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Market efficiency and liquidity in financial market during crises

Covid-19 and Russia's invasion of Ukraine

Jakob Hansen and Morten Halvorsen

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This report is a component of our final master’s degree in Economics and Administration at the Business School, University of Tromsø - Arctic University of Norway (UiT). Completed in spring 2023, the master's thesis carries 30 credits. We have chosen finance as our area of specialization for the thesis.

Crafting this master´s thesis has proven both engaging and enlightening, as it allowed us to expand our knowledge in various finance domains. The work of Chordia et al., (2008), has been instrumental in this process. We wish to express our sincere gratitude to our supervisor, Thomas Leirvik, whose invaluable guidance and insights have significantly contributed to the completion of our master's thesis this semester. His expertise in finance, particularly in market efficiency and liquidity, has been immensely helpful. During the proofreading of our master's thesis, we utilized ChatGPT to enhance the academic language based on our supervisor's recommendation. It is important to note that ChatGPT was only employed for this purpose and did not assist us in any calculations, conclusions, or similar tasks.

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Abstract

In this thesis, we examine the relationship between market efficiency and market liquidity, focusing on financial markets during crises. Our work draws upon the article *Liquidity and market efficiency* (Chordia et al., 2008), and investigates the connection between market efficiency and liquidity in crisis periods.

The research is based on analyses of ETFs (Exchange Traded Fund) in G7 countries and Norway, exploring the effects of crises on efficiency and liquidity in various time frames. The analyses utilize historical ETF prices from 2015 to 2022. We conduct multiple analyses using Microsoft Excel and RStudio 2022.02.0 to process the data.

The analysis identifies a correlation between market efficiency and liquidity, a correlation that often intensifies during crisis periods. The findings illustrate that while financial crises aren't the exclusive determinants of this correlation, they certainly contribute significantly to the overall scenario.

The findings of this study have substantial implications for investors, shedding light on the behavior of the financial market during crises. Moreover, this thesis examines a current and crucial topic that explores the impact of global crises on financial markets. Understanding this relationship is of valuable importance for investors, decision-makers, and the broader economy. The analysis reveals a crucial explanatory factor, highlighting the relationship between market efficiency and liquidity, which significantly influences the functioning of the financial market.

Keywords: Market efficiency, market liquidity, financial market, crises, covid-19 and Russia's invasion of Ukraine

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1 Introduction

1.1 Actualization

In recent years, several significant global events have unfolded, capturing substantial attention. Two noteworthy events that have garnered particular focus are the emergence of the Covid-19 pandemic in the spring of 2020 and the subsequent invasion of Ukraine by Russia in the spring of 2022 (Boungou & Yatié, 2022; Rehman et al., 2021). The stock market is significantly influenced by these international occurrences, necessitating a comprehensive examination of their impact on market dynamics.

In the spring of 2020, global stock exchanges witnessed a substantial decline, affecting markets worldwide. The turning point came on March 16, 2020, when the impact of Covid-19 became vividly apparent to investors. On this day, the S&P 500 experienced a significant drop of 12%, reflecting an extraordinary change within a single day. This particular week marked a collective realization that an extended period of economic shutdown lay ahead (CNBC, 2021).

To comprehend the complexity of these market fluctuations, it is crucial to investigate the interplay between market efficiency and liquidity. Prior research indicates similarities between these two units, often displaying parallel trends (Chordia et al., 2008). Through a comprehensive analysis of the pre, during, and post-event dynamics, valuable insights can be obtained regarding the behavior of market efficiency and liquidity during times of crisis. Drawing upon relevant literature about the given topics, the intention is to determine the complex connections between market efficiency and liquidity at various stages of a crisis. Efficiency and liquidity play a crucial role in comprehending the functioning of the financial market, serving as significant factors that strongly influence its dynamics.

This empirical study aims to contribute to the existing body of knowledge on financial markets by conducting an empirical analysis and statistical examination. By comprehensively examining the relationship between market efficiency and liquidity during crisis periods, this study's findings hold the potential to enhance investment strategies and risk management approaches. The following sections provide a detailed overview of the methodology employed, the conducted data analysis, and a comprehensive interpretation of the obtained findings.

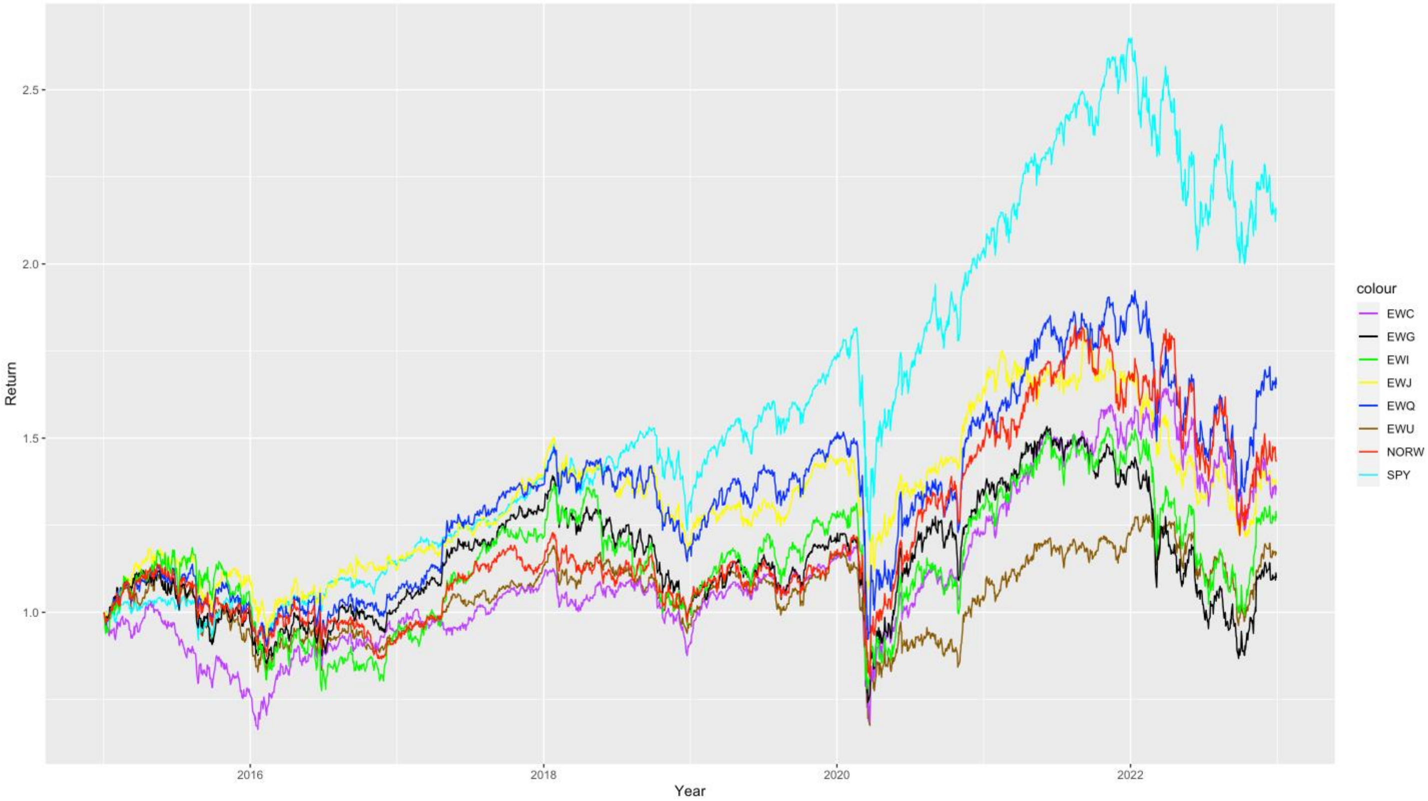
By delving into the complexities inherent in these concepts, the intention is to shed light on the underlying mechanisms that drive market behavior and provide valuable insights for market participants, policymakers, and researchers alike. Through our analysis, we strive to contribute to the broader understanding of how market efficiency and liquidity evolve in response to crises and their potential impacts on financial stability and investment strategies.

1.2 Purpose and research questions

In the ever-evolving global financial landscape, understanding the relationship between market efficiency and liquidity in the face of political turmoil is paramount. Market efficiency, characterized by the incorporation of all available information into asset prices, and market liquidity, a measure of how easily an asset can be bought or sold without affecting its price, are two key attributes of a well-functioning financial market (Amihud & Mendelson, 1986; Fama, 1970). While there is a large amount of literature on market efficiency and liquidity, there is not much literature on their interaction and correlation during financial crises and geopolitical conflicts in recent years. Particularly, with a focus on the G7 countries and Norway. The G7 consists of prominent countries including United Kingdom, United States, Japan, Canada, Germany, France, and Italy. These countries are selected as they represent the world's seven wealthiest democracies, providing a level playing field for comparison. The G7, established in 1973, serves as a forum for the wealthiest nations to address global economic crises. Collectively, the G7 countries boast an annual GDP of 40 trillion dollars, accounting for nearly half of the world's economy (Reuters, 2022a). Hence, analyzing the G7 countries is highly relevant, as they significantly contribute to the global economy. Norway is included in the thesis to facilitate a compelling comparison with the world's leading economies, as it offers an intriguing perspective for analysis and evaluation.

International crises, ranging from geopolitical conflicts to economic upheavals, can lead to increased market volatility, uncertainty, and investor anxiety (Meinen & Röhe, 2017). These factors may, in turn, have profound consequences for both market efficiency and liquidity, as investors reassess their strategies, and financial institutions adjust their operations to cope with the evolving environment. It is crucial to explore how these factors interplay in the context of Norway and the G7 countries, as these economies play significant roles in the global financial system and are often seen as bellwethers of broader market trends. Given the importance of understanding the implications of global political turmoil on market efficiency and liquidity, this article aims to shed light on this relationship in the context of the G7 countries and Norway.

Figure 1: The evolution of each ETF



List of all ETFs from 2015 to 2022. The descriptive statistics are located in the appendix of the thesis, specifically in Chapter 9, Tables 6 and 7.

Figure 1 above displays the progression of returns for different ETFs spanning the period from 2015 to 2022. An ETF, or "Exchange Traded Fund," is a collection of securities that can be traded on an exchange, much like stocks. ETFs may consist of stocks, bonds, commodities, or a combination of these and typically follow an index (Nordnet, 2023). In this figure, the focus is on day-to-day returns rather than ETF prices, as finding a common currency to compare ETFs from different countries worldwide is challenging. Examining returns offers a clearer understanding of the long-term development. Notably, all ETFs exhibit growth from 2015 to 2020. Around March 2020, when COVID-19 emerged, all ETFs experienced a sharp decline. After this downturn, ETFs stabilized and rose significantly throughout 2020 and 2021. In 2022, the ETFs appear to peak before Russia's invasion leads to stagnation and uncertainty in financial markets, resulting in a negative trend until mid-2022. Markets then stabilize towards the end of the year.

The research question for this master's thesis revolves around the impact of crises on financial markets in the G7 countries, with a comparative analysis involving Norway. Specifically, the intention is to investigate the following research question:

> *"What are the implications of international crises on market efficiency, liquidity and stakeholders in Norway and the G7 financial markets?"*

1.2.1 Main research question

The main research question is divided into several sub-questions:

- What impact does Covid-19 have on the financial markets?
- What impact does the invasion of Ukraine have on the financial markets?
- What is the impact on market efficiency?
- What is the impact on market liquidity?
- What is the relationship between liquidity and efficiency over the last few years?

The research questions outlined in this study are designed to facilitate a comprehensive understanding of the topic at hand. The objective of this study is to identify the key factors that have a significant impact on market efficiency and analyze the underlying mechanisms that govern its functioning. The research questions in this study aim to investigate the impact of market efficiency and liquidity on the financial market during different phases, including before, during, and after crises. Furthermore, the thesis will explore the correlation between these factors and their potential interrelationships.

1.3 Description of the study

The research examines the financial market during crises and the relationship between market efficiency and liquidity. It is essential to examine these two factors in the context of geopolitical conflicts, economic disruptions, and uncertainties surrounding crises. By comparing before, during, and after crises, the objective is to gain a deeper understanding of how an investor should navigate crises to best comprehend the market dynamics.

This master's thesis carries out an analysis that utilizes ETFs from the G7 countries and Norway. They are used because of their ubiquitous presence, in contrast to certain national indexes that may involve restrictive access or necessitate financial commitment. This selection facilitates an exhaustive exploration of market dynamics, devoid of constraints imposed by data access restrictions.

An analysis is conducted on one ETF from each of the eight countries, with each tracking the primary index of its respective country. This approach allows for a focused examination of market performance and dynamics within each specific market. These ETFs will be examined to calculate measures of market efficiency and liquidity, and their relationship from 2015 to 2022. The study adopts a starting point of 2015 to provide a comprehensive understanding of each country's financial market, encompassing a significant period leading up to the Covid-19 outbreak. The analysis period concludes on December 31, 2022. This timeframe enables a robust assessment of market dynamics and the impact of various events on the selected ETFs.

2 Theoretical framework

This chapter unveils the theoretical framework underlying market efficiency and liquidity, including diverse theories for their respective measurements. These calculations will be instrumental in our analysis. In conclusion, this chapter presents essential theories that are crucial for comparing market efficiency and liquidity. These theories provide a framework for understanding the relationship between these two important aspects of financial markets. By exploring and analyzing these theories, the study can provide insights into how market efficiency and liquidity interact and influence each other, and their impact on the financial market.

2.1 Market efficiency

The purpose of this chapter is to explain the concept of the efficient market hypothesis, and further come up with theories around the calculation of various units of measurement.

The theory behind market efficiency is based on Kendall and Hill (1953) where the author argues that the stock market follows a random path and that all movements that occur are a random walk (Kendall & Hill, 1953). Later came the hypothesis that all share prices are based on all available information about the company's shares (Fama, 1970). In the theory of Fama, all shares will have the correct price in the market as they reflect all available information about the share in the market. Behind this theory, Fama defined market efficiency as *"A market in which prices always fully reflect available information is called efficient"* (Fama, 1970, p. 383). A truly efficient market makes it impossible for a trader to beat the market, as all information is already reflected in the share price.

Fama formulated four assumptions that are fundamental for a financial market to be considered efficient. These four assumptions were:

- No transaction costs.
- The information must be free to obtain.
- The information must be able to be interpreted homogeneously.
- Investors must be sensible and rational.

2.1.1 Forms of market efficiency

Fama (1970), acknowledging the wide scope of market efficiency, further classified the concept into three distinct forms: weak, semi-strong, and strong. This division allowed for a more precise testing of the market efficiency hypothesis across different contexts (Fama, 1970).

Weak form

In the weak form of market efficiency, the share price reflects only historical prices. This information, readily available to all, does not require payment for access. Since all market participants possess the same information, and it is already incorporated into the share price, technical analysis does not yield any reliable insight.

Semi-strong form

Under the semi-strong form of market efficiency, the current share price incorporates all publicly available information, including historical price data. Given that prices have already been adjusted for prior pricing and public information, investors would require insider information to outperform the market.

Strong form

In the strong form of market efficiency, the share price captures all information, both public and private, suggesting that even insider information is integrated into the price. This implies that possessing insider information offers no advantage, as the price has already been adjusted to accommodate this information. Consequently, it becomes impossible for investors to secure a risk-adjusted excess return on their investments, irrespective of the extent of their analyses. However, this form of market efficiency is theoretical, as achieving it in a real financial market presents significant challenges (Fama, 1970).

2.1.2 Variance ratio

The variance-ratio test, developed by Lo and MacKinlay, serves as a statistical technique for testing market efficiency (Lo & MacKinlay, 1988). The test is based on the Random Walk Hypothesis (RWH), which posits that asset prices follow a random walk and are therefore unpredictable. If the RWH proves accurate, it indicates an efficient financial market, with asset prices embodying all accessible information, thus eliminating persistent profit opportunities.

The variance-ratio test evaluates the RWH by comparing the variances of returns over different holding periods. Consistent with the hypothesis, the variance of the returns should have a linear relationship with the length of the holding period. Meaning, the variance of returns for a holding period of *k* periods should be *k* times the variance of returns for a holding period of one period.

The variance ratio (VR) is computed using the following formula:

$$VR(k) = \frac{Var(r_k)}{k * Var(r_1)}$$

Where:

$VR(k)$ is the variance ratio for a holding period of *k* periods.

$Var(r_k)$ is the variance of returns for a holding period of *k* periods.

$Var(r_1)$ is the variance of returns for a holding period of one period.

If the market is efficient and the RWH holds, the variance ratio should be equal to 1 for all holding periods. A variance ratio significantly diverging from 1 implies a possible departure from the RWH, suggesting potential market inefficiency.

To determine the statistical significance of the results, Lo and MacKinlay (1988) proposed a test statistic called the standardized variance ratio (Z), which follows a standard normal distribution when the RWH is true. The calculation for this test statistic is as follows:

$$Z(k) = \frac{VR(k) - 1}{S(k)}$$

Where:

$S(k)$ is the standard deviation of the $VR(k)$ under the null hypothesis of the RWH.

By applying the variance-ratio test to historical asset price data, one can evaluate whether the market exhibits characteristics consistent with efficiency. If the test results indicate a significant departure from the RWH, it may suggest that there are opportunities for investors to predict future price movements and earn abnormal returns, challenging the efficient market hypothesis.

2.1.3 Adjusted Market Inefficiency Magnitude

Market efficiency is evaluated using Tran and Leirvik´s (2019) method. In their 2019 publication, Tran and Leirvik proposed a simple technique to measure market efficiency. They introduced an indicator named Adjusted Market Inefficiency Magnitude (AMIM), which escalates when market efficiency diminishes. AMIM's maximum value is one, signifying high market inefficiency. The indicator has no defined lower boundary, a negative value implies market efficiency. Thus, interpreting AMIM is straightforward, a positive value denotes an inefficient market, while a negative value signifies an efficient market (Tran & Leirvik, 2019). We calculate AMIM as follows:

$$AMIM_t = \frac{MIM_t - R_{CI}}{1 - R_{CI}}$$

Where the extent of market efficiency is calculated as follows:

$$MIM_t = \frac{\sum_{j=1}^{q} |\hat{\beta}_{j,t}^{standard}|}{1 + \sum_{j=1}^{q} |\hat{\beta}_{j,t}^{standard}|}$$

R_{CI} = is defined as the "range of the confidence interval" and is the distance between zero and 95%.

2.1.4 Time-varying market efficiency

The concept of time-varying market efficiency suggests that a market's efficiency can fluctuate over time. Consequently, prices might not consistently reflect all available information to the same degree, as this can vary with time.

Lo and MacKinlay (1988) calculated the variance ratio across various time intervals, demonstrating that market efficiency indeed fluctuates over time. In this research, it turned out that stock market prices show patterns and trends. This suggests that market efficiency can vary over time (Lo & MacKinlay, 1988). Later, in another article by Lo (2004), a concept was developed, namely adaptive market efficiency. This concept suggests that market efficiency is not something static, but rather comes from different interactions between individual agents in the market (Lo, 2004). According to the adaptive market's hypothesis, market efficiency arises because of how the agents relate to their environment, as well as the market and its participants. It means that market efficiency can change over time, depending on the agent's approach.

2.2 Market liquidity

Liquidity can be defined as the speed and ease with which a share can be bought or sold in the market at a fair price (Bodie et al., 2020). High liquidity indicates a market with many buyers and sellers, making it easier to trade shares without significantly impacting their prices. Large companies often he high liquidity due to the high trading volumes of their shares. In contrast, smaller companies typically have lower liquidity as their shares are traded less frequently. Low liquidity is associated with fewer market participants (Diamond, 1997), leading to potential price volatility when buying or selling shares. This is because the limited number of participants may struggle to counteract price fluctuations.

As discussed in previous chapters, market efficiency and liquidity share a close and interconnected relationship. Market liquidity plays a vital role in achieving market efficiency by enabling smooth transactions and minimizing transaction costs. Efficient markets require sufficient liquidity to ensure fair pricing and allow investors to enter and exit positions without significant price impact. Therefore, understanding the relationship between market efficiency and liquidity is crucial for comprehending the dynamics of financial markets.

Amihud and Mendelson (1986) examine the relationship between stock returns and market liquidity. Their study is a well-known contribution to the literature on stock market liquidity, highlighting that investors in efficient markets respond rationally to trading friction and transaction costs. They conclude that a lower bid-ask spread is associated with an increase in asset value (Amihud & Mendelson, 1986).

2.2.1 Illiquidity

Illiquidity can be defined as the premium paid by buyers or the reluctance of sellers when executing market orders for shares, commonly referred to as the bid-ask spreads (Clarke & Shastri, 2000). The difference between the purchase and sale prices encompasses two main components: the stock-specific element and the portion attributed to adverse selection. Additionally, a liquidity measure not only captures the level of asymmetric information but also provides insights into the market's available information about the company (Glosten & Milgrom, 1985; Kyle, 1985). These studies describe an illiquid market where the buying and selling prices for a stock differ. One approach to measure illiquidity (Amihud, 2002), is defined in the formula below:

$$ILLIQ_{i,t} = \frac{1}{D}\sum_{t=1}^{d_t}\frac{r_{i,t}}{dVol_{i,t}}$$

The liquidity target for asset i on day t is defined by the absolute return divided by dollar-volume. Hence, $ILLIQ$ represents the average of this over a period of D days. This target can be understood as the price response per dollar trading volume, positioning $ILLIQ$ as an approximate measure of price impact during trading.

2.2.2 Bid-Ask spread

The bid-ask spread is considered a key determinant of stock market liquidity. The bid-ask spread is the gap between the price an investor is willing to pay for a stock versus what another is willing to sell the stock for (Amihud & Mendelson, 1986). If this difference is large, the stock is said to be illiquid, and if the difference is small, the stock is liquid. It is, however, difficult to obtain observations for the bid- and ask- prices of stocks, hence an observation of the bid-ask spread is often not available. One way to circumvent this challenge is to construct an estimator that captures the liquidity.

Over the last four decades, several estimators of the bid-ask spread have been proposed in academic literature, including the Corwin-Schultz (2012) spread, the Roll (1984) spread, and the Abdi-Ranaldo (2017) spread, among others. The Abdi-Ranaldo spread has gained popularity in recent years due to its ability to capture the asymmetric nature of bid-ask spreads and its robustness to market frictions. Abdi and Ranaldo include close, high and low prices in their method in contrast to Roll which only uses close prices (Abdi & Ranaldo, 2017; Roll, 1984). Abdi & Ranaldo's formula is calculated as follows:

$$Spread = \sqrt{E[(C_t - n_t)(C_t - n_{t+1})]}$$

Where:

C= Daily close log-price

n = Daily mid-range (Average of daily high and low log-prices)

2.3 Portfolio theory

Markowitz's (1952) theory is employed to understand the construction of ETFs and their alignment with index weighting (Markowitz, 1952). This approach provides insights into how the shares within the ETF are structured to replicate the target index's composition. For instance, the Japanese ETF, EWJ, aims to maintain a similar weighting of Toyota shares as the corresponding Japanese Index. The theory is based on simple portfolio returns where the sum of individual shares is added together to calculate the overall return on a portfolio and is calculated as follows:

$$E(r_p) = \sum_{i=1}^{n} w_i \, E(r_i)$$

Where:

$E(r_p)$ = Expected return on portfolio

w_i = The weight of the portfolio on stock *i*

$E(r_i)$ = Expected return on stock *i*

3 Methods

This section first outlines the process for downloading data for the analysis, followed by a presentation of the empirical data included in the study. Subsequently, time series analyses probe the reactions of the stock market to the Covid-19 pandemic and the invasion of Ukraine.

The ETFs, sourced from Yahoo Finance, encompass all eight countries under study. Within the scope of this master's thesis, each index represents the respective country's stock index. The ETFs utilized in the analysis include EWU (United Kingdom), SPY (USA), EWJ (Japan), EWC (Canada), EWG (Germany), EWQ (France), EWI (Italy), and NORW (Norway).

3.1 Market efficiency

In assessing market efficiency, the analysis chapter computes two distinct targets, variance ratio by Lo and MacKinlay (1988), and AMIM by Leirvik and Tran (2019). In an article by Vuong et.al, (2022) it states that the American financial market bore the brunt of Covid-19 (Vuong et al., 2022). The analysis seeks to explore if other indexes likewise succumbed to the pandemic's impact.

The calculation of the variance ratio partitions our time series into four segments: *Pre Covid-19*, *During Covid-19*, *Between Crises*, and *During Invasion*. This segmentation empowers the variance ratio as a robust tool for market efficiency testing, effectively discerning whether stock price movements are random or patterned within each individual period. This period-specific insight could potentially serve traders in times of crisis.

The AMIM analysis presents a time series analysis, showcasing the progression of market efficiency from 2015 through 2022. By analyzing this target across the entire time series instead of set periods, comparison with liquidity measures becomes more feasible, facilitating the search for correlation.

3.2 Market liquidity

Two metrics, illiquidity by Amihud (2002) and the bid-ask spread by Abdi and Ranaldo (2017), are employed to assess liquidity among the ETFs. These two analyses utilize time series from 2015 to 2022. The bid-ask spread metric follows Abdi & Ranaldo's method, a recent approach for computing this liquidity indicator. This is a measure that is adjusted for the autocorrelation of the price series. The logarithm of the mid-price for each ETF is computed as the average of the logarithm of the low and high prices of the respective ETF. Next, the logarithm of the closing price is computed for each ETF. Finally, the rolling mean of the Abdi-Ranaldo spread is calculated over a window of size 5. This means that the bid-ask spread is calculated for each individual data point, and then the mean spread is calculated for every group of 5 data points. The rolling mean is then used as a measure of the average spread over the entire data series and can be used to identify trends or patterns in the spread over time.

Applying time series analysis to both AMIM and illiquidity enables us to juxtapose these measures to investigate potential correlation. This comparison manifests as a rolling correlation between AMIM and illiquidity. In the rolling correlation analysis, a 200-day rolling window is employed. For each time point, the function in R incorporates the 200 most recent observations of both variables and calculates the correlation coefficient between them using the correlation function. This analysis reveals if market efficiency and liquidity correlate.

3.3 Limitations

While the method section provides a robust framework for conducting this study, it is important to acknowledge certain limitations that may affect the interpretation and generalizability of the findings. By acknowledging these limitations, the goal is to provide a balanced assessment of the study's scope and potential constraints.

Firstly, it is essential to recognize the sample size used in this study. The analysis relies on a relatively small sample of eight selected ETFs, which may not fully represent the entire financial market. Consequently, the findings should be interpreted within the context of this limited sample, and caution should be exercised when generalizing the results to other ETFs or financial instruments. Another limitation pertains to the potential similarity of the selected ETFs. Given that the chosen ETFs may share similar characteristics or follow the same sectors, the sample may not adequately capture the diversity and representativeness of the broader market. This factor may introduce a level of similarity among the ETFs, potentially influencing the study's outcomes and restricting their applicability.

Furthermore, the utilization of daily observations in the analysis should be considered. While daily observations provide valuable insights into short-term fluctuations, they may also introduce noise and hinder the capture of long-term trends. Consequently, the study may not comprehensively analyze the long-term effects of international crises on market efficiency and liquidity.

The availability and quality of the data also pose potential limitations. Variations in data availability and reliability among the selected ETFs may impact the accuracy and consistency of the analysis. Data gaps, missing values, or inconsistencies within the dataset may introduce biases or limitations in the findings, which should be carefully considered during the interpretation of the results.

Lastly, it is important to acknowledge that factors beyond the specific crises under investigation may influence market efficiency and liquidity during the study period. These external factors, such as regulatory changes or macroeconomic conditions, may introduce additional complexity and potential confounding effects that should be taken into account when interpreting the study's outcomes. By recognizing these limitations, we aim to enhance the transparency and validity of the study, providing researchers and stakeholders with a comprehensive understanding of the potential constraints associated with the research design and data analysis methodologies employed in this investigation.

4 Data

This chapter discusses the collection and utilization of the study's data. The dataset used for analyzing stock exchange returns encompasses the G7 countries and Norway. The chosen data spans from January 1, 2015 to December 31, 2022. Providing a comprehensive view of the financial market's behavior in the years leading up to the Covid-19 pandemic. The ETFs used in the analysis are downloaded from Yahoo Finance, providing daily observations over the past 8 years. This extensive dataset enables us to conduct further analyses to examine the impact on various financial markets.

4.1 Data collection

ETFs aim to replicate the weightings of specific indexes that they track. ETFs are traded similarly to individual shares or funds. In this study ETFs were chosen due to their cost-effectiveness and widespread availability.

Historical data for the ETFs is readily accessible and freely available through Yahoo Finance. This data exhibits a close alignment with the corresponding indexes under investigation. Each ETF exhibits unique sector weightings specific to each country. The subsequent section provides an overview of the analyzed ETFs, along with comprehensive information regarding sector weightings. The selected ETFs for analysis are as follows:

- EWU tracks the MSCI United Kingdom index, encompassing large- and mid-cap companies listed on the London Stock Exchange (LSE). The fund maintains an equal weight allocation across multiple sectors, including *financial services*, *healthcare*, and *energy,* each accounting for approximately 15% of the portfolio. Notably, the *consumer defensive* sector holds the highest weightage, constituting approximately 20% of the ETFs total assets (Yahoo Finance, 2023g).

- SPY tracks the S&P 500 index, representing the 500 largest publicly traded companies in the United States. Within this fund, the *technology* sector commands a substantial weight of 26%, primarily driven by the significant weighting of prominent international companies like Apple Inc. and Microsoft. Additionally, it is noteworthy that sectors such as *healthcare*, *financial services*, and *consumer cyclical* each carry a weight of slightly above 10% (Yahoo Finance, 2023h).

- EWJ tracks the MSCI Japan index, comprising large- and mid-cap Japanese stocks. EWJ exhibits a notable weight of 23% in the *industrials* sector. Additionally, the fund holds shares in the *technology* and *consumer cyclical* sectors, with respective weights of 16% and 15% (Yahoo Finance, 2023f).

- EWC tracks the MSCI Canada index, encompassing the large- and mid-cap segments of the Canadian market. The fund allocates a significant weight of 35% to the *financial services* sector. Furthermore, the *energy* sector holds a weight of 18% within the fund's portfolio (Yahoo Finance, 2023b).

- EWG tracks the MSCI Germany index, serving as the benchmark for the German market and including large- and mid-cap stocks. The holdings in this fund are evenly distributed among the *consumer cyclical*, *financial services*, *industrials*, and *technology* sectors, with each sector carrying a weight ranging from 14% to 18% (Yahoo Finance, 2023d).

- EWQ tracks the MSCI France index, consisting of large- and mid-cap companies listed on the French stock exchange. The *industrials* and *consumer cyclical* sectors emerge as prominent components in France's fund, with respective weightings of 23% and 21% (Yahoo Finance, 2023c).

- EWI tracks the MSCI Italy index, comprising large- and mid-cap companies listed on the Italian stock exchange. EWI displays significant weightings in the *financial services*, *utilities*, and *consumer cyclical* sectors, with respective weights of 27%, 20%, and 17% (Yahoo Finance, 2023e).

- NORW tracks the MSCI Norway IMI 25/50 index, representing the large- and mid-cap segments of the Norwegian market. In NORW, the *energy* sector carries a substantial weight, accounting for 29% of the portfolio. Additionally, the *financial services* sector holds a weight of 19%, while the *consumer defensive* sector maintains a weight of 15% (Yahoo Finance, 2023a).

4.2 Sample selection

To facilitate analysis and distinguish between time periods, we divide the dataset, which comprises daily observations from 2015 to 2022. This division allows for a clearer interpretation of the analysis and enables us to better understand the dynamics across different periods. We have chosen to first separate the periods based on the events, i.e., Covid-19 and the invasion of Ukraine. We categorize the time periods associated with Covid-19 as *Pre Covid-19* and *During Covid-19*. While the periods associated with Ukraine invasion are referred to as *Between crises* and *During invasion*. There is no period for post invasion as the war is not over by December 31, 2022.

For the period *Pre Covid 19*, the period from January 1, 2015, to March 11, 2020, has been chosen. This was the date when The World Health Organization (WHO) declared COVID-19 as a pandemic (World Health Organization, 2023). In the *During Covid-19* period, the period spans from March 12, 2020, to February 11, 2022 (Regjeringen, 2022). The *Between crises* period spans from February 12, 2022 to February 23, 2022, consisting of only 7 observations. Despite the limited number of observations, the period is included in the analysis to maintain the integrity of the entire dataset covering the period from 2015 to 2022. While acknowledging the smaller sample size, this period is compared in the same manner as others, as excluding it would be imprudent. Note that the *Between crises* period contains fewer observations compared to other periods. The period for *During invasion* is set from February 25, 2022 to December 30, 2022, starting from the day after the innovation occurred (Reuters, 2022b).

Distributing the data into different time periods enhances the ease and clarity of examining the dataset. Each period provides a more accurate representation of the market within that specific period, enabling meaningful comparisons between periods. This approach enables a comprehensive understanding of the impact of Covid-19 and the invasion of Ukraine on market efficiency. The calculation of the variance ratio necessitates dividing the dataset into different periods. These periods enable a focused analysis of the variance ratio. However, for the remaining calculations, a single dataset suffices, allowing for analysis across different periods. The need to present the calculations in different formats arises from the distinct nature of the variance ratio calculation. While the remaining results can be effectively conveyed through graphs, the variance ratio requires a table presentation. Using one dataset would result in a confusing and unclear representation of the results.

5 Empirical Results

In this section, we analyze ETF performance from the beginning of the time series in 2015 through the end of 2022. We delve deeper into the analysis and present key figures from the ETFs, which enhance our understanding of stock market behavior during crises.

5.1 Variance ratio

Lo and MacKinlay's variance ratio for the different periods is calculated using the *vrtest* package in R. The test was conducted for holding periods of 2, 4, 8, and 16 days. Below at Table 2,3 and 5 are the holding period represented by $K=16$. In Table 4, we utilize $K=4$ due to an insufficient number of observations for computing $K=16$, since this period only contains seven observations. The different periods consist of different numbers of observations. After careful consideration, the holding period of 16 days has been determined as the most suitable for inclusion in the study. This longer holding period allows for a reduction in noise and provides a broader perspective to observe trends over an extended period. Furthermore, the p-value is specifically associated with the 16-day holding period. The decision was made not to include the other holding periods in the study to maintain clarity and avoid clutter in the presentation of results. Focusing on the 16-day holding period allows for a concise and meaningful analysis of the data.

If the p-value is less than the predetermined significance level of 5%, we reject the null hypothesis and conclude that there is evidence of serial correlation or deviation from randomness. However, if the p-value is greater than the significance level, we fail to reject the null hypothesis and conclude that there is no statistically significant evidence of serial correlation or deviation from randomness. Since it is a two-sided test, the confidence interval needs to show both the lower and upper bounds of the range.

To provide an interpretation of the test values presented in the tables below, it is important to understand what the test can reveal. A value close to 1 indicates that the prices are randomly distributed and follow a random walk, which is consistent with market efficiency. On the other hand, values significantly higher than 1 suggest that the prices are more predictable than would be expected from a random walk, which could be interpreted as evidence of inefficiency in the market. Conversely, values significantly lower than 1 may suggest that the prices are less predictable than would be expected from a random walk, which could also indicate market inefficiency, or the presence of non-random factors such as transaction costs or institutional constraints.

Table 2: Variance ratio, pre-Covid-19.

	EWU	SPY	EWJ	EWC	EWG	EWQ	EWI	NORW
Lower tail								
K=16	0,152	0,129	0,170	0,576	0,142	0,102	0,180	0,106
Upper tail								
K=16	0,412	0,415	0,300	0,788	0,259	0,261	0,329	0,212
P-Value	*0,606*	*0,490*	*0,244*	*0,384*	*0,348*	*0,448*	*0,608*	*0,206*

1 Jan 2015 – 11 Mar 2020, $n = 1306$

The absence of significant evidence against the RWH, as indicated by the non-significant p-values and the test values, suggests that there is no strong evidence of predictability or autocorrelation in the returns of the ETFs for the *Pre-Covid-19* period. We fail to reject the null hypothesis of no autocorrelation at the corresponding holding periods. This suggests that the returns in the data may follow a random walk process. In conclusion, the provided test results do not directly indicate the efficiency of the market but rather suggest the absence of significant evidence against the RWH.

Table 3: Variance ratio, during Covid-19

	EWU	SPY	EWJ	EWC	EWG	EWQ	EWI	NORW
Lower tail								
K=16	0, 085	0,085	0,204	0,093	0,228	0,149	0,205	0,153
Upper tail								
K=16	0,363	0,404	0,380	0,444	0,515	0,434	0,458	0,375
P-Value	*0,144*	*0,146*	*0,196*	*0,186*	*0,358*	*0,228*	*0,274*	*0,172*

12 Mar 2020 – 11 Feb 2022, $n = 486$

Using a 5% significance level, none of the p-values are statistically significant. Therefore, we cannot reject the null hypothesis that the returns are independently and identically distributed for the *During Covid-19* period.

Table 4: Variance ratio, between crises

	EWU	SPY	EWJ	EWC	EWG	EWQ	EWI	NORW
Lower tail								
K=4	0,653	0,634	0,619	0,632	0,722	0,704	0,679	0,518
Upper tail								
K=4	0,532	0,413	0,398	0,389	0,358	0,286	0,405	0,491
P-Value	*0,872*	*0,974*	*0,898*	*0,916*	*0,730*	*0,878*	*0,988*	*0,652*

12 Feb 2022 – 23 Feb 2022, $n = 7$

Given the limited number of observations in the *Between-Crises* dataset, the Lo & Mackinlay test had to be modified or adapted. The holding period is reduced from 16 to 4 as the dataset only contains seven observations. For this dataset, we use the p-value of a holding period of four days. Based on the p-values, we cannot reject the null hypothesis that the returns of the ETFs follow a random walk with zero drift at a 5% significance level for all holding periods.

Table 5: Variance ratio, during invasion

	EWU	SPY	EWJ	EWC	EWG	EWQ	EWI	NORW
Lower tail								
K=16	1,013	0,652	1,290	0,962	0,864	0,726	0,977	1,791
Upper tail								
K=16	1,039	0,656	1,286	0,978	0,908	0,781	1,027	0,789
P-Value	*0,826*	*0,494*	*0,964*	*0,764*	*0,766*	*0,662*	*0,912*	*0,854*

24 Feb 2022 – 31 Des 2022, $n = 215$

A high p-value, exceeding 0.05, implies insufficient evidence to refute the null hypothesis, suggesting the potential for efficient pricing in the data. The same applies for the *During invasion* period, as in the periods above we cannot reject the null hypothesis at a 5% significance level.

In all periods examined, the null hypothesis cannot be rejected at a 5% significance level. Rejection of the null hypothesis would imply the absence of independent and identically distributed returns across the periods. The statistical test yields various p-values, with the lowest values observed in the *During Covid-19* period, although none of them fall below 5%. A lower p-value indicates stronger evidence against the null hypothesis and suggests that the data in the *During Covid-19* period deviates more significantly from a random walk. This could imply the presence of predictability or autocorrelation in the returns of the ETFs. It could suggest that market participants were able to exploit patterns or information to generate abnormal returns, potentially indicating a less efficient market.

The theory of market efficiency posits that share prices reflect all relevant information pertaining to a company's shares. The utilization of Lo & MacKinlay's variance ratio test allows for the examination of predictability based on historical data and the identification of autocorrelation in asset returns. However, it is important to note that this test alone does not provide a conclusive determination of market efficiency.

5.2 Bid-ask spread

The bid-ask spread by Abdi and Ranaldo (2017) was computed using R, with the application of logarithmic prices..There are several different methods to calculate bid-ask spread. Abdi and Ranaldo's method is a modified version of the Corwin-Schultz (2012) bid-ask spread, designed to address some of the limitations of the original measure. The Abdi-Ranaldo spread has been shown to be a good measure of market liquidity, particularly in high-frequency trading environments, where the bid-ask spread can fluctuate rapidly. Overall, the Abdi-Ranaldo spread is considered a more robust and reliable measure of market liquidity than the original Corwin-Schultz spread, particularly in high-frequency trading environments (Abdi & Ranaldo, 2017; Corwin & Schultz, 2012).

Instead of presenting results for specific periods as previously done, the development from 2015 to 2022 is now illustrated, enabling a continuous view of bid-ask spread trends.

Figure 2. Abdi and Ranaldo's bid-ask spread in United Kingdom

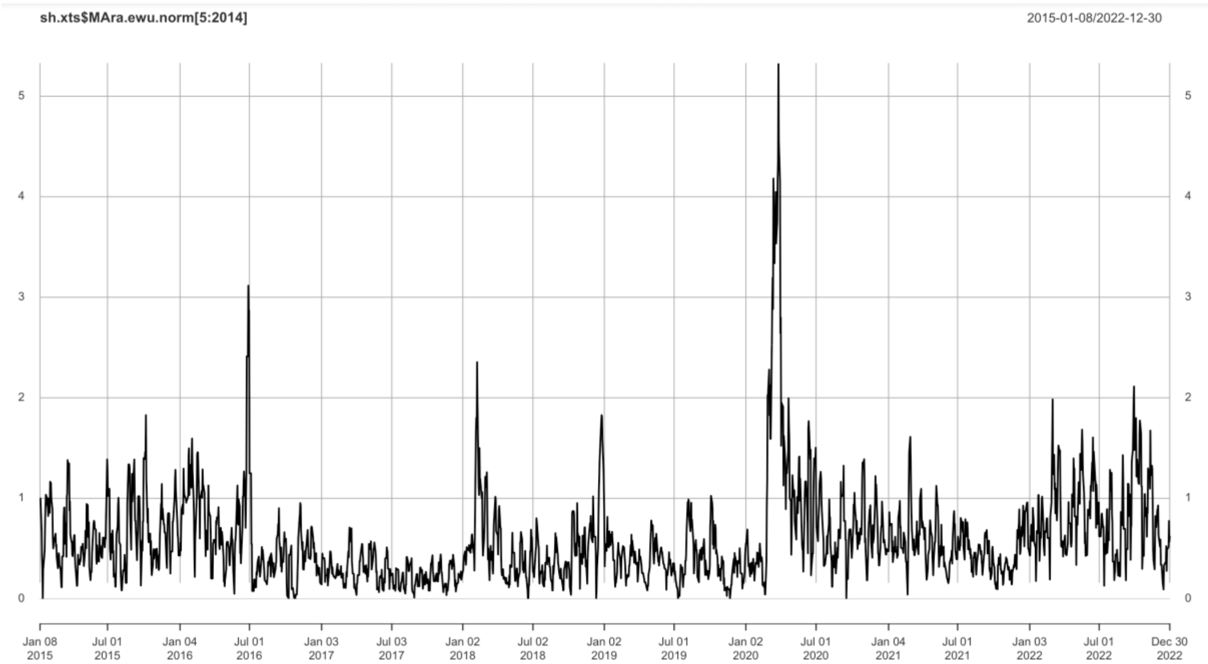


Figure 3. Abdi and Ranaldo's bid-ask spread in United States

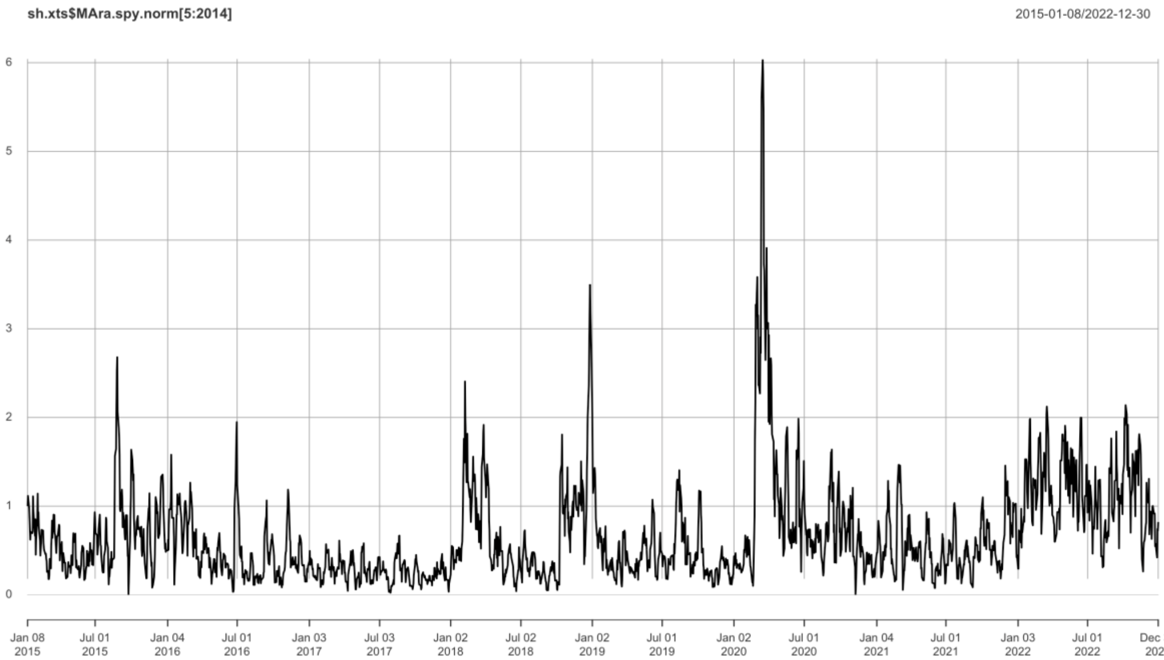


Figure 4. Abdi and Ranaldo's bid-ask spread in Japan

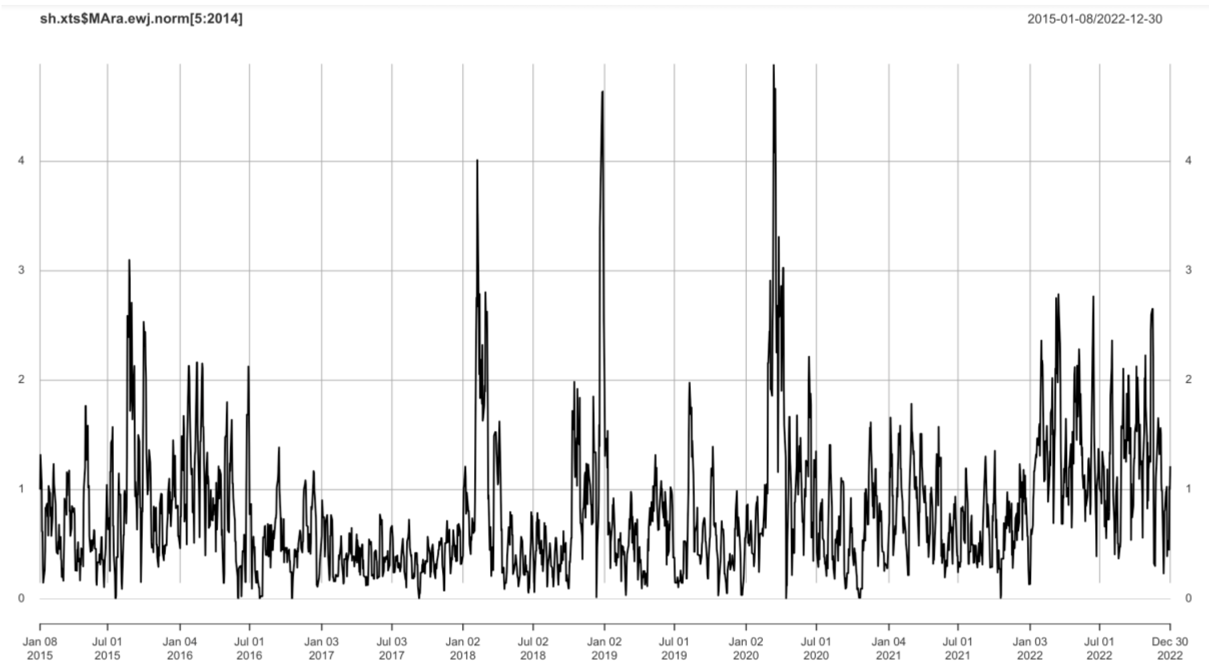


Figure 5. Abdi and Ranaldo's bid-ask spread in Canada

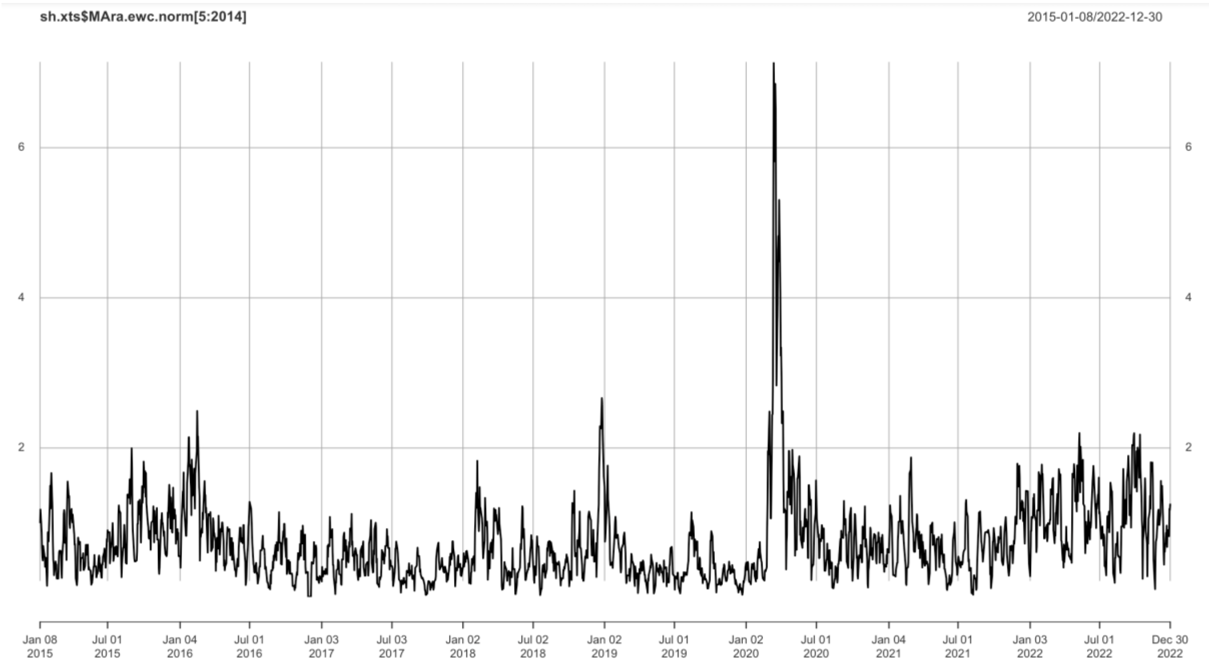


Figure 6. Abdi and Ranaldo's bid-ask spread in Germany

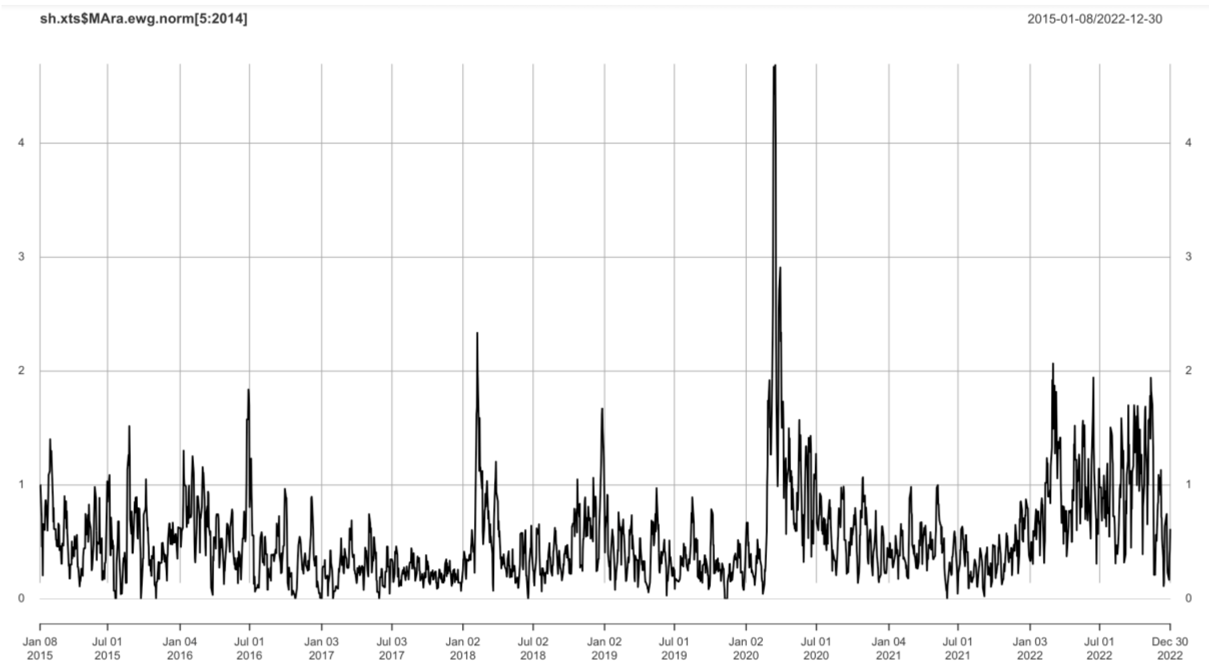


Figure 7. Abdi and Ranaldo's bid-ask spread in France

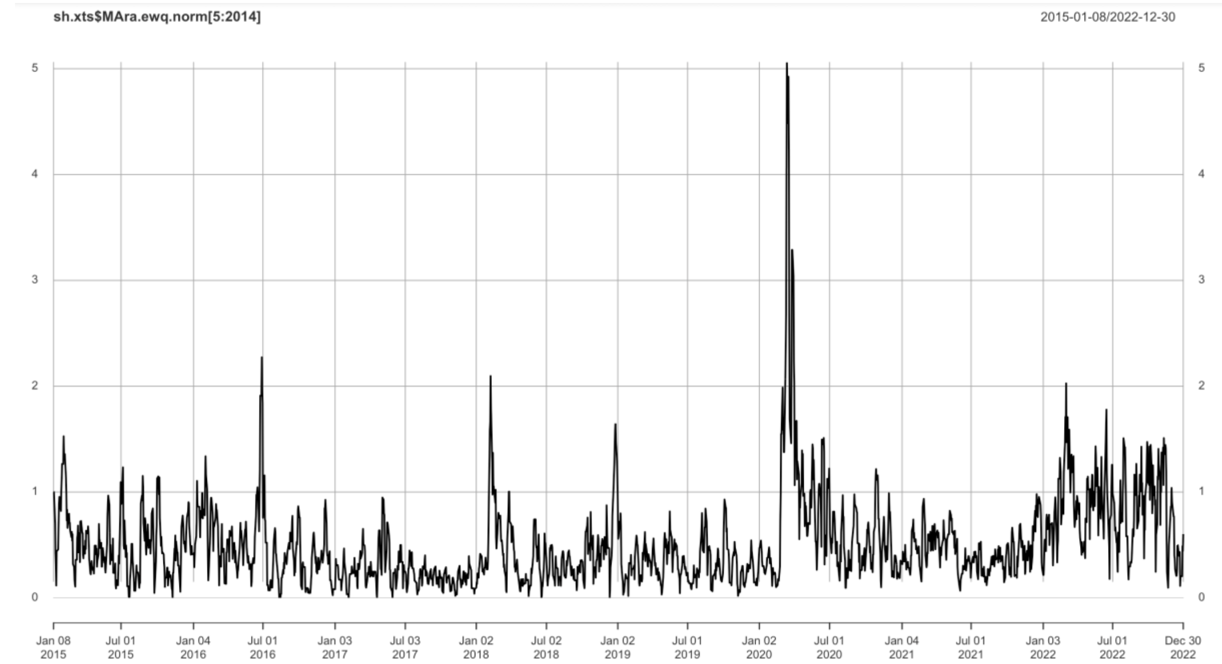


Figure 8. Abdi and Ranaldo's bid-ask spread in Italy

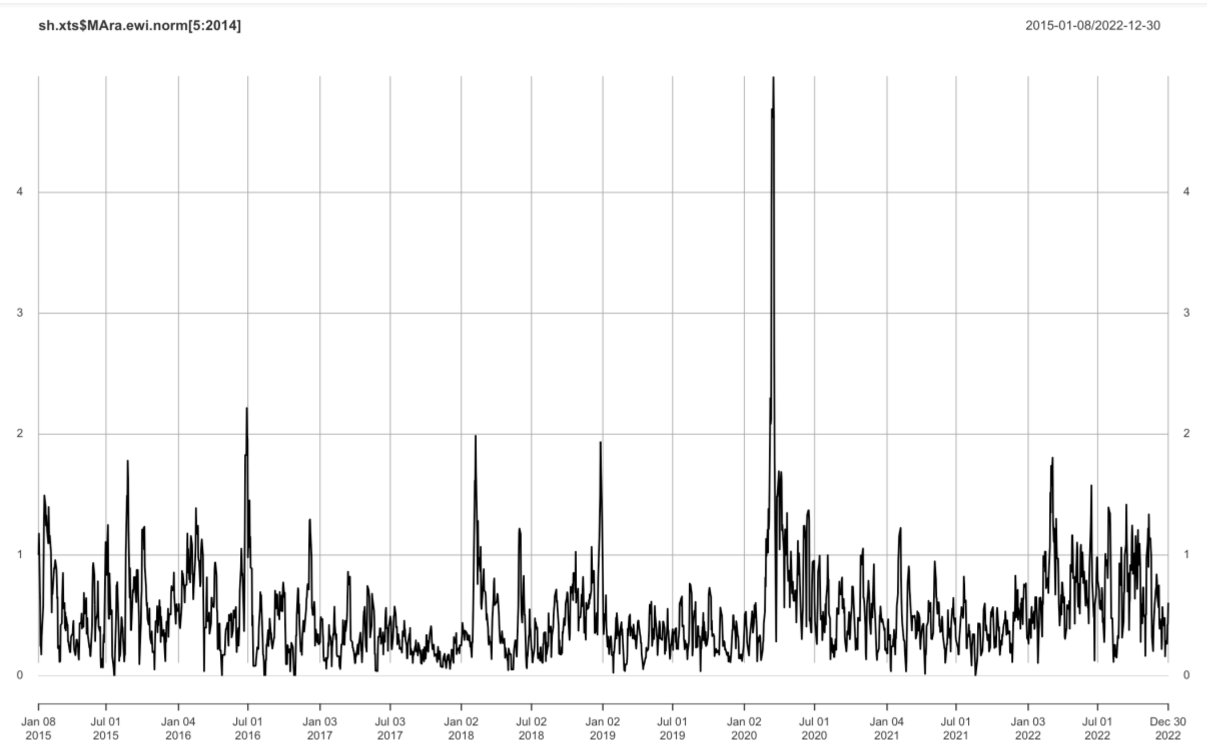
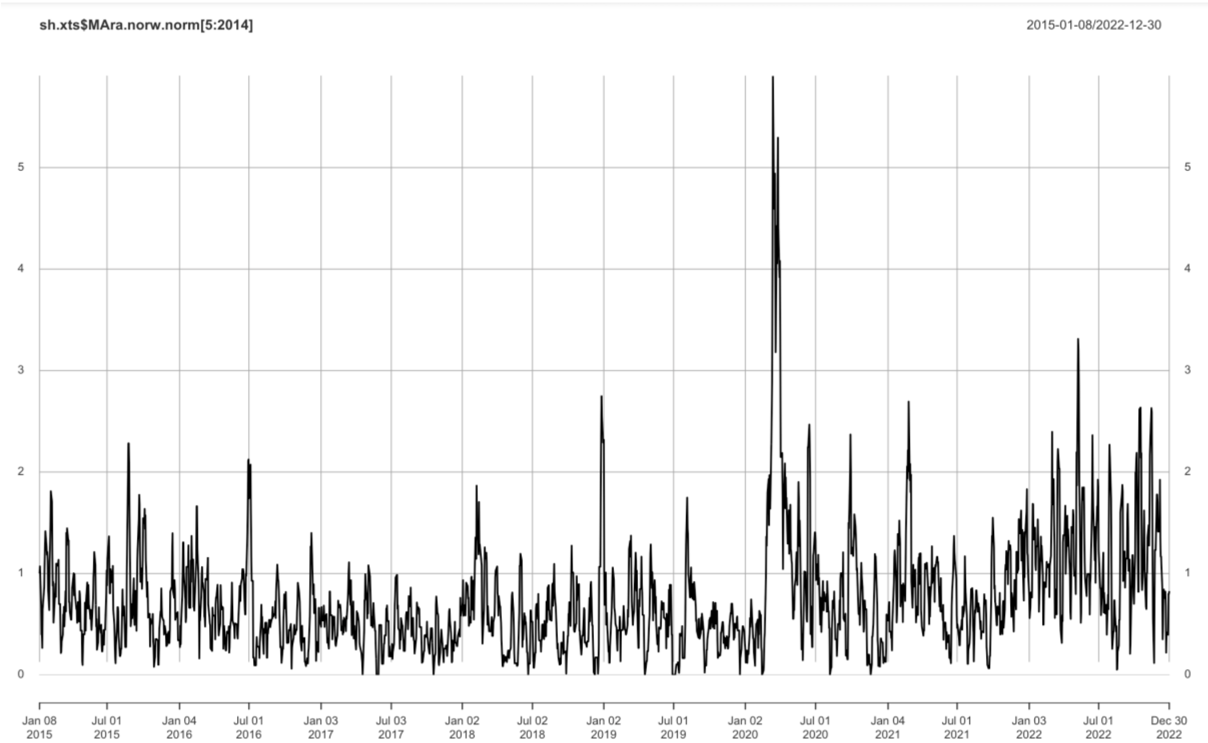


Figure 9. Abdi and Ranaldo's bid-ask spread in Norway



Figures 10 through 17 delineate the bid-ask spread across various ETFs. The analysis reveals that each country experiences a surge in the bid-ask spread during the arrival of the Covid-19 pandemic, specifically around March 2020. An elevated bid-ask spread signifies higher transaction costs, thereby indicating a less liquid market. During the period of Ukraine's invasion, the bid-ask spread also experiences a rise, albeit less dramatic than the escalation observed during Covid-19. This implies that the financial markets have not experienced the same level of impact from the invasion as from Covid-19.

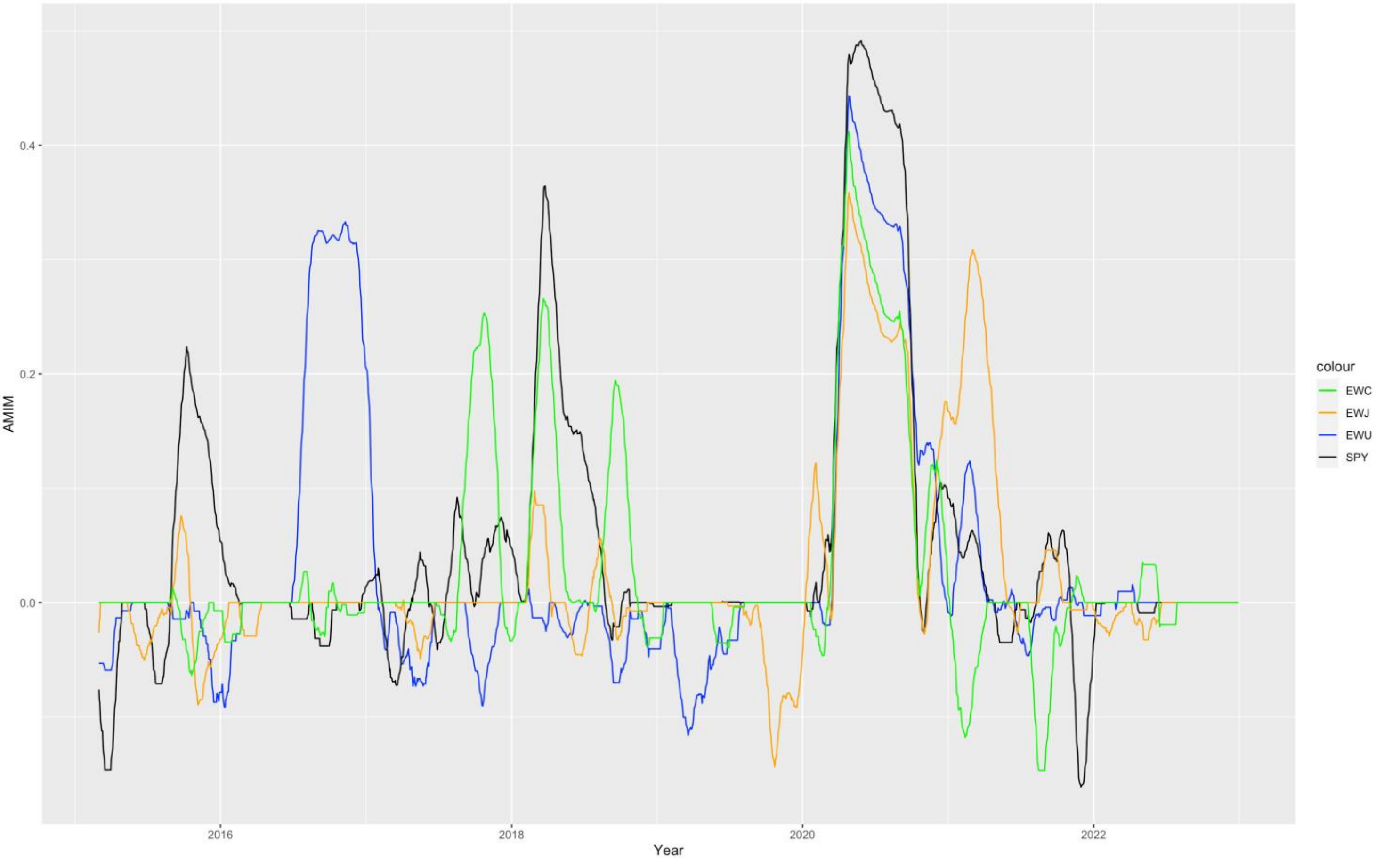
During the timeframe of 2015 to 2020, the bid-ask spread records a comparatively lower magnitude relative to the subsequent periods in the time series. Although this timeframe experiences sporadic spikes in the bid-ask spread, it exhibits a generally more stable pattern in comparison to the period stretching from 2020 to 2022.

From the observed analysis outcomes, it can be concluded that financial markets represented in the selected ETFs exhibit reduced liquidity amid periods of unrest and uncertainty, exemplified by the time around Covid-19's onset. It is also evidenced that geopolitical events, like Ukraine's invasion, lead to diminished liquidity measures. Although various other factors undoubtedly influence the calculation of liquidity over time, geopolitical events or financial crises evidently wield a substantial impact on an asset's liquidity.

5.3 Adjusted Market Inefficiency Magnitude

In this study, the metric unit established by Leirvik and Tran (2019), known as AMIM, serves as an additional determinant of market efficiency. Custom functions were implemented in R to calculate AMIM values for the datasets used in this study. These function's development aligns with the methodology suggested by Tran and Leirvik, securing alignment with their AMIM computation method. The succeeding pair of graphs represent calculations for all eight ETFs, demonstrating the progression of this measurement over the stipulated period, as portrayed in Figures 10 and 11.

Figure 10. AMIM for United Kingdom, United States, Japan and Canada



The progress of AMIN for EWU, SPY, EWJ and EWC in the period 2015-2022.

Figure 10 delineates the adjusted market efficiency for the ETFs, namely, EWU, SPY, EWJ, and EWC. Concurrent with the onset of Covid-19, early in 2020, there is a noticeable peak for this measurement across all ETFs, suggesting a period of market inefficiency. All four ETFs echo a similar pattern, with SPY exhibiting the most substantial response. Post-March 2020, there is a discernible decrease in this measurement, signifying a decline in market inefficiency. Thus, it can be concluded that the Covid-19 pandemic acts as a primary determinant of market efficiency during this period.

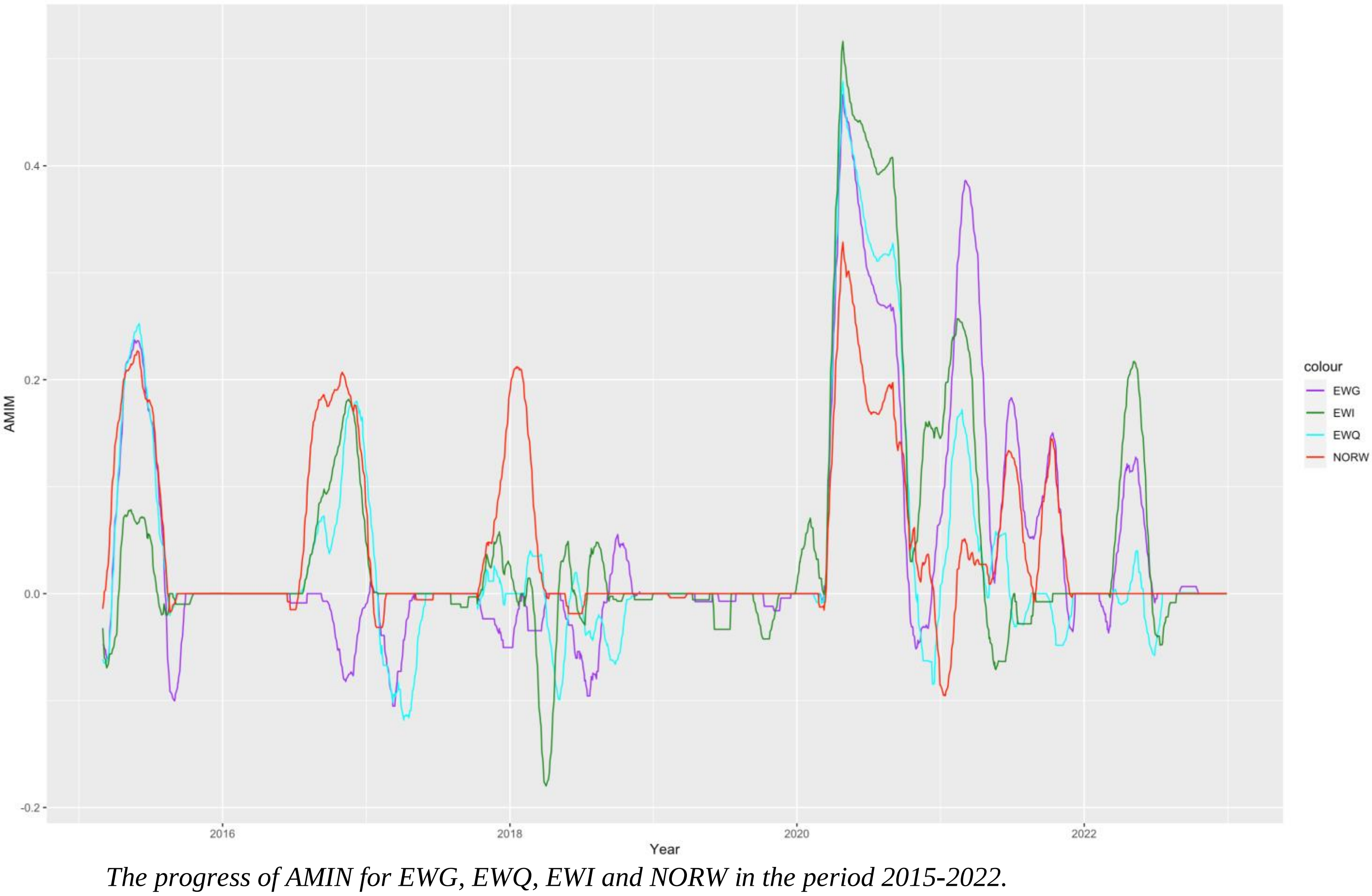
Prior to Covid-19, we observed some fluctuations in AMIM, with the ETFs demonstrating significant differences in their reactions. The underlying reasons for these discrepancies are uncertain and may be attributed to national events. However, the precise impact of these events on the market cannot be determined conclusively. These events do not appear to have affected other international financial markets.

In early 2018, both the USA and Canada ETFs demonstrate an upward trend, suggesting that an event in America may have influenced market efficiency in both countries. The US market received a boost in late 2017 and early 2018 when Donald Trump signed a tax cut. This cut, which reduced the corporate tax rate, increased corporate profits, thereby boosting stock prices. The increased profits also led to many companies buying back their own shares, which further inflated stock prices. Consequently, the market had its best start in 31 years and remained bullish throughout most of 2018. However, the market took a downturn due to Trump's trade war with China and the economic growth slowdown, leading to a more pessimistic market (CNBC, 2018; PBS, 2018). In contrast, the ETFs from the United Kingdom and Japan remain low during this period.

In the period toward the end of 2016, the United Kingdom ETF exhibits an AMIM measure slightly above 0.3, while other countries in Figure 10 do not show a similar response. However, Figure 11 reveals a rise in AMIM for European countries like Italy, France, and Norway, suggesting a potential event in Europe causing this reaction. In 2016, Brexit emerged as a significant focal point when a referendum in the United Kingdom indicated the majority of the population's desire to exit the European Union (UK Parliament, 2021). The influence of Brexit on other opponents of the European Union may contribute to the creation of uncertainty among European countries (E24, 2016). This political unrest can serve as a potential explanatory factor for the presence of uncertainty in the financial market, leading to the observation of AMIM scoring as an inefficient market during this period.

Furthermore, Russia's invasion of Ukraine has a minimal effect on AMIM and market efficiency, as the measure stays close to zero in 2022. Based on the analysis, it can be confidently stated that the Covid-19 pandemic has a more pronounced impact on market efficiency and AMIM in comparison to the invasion of Ukraine. This observation likely results from the pandemic's global scope, impacting the entire world extensively. While Russia's invasion of Ukraine also affects many, it is reasonable to assume that Europe experiences a greater impact than America and other continents, given the conflict's location in Europe. With the United States, Canada, and Japan included in Figure 10, their geographical distance from the war implies why they may not be significantly affected.

Figure 11. AMIM for Germany, France, Italy and Norway



The progress of AMIN for EWG, EWQ, EWI and NORW in the period 2015-2022.

In Figure 11, an increase in AMIM is observed when Covid-19 hit, which indicates that the market becomes more inefficient in this period. Germany, Italy, and France have an AMIM peak of around 0.5, while Norway's peak is just over 0.3 during the same period. The AMIM for these four countries declines during the pandemic and reaches zero at the turn of the year 2021 and 2022. At the beginning of 2022, a slight increase in AMIM is observed in Italy, Germany, and France. Italy shows the most significant reaction with an AMIM of around 0.2, while Germany has an AMIM of around 0.1, and France has a small rise. Norway's AMIM target remains at zero throughout 2022, indicating that Russia's invasion of Ukraine plays little role in market efficiency in the target of AMIM, while Covid-19 has a greater impact.

Looking at the years before 2020 and Covid-19, three clear increases in AMIM are observed over this period. From the start in 2015, Germany, France, and Norway show a similar increase and reach an AMIM of approximately 0.25, while Italy's increase is not as noticeable. According to Reuters (2020), daily share trading approximately doubles between 2014 and 2019. However, a high trading volume does not necessarily indicate market efficiency. It may be a sign of better liquidity and active market participants, which are positive indicators for market efficiency (Reuters, 2020).

Additionally, towards the end of 2016, France, Italy, and Norway exhibit an increase in AMIM, with each country having an AMIM value of 0.2. During this period, Germany reacts differently and gets an AMIM of about -0.1. As previously noted, this analysis encompasses the period during which Brexit was under discussion in the United Kingdom and potentially exerted influence on other European Union members.

Upon examination and comparison of both graphs, it is evident that all ETFs display high AMIM scores during the Covid-19 pandemic. High AMIM values indicate low market efficiency, implying that efficiency is low during the pandemic. The ETFs reactions during the invasion of Ukraine are less evident due to significant variation. However, it is apparent that efficiency in European countries is more affected than in countries outside Europe.

5.4 Illiquidity

According to Amihud's (2002) theory, his illiquidity measure undergoes calculation using Excel. The computation of Amihud's measure, along with the subsequent analysis, employs standard practices rooted in liquidity theory.

In the upcoming pages, graphs display the progression of illiquidity between 2015 and 2022. Note that the term illiquidity is used to indicate low liquidity. Therefore, a high value in the measure reflects a lower level of liquidity.

Figure 12. Amihud illiquidity in United Kingdom

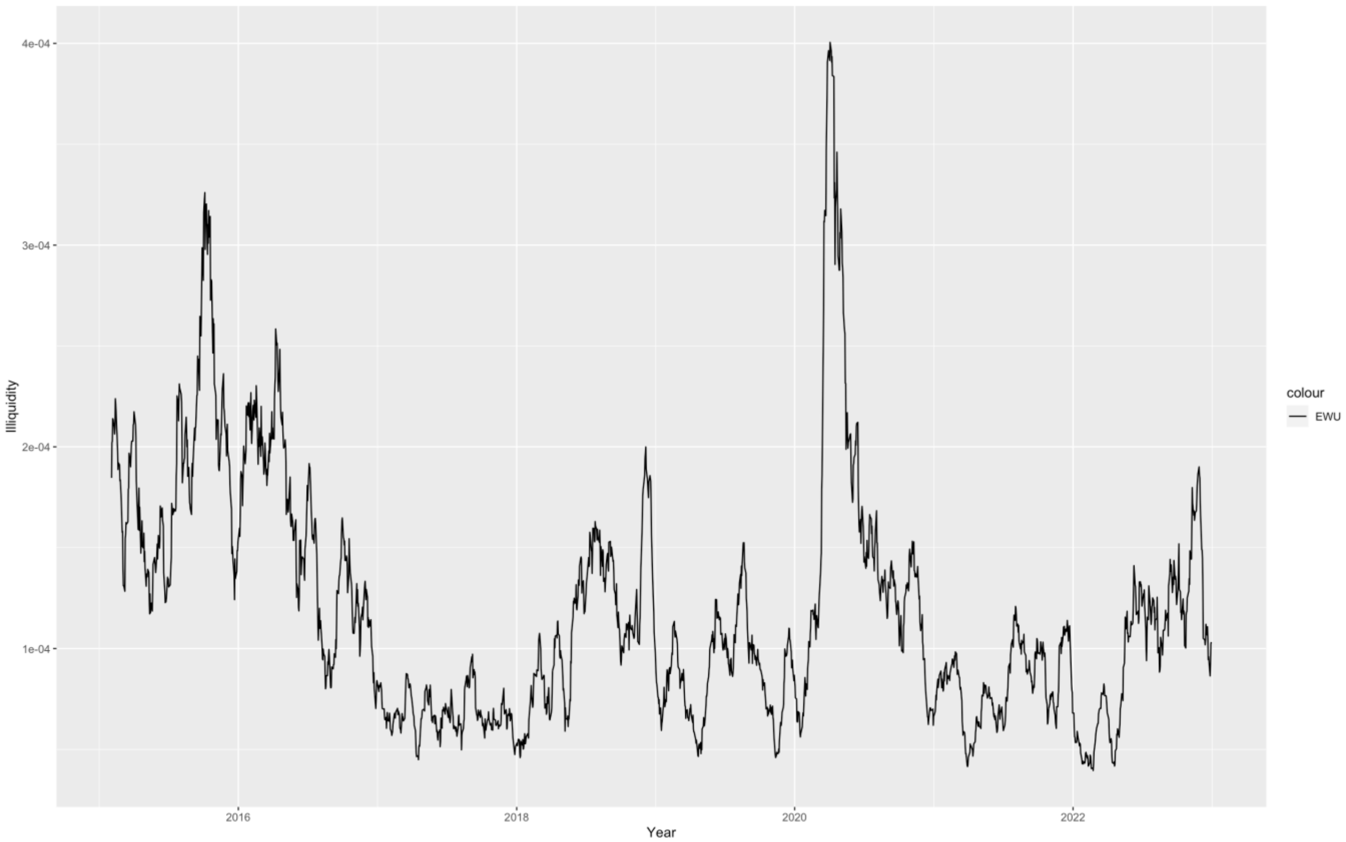


Figure 13. Amihud illiquidity in United States

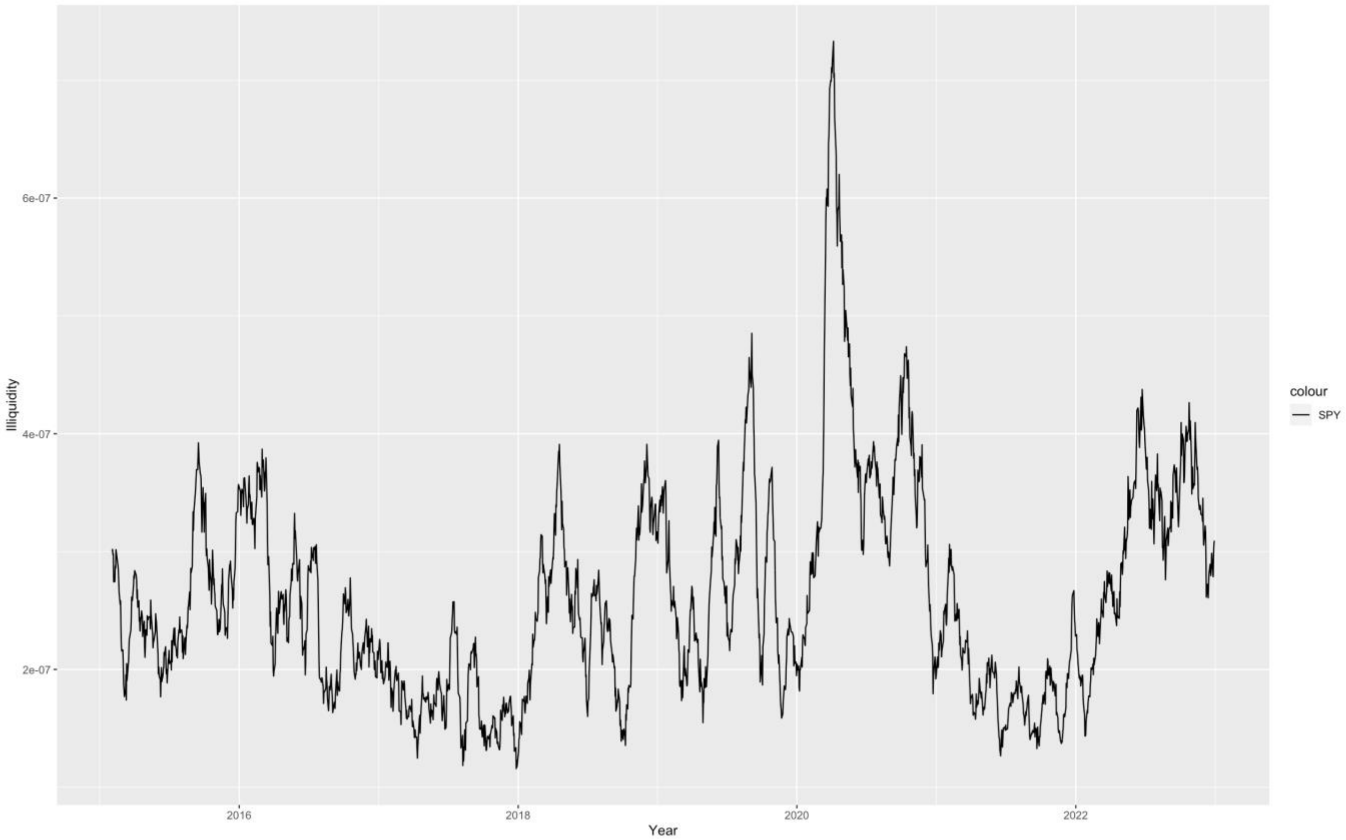


Figure 14. Amihud illiquidity in Japan

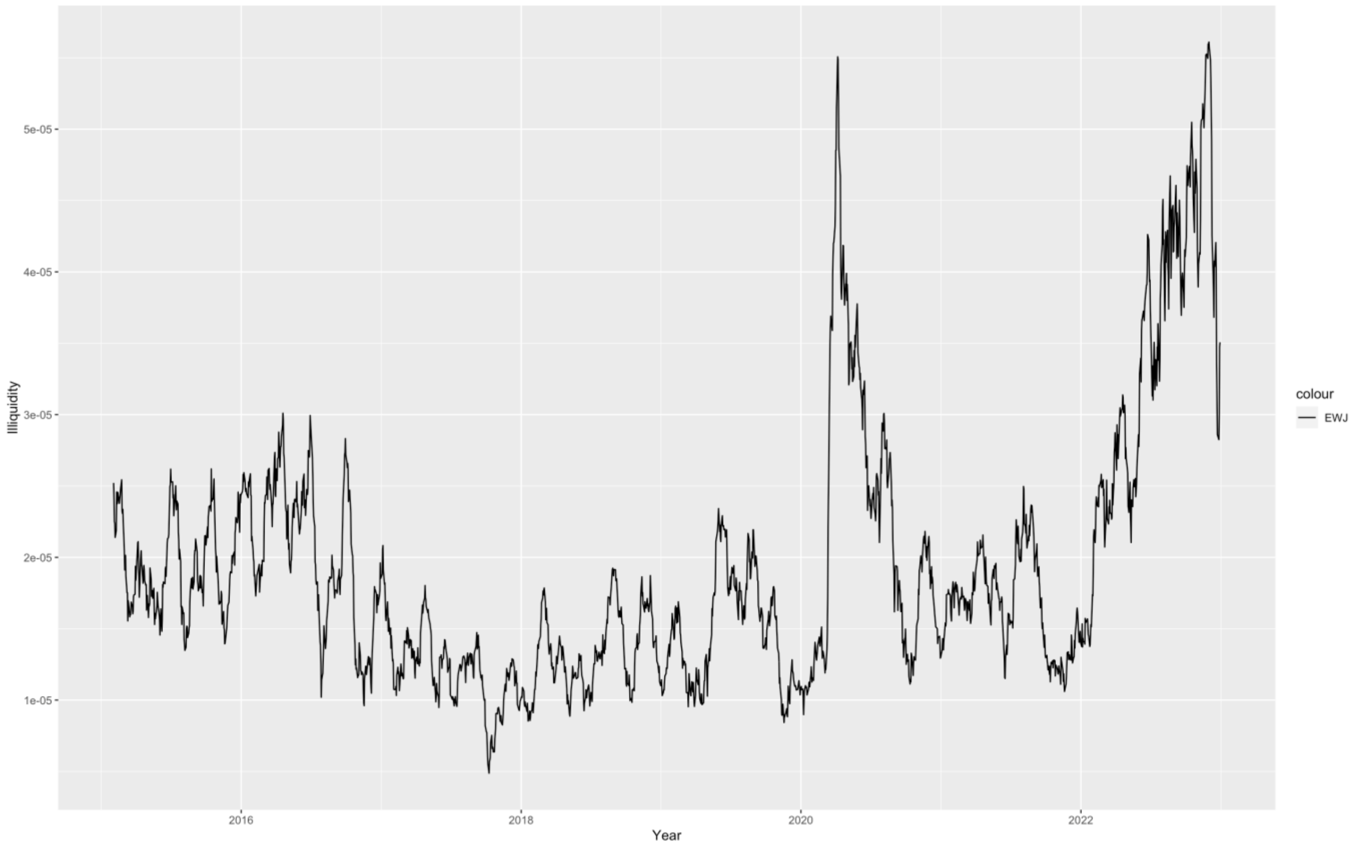


Figure 15. Amihud illiquidity in Canada

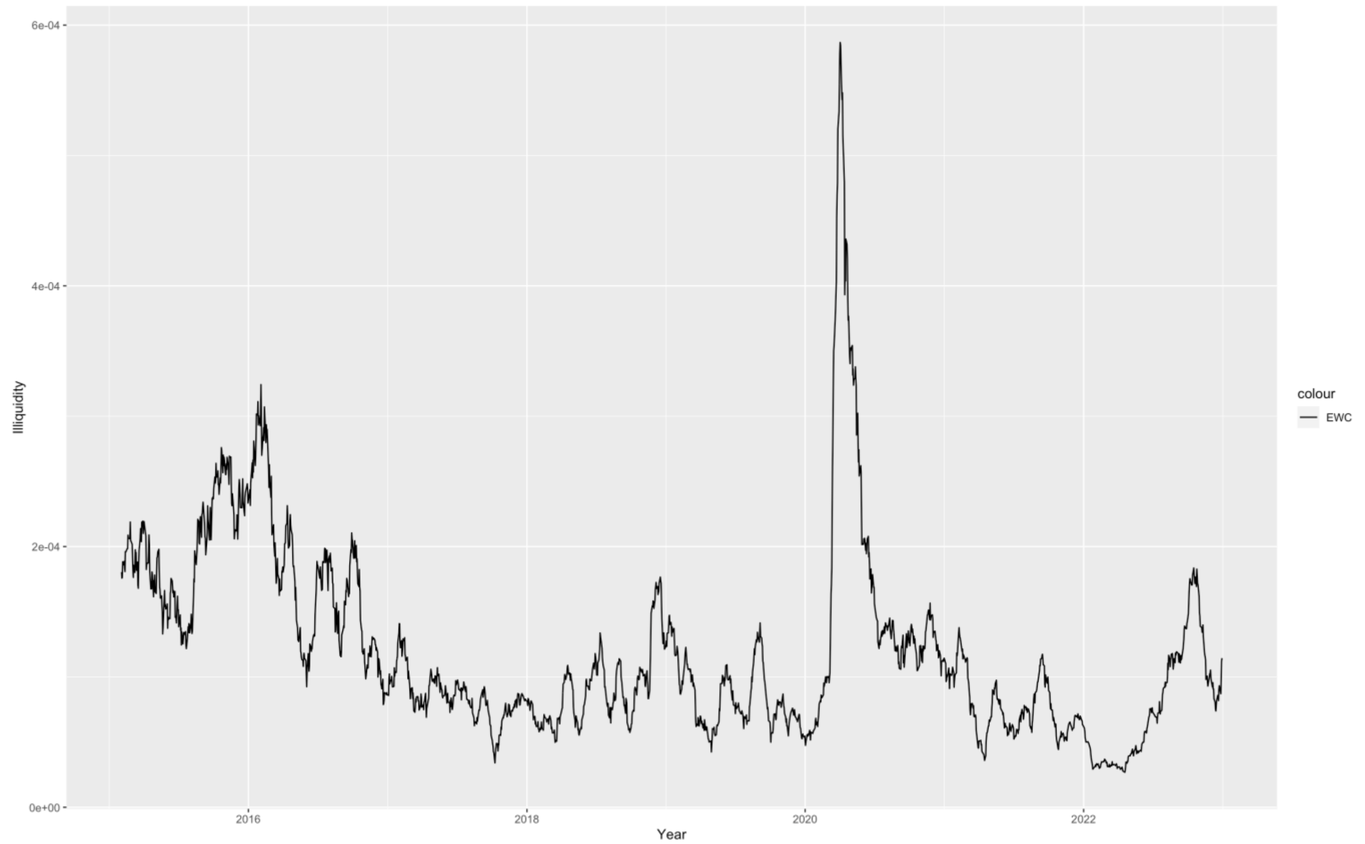


Figure 16. Amihud illiquidity in Germany

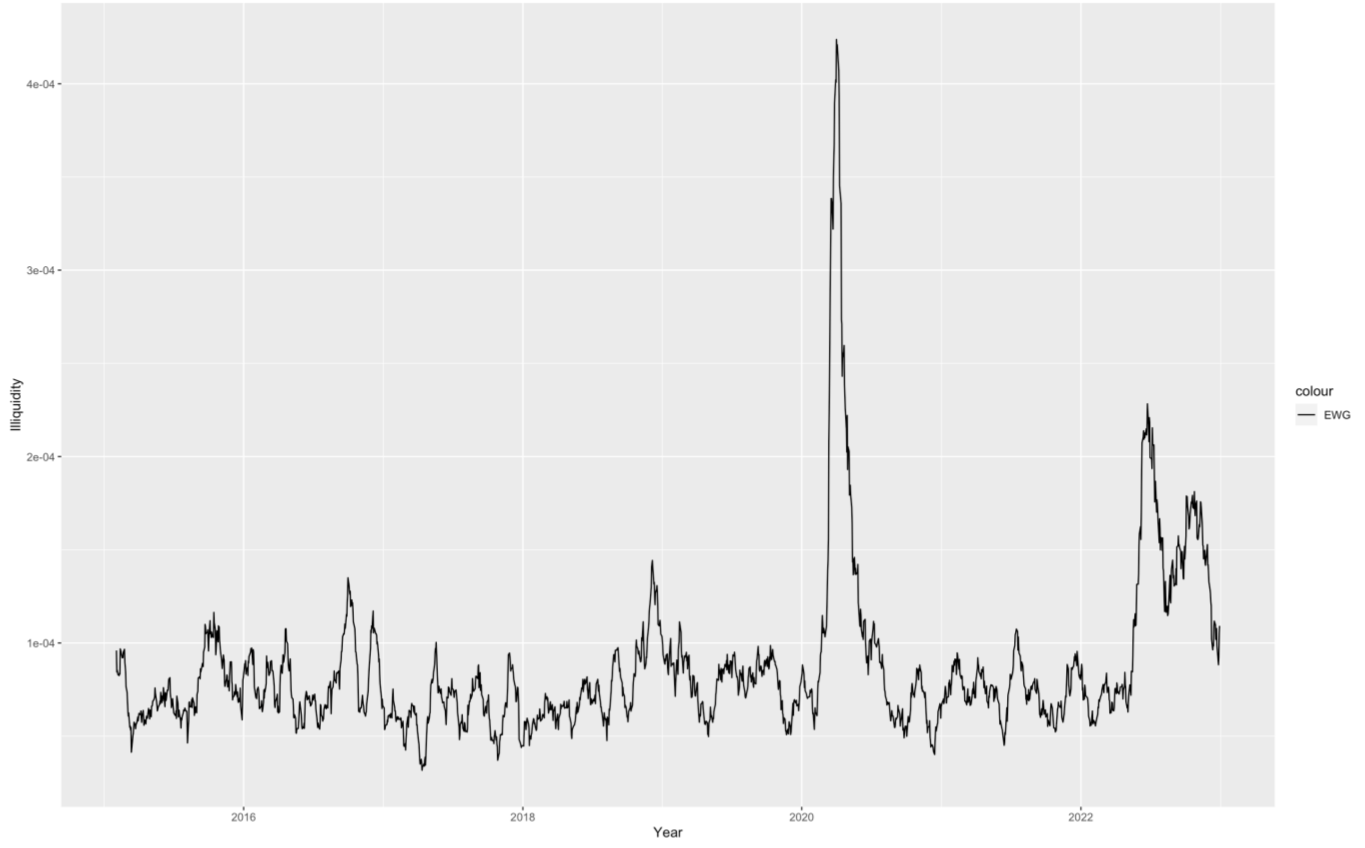


Figure 17. Amihud illiquidity in France

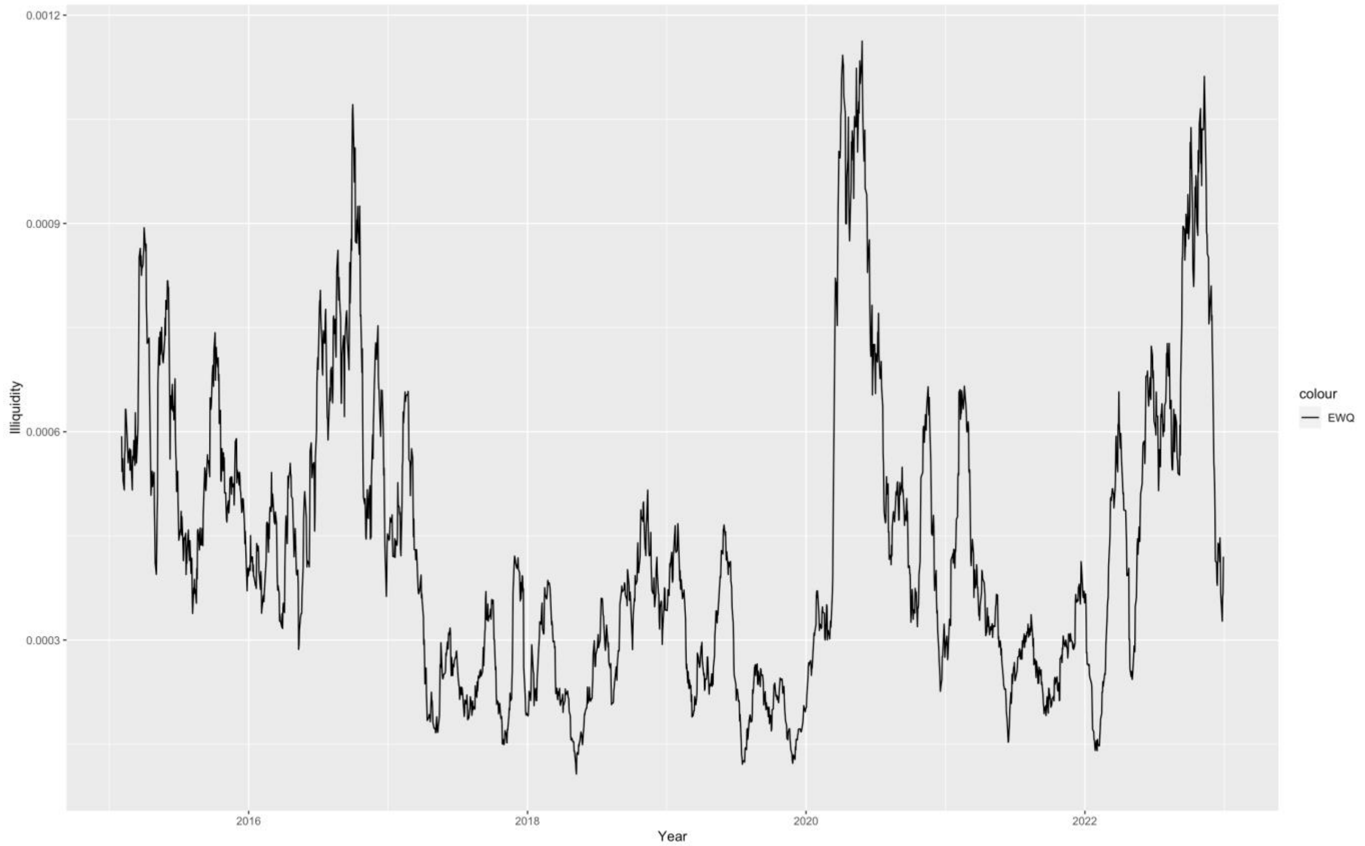


Figure 18. Amihud illiquidity in Italy

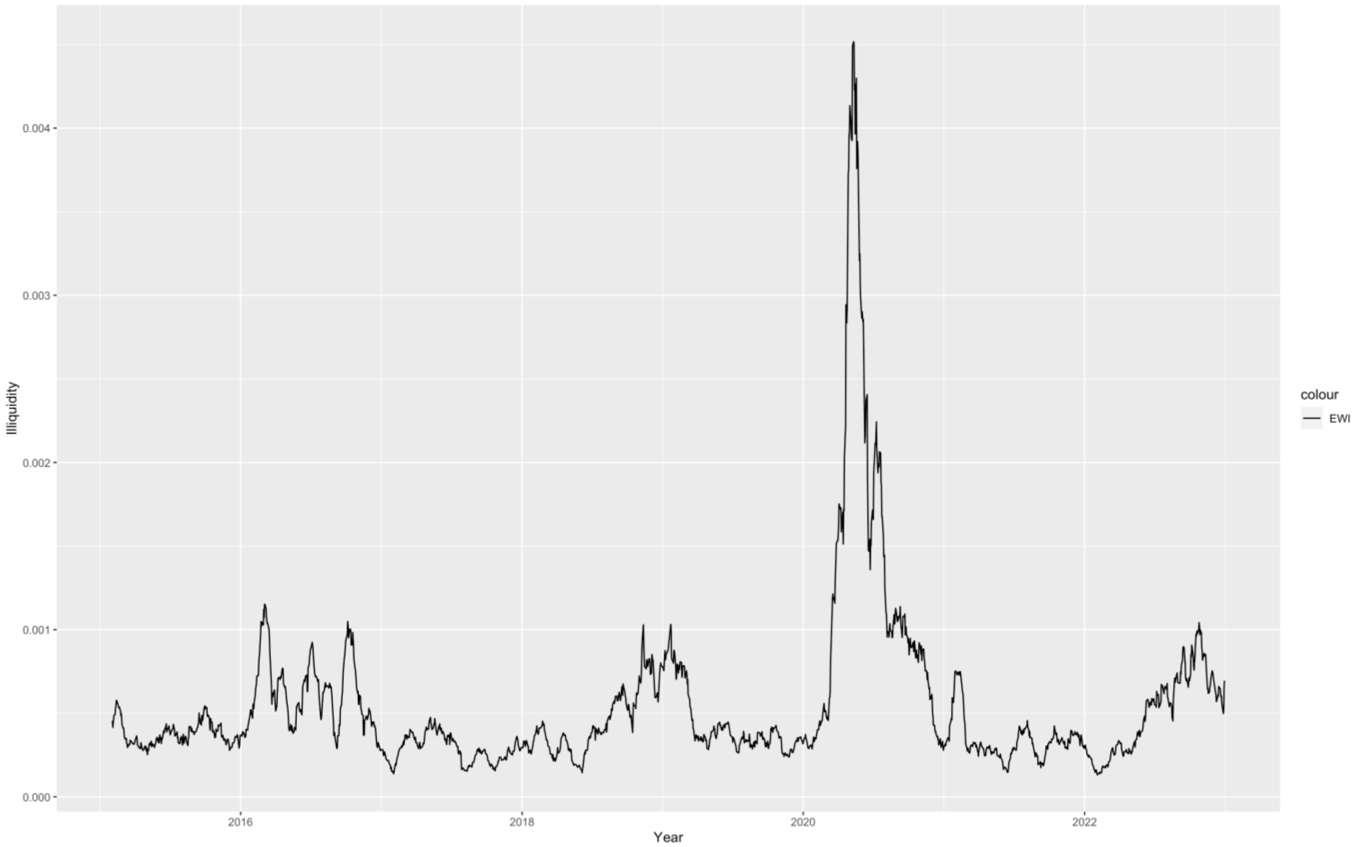
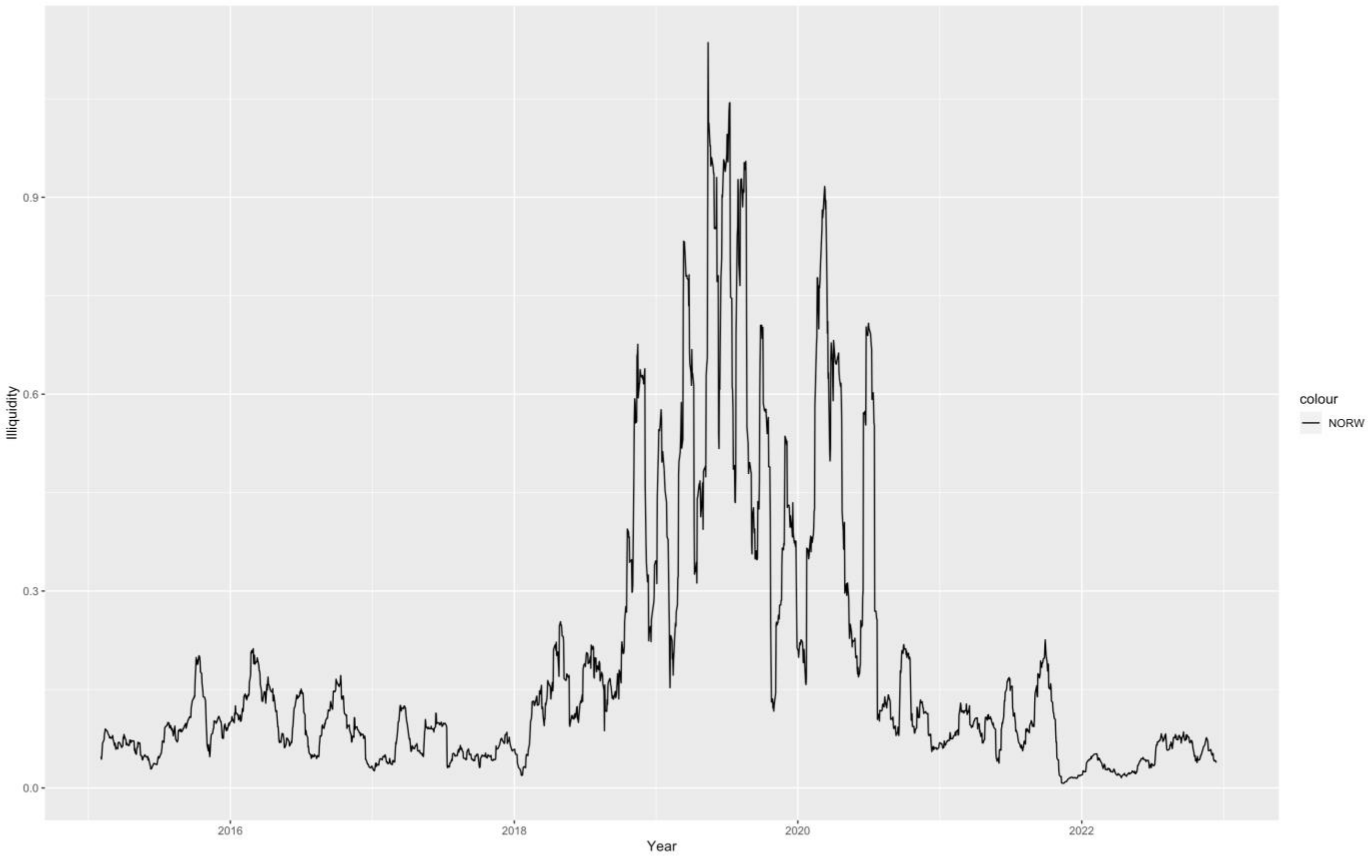


Figure 19. Amihud illiquidity in Norway



The analysis of Amihud's (2002) illiquidity measure provides insights into the costs associated with trading a stock, considering its liquidity characteristics. Higher measures of illiquidity indicate higher trading costs and a less liquid stock.

The eight graphs presented above illustrate the development of illiquidity over our chosen period. In March 2020, when Covid-19 hit, the measure of illiquidity was at its highest for all ETFs except NORW. Before the pandemic, there was significant variation between the countries, with some experiencing high levels of noise and others displaying low and stable illiquidity, like Germany and Italy. Norway experienced considerable fluctuations in illiquidity from 2019 to 2021, with some of these changes occurring before the pandemic. In the first quarter of 2022, there was a noticeable increase in illiquidity across all G7 countries, except for Norway. Since NORW is the only ETF with a significant weighting in the energy sector (Yahoo Finance, 2023a), it is reasonable to claim that this factor contributes to NORW not scoring low on liquidity, compared to other countries in early 2022. Russia had a decline in gas exports of 45.5% in 2022 compared to 2021 (E24, 2023). This export applies to countries that were not the former Soviet Union. This export decline could potentially explain

Norway's absence of liquidity decrease in 2022, as opposed to the experiences of other nations.

In their study, Næs, Skjeltorp, and Ødegaard (2011) investigate liquidity during recession periods, which represent economic downturns or contractions. Analyzing a dataset from 1947 to 2008, the study demonstrates a substantial increase in illiquidity levels preceding recessions, indicating a decrease in financial market liquidity. This finding supports the notion that liquidity varies over time, with economic downturns playing a significant role in this variation (Næs et al., 2011). Similar to this study, we observe an increase in illiquidity in the period before Covid-19, which can be interpreted as a recessionary period. This indicates that the financial markets in this study experience a significant decline in liquidity leading up to crises.

The calculations show that all ETFs experienced low liquidity at the outbreak of Covid-19, followed by an increase during the pandemic and a subsequent decrease in liquidity at the start of the invasion of Ukraine. When a stock becomes less liquid, it is traded less frequently, which can result in unfavorable prices for buyers or sellers due to sales pressure or a lack of interest.

5.5 AMIM and illiquidity

This chapter compares AMIM and illiquidity as units of measurement. The figures below display a total of eight graphs, with AMIM in blue and Illiquidity in red. If they correlate, they will react similarly. The graphs in this study are created using R and are based on previous graphical representations related to the AMIM and illiquidity. Figure 24 shows how AMIM and illiquidity correlate in each country.

To enable a meaningful comparison between illiquidity and AMIM, the illiquidity value was systematically multiplied by 10 until reaching a level similar to that of AMIM. It is important to point out that this change does not change the outcome of the analysis. This adjustment was necessary to facilitate a more accurate and appropriate comparison of the two values, considering that the initial value for illiquidity was considerably small.

Figure 20: AMIM and Illiquidity in United Kingdom and United States.

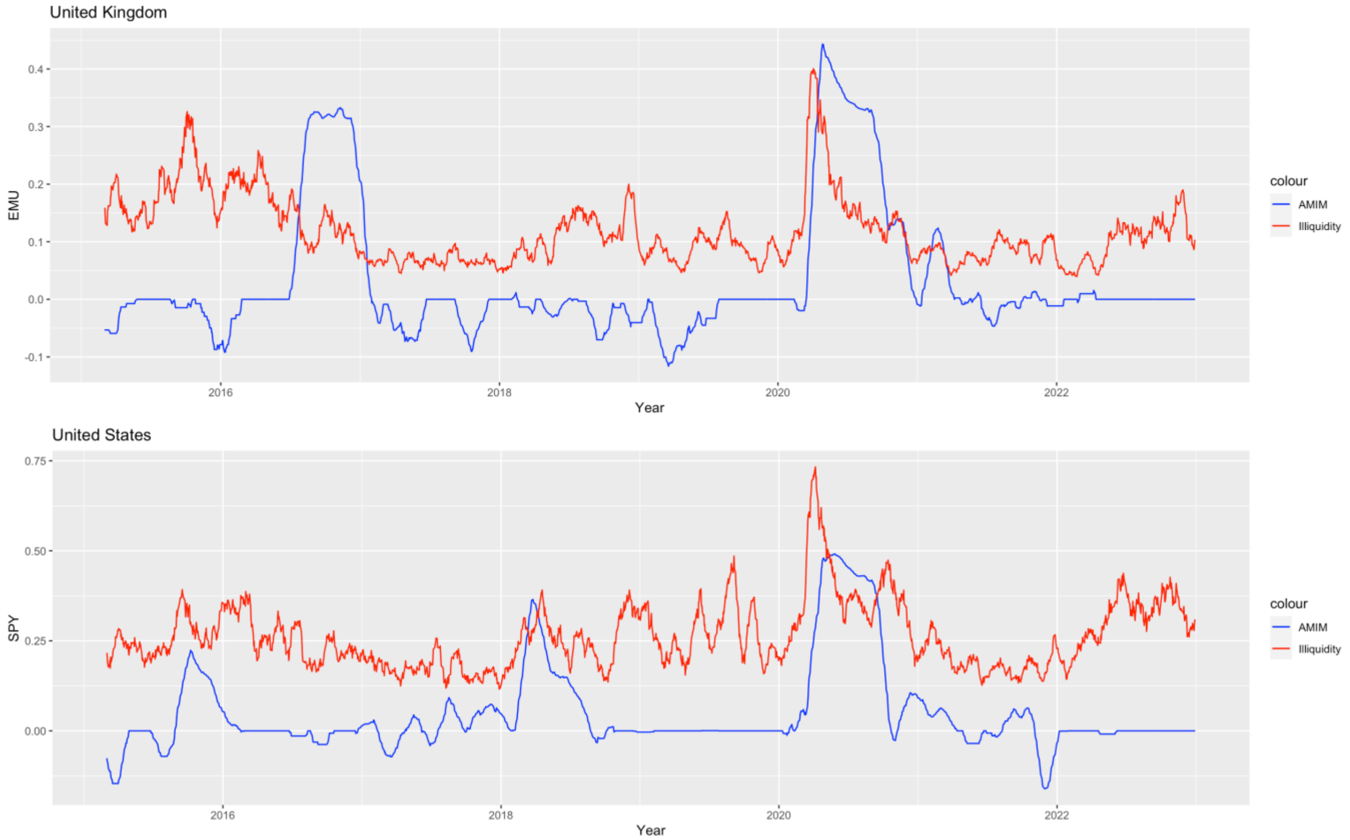


Figure 21: AMIM and Illiquidity in Japan and Canada.

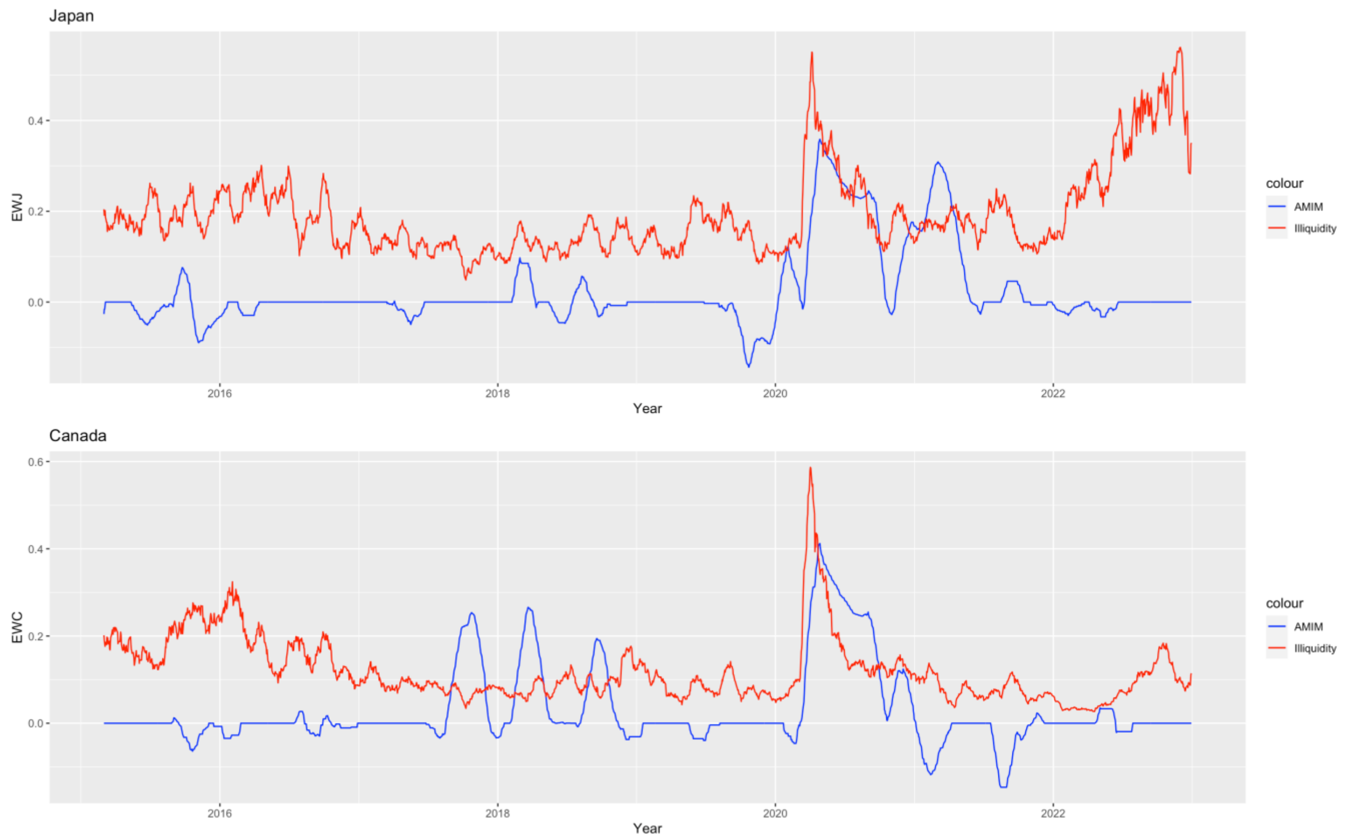


Figure 22: AMIM and Illiquidity in Germany and France

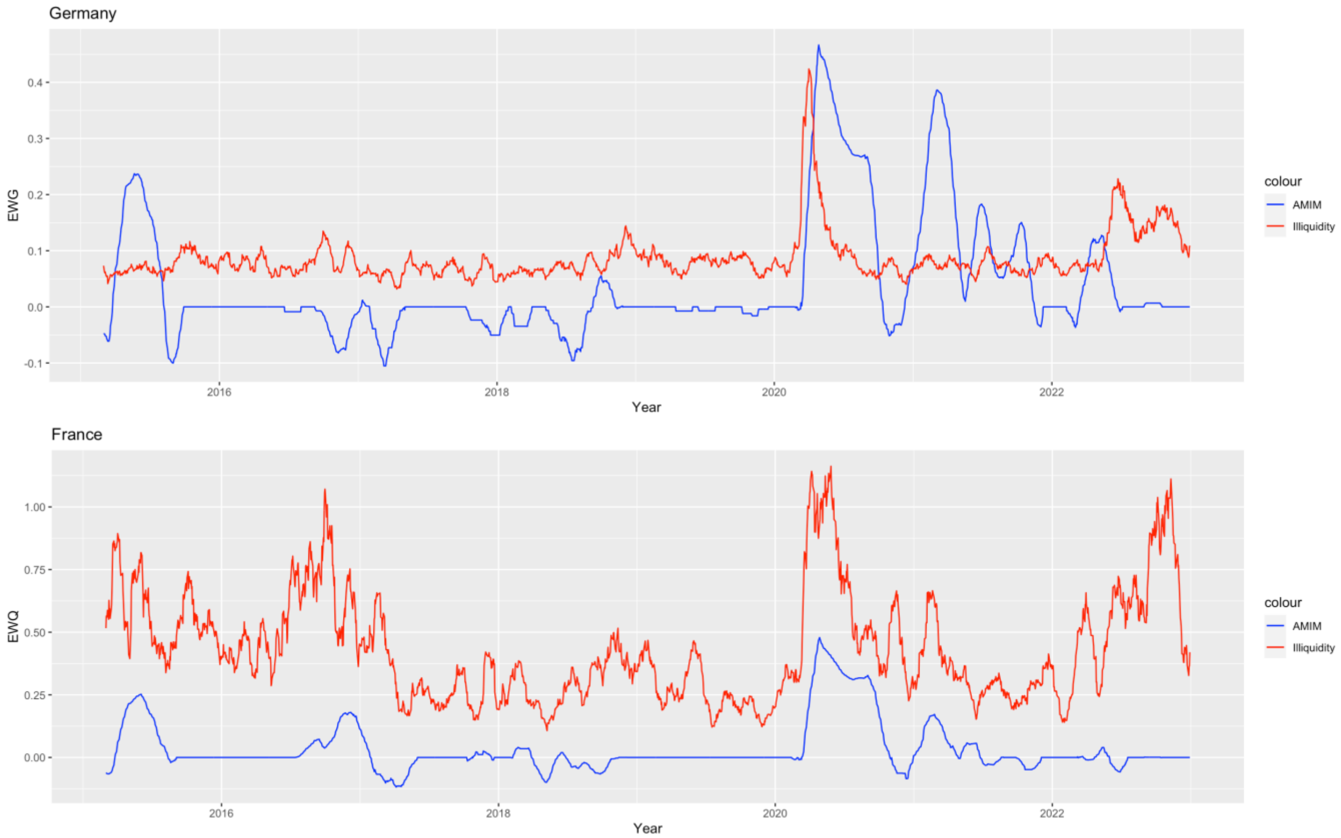
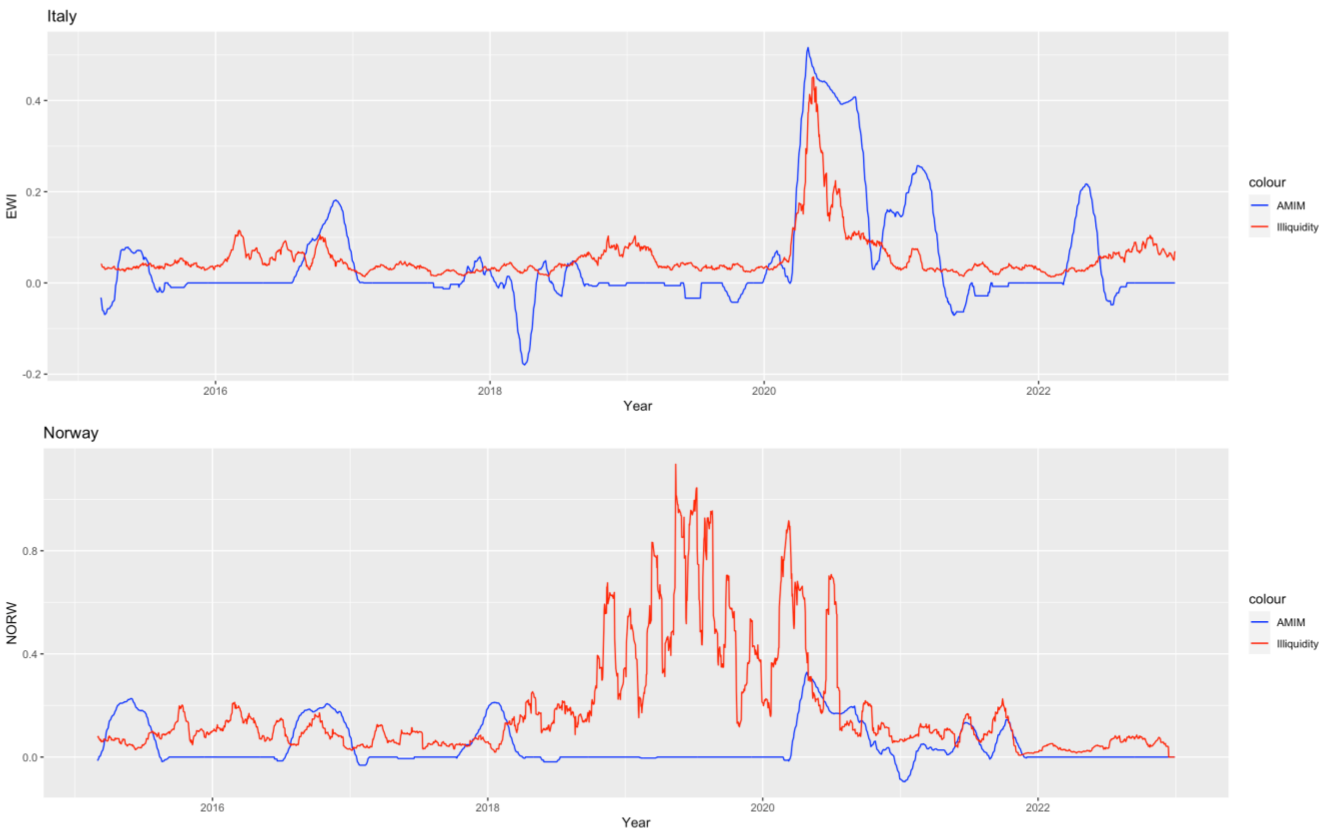


Figure 23: AMIM and Illiquidity in Italy and Norway



The comparison of AMIM and illiquidity measures is presented in the eight graphs above. It is evident that both measures experienced an increase around March 2020, coinciding with the impact of Covid-19. This trend is observed in all countries, except for Norway where AMIM experienced an increase in March 2020 and illiquidity had some noise before Covid-19 hit. The analysis suggests that ETFs had low liquidity and were inefficient in the G7 countries during the Covid-19 pandemic.

5.5.1 Rolling Correlation

The relation between AMIM and illiquidity is examined using a rolling correlation approach, resulting in the generation of the graph presented below. Instead of measuring the correlation over a specific period, a moving time window is utilized to calculate the rolling correlation. The rolling window in the analysis is set to 200 days, representing a rolling window size of 200 time periods. This approach allows for a thorough examination of the correlation over a specific time frame. In other words, for each point in time, the function in R takes the 200 most recent observations of both variables and calculates the correlation coefficient between them. The resulting correlation coefficient is then associated with the last time point in the rolling window. This process is repeated for every time point in the time series, resulting in a rolling correlation coefficient time series (Ilalan & Pirgaip, 2019).

A larger window size such as 200 days results in smoother rolling correlation, allowing for a clearer interpretation of the data and a more stable estimate. Utilizing a larger window also reduces the impact of short-term fluctuations and noise that may arise when using a smaller window size. A smaller window size gives a more dynamic estimate of the correlation between the two variables over time. This method enables us to detect trends and patterns that may have gone unnoticed if we had utilized a smaller window. The data used for our analysis was obtained from Figures 20 to 23, which depict the AMIM and illiquidity measures. These figures provide visual representations of the data, allowing for a comprehensive understanding of the trends and patterns in market efficiency and liquidity.

Figure 24. Rolling Correlation between AMIM and Illiquidity

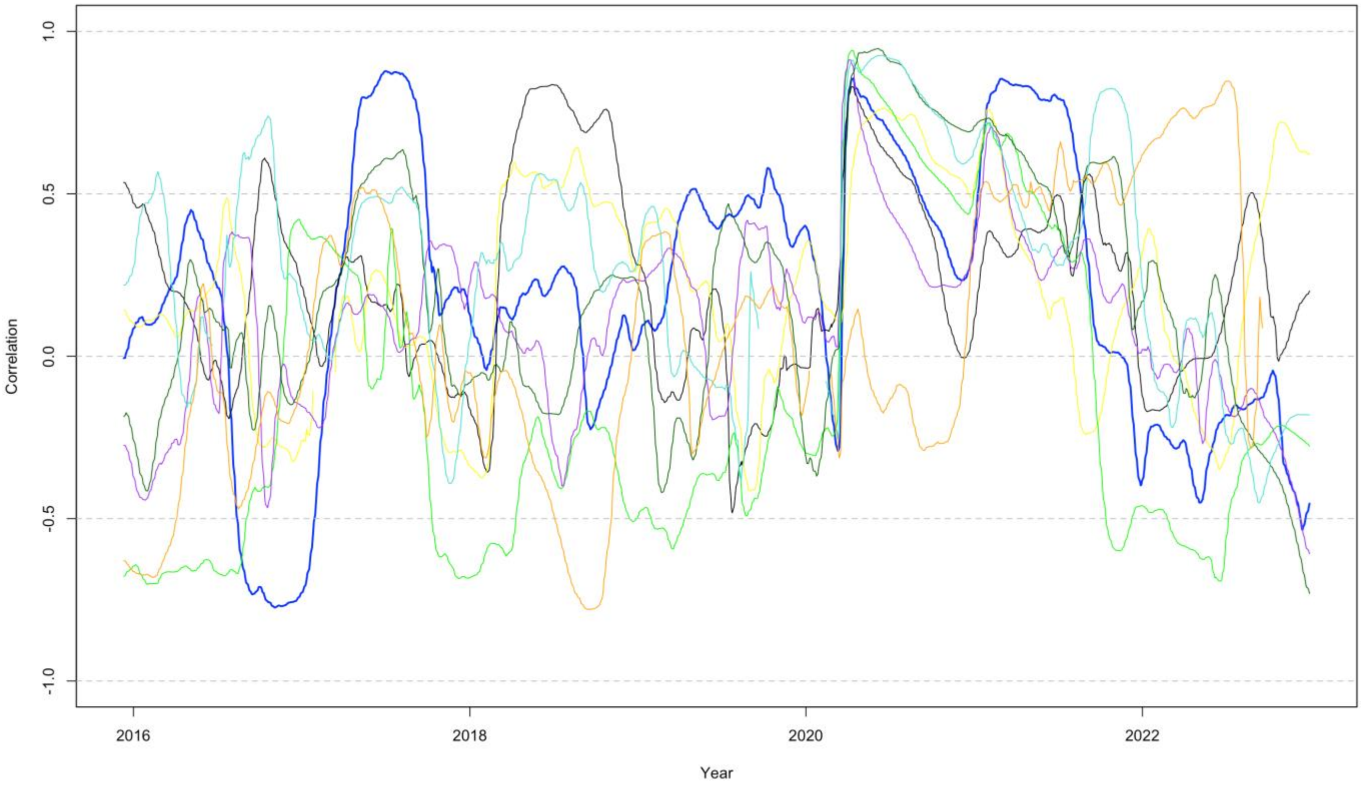


Figure 25. Overview of color-codes in figure 24.

Figure 24 presents the correlations between different ETFs with respect to AMIM and illiquidity. This graphical representation allows us to visualize the relationship between market efficiency and liquidity. The correlations depicted in the figure provide insights into the degree of association between these two factors and highlight the interplay between market efficiency and liquidity in the financial market. When an ETF scores 1, efficiency and liquidity are perfectly positively correlated, while a score of -1 indicates an negative correlation.

Upon examining the results depicted in figure 24, it is evident that there is substantial variation among the different ETFs. The correlations between AMIM and illiquidity exhibit diverse patterns across the ETFs, indicating varying degrees of relationship between market efficiency and liquidity. During the onset of the Covid-19 pandemic, there is a strong positive correlation between AMIM and illiquidity for all G7 countries, reaching up to 1. However, Norway exhibits a lower correlation, only achieving a small positive correlation between 0.1 and 0.2.

Before the pandemic, the graph depicts considerable fluctuations, with ETFs oscillating between positive and negative correlations. During Russia's invasion of Ukraine, the correlation does not echo the pandemic's pattern. Yet, a slight increase is observable at the outset of 2022. This increase does not match the significant correlation observed at the advent of Covid-19. While the correlation marginally amplifies during the invasion, the ETFs exhibit slightly enhanced correlation during this period. Given this minimal correlation, it is evident that the pandemic induces a substantially higher correlation between efficiency and liquidity compared to the invasion.

Figure 24 illustrates the varying correlation between market efficiency and liquidity over time. The correlation can be positive in certain periods and negative in others. Several factors contribute to this fluctuation, including changes in economic conditions, investor behavior, trading patterns, regulatory changes, and market structure. Additionally, external factors like geopolitical events or financial crises may also influence the correlation.

While this thesis places a greater emphasis on financial crises, it is important to note that they are not the sole determining factor for the correlation between market efficiency and liquidity.

6 Conclusion

In this chapter, the essential elements from the findings and discussions are summarized in order to link the main conclusion to the research question:

"What are the implications of international crises on market efficiency, liquidity and stakeholders in Norway and the G7 financial markets?"

The research findings suggest that the correlation between market efficiency and liquidity is not consistently uniform, despite their frequent exhibition of parallel tendencies. Through a thorough examination of ETFs from various countries, both distinct differences and notable similarities are observed in the patterns of market efficiency and liquidity.

The onset of Covid-19 marks the peak of the correlation between market efficiency and liquidity, a period that distinctly stands out across all our analyses. This onset ushered in a wave of uncertainty, particularly within the financial market, leading to a parallel drop in both market efficiency and liquidity. The ensuing global trading slowdown rendered financial markets less liquid, triggering higher transaction costs and market inefficiency. As a result, the security price could no longer be inferred from historical data and available information.

Upon revisiting the crises under study, it emerges that the Covid-19 pandemic predominantly shapes the global perspective, while the invasion of Ukraine primarily leaves its mark on European stock markets. This pattern corresponds naturally with the global reach of Covid-19 and the localized impact of the conflict in Ukraine.

In summary, the research suggests a general trend of correlation between market efficiency and liquidity, given their shared structural traits. The analysis uncovers a dynamic and potentially situational relationship between the measures of market efficiency and liquidity, with the extent of correlation influenced by financial crises or geopolitical conflicts.

7 Further research

While the study provides valuable insights, it also paves the way for future research. Future studies could delve deeper into the specific mechanisms through which crises affect the relationship between market efficiency and liquidity, exploring additional factors that may mediate or moderate this relationship. Furthermore, investigating the implications of these effects on investment strategies and policy decisions would offer practical guidance in managing risks and promoting market resilience.

We hope that our research contributes to the broader literature on market efficiency, liquidity, and their interactions with crises, fostering informed decision-making in the realm of finance.

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9 Appendix

Table 6. Descriptive statistics of EWU, SPY, EWJ and EWC

	EWU	SPY	EWJ	EWC
Mean	*1,048*	*1,582*	*1,324*	*1,171*
Standard error	*0,002*	*0,011*	*0,004*	*0,006*
Median	*1,061*	*1,468*	*1,308*	*1,103*
Mode	*0,979*	*1,024*	*1,036*	*1,000*
Standard deviation	*0,104*	*0,493*	*0,197*	*0,209*
Sample variance	*0,011*	*0,243*	*0,039*	*0,044*
Kurtosis	*-0,492*	*-0,952*	*-0,551*	*-1,242*
Skewness	*-0,191*	*0,552*	*0,418*	*0,166*
Range	*0,606*	*1,740*	*0,891*	*0,924*
Minimum	*0,675*	*0,909*	*0,928*	*0,644*
Maximum	*1,281*	*2,649*	*1,819*	*1,568*

Table 7. Descriptive statistics of EWG, EWQ, EWI and NORW

	EWG	EWQ	EWI	NORW
Mean	*1,150*	*1,338*	*1,147*	*1,214*
Standard error	*0,004*	*0,006*	*0,004*	*0,006*
Median	*1,122*	*1,345*	*1,138*	*1,123*
Mode	*0,988*	*1,088*	*0,843*	*0,947*
Standard deviation	*0,161*	*0,255*	*0,174*	*0,251*
Sample variance	*0,026*	*0,065*	*0,030*	*0,063*
Kurtosis	*-0,505*	*-0,723*	*-0,556*	*-0,375*
Skewness	*0,418*	*0,366*	*0,090*	*0,935*
Range	*0,793*	*1,021*	*0,756*	*1,012*
Minimum	*0,741*	*0,903*	*0,775*	*0,813*
Maximum	*1,534*	*1,924*	*1,531*	*1,824*