira, L. A., & de Oliveira, A. L. I. (2010). A method for automatic stock trading combining technical analysis and nearest neighbor classification. *Expert Systems with Applications*, *37*(10), 6885–6890. https://doi.org/https://doi.org/10.1016/j.eswa.2010.03.033

U, T. S.-C., Lin, Y., & Wang, Y. (2024). The impact of the russia–ukraine war on volatility spillovers. *International Review of Financial Analysis*, *93*, 103194. https://doi.org/https://doi.org/10.1016/j.irfa.2024.103194

Ullah, S., Khan, S., Hashmi, N. I., & Alam, M. S. (2023). Covid-19 pandemic and financial market volatility: A quantile regression approach. *Heliyon*, *9*(10), e21131. https://doi.org/https://doi.org/10.1016/j.heliyon.2023.e21131

Urak, F., Bilgic, A., Florkowski, W. J., & Bozma, G. (2024). Confluence of covid-19 and the russia-ukraine conflict: Effects on agricultural commodity prices and food security. *Borsa Istanbul Review*. https://doi.org/https://doi.org/10.1016/j.bir.2024.02.008

World Health Organization. (2020a). Covid-19 public health emergency of international concern (pheic) global research and innovation forum [Accessed: 2024-03-28]. https://www.who.int/publications/m/item/covid-19-public-health-emergency-of-international-concern-(pheic)-global-research-and-innovation-forum

World Health Organization. (2020b). WHO Director-General's opening remarks at the media briefing on COVID-19 - 11 March 2020 [Accessed: 2024-03-28]. https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---11-march-2020

Yan, Y., & Zhang, S. (2012). An improved estimation method and empirical properties of the probability of informed trading. *Journal of Banking Finance*, *36*(2), 454–467. https://doi.org/https://doi.org/10.1016/j.jbankfin.2011.08.003

Yan, Y., & Zhang, S. (2014). Quality of pin estimates and the pin-return relationship. *Journal of Banking Finance*, *43*, 137–149. https://doi.org/https://doi.org/10.1016/j.jbankfin.2014.03.006

Zakamulin, V. (2016). Revisiting the profitability of market timing with moving averages. *SSRN Electronic Journal*. https://doi.org/https://doi.org/10.2139/ssrn.2743119

Zakamulin, V. (2017). *Market timing with moving averages*. Springer International Publishing. https://doi.org/10.1007/978-3-319-60970-6

Zhu, H., Jiang, Z.-Q., Li, S.-P., & Zhou, W.-X. (2015). Profitability of simple technical trading rules of chinese stock exchange indexes. *Physica A: Statistical Mechanics and its Applications*, *439*, 75–84. https://doi.org/https://doi.org/10.1016/j.physa.2015.07.032

Zhu, Y., & Zhou, G. (2009). Technical analysis: An asset allocation perspective on the use of moving averages. *Journal of Financial Economics*, *92*(3), 519–544. https://doi.org/https://doi.org/10.1016/j.jfineco.2008.07.002

Appendix A

Datasheet

A.1 MAC vs. BH Plots

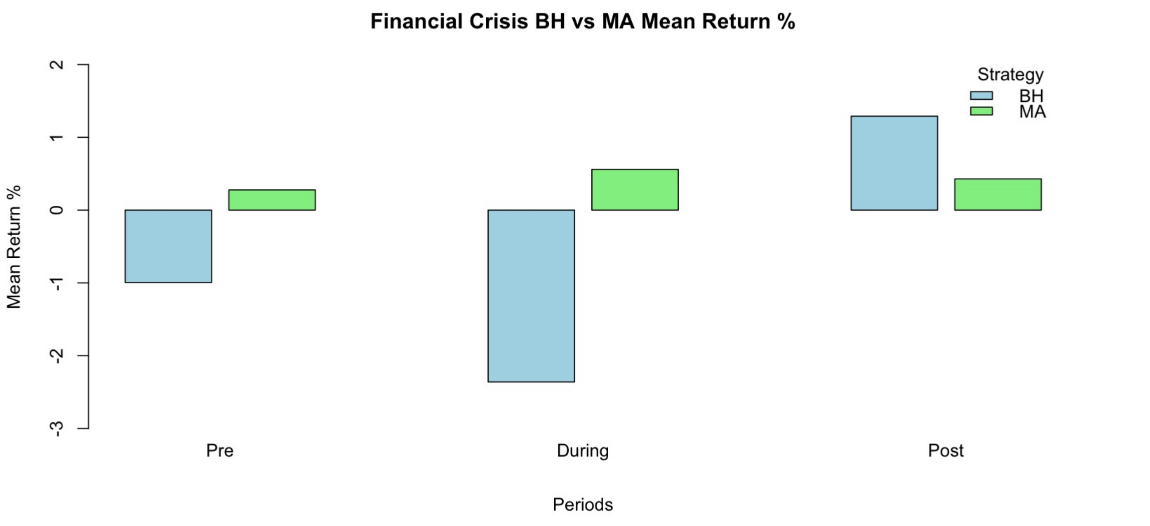


Figure A.1: Mean Return Comparison of BH and MAC Strategies during the Financial Crisis

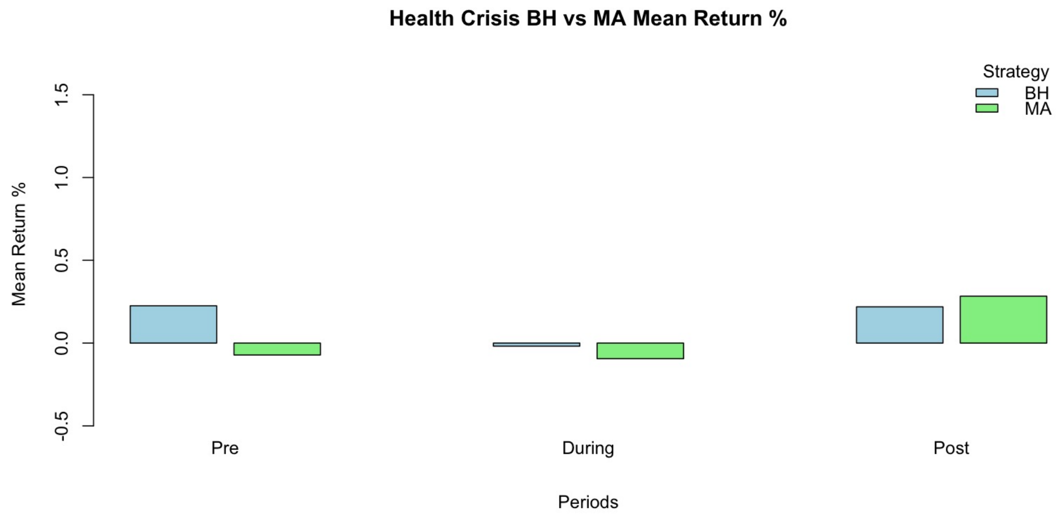


Figure A.2: Mean Return Comparison of BH and MAC Strategies during the Health Crisis

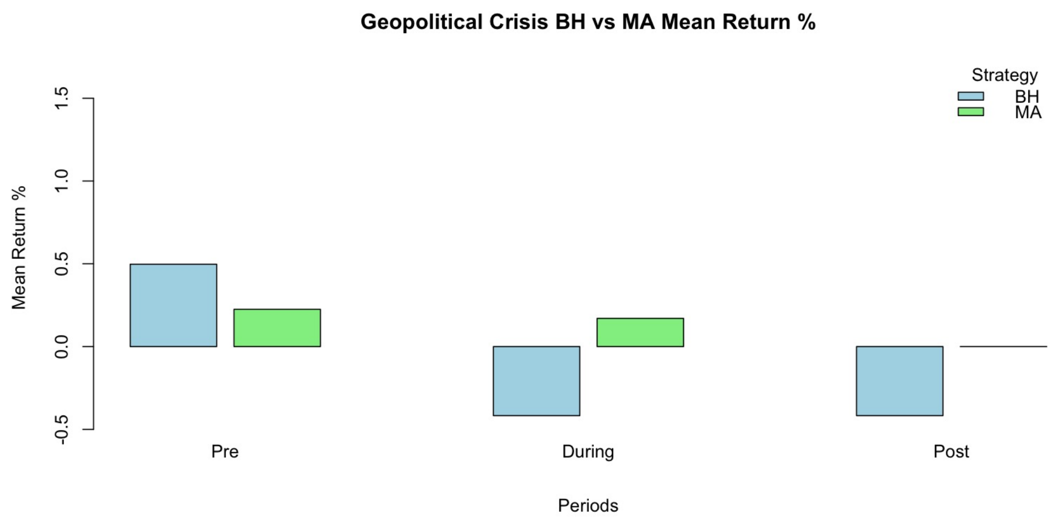


Figure A.3: Mean Return Comparison of BH and MAC Strategies during the Geopolitical Crisis

A.2 MACD vs. BH Plots

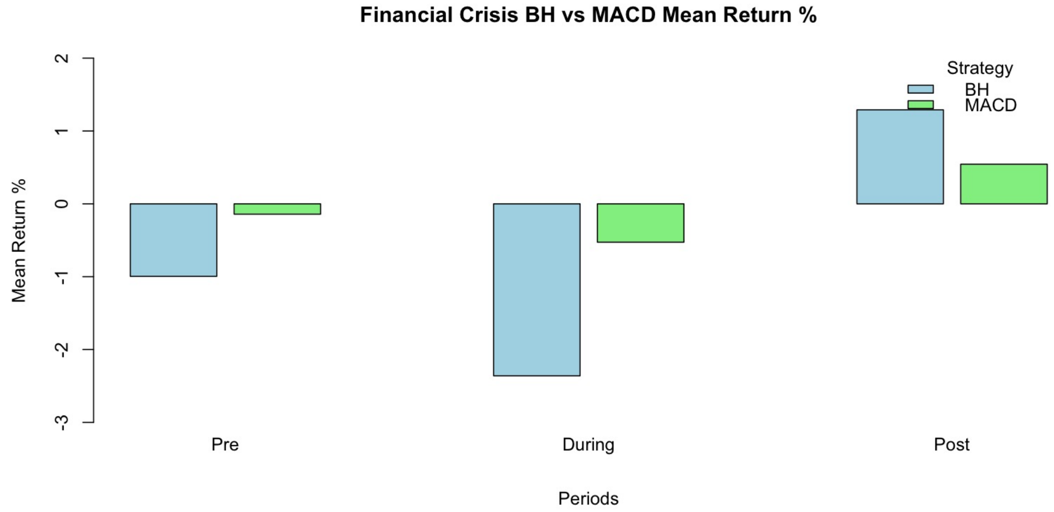


Figure A.4: Mean Return Comparison of BH and MACD Strategies during the Financial Crisis

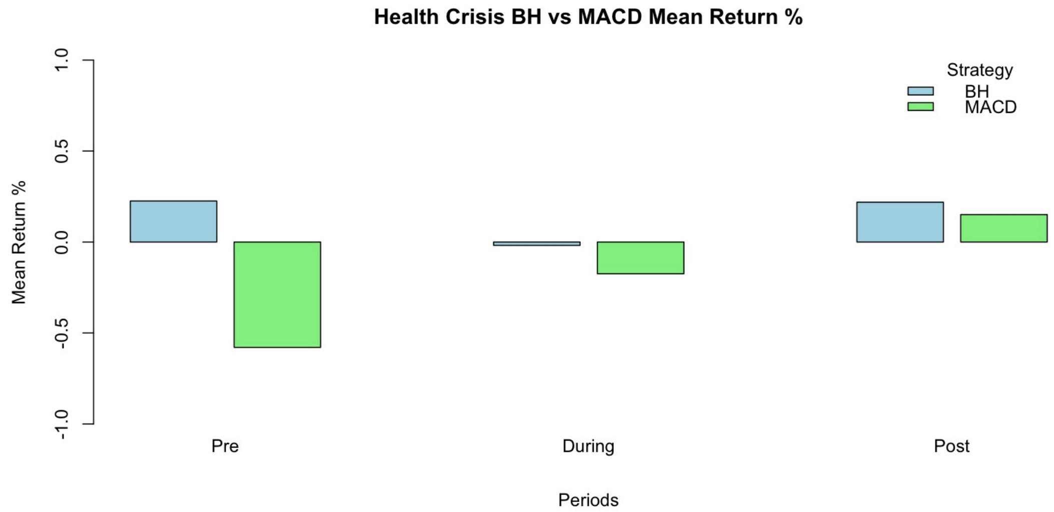


Figure A.5: Mean Return Comparison of BH and MACD Strategies during the Health Crisis

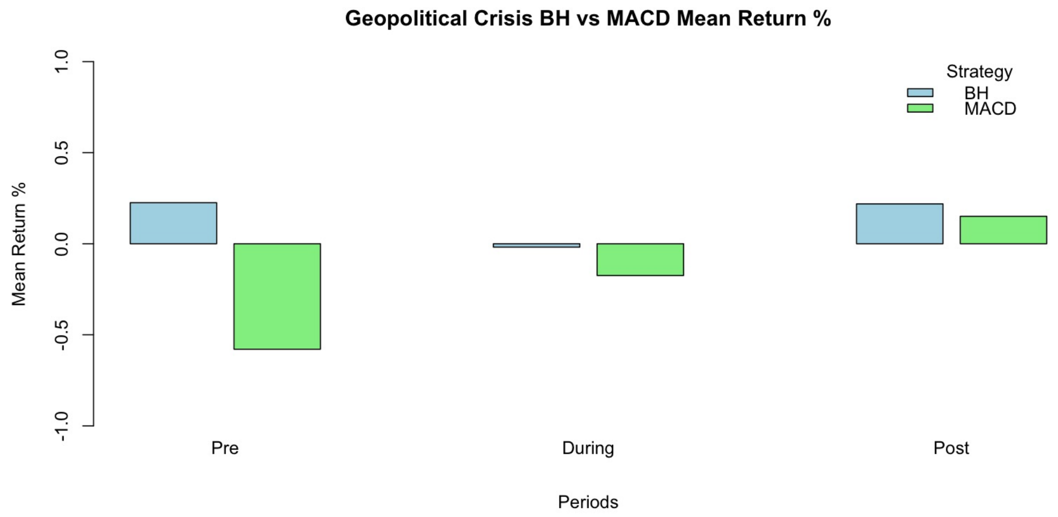


Figure A.6: Mean Return Comparison of BH and MACD Strategies during the Geopolitical Crisis

A.3 R Code

A.3.1 Historic Price Plots Program

```
rm(list=ls(all=TRUE))
library(InfoTrad)
library(lubridate)
library(dplyr)
library(PINstimation)
library(xtable)
library(ggplot2)

################################################################################
# Oslo Stock Exchange 10 Company Portfolio
################################################################################
stock_symbols <- c("EQNR.OL", "YAR.OL", "MOWI.OL", "NHY.OL", "TEL.OL",
                   "DNB.OL", "ORK.OL", "STB.OL", "SNI.OL", "TOM.OL")

# Initialize an environment to store stock data
stock_data <- new.env()

lapply(stock_symbols, function(symbol) {
```

```r
  getSymbols(symbol, env = stock_data, src = "yahoo", from = "2005-09-01",
             to = "2024-01-01", auto.assign = TRUE)
})

# Review the data
print(ls(stock_data))

# Combine the Close prices into one xts object
portfolio_prices <- do.call(merge, eapply(stock_data, function(x) Ad(x)))
class(portfolio_prices)
head(portfolio_prices)

# Calculate the equally weighted portfolio
OSE <- rowMeans(portfolio_prices)

# Create a new xts object for the equally weighted portfolio
OSE <- xts(OSE, order.by = index(portfolio_prices))

head(OSE)

sum(is.na(OSE))
OSE <- na.omit(OSE)
sum(is.na(OSE))

################################################################################
# Stockholm Stock Exchange 10 Company Portfolio
################################################################################
stock_symbols <- c("ABB.ST", "ASSA-B.ST", "ATCO-A.ST", "AZN.ST",
                   "HEXA-B.ST", "HM-B.ST", "INVE-B.ST",
                   "SAND.ST", "SEB-A.ST", "VOLV-B.ST")

# Initialize an environment to store stock data
stock_data <- new.env()
```

```r
lapply(stock_symbols, function(symbol) {
  getSymbols(symbol, env = stock_data, src = "yahoo", from = "2005-01-01",
             to = "2024-01-01", auto.assign = TRUE)
})

# Review the data
print(ls(stock_data))

# Combine the Close prices into one xts object
portfolio_prices <- do.call(merge, eapply(stock_data, function(x) Ad(x)))
class(portfolio_prices)

# Calculate the equally weighted portfolio
SSE <- rowMeans(portfolio_prices)

# Create a new xts object for the equally weighted portfolio
SSE <- xts(SSE, order.by = index(portfolio_prices))

sum(is.na(SSE))
SSE <- na.omit(SSE)
sum(is.na(SSE))

################################################################################
# Copenhagen Stock Exchange 10 Company Portfolio
################################################################################
stock_symbols <- c("CARL-B.CO", "COLO-B.CO", "DANSKE.CO", "DEMANT.CO",
                   "DSV.CO", "GMAB.CO", "MAERSK-B.CO", "NOVO-B.CO",
                   "TRYG.CO", "VWS.CO")

# Initialize an environment to store stock data
stock_data <- new.env()
```

```r
lapply(stock_symbols, function(symbol) {
  getSymbols(symbol, env = stock_data, src = "yahoo", from = "2005-01-01",
             to = "2024-01-01", auto.assign = TRUE)
})

# Review the data
print(ls(stock_data))

# Combine the Close prices into one xts object
portfolio_prices <- do.call(merge, eapply(stock_data, function(x) Ad(x)))
class(portfolio_prices)

# Calculate the equally weighted portfolio
CSE <- rowMeans(portfolio_prices)

# Create a new xts object for the equally weighted portfolio
CSE <- xts(CSE, order.by = index(portfolio_prices))

sum(is.na(CSE))
CSE <- na.omit(CSE)
sum(is.na(CSE))

################################################################################
# Set time windows
################################################################################
fin_start <- "2007-09-15"
fin_end <- "2010-09-15"

hlt_start <- "2019-03-30"
hlt_end <- "2021-09-29"

geo_start <- "2021-04-24"
geo_end <- "2023-10-23"
```

```r
################################################################################
# Extract time windows and plot the respective crisis periods
################################################################################
names <- c("OSE 10 Stock Portfolio", "SSE 10 Stock Portfolio",
           "CSE 10 Stock Portfolio")

OSEFIN <- window(OSE, start = fin_start, end = fin_end)
SSEFIN <- window(SSE, start = fin_start, end = fin_end)
CSEFIN <- window(CSE, start = fin_start, end = fin_end)

FIN <- merge(OSEFIN, SSEFIN, CSEFIN, all = TRUE)
colnames(FIN) <- names

plot(FIN, multi.panel=TRUE, col=c("black", "black", "black"), yaxis.same=FALSE,
     main = "Financial Crisis")


OSEHLT <- window(OSE, start = hlt_start, end = hlt_end)
SSEHLT <- window(SSE, start = hlt_start, end = hlt_end)
CSEHLT <- window(CSE, start = hlt_start, end = hlt_end)

HLT <- merge(OSEHLT, SSEHLT, CSEHLT, all = TRUE)
colnames(HLT) <- names

plot(HLT, multi.panel=TRUE, col=c("black", "black", "black"), yaxis.same=FALSE,
     main = "Health Crisis")


OSEGEO <- window(OSE, start = geo_start, end = geo_end)
SSEGEO <- window(SSE, start = geo_start, end = geo_end)
CSEGEO <- window(CSE, start = geo_start, end = geo_end)

GEO <- merge(OSEGEO, SSEGEO, CSEGEO, all = TRUE)
colnames(GEO) <- names
```

```
plot(GEO, multi.panel=TRUE, col=c("black", "black", "black"), yaxis.same=FALSE,
     main = "Geopolitical Crisis")
```

A.3.2 PIN Estimation Program

```
    rm(list=ls(all=TRUE))
library(InfoTrad)
library(lubridate)
library(dplyr)
library(PINstimation)
library(xtable)
library(ggplot2)

###############################################################################
# PIN Estimation Data work
###############################################################################
# Oslo Stock Exchange Data
###############################################################################
EQNR <- read.csv("~/Documents/UIA/Master/intraday_data/OSE/EQNR_15min.csv")
YAR <- read.csv("~/Documents/UIA/Master/intraday_data/OSE/YAR_15min.csv")
MOWI <- read.csv("~/Documents/UIA/Master/intraday_data/OSE/MOWI_15min.csv")
NHY <- read.csv("~/Documents/UIA/Master/intraday_data/OSE/NHY_15min.csv")
TEL <- read.csv("~/Documents/UIA/Master/intraday_data/OSE/TEL_15min.csv")
DNB <- read.csv("~/Documents/UIA/Master/intraday_data/OSE/DNB_15min.csv")
ORK <- read.csv("~/Documents/UIA/Master/intraday_data/OSE/ORK_15min.csv")
STB <- read.csv("~/Documents/UIA/Master/intraday_data/OSE/STB_15min.csv")
SNI <- read.csv("~/Documents/UIA/Master/intraday_data/OSE/SNI_15min.csv")
TOM <- read.csv("~/Documents/UIA/Master/intraday_data/OSE/TOM_15min.csv")


OSE <- list(DNB = DNB, EQNR = EQNR, MOWI = MOWI, NHY = NHY, ORK = ORK,
```

```r
                    SNI = SNI, STB = STB, TEL = TEL, TOM = TOM, YAR = YAR)


# Choosing and set the correct order of the variables.
col_order <- c("Time", "Close", "High","Low")

# Function to reorder columns
reorder_columns <- function(df, order) {
  df[, order, drop = FALSE]
}

# Reorder for every stock
OSE <- lapply(OSE, reorder_columns, order = col_order)



# Set time varible to a POSIXct
OSE <- lapply(OSE, function(df) {
  df$Time <- as.POSIXct(df$Time, format = "%Y-%m-%d %H:%M:%S")
  return(df)
})



################################################################################
# Stockholm Stock Exchange Data
################################################################################
ABB <- read.csv("~/Documents/UIA/Master/intraday_data/SSE/ABB_15min.csv")
ASSA <- read.csv("~/Documents/UIA/Master/intraday_data/SSE/ASSA_15min.csv")
ATCO <- read.csv("~/Documents/UIA/Master/intraday_data/SSE/ATCO_15min.csv")
AZN <- read.csv("~/Documents/UIA/Master/intraday_data/SSE/AZN_15min.csv")
HEXA <- read.csv("~/Documents/UIA/Master/intraday_data/SSE/HEXA_15min.csv")
HM <- read.csv("~/Documents/UIA/Master/intraday_data/SSE/HM_15min.csv")
INVE <- read.csv("~/Documents/UIA/Master/intraday_data/SSE/INVE_15min.csv")
SAND <- read.csv("~/Documents/UIA/Master/intraday_data/SSE/SAND_15min.csv")
SEB <- read.csv("~/Documents/UIA/Master/intraday_data/SSE/SEB_15min.csv")
```

```r
VOLV <- read.csv("~/Documents/UIA/Master/intraday_data/SSE/VOLV_15min.csv")


# List the stocks
SSE <- list(ABB = ABB, ASSA = ASSA, ATCO = ATCO, AZN = AZN, HEXA = HEXA,
                   HM = HM, INVE = INVE, SAND = SAND, SEB = SEB, VOLV = VOLV)


# Choosing and set the correct order of the variables.
col_order <- c("Time", "Close", "High","Low")

# Function to reorder columns
reorder_columns <- function(df, order) {
  df[, order, drop = FALSE]
}

# reorder for each stock
SSE <- lapply(SSE, reorder_columns, order = col_order)


# Set time varible to a POSIXct
SSE <- lapply(SSE, function(df) {
  df$Time <- as.POSIXct(df$Time, format = "%Y-%m-%d %H:%M:%S")
  return(df)
})

################################################################################
# Copenhagen Stock Exchange Data
################################################################################
CARL <- read.csv("~/Documents/UIA/Master/intraday_data/CSE/CARL_15min.csv")
COLO <- read.csv("~/Documents/UIA/Master/intraday_data/CSE/COLO_15min.csv")
DANSKE <- read.csv("~/Documents/UIA/Master/intraday_data/CSE/DANSKE_15min.csv")
DEMANT <- read.csv("~/Documents/UIA/Master/intraday_data/CSE/DEMANT_15min.csv")
DSV <- read.csv("~/Documents/UIA/Master/intraday_data/CSE/DSV_15min.csv")
```

```r
GMAB <- read.csv("~/Documents/UIA/Master/intraday_data/CSE/GMAB_15min.csv")
MAERSK <- read.csv("~/Documents/UIA/Master/intraday_data/CSE/MAERSK_15min.csv")
NOVO <- read.csv("~/Documents/UIA/Master/intraday_data/CSE/NOVO_15min.csv")
TRYG <- read.csv("~/Documents/UIA/Master/intraday_data/CSE/TRYG_15min.csv")
VWS <- read.csv("~/Documents/UIA/Master/intraday_data/CSE/VWS_15min.csv")


# Create list of stocks
CSE <- list(CARL = CARL, COLO = COLO, DANSKE = DANSKE, DEMANT = DEMANT,
                   DSV = DSV, GMAB = GMAB, MAERSK = MAERSK, NOVO = NOVO,
                   TRYG = TRYG, VWS = VWS)


# Choosing and set the correct order of the variables.
col_order <- c("Time", "Close", "High","Low")

# Function to reorder columns
reorder_columns <- function(df, order) {
  df[, order, drop = FALSE]
}

# Reorder for each stock
CSE <- lapply(CSE, reorder_columns, order = col_order)


# Set time varible to a POSIXct
CSE <- lapply(CSE, function(df) {
  df$Time <- as.POSIXct(df$Time, format = "%Y-%m-%d %H:%M:%S")
  return(df)
})


################################################################################
```

```r
# select the Stock Data
##############################################################################
# 1 = Oslo Stock Exchange, 2 = Stockholm Stock Exchange,
# 3 = Copenhagen Stock Exchange
##############################################################################
dataSet <- "1"

switch(dataSet,
       "1" = {
         stock.list <- OSE
         dataset.name <- "OSE"
       },

       "2" = {
         stock.list <- SSE
         dataset.name <- "SSE"
       },

       "3" = {
         stock.list <- CSE
         dataset.name <- "CSE"
       },
       {
         stop("Unknown data set!")
       }
)
##############################################################################
# Set the time windows for the given pre-, during, and post-crisis
##############################################################################
# Financial crisis time period
##############################################################################
# Pre financial crisis period
start_date <- as.POSIXct("2006-03-02 00:00:00")
end_date <- as.POSIXct("2007-09-01 23:59:59")
```

```r
# Filtering data frames within the list
pre_fin <- lapply(stock.list, function(df) {
  df %>%
    filter(Time >= start_date & Time <= end_date) %>%
    arrange(Time)
})

################################################################################
# Classify the buy and sell initiated trades
################################################################################
stock.trades <- lapply(pre_fin, aggregate_trades, algorithm = "LR")

################################################################################
# PIN Estimation
################################################################################
# Initialize an empty vector to store PIN values
PIN_values <- numeric()

# For loop to make PIN estimation
for (i in seq_along(stock.trades)) {
  pin <- YZ(stock.trades[[i]], likelihood = c("LK"))
  PIN_values <- c(PIN_values, pin$PIN)
  # Assign name to PIN value based on stock name
  names(PIN_values)[length(PIN_values)] <- names(stock.trades)[i]
}

print(PIN_values)

pre_fin_pin <- PIN_values
pre_fin_m <- mean(PIN_values)

################################################################################
# Model Parameters
```

```r
################################################################################
# Make empty list to store results
result_list <- list()

# Iterate over each stock in the list
for (i in seq_along(stock.trades)) {
  pin <- YZ(stock.trades[[i]], likelihood = c("LK"))
  result_list[[names(stock.trades)[i]]] <- pin
}

# Combine the results into a dataframe
parameter_df <- do.call(rbind, result_list)

# Remove the LK value
parameter_df <- subset(parameter_df, select = -c(LKval, PIN))

# Transpose the dataframe
parameter_df <- t(parameter_df)

# Replace non-numeric values with NA
parameter_df_num <- as.matrix(apply(parameter_df, 2,
                                    function(x) as.numeric(as.character(x))))

# Calculate the mean for each row
row_means <- rowMeans(parameter_df_num, na.rm = TRUE)

# Create a new object with only one column containing the mean for each row
pre_fin_par <- data.frame("Pre-Financial Crisis" = row_means)

# Add stock names as row names
rownames(pre_fin_par) <- rownames(parameter_df)

# Print the resulting object
print(pre_fin_par)
```

```r
###############################################################################
# During financial crisis period
###############################################################################
start_date <- as.POSIXct("2008-09-15 00:00:00")
end_date <- as.POSIXct("2009-09-14 23:59:59")

# Filtering data frames within the list
fin <- lapply(stock.list, function(df) {
  df %>%
    filter(Time >= start_date & Time <= end_date) %>%
    arrange(Time)
})

###############################################################################
# Classify the buy and sell initiated trades
###############################################################################
stock.trades <- lapply(fin, aggregate_trades, algorithm = "LR")


###############################################################################
# PIN Estimation
###############################################################################
# Initialize an empty vector to store PIN values
PIN_values <- numeric()

# For loop to make PIN estimation
for (i in seq_along(stock.trades)) {
  pin <- YZ(stock.trades[[i]], likelihood = c("LK"))
  PIN_values <- c(PIN_values, pin$PIN)
  # Assign name to PIN value based on stock name
  names(PIN_values)[length(PIN_values)] <- names(stock.trades)[i]
}
```

```r
print(PIN_values)

fin_pin <- PIN_values
fin_m <- mean(PIN_values)

################################################################################
# Model Parameters
################################################################################
# Make empty list to store results
result_list <- list()

# Iterate over each stock in the list
for (i in seq_along(stock.trades)) {
  pin <- YZ(stock.trades[[i]], likelihood = c("LK"))
  result_list[[names(stock.trades)[i]]] <- pin
}

# Combine the results into a dataframe
parameter_df <- do.call(rbind, result_list)

# Remove the LK value
parameter_df <- subset(parameter_df, select = -c(LKval, PIN))

# Transpose the dataframe
parameter_df <- t(parameter_df)

# Replace non-numeric values with NA
parameter_df_num <- as.matrix(apply(parameter_df, 2,
                                    function(x) as.numeric(as.character(x))))

# Calculate the mean for each row
row_means <- rowMeans(parameter_df_num, na.rm = TRUE)
```

```r
# Create a new object with only one column containing the mean for each row
fin_par <- data.frame("Financial Crisis" = row_means)

# Add stock names as row names
rownames(fin_par) <- rownames(parameter_df)

# Print the resulting object
print(fin_par)


###############################################################################
# Post financial crisis period
###############################################################################
start_date <- as.POSIXct("2009-09-15 00:00:00")
end_date <- as.POSIXct("2010-09-15 23:59:59")

# Filtering data frames within the list
post_fin <- lapply(stock.list, function(df) {
  df %>%
    filter(Time >= start_date & Time <= end_date) %>%
    arrange(Time)
})

###############################################################################
# Classify the buy and sell initiated trades
###############################################################################
stock.trades <- lapply(post_fin, aggregate_trades, algorithm = "LR")


###############################################################################
# PIN Estimation
###############################################################################
# Initialize an empty vector to store PIN values
PIN_values <- numeric()
```

```r
# For loop to make PIN estimation
for (i in seq_along(stock.trades)) {
  pin <- YZ(stock.trades[[i]], likelihood = c("LK"))
  PIN_values <- c(PIN_values, pin$PIN)
  # Assign name to PIN value based on stock name
  names(PIN_values)[length(PIN_values)] <- names(stock.trades)[i]
}

print(PIN_values)

post_fin_pin <- PIN_values
post_fin_m <- mean(PIN_values)

################################################################################
# Model Parameters
################################################################################
# Make empty list to store results
result_list <- list()

# Iterate over each stock in the list
for (i in seq_along(stock.trades)) {
  pin <- YZ(stock.trades[[i]], likelihood = c("LK"))
  result_list[[names(stock.trades)[i]]] <- pin
}

# Combine the results into a dataframe
parameter_df <- do.call(rbind, result_list)

# Remove the LK value
parameter_df <- subset(parameter_df, select = -c(LKval, PIN))

# Transpose the dataframe
parameter_df <- t(parameter_df)
```

```r
# Replace non-numeric values with NA
parameter_df_num <- as.matrix(apply(parameter_df, 2,
                        function(x) as.numeric(as.character(x))))

# Calculate the mean for each row
row_means <- rowMeans(parameter_df_num, na.rm = TRUE)

# Create a new object with only one column containing the mean for each row
post_fin_par <- data.frame("Post-Financial Crisis" = row_means)

# Add stock names as row names
rownames(post_fin_par) <- rownames(parameter_df)

# Print the resulting object
print(post_fin_par)


###############################################################################
# Health crisis time period
###############################################################################
###############################################################################
# Pre-health Crisis
###############################################################################
start_date <- as.POSIXct("2019-03-30 00:00:00")
end_date <- as.POSIXct("2020-01-29 23:59:59")

# Filtering data frames within the list
pre_health <- lapply(stock.list, function(df) {
  df %>%
    filter(Time >= start_date & Time <= end_date) %>%
    arrange(Time)
})
```

```r
##############################################################################
# Classify the buy and sell initiated trades
##############################################################################
stock.trades <- lapply(pre_health, aggregate_trades, algorithm = "LR")

##############################################################################
# PIN Estimation
##############################################################################
# Initialize an empty vector to store PIN values
PIN_values <- numeric()

# For loop to make PIN estimation
for (i in seq_along(stock.trades)) {
  pin <- YZ(stock.trades[[i]], likelihood = c("LK"))
  PIN_values <- c(PIN_values, pin$PIN)
  # Assign name to PIN value based on stock name
  names(PIN_values)[length(PIN_values)] <- names(stock.trades)[i]
}

print(PIN_values)

pre_health_pin <- PIN_values
pre_health_m <- mean(PIN_values)

##############################################################################
# Model Parameters
##############################################################################
# Make empty list to store results
result_list <- list()

# Iterate over each stock in the list
for (i in seq_along(stock.trades)) {
  pin <- YZ(stock.trades[[i]], likelihood = c("LK"))
  result_list[[names(stock.trades)[i]]] <- pin
```

```r
}

# Combine the results into a dataframe
parameter_df <- do.call(rbind, result_list)

# Remove the LK value
parameter_df <- subset(parameter_df, select = -c(LKval, PIN))

# Transpose the dataframe
parameter_df <- t(parameter_df)

# Replace non-numeric values with NA
parameter_df_num <- as.matrix(apply(parameter_df, 2,
                                    function(x) as.numeric(as.character(x))))

# Calculate the mean for each row
row_means <- rowMeans(parameter_df_num, na.rm = TRUE)

# Create a new object with only one column containing the mean for each row
pre_health_par <- data.frame("Pre-Health Crisis" = row_means)

# Add stock names as row names
rownames(pre_health_par) <- rownames(parameter_df)

# Print the resulting object
print(pre_health_par)

###############################################################################
# During Health Crisis
###############################################################################
start_date <- as.POSIXct("2020-01-30 00:00:00")
end_date <- as.POSIXct("2020-11-29 23:59:59")

# Filtering data frames within the list
```

```r
health <- lapply(stock.list, function(df) {
  df %>%
    filter(Time >= start_date & Time <= end_date) %>%
    arrange(Time)
})

################################################################################
# Classify the buy and sell initiated trades
################################################################################
stock.trades <- lapply(health, aggregate_trades, algorithm = "LR")
stock.trades

################################################################################
# PIN Estimation
################################################################################
# Initialize an empty vector to store PIN values
PIN_values <- numeric()

# For loop to make PIN estimation
for (i in seq_along(stock.trades)) {
  pin <- YZ(stock.trades[[i]], likelihood = c("LK"))
  PIN_values <- c(PIN_values, pin$PIN)
  # Assign name to PIN value based on stock name
  names(PIN_values)[length(PIN_values)] <- names(stock.trades)[i]
}

print(PIN_values)

health_pin <- PIN_values
health_m <- mean(PIN_values)

################################################################################
# Model Parameters
################################################################################
```

```r
# Make empty list to store results
result_list <- list()

# Iterate over each stock in the list
for (i in seq_along(stock.trades)) {
  pin <- YZ(stock.trades[[i]], likelihood = c("LK"))
  result_list[[names(stock.trades)[i]]] <- pin
}

# Combine the results into a dataframe
parameter_df <- do.call(rbind, result_list)

# Remove the LK value
parameter_df <- subset(parameter_df, select = -c(LKval, PIN))

# Transpose the dataframe
parameter_df <- t(parameter_df)

# Replace non-numeric values with NA
parameter_df_num <- as.matrix(apply(parameter_df, 2,
                                    function(x) as.numeric(as.character(x))))

# Calculate the mean for each row
row_means <- rowMeans(parameter_df_num, na.rm = TRUE)

# Create a new object with only one column containing the mean for each row
health_par <- data.frame("Health Crisis" = row_means)

# Add stock names as row names
rownames(health_par) <- rownames(parameter_df)

# Print the resulting object
print(health_par)
```

```r
################################################################################
# Post-health Crisis
################################################################################
start_date <- as.POSIXct("2020-11-30 00:00:00")
end_date <- as.POSIXct("2021-09-29 23:59:59")

# Filtering data frames within the list
post_health <- lapply(stock.list, function(df) {
  df %>%
    filter(Time >= start_date & Time <= end_date) %>%
    arrange(Time)
})

################################################################################
# Classify the buy and sell initiated trades
################################################################################
stock.trades <- lapply(post_health, aggregate_trades, algorithm = "LR")
stock.trades

################################################################################
# PIN Estimation
################################################################################
# Initialize an empty vector to store PIN values
PIN_values <- numeric()

# For loop to make PIN estimation
for (i in seq_along(stock.trades)) {
  pin <- YZ(stock.trades[[i]], likelihood = c("LK"))
  PIN_values <- c(PIN_values, pin$PIN)
  # Assign name to PIN value based on stock name
  names(PIN_values)[length(PIN_values)] <- names(stock.trades)[i]
}

print(PIN_values)
```

```r
post_health_pin <- PIN_values
post_health_m <- mean(PIN_values)

################################################################################
# Model Parameters
################################################################################
# Make empty list to store results
result_list <- list()

# Iterate over each stock in the list
for (i in seq_along(stock.trades)) {
  pin <- YZ(stock.trades[[i]], likelihood = c("LK"))
  result_list[[names(stock.trades)[i]]] <- pin
}

# Combine the results into a dataframe
parameter_df <- do.call(rbind, result_list)

# Remove the LK value
parameter_df <- subset(parameter_df, select = -c(LKval, PIN))

# Transpose the dataframe
parameter_df <- t(parameter_df)

# Replace non-numeric values with NA
parameter_df_num <- as.matrix(apply(parameter_df, 2,
                                    function(x) as.numeric(as.character(x))))

# Calculate the mean for each row
row_means <- rowMeans(parameter_df_num, na.rm = TRUE)

# Create a new object with only one column containing the mean for each row
post_health_par <- data.frame("Post-Health Crisis" = row_means)
```

```r
# Add stock names as row names
rownames(post_health_par) <- rownames(parameter_df)

# Print the resulting object
print(post_health_par)


################################################################################
# Geopolitical crisis time period
################################################################################
################################################################################
# Pre-geopolitical Crisis
################################################################################
start_date <- as.POSIXct("2021-04-24 00:00:00")
end_date <- as.POSIXct("2022-02-23 23:59:59")

# Filtering data frames within the list
pre_geo <- lapply(stock.list, function(df) {
  df %>%
    filter(Time >= start_date & Time <= end_date) %>%
    arrange(Time)
})

################################################################################
# Classify the buy and sell initiated trades
################################################################################
stock.trades <- lapply(pre_geo, aggregate_trades, algorithm = "LR")
stock.trades

################################################################################
# PIN Estimation
################################################################################
# Initialize an empty vector to store PIN values
```

```r
PIN_values <- numeric()

# For loop to make PIN estimation
for (i in seq_along(stock.trades)) {
  pin <- YZ(stock.trades[[i]], likelihood = c("LK"))
  PIN_values <- c(PIN_values, pin$PIN)
  # Assign name to PIN value based on stock name
  names(PIN_values)[length(PIN_values)] <- names(stock.trades)[i]
}

print(PIN_values)

pre_geo_pin <- PIN_values
pre_geo_m <- mean(PIN_values)

################################################################################
# Model Parameters
################################################################################
# Make empty list to store results
result_list <- list()

# Iterate over each stock in the list
for (i in seq_along(stock.trades)) {
  pin <- YZ(stock.trades[[i]], likelihood = c("LK"))
  result_list[[names(stock.trades)[i]]] <- pin
}

# Combine the results into a dataframe
parameter_df <- do.call(rbind, result_list)

# Remove the LK value
parameter_df <- subset(parameter_df, select = -c(LKval, PIN))

# Transpose the dataframe
```

```r
parameter_df <- t(parameter_df)

# Replace non-numeric values with NA
parameter_df_num <- as.matrix(apply(parameter_df, 2,
                                    function(x) as.numeric(as.character(x))))

# Calculate the mean for each row
row_means <- rowMeans(parameter_df_num, na.rm = TRUE)

# Create a new object with only one column containing the mean for each row
pre_geo_par <- data.frame("Pre-Geopolitical Crisis" = row_means)

# Add stock names as row names
rownames(pre_geo_par) <- rownames(parameter_df)

# Print the resulting object
print(pre_geo_par)


################################################################################
# During geoplotical Crisis
################################################################################
start_date <- as.POSIXct("2022-02-24 00:00:00")
end_date <- as.POSIXct("2022-12-23 23:59:59")

# Filtering data frames within the list
geo <- lapply(stock.list, function(df) {
  df %>%
    filter(Time >= start_date & Time <= end_date) %>%
    arrange(Time)
})

################################################################################
# Classify the buy and sell initiated trades
```

```r
################################################################################
stock.trades <- lapply(geo, aggregate_trades, algorithm = "LR")
stock.trades

################################################################################
# PIN Estimation
################################################################################
# Initialize an empty vector to store PIN values
PIN_values <- numeric()

# For loop to make PIN estimation
for (i in seq_along(stock.trades)) {
  pin <- YZ(stock.trades[[i]], likelihood = c("LK"))
  PIN_values <- c(PIN_values, pin$PIN)
  # Assign name to PIN value based on stock name
  names(PIN_values)[length(PIN_values)] <- names(stock.trades)[i]
}

print(PIN_values)

geo_pin <- PIN_values
geo_m <- mean(PIN_values)

################################################################################
# Model Parameters
################################################################################
# Make empty list to store results
result_list <- list()

# Iterate over each stock in the list
for (i in seq_along(stock.trades)) {
  pin <- YZ(stock.trades[[i]], likelihood = c("LK"))
  result_list[[names(stock.trades)[i]]] <- pin
}
```

```r
# Combine the results into a dataframe
parameter_df <- do.call(rbind, result_list)

# Remove the LK value
parameter_df <- subset(parameter_df, select = -c(LKval, PIN))

# Transpose the dataframe
parameter_df <- t(parameter_df)

# Replace non-numeric values with NA
parameter_df_num <- as.matrix(apply(parameter_df, 2,
                                    function(x) as.numeric(as.character(x))))

# Calculate the mean for each row
row_means <- rowMeans(parameter_df_num, na.rm = TRUE)

# Create a new object with only one column containing the mean for each row
geo_par <- data.frame("Geopolitical Crisis" = row_means)

# Add stock names as row names
rownames(geo_par) <- rownames(parameter_df_num)

# Print the resulting object
print(geo_par)

################################################################################
# Post-geopolitical crisis
################################################################################
start_date <- as.POSIXct("2022-12-24 00:00:00")
end_date <- as.POSIXct("2023-10-23 23:59:59")

# Filtering data frames within the list
post_geo <- lapply(stock.list, function(df) {
```

```r
  df %>%
    filter(Time >= start_date & Time <= end_date) %>%
    arrange(Time)
})

################################################################################
# Classify the buy and sell initiated trades
################################################################################
stock.trades <- lapply(post_geo, aggregate_trades, algorithm = "LR")
stock.trades

################################################################################
# PIN Estimation
################################################################################
# Initialize an empty vector to store PIN values
PIN_values <- numeric()

# For loop to make PIN estimation
for (i in seq_along(stock.trades)) {
  pin <- YZ(stock.trades[[i]], likelihood = c("LK"))
  PIN_values <- c(PIN_values, pin$PIN)
  # Assign name to PIN value based on stock name
  names(PIN_values)[length(PIN_values)] <- names(stock.trades)[i]
}

print(PIN_values)

post_geo_pin <- PIN_values
post_geo_m <- mean(PIN_values)

################################################################################
# Model Parameters
################################################################################
# Make empty list to store results
```

```r
result_list <- list()

# Iterate over each stock in the list
for (i in seq_along(stock.trades)) {
  pin <- YZ(stock.trades[[i]], likelihood = c("LK"))
  result_list[[names(stock.trades)[i]]] <- pin
}

# Combine the results into a dataframe
parameter_df <- do.call(rbind, result_list)

# Remove the LK value
parameter_df <- subset(parameter_df, select = -c(LKval, PIN))

# Transpose the dataframe
parameter_df <- t(parameter_df)

# Replace non-numeric values with NA
parameter_df_num <- as.matrix(apply(parameter_df, 2,
                                    function(x) as.numeric(as.character(x))))

# Calculate the mean for each row
row_means <- rowMeans(parameter_df_num, na.rm = TRUE)

# Create a new object with only one column containing the mean for each row
post_geo_par <- data.frame("Post-Geopolitical Crisis" = row_means)

# Add stock names as row names
rownames(post_geo_par) <- rownames(parameter_df)

# Print the resulting object
print(post_geo_par)
```

```r
################################################################################
# Plotting the PIN values in barplots
################################################################################
################################################################################
# Financial crisis PIN plot
################################################################################
fin_plot <- c("Pre-Crisis" = pre_fin_m, "During Crisis" = fin_m,
              "Post-Crisis" = post_fin_m)
barplot(fin_plot, main = "CSE Financial Crisis PIN",
        col=c("lightgreen","orange", "lightblue"), ylim = c(0, 0.40))


################################################################################
# Health crisis PIN plot
################################################################################
health_plot <- c("Pre-Crisis" = pre_health_m,"During Crisis" = health_m,
               "Post-Crisis" = post_health_m)
barplot(health_plot, main = "CSE Health Crisis PIN",
        col=c("lightgreen","orange", "lightblue"), ylim = c(0, 0.40))


################################################################################
# Geopolitical crisis PIN plot
################################################################################
geo_plot <- c("Pre-Crisis" = pre_geo_m,"During Crisis" = geo_m,
              "Post-Crisis" = post_geo_m)
barplot(geo_plot, main = "CSE Geopolitical Crisis PIN",
        col=c("lightgreen","orange", "lightblue"), ylim = c(0, 0.40))
```

```
################################################################################
# Model Parameter tables
################################################################################
################################################################################
# Financial crisis PIN plot
################################################################################

# Combine the three data frames
combined_fin <- data.frame(
  Pre.Financial.Crisis = pre_fin_par$Pre.Financial.Crisis,
  Financial.Crisis = fin_par$Financial.Crisis,
  Post.Financial.Crisis = post_fin_par$Post.Financial.Crisis,
  row.names = rownames(pre_fin_par)
)

xtable(combined_fin)

################################################################################
# Health crisis PIN plot
################################################################################
# Combine the three data frames
combined_health <- data.frame(
  Pre.Health.Crisis = pre_health_par$Pre.Health.Crisis,
  Health.Crisis = health_par$Health.Crisis,
  Post.Health.Crisis = post_health_par$Post.Health.Crisis,
  row.names = rownames(pre_health_par)
)

xtable(combined_health)

################################################################################
# Geopolitical crisis PIN plot
```

```
################################################################################
# Combine the three data frames
combined_geo <- data.frame(
  Pre.Geo.Crisis = pre_geo_par$Pre.Geopolitical.Crisis,
  Geo.Crisis = geo_par$Geopolitical.Crisis,
  Post.Geo.Crisis = post_geo_par$Post.Geopolitical.Crisis,
  row.names = rownames(pre_geo_par)
)

xtable(combined_geo)
```

A.3.3 Technical Analysis Program

```
    rm(list=ls(all=TRUE))
install.packages("~/Downloads/matiming_1.0.tar", repos = NULL, type = "source")

library(matiming)
library(xtable)
library(zoo)
library(np)
library(Hmisc)
library(tseries)
library(PerformanceAnalytics)


################################################################################
# Data Gathering
################################################################################
# Read data from txt file
rf <- read.table("Rf_daily.txt", header = TRUE, sep = ",")

# Convert Date column to Date format
rf$Date <- as.Date(as.character(rf$Date), format = "%Y%m%d")

# Rename columns
```

```r
colnames(rf) <- c("Date", "RF")

rf$RF <- rf$RF
rf
head(rf)

################################################################################
# List of stock symbols on the Oslo Stock Exchange for return calculations
################################################################################
stock_symbols <- c("EQNR.OL", "YAR.OL", "MOWI.OL", "NHY.OL", "TEL.OL",
                   "DNB.OL", "ORK.OL", "STB.OL", "SNI.OL", "TOM.OL")

# Initialize an environment to store stock data
stock_data <- new.env()

################################################################################
# Total Return
################################################################################
lapply(stock_symbols, function(symbol) {
  getSymbols(symbol, env = stock_data, src = "yahoo", from = "2005-09-01",
             to = "2024-01-01", auto.assign = TRUE)
})

# Review the data
print(ls(stock_data))

# Combine the Close prices into one xts object
portfolio_prices <- do.call(merge, eapply(stock_data, function(x) Ad(x)))
class(portfolio_prices)
head(portfolio_prices)

R_t = diff(portfolio_prices) / portfolio_prices
R_t <- na.omit(R_t)
head(R_t)
```

```r
totret <- Return.portfolio(R_t)
totret <- data.frame(Date = index(totret), coredata(totret))


###############################################################################
# Capital Gain Returns
###############################################################################
# Data Periods
# Pre-Crisis Fianncial
# Combine the Close prices into one xts object
portfolio_prices <- do.call(merge, eapply(stock_data, function(x) Cl(x)))

R_t = diff(portfolio_prices) / portfolio_prices
R_t <- na.omit(R_t)
head(R_t)

capret <- Return.portfolio(R_t)
capret <- data.frame(Date = index(capret), coredata(capret))


###############################################################################
# Extract the time window needed for the analysis
###############################################################################
start_date <- as.Date("2005-09-01")
end_date <- as.Date("2024-01-01")
totret <- totret[totret$Date >= start_date & totret$Date <= end_date, ]


start_date <- as.Date("2005-09-01")
end_date <- as.Date("2024-01-01")
rf <- rf[rf$Date >= start_date & rf$Date <= end_date, ]
```

```r
start_date <- as.Date("2005-09-01")
end_date <- as.Date("2024-01-01")
capret <- capret[capret$Date >= start_date & capret$Date <= end_date, ]

################################################################################
# Generate numeric values
################################################################################
totret.num <- as.numeric(totret$portfolio.returns)
totret <- zoo(totret.num, order.by = as.Date(totret$Date, format = "%Y-%m-%d"))

rf.num <- as.numeric(rf$RF)
rf <- zoo(rf.num, order.by = as.Date(rf$Date, format = "%Y-%m-%d"))

capret.num <- as.numeric(capret$portfolio.returns)
capret <- zoo(capret.num, order.by = as.Date(capret$Date, format = "%Y-%m-%d"))

################################################################################
# Check the data
################################################################################
head(totret)
head(capret)
head(rf)

length(totret)
length(capret)
length(rf)

################################################################################
# NA work
################################################################################
data <- data.frame(cbind(totret, capret, rf))
colnames(data) <- c("totret", "capret", "rf")

# Omit NA´s
```

```r
sum(is.na(data))
data <- na.omit(data)
sum(is.na(data))

# Make data a zoo variable
data <- zoo(data, order.by=as.Date(row.names(data)))

###############################################################################
# Data Descriptive Statistics
###############################################################################
start_dates <- c("2007-09-15", "2019-03-30", "2021-04-24")
end_dates <- c("2010-09-14", "2021-09-29", "2023-10-23")

data_windows <- list()

# Loop through the periods and extract data
for (i in 1:length(start_dates)) {
  period_start <- as.Date(start_dates[i])
  period_end <- as.Date(end_dates[i])
  # Extract the window
  data_windows[[i]] <- window(data, start = period_start, end = period_end)
}

# Function to compute statistics including the Jarque-Bera test
compute_stats <- function(zoo_obj) {
  results <- apply(coredata(zoo_obj), 2, function(x) {
    # Basic statistics
    basic_stats <- c(
      mean = mean(x) * 100,
      sd = sd(x) * 100,
      min = min(x) * 100,
      max = max(x) * 100,
      skewness = skewness(x),
      kurtosis = kurtosis(x)
```

```
    )

    # Jarque-Bera test
    jb_test <- jarque.bera.test(x)

    # Combine results
    c(basic_stats, jb_statistic = jb_test$statistic,
      jb_p_value = jb_test$p.value)
  })
  return(results) # Transpose for better formatting
}

# Apply the statistics function to each data window
stats_list <- lapply(data_windows, compute_stats)
stats_list

xtable(stats_list[[1]])
xtable(stats_list[[2]])
xtable(stats_list[[3]])

################################################################################
# Create the variables for our simulation
################################################################################
dates <- index(data)
data <- coredata(data)
totret <- data[,"totret"]
capret <- data[,"capret"]
rfret <- data[,"rf"]



################################################################################
# Choose the Fast and Sloww MA and transaction costs
################################################################################
```

```r
tc <- 0.0008
fast <- c(50)
slow <- c(200)
shorts <- F


###############################################################################
# Choose the strategy
###############################################################################

data.switch <- "1"

switch(data.switch,
       "1" = {
         results <- sim.mac.strategy(totret=totret, rfret=rfret, dates=dates,
                                     capret=capret, tc=tc, shorts=shorts,
                                     fast=fast, slow=slow, FUN=SMA)
         dataset.name <- "MA"
       },

       "2" = {
         results <- sim.macd.strategy(totret, rfret, dates, capret=capret,
                                      tc=tc, shorts = shorts, fast=12, slow=26,
                                      final=9, FUN=EMA)
         dataset.name <- "MACD"
       },
       {
         stop("Unknown data set!")
       }
)


###############################################################################
# Financial Crisis Period
```

```
################################################################################
# Pre Crisis Window
################################################################################
# define the starting point to compute the performance of the strategy
sim.start.date <- as.Date("2007-09-14", format="%Y-%m-%d")
# find the index of the first date
ind <- which(dates==sim.start.date)

# find the start date in the sample
start.date <- dates[ind - slow]

# define the end date
end.date <- as.Date("2008-09-15", format="%Y-%m-%d")

# Back test the strategy
res.pre.fin <- back.test(results, start.date, end.date)

# Statistics
df.pre.fin <- descriptive.statistics(res.pre.fin)


################################################################################
# During Crisis Window
################################################################################
# define the starting point to compute the performance of the strategy
sim.start.date <- as.Date("2008-09-15", format="%Y-%m-%d")
# find the index of the first date
ind <- which(dates==sim.start.date)

# find the start date in the sample
start.date <- dates[ind - slow]

# define the end date
end.date <- as.Date("2009-09-15", format="%Y-%m-%d")
```

```r
# Back test the strategy
res.dur.fin <- back.test(results, start.date, end.date)

# Statistics
df.dur.fin <- descriptive.statistics(res.dur.fin)


################################################################################
# Post Crisis Window
################################################################################
# define the starting point to compute the performance of the strategy
sim.start.date <- as.Date("2009-09-15", format="%Y-%m-%d")
# find the index of the first date
ind <- which(dates==sim.start.date)

# find the start date in the sample
start.date <- dates[ind - slow]

# define the end date
end.date <- as.Date("2010-09-15", format="%Y-%m-%d")

# Back test the strategy
res.post.fin <- back.test(results, start.date, end.date)

# Statistics
df.post.fin <- descriptive.statistics(res.post.fin)

################################################################################
# Health Crisis Period
################################################################################
# Pre Crisis Window
################################################################################
# define the starting point to compute the performance of the strategy
```

```r
sim.start.date <- as.Date("2019-03-29", format="%Y-%m-%d")
# find the index of the first date
ind <- which(dates==sim.start.date)

# find the start date in the sample
start.date <- dates[ind - slow]

# define the end date
end.date <- as.Date("2020-01-29", format="%Y-%m-%d")

# Back test the strategy
res.pre.hlt <- back.test(results, start.date, end.date)

# Statistics
df.pre.hlt <- descriptive.statistics(res.pre.hlt)


################################################################################
# During Crisis Window
################################################################################
# define the starting point to compute the performance of the strategy
sim.start.date <- as.Date("2020-01-30", format="%Y-%m-%d")
# find the index of the first date
ind <- which(dates==sim.start.date)

# find the start date in the sample
start.date <- dates[ind - slow]

# define the end date
end.date <- as.Date("2020-11-29", format="%Y-%m-%d")

# Back test the strategy
res.dur.hlt <- back.test(results, start.date, end.date)
```

```r
# Statistics
df.dur.hlt <- descriptive.statistics(res.dur.hlt)


##############################################################################
# Post Crisis Window
##############################################################################
# define the starting point to compute the performance of the strategy
sim.start.date <- as.Date("2020-11-30", format="%Y-%m-%d")
# find the index of the first date
ind <- which(dates==sim.start.date)

# find the start date in the sample
start.date <- dates[ind - slow]

# define the end date
end.date <- as.Date("2021-09-29", format="%Y-%m-%d")

# Back test the strategy
res.post.hlt <- back.test(results, start.date, end.date)

# Statistics
df.post.hlt <- descriptive.statistics(res.post.hlt)


##############################################################################
# Geopolitical Crisis Period
##############################################################################
# Pre Crisis Window
##############################################################################
# define the starting point to compute the performance of the strategy
sim.start.date <- as.Date("2021-04-23", format="%Y-%m-%d")
# find the index of the first date
ind <- which(dates==sim.start.date)
```

```
# find the start date in the sample
start.date <- dates[ind - slow]

# define the end date
end.date <- as.Date("2022-02-23", format="%Y-%m-%d")

# Back test the strategy
res.pre.geo <- back.test(results, start.date, end.date)

# Statistics
df.pre.geo <- descriptive.statistics(res.pre.geo)

################################################################################
# During Crisis Window
################################################################################
# define the starting point to compute the performance of the strategy
sim.start.date <- as.Date("2022-02-24", format="%Y-%m-%d")
# find the index of the first date
ind <- which(dates==sim.start.date)

# find the start date in the sample
start.date <- dates[ind - slow]

# define the end date
end.date <- as.Date("2022-12-23", format="%Y-%m-%d")

# Back test the strategy
res.dur.geo <- back.test(results, start.date, end.date)

# Statistics
df.dur.geo <- descriptive.statistics(res.dur.geo)

################################################################################
```

```
# Post Crisis Window
##############################################################################
# define the starting point to compute the performance of the strategy
sim.start.date <- as.Date("2022-12-23", format="%Y-%m-%d")
# find the index of the first date
ind <- which(dates==sim.start.date)

# find the start date in the sample
start.date <- dates[ind - slow]

# define the end date
end.date <- as.Date("2023-10-23", format="%Y-%m-%d")

# Back test the strategy
res.post.geo <- back.test(results, start.date, end.date)

# Statistics
df.post.geo <- descriptive.statistics(res.post.geo)

# If the strategy is MAC, replicate NA´s as there are no signals.
if (data.switch == "1") {
  na <- c(rep("0", 13))
  df.post.geo <- df.dur.geo
  df.post.geo["MA"] <- na
}


##############################################################################
# Mean return Plots
##############################################################################
# Financial Crisis
##############################################################################
a <- cbind(df.pre.fin[1,], df.dur.fin[1,], df.post.fin[1,])
a <- as.matrix(a)
```

```r
# Create vector with spacing
space_vector <- c(0, 0.2, 2, 0.2, 2, 0.2)
colors <- c("lightblue", "lightgreen")


aplot <- barplot(height = a,
              beside = TRUE,
              col = colors,
              space = space_vector,
              ylim = c(-3,2),
              axes = TRUE,
              xaxt = "n")

# Add labels
group_labels <- c("Pre", "During", "Post")
midpoints <- c(mean(aplot[1:2]), mean(aplot[3:4]), mean(aplot[5:6]))
axis(1, at = midpoints, labels = group_labels, tick = FALSE, line = -0.5)

# Add title and legend
title(main = paste("Financial Crisis BH vs", dataset.name, "Mean Return %"),
      xlab = "Periods", ylab = "Mean Return %")
legend("topright",
       legend = c("BH", dataset.name),
       fill = c("lightblue", "lightgreen"),
       title = "Strategy",
       cex = 1,
       bty = "n")

###############################################################################
# Health Crisis
###############################################################################
b <- cbind(df.pre.hlt[1,], df.dur.hlt[1,], df.post.hlt[1,])
b <- as.matrix(b)
```

```r
bplot <- barplot(height = b,
              beside = TRUE,
              col = colors,
              space = space_vector,
              ylim = c(-1,1),
              axes = TRUE,
              xaxt = "n")

# Add labels
group_labels <- c("Pre", "During", "Post")
midpoints <- c(mean(bplot[1:2]), mean(bplot[3:4]), mean(bplot[5:6]))
axis(1, at = midpoints, labels = group_labels, tick = FALSE, line = -0.5)


# Add title and legend
title(main = paste("Health Crisis BH vs", dataset.name, "Mean Return %"),
      xlab = "Periods", ylab = "Mean Return %")
legend("topright",
       legend = c("BH", dataset.name),
       fill = c("lightblue", "lightgreen"),
       title = "Strategy",
       cex = 1,
       bty = "n")


################################################################################
# Geopolitical Crisis
################################################################################
c <- cbind(df.pre.hlt[1,], df.dur.hlt[1,], df.post.hlt[1,])
c <- as.matrix(c)

if (data.switch == "1") {
  df.post.geo <- df.dur.geo
```

```
  df.post.geo[, 2] <- as.numeric(0)
  c <- cbind(df.pre.geo[1, ], df.dur.geo[1, ], df.post.geo[1, ])
  c <- as.matrix(c)
}


cplot <- barplot(height = c,
                 beside = TRUE,
                 col = colors,
                 space = space_vector,
                 ylim = c(-1,1),
                 axes = TRUE,
                 xaxt = "n")


# Add labels
group_labels <- c("Pre", "During", "Post")
midpoints <- c(mean(cplot[1:2]), mean(cplot[3:4]), mean(cplot[5:6]))
axis(1, at = midpoints, labels = group_labels, tick = FALSE, line = -0.5)



# Add title and legend
title(main = paste("Geopolitical Crisis BH vs", dataset.name, "Mean Return %"),
      xlab = "Periods", ylab = "Mean Return %")
legend("topright",
       legend = c("BH", dataset.name),
       fill = c("lightblue", "lightgreen"),
       title = "Strategy",
       cex = 1,
       bty = "n")


################################################################################
```

```r
# Statistiscs
##############################################################################
# Financial Crisis
##############################################################################
fin.stats <- data.frame(df.pre.fin, df.dur.fin, df.post.fin)
colnames(fin.stats) <- c("BH", dataset.name, "BH", dataset.name, "BH",
                         dataset.name)
round(fin.stats, 3)
xtable(fin.stats)

##############################################################################
# Health Crisis
##############################################################################
hlt.stats <- data.frame(df.pre.hlt, df.dur.hlt, df.post.hlt)
colnames(hlt.stats) <- c("BH", dataset.name, "BH", dataset.name, "BH",
                         dataset.name)
round(hlt.stats, 3)
xtable(hlt.stats)

##############################################################################
# Geopolitical Crisis
##############################################################################
geo.stats <- data.frame(df.pre.geo, df.dur.geo, df.post.geo)
colnames(geo.stats) <- c("BH", dataset.name, "BH", dataset.name, "BH",
                         dataset.name)
round(geo.stats, 3)
xtable(geo.stats)
```

Appendix B

Discussion paper – Trym Løvmo Endresen: Responsability

Introduction

The title of my master's thesis is "Information Asymmetry and Performance of Technical Trading during Crises in the Scandinavian Market," which examines changes in trading behavior and market dynamics under crises. It does this by studying three major crisis periods: the financial crisis of 2008, the COVID-19 pandemic, and the Russia-Ukraine war, focusing on Norwegian, Swedish, and Danish stock exchanges.

Using analytical methods, I examined the usefulness of MAC (Moving Average Crossover) and MACD (Moving Average Convergence Divergence) as technical analysis tools on Oslo Stock Exchange. This research breaks these crises down into pre-crisis, mid-crisis and post-crisis periods where probabilities of informed trading are calculated separately for each period. There was a higher probability of informed trading during financial crisis than health or geopolitical; Scandinavian markets had different levels of PINs. Moreover, it finds that using a MAC strategy prior to and during the financial crisis outperforms a simple buy-and-hold strategy.

This discussion paper will look into how my thesis relates to the concept of responsibility. I will discuss the ethical challenges of information asymmetry in financial markets and propose ways to manage these challenges. This exploration aims to show how responsible practices can help maintain fairness and integrity in financial markets, especially during turbulent times.

Relationship to Responsibility

The responsibility in financial markets is critical, especially in the context of my thesis on information asymmetry and technical analysis during crises. Responsibility involves ensuring fairness, transparency, and the ethical treatment of all market participants. In my research, several aspects of responsibility emerge as particularly relevant.

First, there is the issue of fairness and market integrity. Information asymmetry, where some investors have access to information that others do not, undermines the principle of a level playing field. This disparity allows informed traders to exploit their knowledge at the expense of less informed investors, which can erode trust in the financial system. Ensuring fairness means that all investors, regardless of their resources or connections, should have equal access to important information.

Transparency is another critical component of responsibility. During crises, the rapid dissemination of accurate and comprehensive information is essential for maintaining market stability. When there is a lack in transparency, it can lead to misinformation, panic, and irrational trading behaviors in the market. For instance, during the COVID-19 pandemic, the initial lack of clear information about the virus's impact led to significant market volatility. By promoting transparency, regulators and market participants can help prevent such instability and ensure that all investors are making decisions based on the same set of facts.

The protection of investors is also a key aspect of responsibility. Investors often have less access to sophisticated information and analytical tools compared to institutional investors. This puts them at a significant disadvantage, making them more vulnerable to market manipulations and sudden market shifts. Ethical responsibility requires that measures are in place to protect these investors, ensuring they are not unfairly disadvantaged. This includes providing clear and accessible information, as well as education on how to interpret market signals and make informed investment decisions.

Responsibility also extends to the broader societal impact of financial markets. The actions of market participants can have far reaching consequences beyond the financial system. For example, during the financial crisis of 2008, the collapse of major financial institutions had devastating effects on economies worldwide, leading to widespread job losses and economic hardship. Market participants have a responsibility to consider the broader implications of their actions and to act in ways that support the stability and health of the overall economy.

Lastly, there is the aspect of long-term sustainability. Responsible investing involves considering not just immediate financial returns, but also the long-term impact of investment decisions. This includes environmental, social, and governance (ESG) factors, which can affect the long-term sustainability of companies and markets. By integrating ESG factors to their investment strategies, investors can promote more sustainable business practices and contribute to a healthier economy and environment.

In conclusion, the concept of responsibility in financial markets encompasses fairness, transparency, the protection of investors, societal impact, and long-term sustainability. Addressing these aspects is critical for maintaining stable and trustworthy financial system, particularly during times of crisis. My thesis highlights the importance of these factors and suggests ways in which responsible practices can mitigate the challenges posed by information asymmetry.

Management of Ethical Challenges

Managing the ethical challenges posed by information asymmetry in financial markets, particularly during times of crisis, requires a comprehensive and multifaceted approach. These challenges, which include ensuring fairness, maintaining transparency, and protecting investors, can be addressed through a combination of regulatory actions, corporate governance, and technological advancements.

Regulatory bodies play a crucial role in reducing the effects of information asymmetry. By enforcing enhanced disclosure requirements, regulators can ensure that all market participants have the same access to information, significantly reducing the advantage that informed traders might have over less informed investors. For instance, during the financial crisis of 2008, the lack of transparent information contributed to widespread panic and volatility. By mandating timely and comprehensive disclosure of financial data and other relevant information, regulators can help stabilize markets and prevent misinformation from exacerbating crises.

In addition to disclosure requirements, regulators must strengthen and rigorously enforce insider trading laws. Insider trading undermines market integrity by allowing those with privileged information to profit at the expense of others. By imposing severe penalties on those caught engaging in insider trading, regulators can deter unethical behavior and promote a fairer trading environment. Regular audits and monitoring of trading activities can further enhance the effectiveness of these regulations.

Corporate governance is another critical component in managing ethical challenges. Companies should implement robust governance frameworks that prioritize ethical behavior, transparency, and accountability. This includes establishing policies that discourage insider trading and make sure that financial reporting is accurate and timely. By fostering a culture of ethical decision making within organizations, companies can contribute to maintaining market integrity.

Effective corporate governance also involves the board of directors and management teams actively monitoring and managing risks associated with information asymmetry. This can include implementing internal controls and compliance programs designed to detect and prevent unethical behavior. Additionally, the importance of ethics and compliance should be regulated through training provided by the companies, reinforcing the organization's commitment to responsible practices.

Advancements in technology can significantly enhance the management of ethical challenges related to information asymmetry. For instance, blockchain technology offers a transparent and immutable ledger that can improve the traceability and transparency of financial transactions. By implementing this can help detect and prevent illegal activities, ensuring that all market participants operate with the same assumptions.

Artificial intelligence (AI) and machine learning are also powerful tools in the fight against unethical trading practices. These technologies can analyze vast amounts of trading data to identify patterns. This can be used to detect irregular trading patterns or other forms of market manipulation. By continuously monitoring trading activities, AI systems can provide early warnings of suspicious behavior, enabling regulators and companies to take swift action.

Furthermore, the use of AI can enhance the accuracy and timeliness of financial reporting. Automated systems can process and analyze financial data more quickly than humans, reducing the likelihood of errors and ensuring that accurate information is disseminated to the market promptly. This can help maintain transparency and trust in the financial system, particularly during periods of crisis.

Education is a vital tool in managing the ethical challenges posed by information asymmetry. Providing investors with the knowledge and tools they need to make informed decisions can level the playing field. Financial literacy programs on market dynamics, investment strategies, and risk management help investors navigate financial markets better.

Transparent communication from financial institutions is also essential. By providing clear and concise information about investment products and market conditions, financial institutions can help investors understand the risks and opportunities available to them. This transparency can reduce the likelihood of investors making decisions based on incomplete or incorrect information, thus protecting them from significant financial losses.

In conclusion, managing the ethical challenges associated with information asymmetry in financial markets requires a multidimensional approach. Regulatory actions, robust corporate governance, technological advancements, and comprehensive investor education are all essential components of this strategy. By implementing these measures, we can create a more transparent, fair, and stable market environment, even during times of crisis. This not only protects the interests of all market participants but also upholds the integrity and trustworthiness of the financial system.

Conclusion

In summary, my discussion paper highlights significant ethical challenges related to information asymmetry in financial markets, especially during crises. This discussion emphasizes the importance of fairness, transparency, and the protection of investors to maintain market integrity. Addressing the challenges from this discussion requires a comprehensive approach that includes regulatory measures, corporate governance, and technological advancements. By fostering a more transparent and equitable market environment, stakeholders can ensure that financial markets operate responsibly, even in times of crisis.

Appendix C

Discussion Paper – Thomas Løining Kjeldsen: International

Introduction

This discussion paper draws on knowledge and experiences gained throughout the master's program, specializing in analytical finance. The program has provided me with a valuable theoretical toolkit that includes mathematics, strategy, and investments, among other areas. This discussion paper aims to explore our thesis topic and findings through the lens of the concept "international". The paper begins with a brief introduction to our thesis, followed by a discussion of international trends and forces in relation to our thesis. Finally, the paper concludes with a summary and precise conclusion.

Our thesis investigates information asymmetry and the performance of technical analysis during times of information asymmetry. The focus is on the Scandinavian market, specifically examining 10 of the largest stocks (by market capitalization) on the Oslo Stock Exchange (OSE), Stockholm Stock Exchange (SSE), and Copenhagen Stock Exchange (CSE). We use the Probability of Informed Trading (PIN) model to measure information asymmetry as a proxy. The PIN Estimation model, which uses a maximum likelihood algorithm, is widely used for measuring information asymmetry.

We employ two moving average strategies in our technical analysis on the OSE: the Moving Average Crossover (MAC) and the Moving Average Convergence/Divergence (MACD). We then compare the performance of these strategies against a Buy-and-Hold (BH) strategy. This allows us to examine the performance of technical analysis across different types of crises, each with varying levels of information asymmetry. The crises analyzed in our thesis include a financial crisis, a health crisis, and a geopolitical crisis. The financial crisis is represented by the global financial crisis of 2007-2008, the health crisis by the COVID-19 pandemic starting in 2020, and the geopolitical crisis by the Russian invasion of Ukraine in 2022.

Discussion

Our research contains international aspects as it explores stock exchanges in three different countries. This broad topic is of high relevance in regards to our thesis. I believe discussing our master thesis with the perspective "international" to be highly interesting. Financial markets are interconnected worldwide, with significant events often causing spillovers to other markets. The crises we studied impacted multiple countries, demonstrating the relevance of international trends and forces. This provides a strong foundation for discussing the international aspects of our thesis.

Financial globalization has made markets more interconnected, allowing political and economic shocks to spread to multiple countries. Our thesis provides evidence that information asymmetry, measured by PIN, is affected by crises. Markets geographically distant from the epicenter of crises can still be affected due to the globalization of markets. Large multinational firms can also be impacted, with trends and forces affecting multiple markets simultaneously.

The Global Financial Crisis of 2008 illustrated that the collapse of Lehman Brothers had widespread effects on the global financial system. Although the Scandinavian market is far from the United States, the impact was still significant. This demonstrated the interconnectedness of modern financial systems. Interestingly, the PIN values estimated during the financial crisis showed different patterns for each stock exchange. This suggests that while modern markets are interconnected, information asymmetry can vary depending on other trends and factors.

The COVID-19 pandemic represents a different type of crisis. Unlike the financial crisis, which directly involved financial institutions, the pandemic in 2020 was a health crisis that heavily impacted market behavior due to uncertainty. Historical prices show a steep decline at the start of the pandemic. The estimated PIN values indicated lower information asymmetry during the crisis compared to the pre- and post-crisis periods. Moreover, the model parameters from our PIN estimation showed a lower arrival rate of informed trades during the crisis, suggesting that the pandemic altered financial trends and information asymmetry across multiple markets.

The Russia-Ukraine war is categorized as a geopolitical crisis. While the conflict directly affects the two countries involved, the spillovers to other markets have been significant. The shock was not as dramatic as in the other crises mentioned, and the impact on the Norwegian, Danish, and Swedish markets varied. Geopolitical conflicts often lead to an increase in crude oil prices, which can significantly affect the international market and especially the Norwegian market.The Oslo Stock Exchange is heavily influenced by oil price fluctuations, as some of its largest companies are related to the oil industry.

Our thesis also explores the performance of technical analysis during crises. The results indicate that using a MAC strategy can outperform a BH strategy before and during a financial crisis, suggesting that technical analysis can be effective during periods of high information asymmetry. Additionally, technical analysis can provide further insights into how these crises might affect other markets.

To further understand the international aspects, it is important to consider the global regulatory environment and its influence on market behavior. Regulatory changes in one country can have effects on markets worldwide. For instance, post-crisis regulations such as the Dodd-Frank Act in the United States had implications for international financial institutions and markets, including those in Scandinavia. These regulations aimed to reduce systemic risk and improve transparency, thereby impacting the level of information asymmetry in global markets.

Moreover, the role of international organizations such as the International Monetary Fund (IMF) and the World Bank in managing the effects of global crises must be considered. These organizations provide financial assistance and policy advice to countries in distress, which in turn affects global market stability. During the 2008 financial crisis, these international organizations may have played an important role in stabilizing economies through its financial support programs.

Another significant international trend is the rise of technology and its impact on financial markets. Technological advancements have enabled faster information dissemination and improved market efficiency. High-frequency trading, driven by algorithms and automated systems, has become prevalent in global markets. These technologies can both lessen and worsen information asymmetry, depending on how they are regulated and implemented. The performance of technical analysis during crises can be linked to these technological advancements, highlighting the importance of adapting trading strategies to the evolving market environment.

Additionally, the influence of international trade and economic policies on financial markets is significant. Trade agreements, tariffs, and economic sanctions can impact market behavior. For example, the trade tensions between the United States and China have affected the global marked, influencing investor sentiment and market volatility. Understanding these international economic policies is crucial for comprehending the broader market dynamics and their implications for information asymmetry.

Furthermore, the interconnectedness of global financial markets means that crises in one region can have spillover effects on other regions. During the 2008 financial crisis, the collapse of major financial institutions in the United States led to a global liquidity crunch, affecting markets worldwide. Similarly, the COVID-19 pandemic resulted in widespread economic disruptions, highlighting the vulnerability of interconnected markets to global health crises.

In our thesis, the analysis of different crisis types provides valuable insights into how markets respond to various international shocks. The findings suggest that while financial markets are interconnected, the degree of information asymmetry and market response can vary significantly depending on the nature of the crisis. This underscores the importance of tailoring trading strategies to specific market conditions and understanding the unique characteristics of each crisis.

Overall, our thesis highlights the complex interplay between international trends and forces in shaping market behavior. The findings contribute to a broader understanding of how global events influence information asymmetry and the effectiveness of technical analysis. By examining these dynamics in the Scandinavian markets, our study offers valuable insights into the global market landscape and the potential strategies for navigating future international crises.

Conclusion

In conclusion, our thesis highlights the significant role of international trends and forces during different crises. The findings suggest that global markets are interconnected and that financial, health, and geopolitical crises can have far-reaching impacts on market behavior and information asymmetry. This discussion has underscored the importance of considering international dimensions in financial analysis. By examining informed trading and technical analysis across Scandinavian markets, this study contributes to a broader understanding of global market dynamics. Finally, this study offers insights into potential strategies for navigating future international crises. The results underscore the need for continuous monitoring of international trends and the adaptation of trading strategies to effectively manage risks and capitalize on opportunities in a globalized financial environment.