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## BTH 36201 Bacheloroppgave - Økonomi og administrasjon

Bachelor thesis 100 %

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**BTH 36201**

Bachelor thesis

BI Norwegian Business School

***Impacts of Short-Selling Bans on the Korean Stock Market***

Date of issue: 08.01.2024

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**Summary**

In this thesis, we examine the impacts of short-selling bans on the Korean stock market, particularly during periods of heightened volatility. Our view of the market can be simplified; we view the market as a large voting machine. The two sides of the market, long and short, are each working against each other in voting on the development of asset prices. Removing short positions can have significant consequences. We will analyse whether the regulators actions gave the intended results in their attempt at stabilizing the market during the market crisis of 2020.

Short-selling is a financial strategy where investors sell securities they do not own, anticipating a price decline to repurchase them at a lower price, thus pocketing a profit. Regulating this practice has historical precedence, with bans often implemented during financial crises in an attempt to reduce the volatility, stabilize markets and protect investors. The thesis specifically focuses on the Korean stock market, which has experienced several regulatory changes in response to recent economic shocks.

Our method consists of determining if there is a statistically significant difference in the volatility of the time series data before and after the ban implemented in 2020, to see if the policy achieved its intended effects. As for our quantitative analysis, we have applied the Standard GARCH, EGARCH and GJR-GARCH - models. In addition, a thorough discussion on measuring changes in time series data will be provided. For our testing, we will examine the variance in the daily returns between the KOSPI 100 and the KOSPI Small Cap indices and examine if there is a heightened volatility ex-post. Our research method consists primarily of a quantitative analysis with a comprehensive review of secondary data.

Our findings indicate that short-selling bans do lead to an increase in volatility, supporting our hypothesis that the policy does not achieve its intended effects. In addition, a thorough discussion on other potentially harmful effects, such as increased price discrepancies from fundamental values and decreased market efficiency will be provided.

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## Chapter 1: Introduction

Short-selling is a strategy where an investor sells a security they do not own, anticipating a price decline to buy it back at a lower cost, thus resulting in a profit. Although controversial, this practice plays a significant role in financial markets around the world. Working as a counterbalance to the long-side, it is an essential component of price discovery and market efficiency. However, short-selling also introduces potential risks such as amplified market volatility and systemic threats, under certain conditions. The strategy traces back to the earliest stock trading records, and it is often regarded as a counterbalance to the optimism of Wall Street (Reuters, 2008).

In this paper, we will look at the Korean stock market, offering a detailed overview of its structure, key characteristics, and the regulatory environment governing market operations. Moreover, we examine the periods of heightened volatility that led to temporary bans on short-selling. In particular, we will emphasize the recent measures taken in response to the market crisis of 2020. We intend to evaluate the effectiveness of these regulatory interventions in stabilizing the market and reducing volatility, thus protecting investors, while also discussing the longer-term implications on market liquidity and the impact on the investor sentiment. Furthermore, we have included an additional clarification of certain key concepts essential to this paper in the appendix.

A primary motive of policymakers for implementing a ban is to bring stability to the market in times of crisis. Essentially, in periods when market volatility is significantly increased, the goal is to mitigate this instability (Kroll, n.d.). Therefore, the research question we will pursue in this thesis is:

*"How does a short-sell ban impact the volatility of the Korean stock market?"*

Our hypothesis is that a short-sell ban leads to an overall increase in the market volatility ex-post, and thus does not work as a stabilizing factor as intended by the policymakers. Moreover, we base our hypothesis on the assumption that short-selling restrictions, in general, remove a key market player responsible for providing a counterbalance to the bullish sentiment of the market. As for the volatility, we build our hypothesis on the assumption that a short-sell ban will work counterintuitively when trying to stabilize the market during times of turmoil. In addition, such a regulation will, over time, harm the market by making it unattractive to investors. As a result, this will lead to lower efficiency and weaker price discovery overall. By banning short sales, you essentially remove a voting party from the market, making the market react slower to negative information, and reducing the overall efficiency of the market (Ni & Pan, 2011, p. 27). In sum, the absence of short-sellers will likely lead to more positive valuations as well as reduced overall liquidity in the market. However, we will be less concerned with the latter, and only briefly discuss the effects on liquidity. We find this subject intriguing, and highly relevant for policymakers, and believe this is a subject that should be explored further.

The thesis is organized as follows: Chapter 1 introduces the research question and hypothesis. Chapter 2 provides an overview of the Korean stock market and regulatory history. Chapter 3 reviews literature on short-selling, market integrity, liquidity, and volatility. Chapter 4 details the methodology, including data collection and GARCH models used to analyze volatility changes. Chapter 5 presents empirical analysis, showing that short-selling bans increase market volatility. Chapter 6 concludes with a summary of findings, discussing implications for market efficiency and offering recommendations for future research. In addition, we have included an appendix where additional clarification of certain key concepts can be found.

## Chapter 2: History of the Korean Stock Market and Short-Selling Regulation

### 2.1 Overview of the Korean Stock Market

Over the last century, South Korea has experienced remarkable economic growth. Once a small nation with minimal industry and seemingly limited economic prospects, it initiated a series of economic reforms in the 1960s.

These reforms transformed the nation's economic outlook by shifting from an inward-focused development strategy to one that emphasized exports. This change set the stage for an extraordinary economic rise. Over the next 50 years, South Korea increased its real gross domestic product per capita (GDP) by approximately 16 times, surpassing the growth achieved by the United States over the past century (Feenstra & Taylor, 2021, p. 720).

The financial market is a key component of any country's economy, providing a platform for the issuance and trading of stocks, bonds and other securities. The Korean stock market is known for its dynamic nature and has been a platform for many companies to achieve rapid growth, especially in the technology and bio-health industries. Furthermore, it has a high level of foreign investment, with foreign investors playing a significant role in the market's liquidity and depth. The Korean stock market primarily consists of two exchanges: the Korea Exchange (KRX) and the Korea New Exchange (KONEX). The KRX, the main stock market in South Korea, encompasses three separate markets: the Korea Composite Stock Price Index (KOSPI) market, the Korea Securities Dealers Automated Quotations (KOSDAQ) market, and the derivatives market.

The KOSDAQ market is the primary market for technology companies in South Korea. The KOSPI index, which tracks the performance of all common stocks listed on the KOSPI market, is widely recognized as a key indicator of the South Korean economy. Moreover, the KOSDAQ market is similar to the NASDAQ in the United States, focusing on small to medium-sized enterprises, particularly those in the technology and bio-health sectors. It provides a more accessible platform for these companies to raise capital.

As for the regulatory components, the Korean stock market is supervised by two regulatory bodies. The Financial Services Commission (FSC) and the Korea Financial Investment Association (KOFIA) are the primary regulatory bodies overseeing the Korean stock market. The FSC is responsible for policy-making and regulation of Korea's financial industry, including the stock market. KOFIA, meanwhile, focuses on self-regulatory functions to ensure fair trading practices. The regulation of the Korean stock market is grounded in the Financial Investment Services and Capital Markets Act (FSCMA), which provides the legal basis for the operation and regulation of financial investment services in Korea, including securities trading (The Legal 500, n.d.). The regulatory framework emphasizes investor protection, with strict rules against insider trading, market manipulation, and other fraudulent activities. The Korea Deposit Insurance Corporation (KDIC) provides protection for investors against the default of brokerage firms. Companies listed on the KRX are required to maintain a high level of transparency, with stringent disclosure requirements to ensure that investors have access to all material information affecting their investment decisions.

### 2.2 History of Short-Selling Regulations

In 1609, Isaac Le Maire, a sizable shareholder in the Dutch East India Company (VOC), attempted to manipulate the company's stock price through short-selling. The manipulation attempt, which aimed at artificially decreasing the market price of VOC shares, is one of the earliest documented instances of short selling. The motivation behind Le Maire's actions was likely to get revenge on the company, after being forced out. The Dutch government soon took action and implemented a ban on short-selling (Hayes, 2024).

Throughout history, short sellers have been a target of criticism, especially during market downturns. Short Sellers were blamed for the Wall Street crash in 1929. Moreover, short sellers were also accused of prolonging the crisis. Following the Wall Street crisis of 1929, the "uptick rule" formally known as rule 10a-1, was introduced in the United States. The rule prohibits traders from shorting any stock at a price lower than the previous price. To be able to short a stock, a trader will have to sell (e.g. go short) at a higher price than the last traded price (an uptick), or the last traded price if it were higher than the previous price in the market. The rationale behind the idea was to withdraw downward pressure on stocks from short sellers and stop short sellers from pushing stocks into further decline (Diether, Lee, & Werner, 2009).

In 2007 the uptick rule was eliminated by the U.S. Securities and Exchange Commission (SEC), as studies showed that the rule did not have the effect that it was supposed to have. A reintroduction of the rule was widely debated in 2009 following the great financial crisis, and in 2010 *Rule 201,* also known as the “alternative uptick rule” was introduced. The rule regulated short selling on stocks that declined by 10% or more intraday (U.S. Securities and Exchange Commission, 2010). The alternative uptick rule protected stocks that were under hard pressure, rather than the whole market.

**2.3 Timeline of Events**

Following the Asian Financial Crisis in 1997-98, South Korea started regulating its financial markets heavily. The outcome of the crisis led to significant reforms, where short-selling in particular, became more regulated (Kim, 2006). Moreover, a short-sell ban was not relevant for this period as short selling was not a common practice in the South Korean stock market. As for the financial crisis of 2008, South Korea was among one of the countries that imposed a temporary ban on short-selling. The main purpose of this was to stabilize the market during periods of high market volatility (Kim, 2023).

On March 16th 2020, just following the covid turmoil, the FSC imposed a complete ban of short-selling across all listed stocks in the Korean stock market (Financial Services Commission, 2020). This measure was taken in response to the severe market volatility during the crash, with the aim of stabilizing the market (Spolaore & Le Moign, 2024). Moreover, this ban was partially lifted when the FSC announced on May 2nd that short-selling was now allowed for large cap stocks only (KOSPI 200 and KOSDAQ 150), effective from May 3rd and onward. A complete short-selling ban was again imposed on all listed stocks on November 5th 2023 (Asia Financial, 2023). This ban was announced to last until June 2024, and it remains in effect as of the time of this writing (Financial Services Commission, 2023).

*Table 1: Timeline of events.*

| Announcement date | Effective date | Event |
|---|---|---|
| 13.03.2020 | 16.03.2020 | Banned across all indexes |
| 02.05.2021 | 03.05.2021 | Lifted for KOSPI200 and KOSDAQ150 |
| 05.11.2023 | 06.11.2023 | Banned across all indexes until June 2024 |

### 2.4 The Role of the Short-Seller

In the short term, one could describe the stock market as a large "voting machine" (Graham & Dodd, 2009, pg. 70). Market participants are continuously voting on different stocks, resulting in either an increase or decrease in value over time. The voting machine can be separated in two different sides, the long (buy) and short (sell) side, each vote results in either an increase or decrease in price.

The role of the short-seller is multifaceted and serves as a key player in the overall dynamics of financial markets. Short-sellers contribute significantly to the process of price discovery (Diamond & Verrecchia, 1987). They sell stocks they believe are overvalued or expected to decline, which helps bring the price of the stock closer to its true value. Furthermore, this activity is essential for maintaining a balance in the market, ensuring that stock prices reflect underlying fundamentals rather than just a bullish sentiment (Şahin & Kuz, 2021).

By taking positions based on thorough research and analysis, short-sellers help in correcting market mispricings, thus enhancing the overall market efficiency. Short-sellers often act on information or perspectives that the majority of market participants may overlook, which can lead to more informed and efficient markets overall. In addition, by selling stocks they do not own, short-sellers add liquidity to the market. This proves especially beneficial in less liquid markets or during times of market stress when liquidity is at a premium. Conversely, in periods of market exuberance or bubbles, short-sellers act as a counterbalance. Their skepticism and actions can help temper over-optimism in the market, potentially preventing or mitigating financial bubbles. All this proves to show that short-sellers do play a critical role in maintaining the balance, efficiency, and integrity of the stock markets.

### 2.5 Impact of Regulations on Market Participants

Our prevailing hypothesis is that by  constraining short sellers from opening short positions, you essentially remove one side of the market, leading to a simultaneous win for the long-side of the market. As a result, one would assume the effect of this will be more positive valuations on the stock market overall, and especially for those securities which are heavily shorted.

Heavily shorted stocks include stocks where there exists a large presence of short-sellers. In addition, we described earlier in this paper the effect of added liquidity in the presence of short sellers. Hence, the effect will be larger for smaller capitalized stocks where the liquidity is lower, thus resulting in a larger bid-ask spread, where the bid-ask spread reflects the difference between the highest price a buyer will pay and the lowest price a seller will accept. As a result, it will be more difficult for investors to close their positions, and one are often at an immediate disadvantage when buying stocks with large spreads. Evidence shows that in the presence of a short sale ban, it takes time for the negative information contained in the options market to get incorporated into stock prices (Ni & Pan, 2011, p. 27). Moreover, based on price discovery theory, one would assume that over time the absence of the short-seller the gap between the theoretical fair value and the market price would increase. As a result, the market will be inflated over time, possibly leading to a bubble. However, this is an aspect that should be studied further but is outside the scope of this paper.

# Chapter 3: Literature Review

## 3.1 Types of Short-Sellers

By understanding who the key participants on the short side are, we will improve our understanding on how the regulation of short-selling has come to light, as well as why they sell short in the first place. The types of financial institutions typically associated with short selling include hedge funds, investment banks and proprietary trading firms. They each engage in short selling for different reasons, often aligned with their investment strategies, risk management practices, and the financial products they offer their customers.

*Hedge funds:*

Hedge funds are perhaps the most active participants in short selling due to their flexible investment mandates and the pursuit of absolute returns. As we have previously discussed, short-selling can be highly speculative and risky, and a flexible mandate makes room for such investments (Nasdaq, n.d.). Hedge funds typically employ short selling as part of different strategies, including short positions based on fundamental analysis of companies believed to be overvalued or facing significant challenges. Moreover, they also use short selling in market-neutral strategies, where they aim to profit from the relative performance of pairs of stocks, shorting the one they expect to underperform and going long on the one they expect to outperform, thereby hedging market risk (Stowell, 2017).

*Investment banks:*

Investment banks engage in short selling primarily through their proprietary trading desks and sometimes to facilitate client trades. Proprietary trading involves the bank trading securities with its own money rather than executing trades on behalf of clients. Investment banks might short-sell as part of arbitrage strategies, looking to exploit price discrepancies between related assets or markets (Nasdaq, n.d.). They also short-sell as a way to hedge positions in their trading portfolios or anticipation of market downturns.

Additionally, investment banks provide securities lending services to other institutions looking to short-sell, earning fees in the process (Stowell, 2017).

*Proprietary trading firms*

Similar to investment banks' proprietary trading desks but operating as independent entities, these firms trade their capital across various markets. Proprietary trading firms engage in short selling as part of high-frequency trading, statistical arbitrage, and other quantitative strategies (Stowell, 2017). These firms rely on advanced algorithms and ultra-fast execution to profit from small price movements, including those exploited through short selling (Nasdaq, n.d.).

*Retail investors*

This segment represents the average public investor who has some savings and is not considered institutional, meaning they commit capital for their personal use, and not on behalf of a company (Nasdaq, n.d.). Individually they are usually small but in sum, they represent a considerable portion of the overall market size. These investors must be protected, as their knowledge of the market and the risks involved are often limited, as opposed to the professional institutional players. Some retail investors speculate using options, or short the stock directly using a margin account, however, this is a small and insignificant group.

Despite its potential benefits, short selling is accompanied by significant risks, such as the possibility of unlimited losses, and the strategy is often costly. Moreover, short sellers often face scrutiny and regulatory oversight, as excessive short selling can exacerbate market declines during turbulent periods.

### 3.2 Theoretical Implications on Market Efficiency and Integrity

Miller (1977) proposes that restrictions on short sales bias asset prices upwards by preventing the incorporation of negative information into the pricing. Over the long term, this implies that the market value of a stock will diverge from its intrinsic value, effectively making the market less efficient and increasing the likelihood of mispricings. Ideally, the market price of any security should incorporate all available information, proving an efficient pricing (Fama, 1970). An interpretation of this can be that by banning short-sales, you essentially exclude one side of the market which represent the bearish sentiment towards the security, reducing its efficiency in securities pricing.

Furthermore, Miller proposes that securities often end up priced based on the most optimistic investor evaluations, particularly when short selling is restricted. This scenario leads to lower-than-expected returns for stocks perceived as higher risk, as these stocks attract investors with the greatest divergence in opinion. The argument of a less efficient market is further reinforced by a study done by Ni & Pan (2011), where they found that during the short sale ban, it took a long time for negative information contained in the options and the credit default swap (CDS) markets to be incorporated into stock prices. This indicates a lag in price adjustment to available market information, essentially showing evidence of a lag in market efficiency.

Providing a different view, a counter argument is made by Diamond and Verrecchia (1987) who proposes that investors factor in trading constraints when forming their expectations, which means that asset prices are not inherently biased upwards. Furthermore, their model on short sales also offers insights into how quickly prices adjust to new information and the skewness of excess returns on days when public information is announced.

Ho (1996) presents data from the Singapore stock market showing that during financial turmoil, short selling bans can negatively impact market integrity. This research is particularly relevant given that numerous developing markets enforce strict short selling regulations to restrict speculation and as an attempt at reducing volatility. Contrary to these measures, the analysis suggests such restrictions may actually heighten volatility. The prohibition of short selling prevents the assimilation of certain negative insights into asset pricing, suppressing bearish sentiments. Consequently, when markets do begin to trend downward, the absence of earlier price adjustments can result in more severe downturns, with the potential to escalate into a market crash. In sum, we see that the consequences regarding the market integrity are highly complex and multifaceted.

### 3.3 Short-Selling Restrictions and Market Liquidity

Another important aspect of the financial markets is liquidity. If there is no liquidity, then there would be no market. One measure of liquidity is illustrated by examining the bid-ask spreads of different stocks. Where a high spread indicates lower liquidity than a stock with a narrow spread. In a study conducted by the Centre for Economic Policy Research (2020) we are provided with evidence where the relative spreads of stocks are reduced during the ban, resulting in an improved liquidity as a result. They argue that this cause is due to the fact that a short-sell ban selectively removes informed traders, who will be more reactive among higher spread stocks, which as a result, improves liquidity there (Fohlin, Lu, & Zhou, 2023; Barardehi, Ruchti, Bird, & Karolyi, 2023). A study conducted by the Office of Financial Research also specifically examined the effects on stocks that trigger Rule 201, and found that to some degree it is likely that at least some short sellers switch from removing liquidity from the bid-side to providing liquidity on the ask-side (Barardehi, Ruchti, Bird, & Karolyi, 2023, pg. 32). As a result, we see an increase in depth at best-ask price.

### 3.4 Short-Selling Restrictions and Market Volatility

In a similar manner, a study conducted by the Bond University, examined instances of changes in volatility for the Australian stock market before and after a ban was implemented during the market crisis of 2008. They applied data from the Canadian stock market as a control group. In their study, they found evidence of stocks subject to the short selling ban suffered a severe degradation in market efficiency. In addition, imposing such constraints resulted in an increase in intraday volatility (Helmes, Henker, & Henker, 2011). Although we do not examine the intraday volatility specifically, these findings are coherent with our prevailing hypothesis of an increased overall volatility for the market the following period.

A meta-analysis by Yale School of Management examined the regulatory response during the market turmoil in 2020 across 17 large economies. Their findings indicate that the restrictions, implemented to reduce volatility and prevent further panic, were viewed as necessary and helped avert potential widespread financial destabilization. However, they highlight evidence that shows increased volatility for the following period after the ban is imposed, as well as some severe consequences that follow this regulation, such as a deterioration of liquidity and weakened price discovery (Nunn & Kulam, 2021). These findings are consistent with our hypothesis and also include other consequences which policymakers need to factor in when making their decisions.

In their study, Barardehi, Ruchti, Bird, and Karolyi (2023), examined the returns for stocks that do and do not trigger Rule 201 short-selling restrictions which works similarly to a complete ban, but is only implemented on stocks experiencing a 10% decline within a day. Their findings state that these restrictions do in fact lower spot volatility, indicating that restrictions on short selling may stabilize prices (p. 4). Furthermore, they also find evidence of narrower spreads and a deeper best ask price suggest that some short sellers are shifting from taking liquidity on the bid side to adding liquidity on the ask side (p. 4). These findings provide an opposite view of our hypothesis and their study specifically examines the Rule 201. Their findings are interesting as it shows an exception where the restrictions applied actually worked as intended and lowered the volatility. However, their study only examines the spot volatility which is measured in 65-minute intervals and they are not examining over a longer period.

According to Le Moign and Spolaore (2020), the 2020 short selling bans were implemented to stabilize financial markets during volatile trading periods. In their study, they find evidence of a lower degree of volatility for the shares in the banned countries during the ban period. In their study they examine using a control and test group where they differentiate between large- and small-cap stocks. They compared both the sample average/median and present a result of an average decrease in volatility between - 6.4% and - 10.3%. They examined both intraday and historical volatility measures. These findings are surprising as it is not in line with the other literature. However, we point out that this evidence is measured by conducting a difference-in-difference method across a large range of economies, where there are a lot of exogenous factors that may be prone to affect the results. Furthermore, this illustrates that further research on this issue may be useful.

## Chapter 4: Methodology

### 4.1 Research Design

Our main emphasis will be on providing a thorough quantitative approach to the problem discussed. In addition, we supplement our study with secondary data and previous studies on the subject to support our findings. We chose this as we mainly believe this subject is not a good fit for a qualitative approach.

Our focus will be to test whether there is a statistically significant difference in volatility before and after the ban of 2020 was implemented. Our test will be applied on both the KOSPI 100 and KOSPI Small Cap Indices. Specifically, we will test whether there is a significant difference between the standard deviations (volatility) in the time series before and after the ban to conclude whether the implemented ban yielded the effects intended by the policymakers.

### 4.2 Data Collection

To gather our data we used Refinitiv as our main source. After careful consideration, ensuring the reliability and comprehensiveness of our data collection, we concluded that Refinitiv, as a reputable provider of financial market data and infrastructure, would be a good source for collecting our data. We have fetched daily close prices from the following indices, and calculated the respective daily returns. From these returns, we derived the daily volatility in our dataset which is the primary data we have applied in our time series testing. From Refinitiv we downloaded data from both the KOSPI 100 and KOSPI Small Cap indices.

Using data from multiple indices will enable us to create control groups to test if the short ban would deviate large-cap stocks from small cap stocks during the period. The dataset was divided into pre-ban, during-ban, and post-ban periods to assess the impact of short-sale ban on the volatility in our time series. The pre-ban segment consists of observations from the start of our dataset 2nd of January 2019 to 13th of March 2020. The during-ban period consists of observations from 13th of March 2020 to 2nd of May 2021. Lastly, the post-ban period consists of data from 2nd of May 2021 to 5th November 2023. The segmentation of the data allows us to make a comparative analysis to identify any significant changes in volatility due to the restrictions on short-sale.

### 4.3 The GARCH Model

For our testing we are primarily using R, supplemented by Excel. According to our hypothesis, we will test if the volatility in our time series sample of daily returns is significantly higher ex-post. We have applied the GARCH, EGARCH and GJR-GARCH -models with one lag order, specifically.

The GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model, introduced in 1986, extends the ARCH model developed by Robert Engle by incorporating past conditional variances into the current variance equation (Dol, 2021). This approach allows for modeling the volatility clustering observed in financial time series, where periods of high volatility are followed by high volatility, and periods of low volatility follow low volatility. The GARCH(1,1) model can be described with the following:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \quad (1)$$

Where $\sigma_t^2$ expresses the current conditional variance as a function of a constant term $\alpha_0$, past squared shocks $\epsilon_{t-i}^2$, and past conditional variances

$\sigma^2_{t-j}$. The (1,1) term in the model refer to the lag used in the past squared shocks and the past conditional variance terms (Dol, 2021).

Moreover, the EGARCH (Exponential GARCH) model, specifically addresses the issue of asymmetric effects of positive and negative shocks on volatility. In EGARCH, the logarithm of the variance equation is used, which ensures that the conditional variance is always positive and allows for a more flexible response to changes in the leverage effect, where negative shocks might have a different impact on volatility compared to positive ones (NYU Stern Volatility Lab, n.d.). The latter is discussed in the *Leverage Effect* section. The asymmetric effects are also captured by the GJR-GARCH model, however, instead of applying a logarithmic transformation, it handles this asymmetry by including a indicator function where the conditional variance increases if the shock is negative (NYU Stern Volatility Lab, n.d.). In conclusion, we believe this makes GJR-GARCH particularly useful in financial markets where leverage effects are pronounced.

This model will be able to tell us whether or not the desired effect of reducing the volatility during times of crisis was achieved or not. Furthermore, we will have grounds to determine the overall success of the regulatory implementation.

**4.4 Limitations**

There are several limitations to our test. We will in this chapter try to clarify how we have treated these limitations, in order to make our testing as trustworthy and valid as possible. Moreover, we will also discuss how we have treated our data in order to make it generalizable, so that it can be applied to other contexts than South Korea, specifically.

In order to keep our data symmetrical we chose to use the same period duration in our analysis. This yields several obstacles, firstly as the period after the ban implemented in 2020 is relatively short, this limits our sample size, and could possibly lead to a false conclusion (Sürücü & Maslakçı, 2020).

Secondly, this excludes the possibility of testing the period after the last complete ban which took place in November 2023. It is therefore clear to us that the length of our sample period is the largest limitation in this study. Moreover, by using the daily returns, and not weekly or monthly, we try to get as accurate a picture as possible. Although, we recognize that we could also include intraday volatility, but we find this may give too much noise in our dataset.

Furthermore, we recognize that exogenous factors such as macro events, economic policy, interest rates and political changes could influence the results of the study. These factors are difficult to incorporate and quantify when testing, however, it is important to acknowledge their presence, as they may reduce the validity and reliability of our findings (Sürücü & Maslakçı, 2020). Additionally, we will analyse the timeframe where the ban was implemented, and then lifted for the large-cap stocks. This gives us a test- and control group, which will aid in reducing the exogenous factors involved, giving us a more reliable test.

Moreover, when selecting the time frame for the analysis it is important to be aware that changes in the time frame can potentially impact the outcome of the analysis. To account for these weaknesses we will try to select time-frames for the analysis which consist of as few exogenous factors as possible. In addition, we chose to support our empirical findings with reviews of more in-depth studies on liquidity and the implications on market stabilization during times of crisis.

### 4.5 Generalizability

It is important to acknowledge that the impact of a short-sale ban on market volatility can vary significantly depending on the market or the chosen time period for the analysis. There are several underlying factors, such as economic conditions, regulatory environment, and market sentiment, which all interact to shape the current market landscape. These factors can influence the outcomes of volatility tests, making it challenging to generalize the results of such time series analyses. Therefore, the difficulty in generalizing these findings across different contexts and periods must be emphasized.

### 4.6 Leverage Effect

As stock prices decline, companies inadvertently become more leveraged because the proportion of their debt increases relative to their equity (Dol, 2021). Consequently, their stock generally becomes riskier and more volatile. This observed phenomenon, commonly referred to in the literature as the "leverage effect," suggests a statistical pattern where stock price declines are typically associated with greater increases in volatility compared to the decreases in volatility seen during stock price rises (Engle & Ng, 1993). This asymmetry is notable, reinforcing the idea that falling markets are usually more turbulent than rising ones. In essence, when interpreting the changes in volatility between two different events, a negative event will add more weight than a positive one, and is also the reason for our selection of the GJR-GARCH model.

## Chapter 5: Empirical Analysis

### 5.1 Data Description

The data selected consists of the daily close from the KOSPI 100 and KOSPI Small Cap indices. The period selected is from the 2nd of January 2019 to the 29th of February. As previously mentioned in chapter 4.4, we chose not to include the data after the 5th of November 2023, due to the short timespan for the last ban. The primary source for the data is Refintiv, to ensure accuracy and reliability. From these numbers we have derived the daily returns. These returns serve as the base of our dataset. The daily returns are calculated using the logarithmic differences between the consecutive closing prices, which is given by:

$$R_t = log\left(\frac{P_t}{P_{t-1}}\right) \tag{2}$$

where $P_t$ is the closing price on day $t$ and $P_{t-1}$ is the closing price on day t - 1.

The daily returns we calculated are critical for our analysis in understanding how volatility and risk changes for the indices. To continue our analysis, we calculated daily volatility using the realized volatility (calculated as the standard deviation of returns over a rolling window of 30 days) and various GARCH model estimations.

**5.2 Shapiro-Wilk Normality Test**

When examining the data for the KOSPI 100 and the KOSPI Small Cap, we mainly focused on the mean return, standard deviation, skewness and kurtosis. According to Ho and Yu (2015), skewness and kurtosis can be used as indicators for the normality of distributions or the lack thereof.. The skewness of the data can range from -∞ to +∞. It tells us how symmetric the distribution of the data is, a value close to zero would indicate symmetric distribution. Moreover a negative number indicate that the distribution has heavier tails at the left side of the distribution, whereas a positive value indicate the opposite. The kurtosis tells us how heavy the tails of the distribution are and can range from 1 to +∞. In a normal distribution the kurtosis would be 3. A higher kurtosis than 3 indicates a distribution with heavier tails than a normal distribution (Ho & Yu, 2015, pg.7).
From table 2 below, we can first look at the KOSPI 100. The skewness of the data tells us that the distribution of the data from the KOSPI 100 is almost symmetric. The kurtosis value of 5.08, however, indicates that the distribution consists of heavier tails, compared to a normal distribution.
Moreover, for the KOSPI Small Cap, the skewness value of -1.77 indicates negative skewness, which in other words mean that the distribution is skewed to the left side, with longer tails on the negative side. Furthermore, the distribution of data indicates a leptokurtic distribution, with a kurtosis value of 15.1. This is greater than 4.0 which is the threshold for a leptokurtic distribution (Corporate Finance Institute, n.d.). This indicates that the distribution of the KOSPI Small Cap has even heavier tails compared to the KOSPI 100, thus showing that the may be prone to extreme values on either side (Corporate Finance Institute, n.d.).

*Table 2: Complete descriptive statistics.*

| Descriptive statistics | KOSPI 100 | KOSPI Small cap |
|---|---|---|
| Mean return | 0.0002615 | 0.000176 |
| Standard deviation | 0.0124587 | 0.012739 |
| Skewness | 0.053739 | -1.77256 |
| Kurtosis | 5.085545 | 15.10972 |

The descriptive statistics indicates deviation from normality for both indices. Based on the skewness and the kurtosis values, the assumption of normality is questionable. Therefore, we need to test it to see if it will be applicable for our purpose. The null hypothesis of the test is that the dataset is normally distributed. Thus, if the p-value is lower than the chosen alpha level (in our case 0.05) the null hypothesis is rejected, and there is significant evidence that the dataset is not normally distributed. Moreover, we have applied this test on the returns of the KOSPI 100 and KOSPI Small Cap. In the Shapiro-Wilk test, a test value close to 1 indicates a normally distributed dataset. Conversely, a value close to 0 indicates a dataset which is not normally distributed (Leslie, Stephens, & Fotopoulos, 1986).

The test statistic of the Shapiro-Wilk test is given by:

$$W = \frac{\left(\sum_{i=1}^{n} \alpha_i x_{(i)}\right)^2}{\sum_{i=1}^{n} (x_i - \bar{x})^2} \tag{3}$$

Where $x_{(i)}$ denotes the sample value in position *i* when sorted in ascending order, $\bar{x}$ is the sample mean and $\alpha_i$ are constants derived from the expected values of a normal distribution (ScienceDirect, n.d.).

In our test output, we received a test value close to 1, indicating an almost normally distributed dataset, however, we also received an extremely low p-value and we can therefore say that we have evidence showing our dataset is not normally distributed. Thus indicating that we have fat tails, which is normal to observe for financial returns. This is due to observations of extremely high or low returns, which are unlikely in a normally distributed dataset (see figure 1 & 2 in the appendix).

**5.3 ARCH-LM Test**

To assess if autoregressive conditional heteroskedasticity (ARCH) effects were present in the returns of the KOSPI 100 and KOSPI Small Cap, we performed an ARCH-LM test. The test is applied to determine whether the residual variances of an autoregressive model is heteroscedastic, which would justify the use of GARCH-models when modelling volatility (Engle, 1982). The null hypothesis of the test is no ARCH-effects (e.g. $\beta_1 = \beta_2 ... = \beta_i$). The alternative hypothesis is that there is significant ARCH effects in our model (e.g. $\beta_i \neq 0$, for at least one *i*). To obtain the residuals we fitted an autoregressive model of the first order, AR(1), to the returns of the KOSPI 100 and KOSPI Small Cap. The AR(1) model is specified as:

$$r_t = \alpha + \phi r_{t-1} + \epsilon_t \tag{4}$$

where $\alpha$ is a constant, $\phi$ is the autoregressive coefficient, and $\epsilon$ the residuals (MathWorks, n.d.).

Furthermore, the ARCH-LM test is applied to the squared residuals of the AR(1) model. The test is done by regressing the squared residuals by their lagged values and computing the test statistic by $T \times R^2$. Here, $T$ is given by the number of observations, and $R^2$ is the coefficient of the determination from the auxiliary regression. The determination coefficient, $R^2$, evaluate how the regression explains the variability of the squared residuals of the model (Engle, 1982). From the ARCH-LM test, as shown in table 4 (see appendix), we obtained high test values, with p-values close to zero. Therefore, our results from the ARCH-LM test indicates that there are significant ARCH effects present in our models, and the null hypothesis is rejected. These results justifies the use of GARCH-models to model the volatility of the indices.

### 5.4 Ljung-Box Test

To further assess if we should pursue GARCH-models when modelling volatility, we want to assess if there is any volatility clustering in our data, meaning that observations correlate at different lags in the time-series. To test for volatility clustering and linear dependencies in our data we used a Ljung-Box test to test for autocorrelation in the squared returns and the returns. The null hypothesis is that there is no observed autocorrelation in the data up to lag *k,* whereas the alternative hypothesis states that there is significant autocorrelation in our dataset. The test statistic is given by:

$$Q = T(T + 2) \sum_{k=1}^{m} \frac{\hat{t}_k^2}{T-k} \tag{5}$$

Where *T* is the sample size, *m* is the number of lags, and $\hat{t}$ is the sample autocorrelation at lag *k* (Statology, n.d.). When performing the Ljung-Box test for both the returns and returns squared, we found that there is a significant autocorrelation for both for both indices, with 10 lags in the test model, as shown in table 4 (see appendix). Thus rejecting the null hypothesis of zero autocorrelation in our data. The results further justifies use of the GARCH-model approach and the inclusion of an AR terms in our GARCH model.

### 5.5 Goodness of fit

As mentioned earlier, it is possible to fit multiple different GARCH-models. We have chosen to fit three GARCH-models: the standard GARCH (1,1), EGARCH (1,1), and GJR-GARCH (1,1). Furthermore, to evaluate their performances, we have chosen to apply two well known error metrics, mean squared error (MSE) and mean absolute error (MAE), for each model. The metrics chosen to evaluate the models compare the predicted volatility to the benchmark volatility (e.g. the rolling standard deviation of 30 days). The MSE and MAE is given by:

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (\sigma_t - \widehat{\sigma}_t)^2 \tag{6}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} \left|\sigma_t - \widehat{\sigma}_t\right| \tag{7}$$

Where $\sigma_t$ represents the benchmark volatility at time $t$, $\widehat{\sigma}_t$ represents the predicted volatility from the models at time $t$, and $n$ represents the number of observations.

As we can see from table 5, the MSE's and MAE's of the models differ by small amounts, with the lowest ones marked in bold. This shows us that there seems to be small differences between the predictive power of the models. Another way to analyse the predictive power of the models would be by applying a Diebold-Mariano test, to determine if the predictive power of a model is significantly more accurate compared to each other. However, we chose not to include this in our thesis, as the main goal of our study is to perform a time-series analysis and not test the predictive power of the different GARCH-models.

*Table 5: Test: Goodness of fit.*

| Model | MSE | MAE |
|---|---|---|
| Standard GARCH | 0.00029785 | 0.0137450 |
| **GJR-GARCH** | **0.00029762** | **0.0136778** |
| EGARCH | 0.00029913 | 0.0136915 |

### 5.6 GJR-GARCH Model

For our testing we applied the GJR-GARCH (1,1) model. As previously mentioned, this model is an extension to the standard GARCH model which captures the asymmetries in volatility. This is due to the leverage effect, meaning that negative shocks may lead to increased volatility compared to positive returns (NYU Stern Volatility Lab, n.d.). The GJR-GARCH model is given by:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \gamma \epsilon_{t-1}^2 I(\epsilon_{t-1} < 0) + \beta_1 \sigma_{t-1}^2 \tag{8}$$

The GJR-GARCH model allows the conditional variance to react differently to positive and negative shocks. Specifically, it captures negative shocks where the indicator function $I(\epsilon_{t-1} < 0)$ allows the model to increase the conditional variance more when a negative shock occurs (NYU Stern Volatility Lab, n.d.).

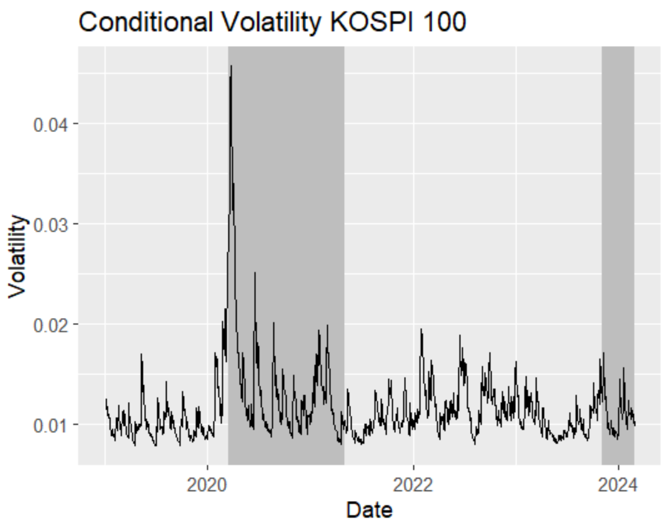


*Figure 3: Conditional Volatility. KOSPI 100, ban period highlighted.*

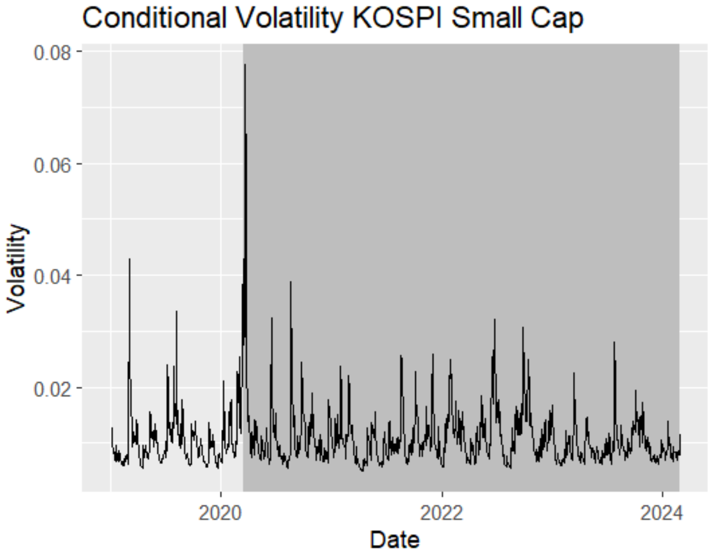


*Figure 4: Conditional Volatility. KOSPI Small Cap, ban period highlighted.*

When fitting the GARCH-models, we have chosen to apply the Student's t-distribution, instead of a normal distribution, due to the heavy tails that we have demonstrated exists in our data. Student's t-Distribution resembles the normal distribution in shape, but has heavier tails, which means that this is prone to producing values that fall far from its mean (Weisstein, n.d.).

### 5.7 Mann-Whitney U Test

To continue our analysis, we segmented our data into three different periods; pre-ban, during-ban, and post-ban. Our next step in the analysis were to conduct a test to see if the volatility of the KOSPI 100 and KOSPI Small Cap increased significantly during the period when the short-sale ban was implemented. To conduct our analysis we used the Mann-Whitney U test to test if the median volatility changed between the periods. The Mann-Whitney U test, also known as the Wilcoxon Rank Sum Test, is given by:

$$U_1 = n_1 n_2 + \frac{n_2(n_2+1)}{2} - R_2;\ U_2 = n_1 n_2 + \frac{n_1(n_1+1)}{2} - R_1 \quad (9)$$

Where $U_1$ and $U_2$ are the U statistics for each sample, $n_1$ and $n_2$ are the sample sizes of the two groups, and $R_1$ and $R_2$ are the rank sums of the two groups (Real Statistics Using Excel, n.d.).

The null hypothesis of the test is that the volatility of the two periods tested are equal. Thus the alternative hypothesis of the test is that the volatility increases. The reasoning behind choosing this specific model is that the model does not assume that the data follows a normal distribution, which we have shown that our data does not follow due to fat tails in the returns.

### 5.8 Results from Econometric Models

In table 6 we have provided the results from our testing based on the GARCH-model as well and the rolling standard deviation which we used as a benchmark for the volatility of the KOSPI 100 and KOSPI Small Cap. As we can see from the table, the p-values related to KOSPI 100 are extremely low, indicating that the volatility is significantly higher during the short-sale ban compared to the periods pre-ban and post-ban. However, when we applied the same testing for the KOSPI Small Cap Index, we were unable to find evidence of a statistically significant difference between the given periods. From table 6, we see that the given p-values from the tests performed on the KOSPI Small Cap Index are both above 0.05. Hence, we should be careful when comparing the Small Cap Index towards the KOSPI 100, due to the large differences between the indices, such as liquidity of the underlying stocks, as well as overall composition. However, our control group tells us that the large cap market (KOSPI 100) seem to be at least to some degree affected by the implementation of the restrictions.

*Table 6: Mann-Whitney U Test Results.*

| Model Specification | U-Statistic | P-value |
|---|---|---|
| Pre-ban vs during-ban GJR-GARCH for the KOSPI 100 | 64403 | <2.2e-16 |
| Post-ban vs during-ban GJR-GARCH for the KOSPI 100 | 142964 | <2.2e-16 |
| Pre-ban vs during-ban Realized volatility for the KOSPI 100 | 67023 | <2.2e-16 |
| Post-ban vs during-ban Realized volatility for the KOSPI 100 | 155835 | <2.2e-16 |
| Pre-ban vs during-ban GJR-GARCH for the KOSPI Small Cap | 43335 | 0.1543 |
| Post-ban vs during-ban GJR-GARCH for the KOSPI Small Cap | 98090 | 0.4839 |

These findings are very interesting, and consistent with the previously presented paper from Centre for Economic Policy Research (2020), where they provided empirical evidence showing a reduction in the relative spreads of stocks included in the high spread group (i.e: Small Cap) during the ban, leading to an improved liquidity as a result. This, due to the fact that the ban selectively removes informed traders who move from the bid-side to providing liquidity on the ask-side (Fohlin, Lu, & Zhou, 2023; Barardehi, Ruchti, Bird, & Karolyi, 2023).

## Chapter 6: Conclusion and Recommendations

### 6.1 Summary of Findings

Our purpose with this thesis was to examine the impacts of short-selling bans on the Korean stock market. Specifically, we were interested in examining the impacts and whether regulators actions yielded the intended results. As we have presented from the literature, imposing the above mentioned regulations sets a constraint which over time weakens the market sentiment. Our findings indicate that the intended result of policymakers were not present as we see an overall increase in volatility of the market during after the ban is implemented.

We also recognize that exogenous factors such as interest rate and economic policy can also aid in increasingly higher valuations overall. In line with the literature on the subject, constraining short sellers from opening short positions contributed to reduced market liquidity, a weakened investor sentiment as well as reduced market efficiency. Additionally, we also find the implementation of a ban also yields some unintended and possibly harmful consequences that for the market in the long run. In sum, we argue that these consequences make for a reduced market integrity.

### 6.2 Recommendations for Future Research

Further research should address the areas where our analyses did not align with previous studies. It would be valuable to see if similar results are obtained by conducting an analysis on a different market. Moreover, we believe one of our biggest limitations was the selected duration of our different periods tested. It would be interesting to see if another study conducted later could give different results than us. Furthermore, we believe further research should be conducted on the effects on liquidity, specifically in the bid-ask spread and its development over the different periods. Initially, this was something we were interested in examining, however, due to our limited Bloomberg license we were not able to fetch the required data to study these changes.

Based on price discovery theory, the absence of short-sellers is likely to widen the gap between the theoretical fair value and the market price over time. This divergence can lead to inflated market prices, potentially resulting in the formation of a bubble. The lack of short-selling eliminates a key mechanism for incorporating negative information into asset prices, thereby skewing valuations upwards. Consequently, this imbalance can distort market efficiency and heighten the risk of abrupt corrections. We believe this is an interesting aspect, which should be studied further.

We are aware that we could have built the model into train-and test models, meaning that we would let the models calculate the observed volatility for some part of the data. This would allow us to compute a test model on the remaining data and test this towards the benchmark volatility to capture which model predicted the volatility in the best way. We chose not to do this because of the nature of our study and the parameters of this thesis, further, our goal was to perform a time-series analysis to find out if the volatility changed significantly between the different periods.

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# 8: Appendices

## 8.1 Definitions

In this section, we will elaborate on some key concepts, which are fundamental to understanding key market functions discussed in our thesis.

*Short-selling:*

Short-selling, often referred to as “shorting”, is a trading strategy used in financial markets. In a covered short, an investor sells borrowed securities they do not currently own, with the expectation that the price of these securities will decrease in the future. This strategy allows investors to profit from the decline in a security's price by buying this back at a lower price and returning them to the borrower. Furthermore, the process of short-selling involves borrowing a security from a broker and selling it on the open market at its current price. The result is that short sales increase the supply of stock on the market by the amount of the outstanding short position (Miller, 1977). Later, if the price of the security falls as the investor anticipates, they can buy back the same number of shares at the lower price, return the shares to the lender (the broker), and pocket the difference as profit. This way the investor has essentially profited from a decline in the stock price. However, if the security price rises instead of falling, the short-seller will incur a loss, as they will have to buy back the shares at a higher price than they sold them for.

Since there is theoretically no upper limit on how high the stock price can go, the investor faces the risk of potentially unlimited losses. In reality, one would close the position quickly in case of a loss. However, this makes the strategy particularly risky compared to traditional investing, where losses are limited to the initial investment. One common reason for short-selling is to hedge against the downside risk of a long position in the same security or in a related one. Traders might also short-sell as part of a more complex trading strategy involving derivatives such as options or futures.

*Naked short:*

A naked short is a type of short-selling strategy where the investor sells shares without first ensuring that they can borrow the shares (Corporate Finance Institute, n.d.). This strategy is controversial, as the investor is essentially selling shares that they neither own nor have confirmed can be borrowed. This strategy is considered more risky than traditional (covered) short-selling because it can potentially lead to situations where the shares cannot be sourced to fulfill the delivery requirements, leading to "failures to deliver." This can magnify the downward pressure on the price of the stock being shorted, as it introduces an additional supply of shares that does not exist.

Due to the risks and potential for market manipulation associated with naked shorting, many financial authorities have strict rules and restrictions against this practice. In some markets, naked shorting is illegal or only allowed under certain conditions. The rationale behind these regulations is to maintain fair and orderly markets, preventing practices that could lead to undue volatility or harm to investors (Corporate Finance Institute, n.d.).

*Options & other derivatives*

According to Hull (2019), an option is a type of financial derivative, meaning a product in which its price *derives* from another financial asset, such as a stock. Moreover, the option gives the holder *the right, but not the obligation,* to buy or sell the underlying asset. Options are usually traded and applied to hedge against risk, speculate on the asset's price or by arbitrageurs. The main types of options are put (sell) or call (buy), and you can either go long (buy) or write (sell) these types of options. By purchasing a put one can essentially replicate a short position on the underlying asset, as the holder will profit on a decline in prices. Furthermore, a credit default swap (also known as a CDS), is a type of derivative where the underlying asset is the debt of a counterparty (CFA Institute, n.d.).

*Price discovery theory:*

Price discovery is a fundamental concept in economics and financial markets, referring to the process through which the price of an asset is determined through interactions between buyers and sellers. Each trade reflects the participants' collective view on what the asset's current value is, given all available information. As new information becomes available, participants may adjust their valuations, leading to changes in buying and selling behavior, which in turn affects the asset's price. This dynamic process ensures that prices remain a real-time reflection of all known information about the asset. The efficiency of price discovery can be influenced by various factors, including market liquidity, transparency, and the presence of asymmetric information among participants. In highly liquid and transparent markets, price discovery tends to be more efficient, as trades are executed quickly and information is disseminated widely. Conversely, in markets where information is not equally available to all participants or where trading is thin, price discovery can be hampered, leading to prices that may not accurately reflect an asset's true value (IG Analyst, 2019).

*Bid-ask spread:*

The bid-ask spread is a fundamental concept in the financial markets, reflecting the difference between the highest price a buyer is willing to pay for an asset (the bid) and the lowest price a seller is willing to accept (the ask). This spread is a key indicator of the liquidity and volatility of the asset; a narrow spread typically indicates a highly liquid market with a large number of buyers and sellers, which means the asset can be easily traded. Conversely, a wider spread suggests lower liquidity, higher volatility, and potentially higher trading costs for investors. Furthermore, the bid-ask spread is important for traders and investors to consider as it directly impacts the execution price of trades. When you buy an asset, you pay the ask price; when you sell, you receive the bid price. The spread, therefore, represents a key transaction cost of trading that asset, in addition to any additional broker fees or commissions (Corporate Finance Institute, n.d.).

## 8.1 Tables & Figures

*Table 1: Timeline of events.*

| Effective date | Announcement date | Event |
|---|---|---|
| 16.03.2020 | 13.03.2020 | Banned across all indexes |
| 03.05.2021 | 02.05.2021 | Lifted for KOSPI200 and KOSDAQ150 |
| 06.11.2023 | 05.11.2023 | Banned across all indexes until June 2024 |

*Table 2: Complete descriptive statistics.*

| Descriptive statistics | KOSPI 100 | KOSPI Small cap |
|---|---|---|
| Mean return | 0.0002615 | 0.000176 |
| Standard deviation | 0.0124587 | 0.012739 |
| Skewness | 0.053739 | -1.77256 |
| Kurtosis | 5.085545 | 15.10972 |

*Table 3. Descriptive statistics for KOSPI 100 Pre-ban, during-ban, post-ban.*

| Descriptive statistics for KOSPI 100 | Pre-ban | During Ban | Post-ban |
|---|---|---|---|
| Mean return | -0.000133 | 0.001930 | -0.000245 |
| Standard deviation | 0.0105925 | 0.0172176 | 0.010748 |
| Skewness | -0.85713 | 0.06689 | 0.09258 |
| Kurtosis | 2.096 | 4.78 | 0.712 |

*Table 4. Tests to determine the use of GARCH approach.*

| Tests to determine the use of GARCH approach KOSPI 100 | Test value | P-value |
|---|---|---|
| Shapiro-Wilk test | 0.95368 | <2.2e-16 |
| Ljung-Box test for returns | 19.241 | 0.03731 |
| Ljung-Box test for squared returns | 1163.6 | <2.2e-16 |
| ARCH-LM test | 420.37 | <2.2e-16 |
| **Tests to determine the use of GARCH approach KOSPI Small Cap** | **Test value** | **P-value** |
| Shapiro-Wilk test | 0.88079 | <2.2e-16 |
| Ljung-Box test for returns | 47.725 | 6.968e-07 |
| Ljung-Box test for squared returns | 508.88 | <2.2e-16 |
| ARCH-LM test | 21.968 | 0.000531 |

*Table 5: Goodness of fit test.*

| Model | MSE | MAE |
|---|---|---|
| Standard GARCH | 0.00029785 | 0.0137450 |
| **GJR-GARCH** | **0.00029762** | **0.0136778** |
| EGARCH | 0.00029913 | 0.0136915 |

*Table 6: Mann-Whitney U Test Results.*

| Model Specification | U Statistic | P-value |
|---|---|---|
| Pre-ban vs during-ban GJR-GARCH for the KOSPI 100 | 64403 | <2.2e-16 |
| Post-ban vs during-ban GJR-GARCH for the KOSPI 100 | 142964 | <2.2e-16 |
| Pre-ban vs during-ban Realized volatility for the KOSPI 100 | 67023 | <2.2e-16 |
| Post-ban vs during-ban Realized volatility for the KOSPI 100 | 155835 | <2.2e-16 |
| Pre-ban vs during-ban GJR-GARCH for the KOSPI Small Cap | 43335 | 0.1543 |
| Post-ban vs during-ban GJR-GARCH for the KOSPI Small Cap | 98090 | 0.4839 |

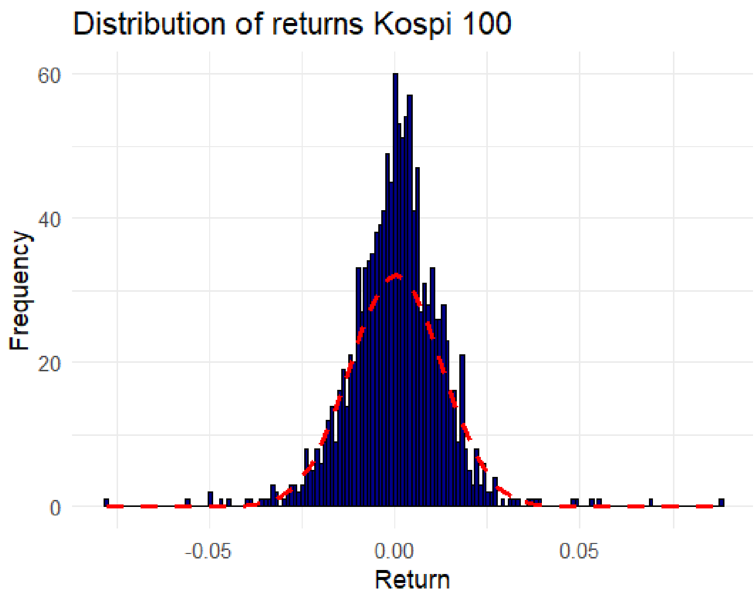


*Figure 1: Distribution of returns for KOSPI 100 Index.*

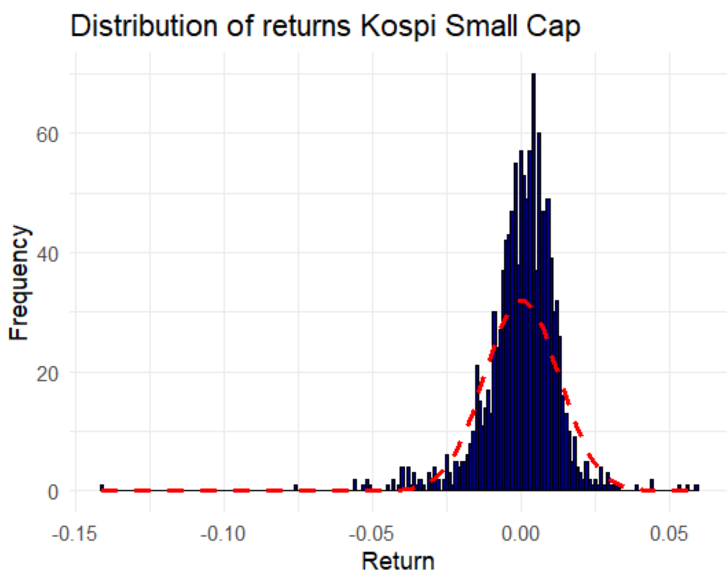


*Figure 2: Distribution of returns for KOSPI Small Cap Index.*

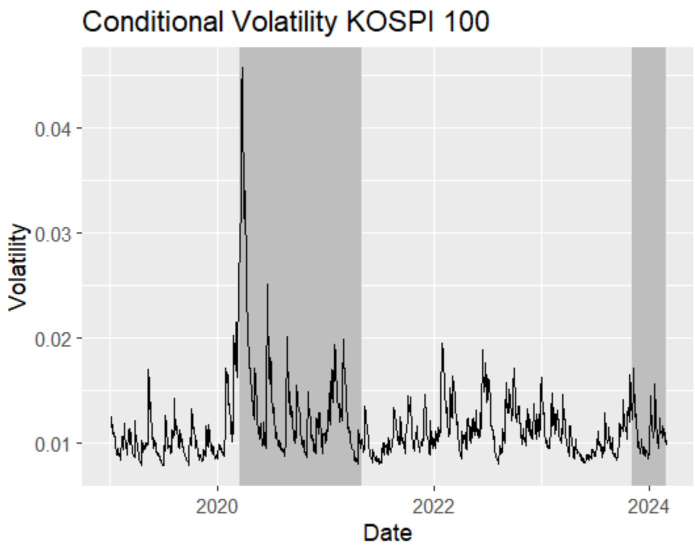


*Figure 3: Conditional Volatility. KOSPI 100, ban period highlighted.*

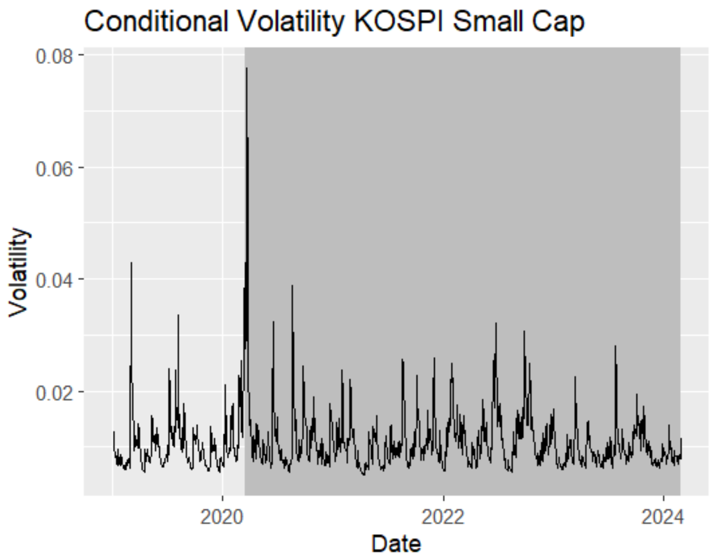


*Figure 4: Conditional Volatility. KOSPI Small Cap, ban period highlighted.*