Unveiling Market Seasonality

The Day-of-the-Week Effect on the Swedish Stock Market Across Different Market Conditions

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Abstract:

This study explores the day-of-the-week effect on the Swedish stock market between 2014 and 2024. The day-of-the-week effect, a phenomenon where stock returns differ predictably depending on the weekday, poses a challenge to the Efficient Market Hypothesis. Our research examines variations in this effect across different market capitalizations and timeframes defined by the COVID-19 pandemic. The results reveal a pronounced day-of-the-week effect within Sweden's small- and mid-capitalization stocks. Further, our findings suggest that Friday returns are significantly higher than other days of the week for small- and mid-capitalization stocks, along with varying results for the different subsamples, indicating that market efficiency may fluctuate based on economic conditions and specific market capitalizations.

Keywords:

Day-of-the-week effect, Size Effect, Volatility Clustering, Efficient Market Hypothesis, Anomalies

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I. Introduction

The day-of-the-week effect states that stock returns exhibit patterns that vary across different trading weekdays. Such seasonality challenges established theories in financial economics, notably the Efficient Market Hypothesis (EMH). As outlined by Fama (1965), the EMH asserts that asset prices fully integrate all available information, theoretically eliminating the possibility of consistently outperforming the market through stock selection or timing. Fama argues that only unforeseen news can influence stock prices since all known public and private information is already reflected in the stock price. Contrary to this theory, research has documented notable differences in stock returns across different days of the week in various financial markets, challenging the notion (Claesson, (1987); Cinko, Avci, Aybars, and Öner, (2015); Cross, (1971); French, (1980); Guidi, (2010); Rogalski, (1984); Smirlock and Starks, (1986); Gibbons and Hess, (1981)).

Studying the day-of-the-week effect in the Swedish stock market can provide valuable insights into market anomalies, investor behavior, and investment strategies. Insights that could result in enhanced portfolio performance, a better understanding of market efficiency, and informed regulatory measures to ensure fair and transparent markets. Additionally, it could contribute to advancing academic research in finance and provide knowledge for investors, financial analysts, policymakers, and regulatory authorities. Our research investigates whether a day-of-the-week effect has been present in the Swedish stock market from 2014 to 2024. It aims to understand to what extent the day-of-the-week effect influences stock returns and how these effects are moderated by stock size and the COVID-19 pandemic.

Cross (1971) examined the S&P 500 stock returns across weekdays from 1953 to 1970, emphasizing the returns observed on Mondays and Fridays. The study revealed significant price fluctuations on these days compared to other weekdays, suggesting distinct market behaviors at the start and end of the trading week. Building on this research, Gibbons and Hess (1981) extended the investigation into the day-of-the-week effect within the U.S. stock market. Utilizing daily observations from both the S&P 500 and the Dow Jones 30 industrials from 1962 to 1978, their study highlighted a persistent negative return on Mondays. Moreover, researchers have examined the day-of-the-week effect by investigating its relationship with company size. Abraham and Ikenberry (1994) released a study on the weekend effect, specifically examining the interplay between Friday and Monday. Their findings indicated that the impact of this effect is more pronounced in small- and mid-capitalization stocks.

Claesson (1987) conducted an extensive study on the Swedish stock market regarding the day-of-the-week effect, analyzing the Stockholm market between 1978 and 1984. Claesson's findings show that the range of variation between the daily returns is 0,25 percentage units. The findings further showcased that for six of the seven years, Tuesdays had the lowest stock return, with five of them possessing a negative average return. The day with the largest return for three years was Friday, Monday for two years, and one year for Wednesday and Thursday. The average daily returns for all days of the week was 0,13%, the highest being Mondays and Fridays at 0,2%, followed by Wednesdays and Thursdays at 0,12%, and Tuesdays having a slightly negative return, suggesting that the market was ineffective. Claesson states that an investor has the theoretical opportunity to create arbitrage, yet questions if it has any practical implications. Furthermore, Claesson states that the standard deviation does not vary much between the days of the week, the largest being Mondays, which slightly declines day for day during the rest of the week. A reason suggested for the effect is that a seller always loses two days of rent if the transaction is placed on a Friday, compared to other days of the week. Hence, the seller could request a higher share

price on a Friday, meaning the return is greater than other days of the week. Consequently, the Monday return is expected to be negative as the price reverts to normal. Practically, Claesson questions whether this logic holds, as the Monday return was the second largest in the sample.

Apart from Claesson's suggested two-day rent premium, the day-of-the-week effect in stock markets may arise from various factors. Michaely, Rubin, and Vedrashko (2016) proposed that companies tend to disclose positive news during the week and delay bad news until the weekend, resulting in a declining Monday price. Groth, Leweillen, Schlarbaum, and Lease (1979) state that investors do not have much time during the week to analyze stocks; hence, they take their stockbroker's suggestions to buy during the week. However, when the investors have time on weekends, they may be more inclined to do their own research and sell more, decreasing the Monday price. According to behavioral finance literature, investors feel pessimistic on Mondays, the first day of the trading week. In contrast, they feel optimistic during Fridays, the last day of the trading week. Hence, stock prices tend to fall on Mondays and rise on Fridays (Lyroudi, Dasilas, Patev, and Kanaryan, 2004).

Behavioral finance delves into the impact of psychological biases and emotional reactions on investors' decision-making, often leading to market anomalies. Slovic (1972) highlighted how biases can divert decisions from rational analysis, setting the stage for a range of non-optimal financial behaviors. Shefrin and Statman (1985) further explored this using behavioral theories to explain the disposition effect, where investors tend to sell winning stocks prematurely while clinging to losing ones due to regret aversion and loss aversion (Kahneman and Tversky, 1979). These biases prevent investors from cutting losses and realizing gains efficiently. Furthermore, concepts such as herd behavior illuminate how investors might follow the majority without independent analysis, driven by a fear of deviating from group norms (Lux, 1995). These behavioral biases, combined with physiological reactions to perceived financial threats or opportunities, underscore how personal perceptions can influence financial behaviors, contributing to, for instance, the day-of-the-week effect.

Findings also remain inconclusive with respect to stock market anomalies, aligning with the EMH in such cases. Apolinario, Caro, Sales, and Santana (2006) analyzed this effect across major European stock markets from 1997 to 2004, concluding that there was no abnormal behavior in the returns of these markets. Similarly, Puja (2010) investigated the presence of the day-of-the-week effect in the S&P 500 from January 1st, 1990, to November 30th, 2004, and found the results insignificant. Supporting the notion of market efficiency in the U.S., Gonzalez-Perez and Guerro (2013) found no evidence of the day-of-the-week effect in the S&P 500 data spanning from 2004 to 2011. Concluding that abnormal returns are unlikely without additional risk, as there was no consistent seasonal pattern. Likewise, a study by Carlucci, Junior, and Lima (2013) on the primary stock exchanges in Canada and the U.S. from 2002 to 2012 corroborated these findings, indicating an absence of the day-of-the-week effect.

Other researchers propose that the day-of-the-week effect was historically significant, yet suggesting that it has declined over time as markets have become more efficient. For instance, Kamara (1997) examined the Monday effect over 31 years from 1962 to 1993, focusing on the daily returns of the S&P 500 and a small-capitalization stock index on the New York Stock Exchange. The study revealed a consistent Monday effect in small-capitalization stocks. However, abnormal Monday returns weakened as the study period concluded. Furthermore, Yamori and Kurihara (2004) discovered that the day-of-the-week effect was present in the 1980s for certain currencies. However, for the 1990s, their research showed that the day-of-the-week effect had vanished for almost all currencies, indicating a more efficient market forming.

Xiao (2016) incorporated subsamples to examine the influence of economic recession or expansion based on the specific period on the day-of-the-week effect. The study investigated the US stock market based on daily observations from the Russell 3000 index between 2000 and 2015. Chusanachoti and Kamath (2002) analyzed the Thai stock price index, focusing on two distinct periods: 1980-1989 and 1990-1998. Their research revealed that the day-of-the-week effect was evident during the 1980s but had completely vanished by the 1990s. Additionally, Högholm and Knif (2009) provide evidence from the Finnish stock market, covering April 2nd, 1993, and June 30th, 2006. The result is documented to differ between the periods: pre-euro and post-euro. Before implementing the euro, the market returns were clean from weekly patterns, while after implementing the new currency, there was an asymmetry in the returns across weekdays.

As in previous studies, our paper investigates whether the effect remains consistent across periods and events. Hence, the data is divided into three subsamples: Pre-, During-, and Post-COVID-19. Additionally, similar to Abraham and Ikenberry (1994), respective stock sizes are grouped to determine if there is a size effect, as previous research suggests that small-capitalization stocks are less efficient than large-capitalization stocks (Brooks 2008). Hence, the data is divided into small-, mid-, and large-capitalization stocks, a novel approach within Swedish research. Moreover, this paper explores the importance of trading volume in relation to the day-of-the-week effect, an aspect previously unexplored in the context of the Swedish market examining the day-of-the-week effect. The scope has been limited to the Swedish stock market from 2014 to 2024, creating opportunities for future research in new markets and timeframes to compare and discuss similarities and differences with the results found in this paper.

Our thesis explores the application of Ordinary Least Squares (OLS) regression, a frequently used econometric methodology in literature studies. It incorporates several dummy variables tailored to the data frequency. When analyzing the day-of-the-week effect on daily data, a separate dummy variable for each weekday is typically included (French, 1980; Gibbons and Hess, 1981; Smirlock and Starks, 1986; Berument and Kıymaz, 2001). Additionally, our research employs the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, a common method to assess the persistence of this phenomenon (Berument and Kiymaz 2001; Guidi 2010). This approach enables us to capture the volatility clustering often observed in financial time series data, providing a more nuanced understanding of market behaviors. Moreover, to investigate the size effect within the data, we utilize a t-test. This statistical test allows us to determine whether the mean returns differ significantly between size capitalizations of stocks. Lastly, a Sharpe ratio analysis covers the risk-adjusted returns (Sharpe, 1966). This model facilitates a more rigorous evaluation of investment performance by accounting for risk, offering a nuanced understanding of returns relative to the associated volatility.

The remainder of this paper is organized as follows. Section II covers data and key variables. Section III discusses the methodology. Section IV presents the results, Section V presents the discussion, and Section VI concludes.

II. Data

A. Data Sources and Sample Selection

We obtain data on closing prices for small-, mid-, and large-capitalization stocks from Nasdaq Stockholm, the primary data source for Stockholm market statistics. It is regulated and governed by the Swedish Securities Market Act (lag (2007:528) om värdepappersmarknaden) and subject to supervision by the Swedish Financial Supervisory

Authority (Sw. Finansinspektionen) (Nasdaq, 2021). The data includes the daily closing values that are gathered from the OMX Stockholm Small Capitalization PI (OMXSSCPI) index, OMX Stockholm Mid Capitalization PI (OMXSMCPI) index, and OMX Stockholm Large Capitalization PI (OMXSLCPI). It should be noted that a shortcoming with the data for our purposes is that the companies in each index are associated with a single location, in this case, Stockholm. Yet, several of the large-capitalization firms operate out of multiple offices. Ideally, we would only like to analyze the Stockholm office.

Similar to the approach used by Claesson (1987), we employ data scraping techniques to remove non-bank days and dates represented as "NA", reducing the dataset to 2511 observations per index. The data is filtered by weekday, with Monday represented as 1, Tuesday represented as 2, etc. The daily return is calculated for respective indexes and illustrated over time in Figure 1. The timeframe of the sampled data ranges from January 07th, 2014, to January 12th, 2024.

For the baseline of our analysis, we restrict the sample to only the small-, mid-, and large-capitalization indexes. Drawing inspiration from Xiao (2016), we refine our approach in subsequent analyses by dividing the dataset into three distinct periods to assess the persistence of the results through different phases of the COVID-19 pandemic. The subsamples are labeled as follows: Subsample 1 - Pre-COVID-19, spanning from the start of our dataset on January 7th, 2014, to the announcement of the first COVID-19 case in Sweden by the Swedish Public Health Agency on January 31st, 2020 (Folkhälsomyndigheten, 2023). Subsample 2 - During-COVID-19, covers the duration of the pandemic, ending on May 5th, 2023, when the WHO declared that COVID-19 was no longer an international threat (WHO, 2023). Subsample 3 - Post-COVID-19 extends from this point until the conclusion of the dataset on January 12th, 2024. The respective number of observations for each subsample are 1522, 816, and 173, introducing challenges due to the varied sample sizes.

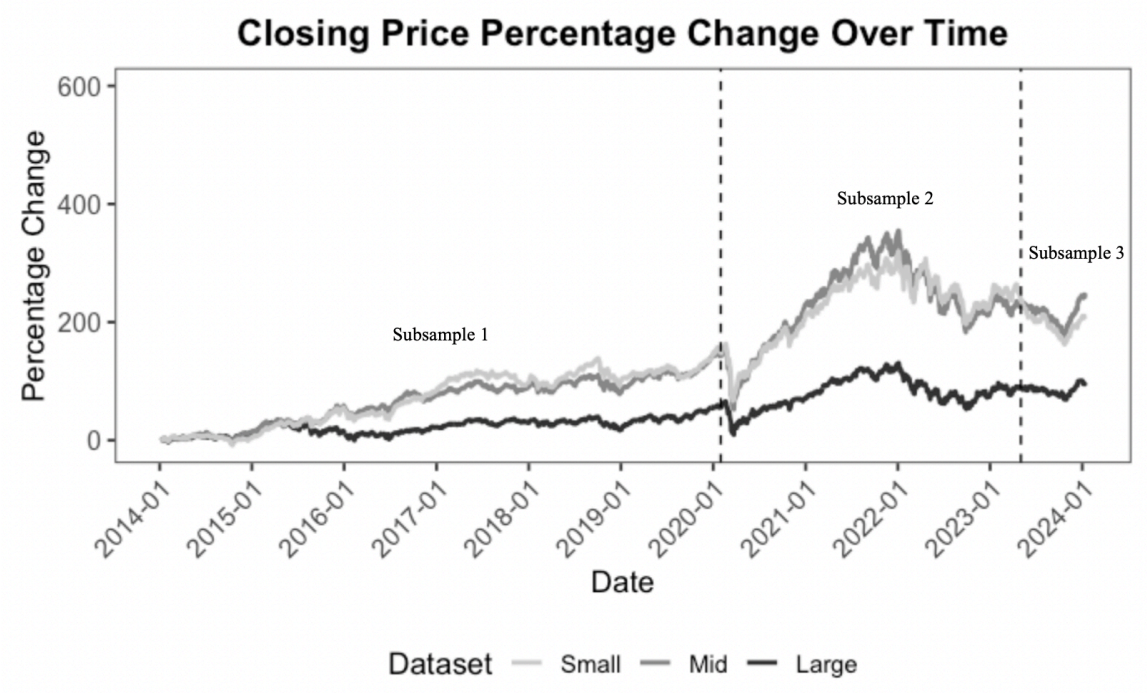


Figure 1: Figure 1 illustrates the percentage change in closing prices across all three indexes. The graph is charted over time and initiated on 2014-01-07. The x-axis represents the time horizon, and the y-axis shows the percentage change. Each index is normalized to start at zero, highlighting the relative performance of each capitalization size. Dashed lines delineate the full period into three subsamples. Subsample 1 spans from January 07th, 2014 to January 31st, 2020, subsample 2 covers

the February 1st, 2020 to May 05th, 2023, and subsample 3 spans from May 06th, 2023 to January 12th, 2024.

The percentage change in stock price calculates the daily returns for each stock size. The daily return for day *t* is calculated using Equation (1).

$$R_t = \left(\frac{P_t - P_{t-1}}{P_{t-1}}\right) * 100 \quad (1)$$

R_t denotes the daily return at day *t*, P_t represents the closing price at day *t*, and P_{t-1} denotes the closing price at day *t-1*. The excess return is calculated using Equation (2), where R_{ER} denotes the daily excess return and R_{rf} represents the daily risk-free rate.

$$R_{ER} = R_t - R_{rf} \quad (2)$$

Data on the risk-free rate is sourced from three-month treasury bills (Svenska stadsskuldsväxlar (SE SSVX) 3 månader), provided by the Swedish Central Bank (Riksbank, 2024). To compute the daily risk-free rate, the annual rate is divided by 252, representing the approximate number of bank days per year. This daily risk-free rate is aligned with the dates from the respective datasets and subtracted from the daily return percentages to adjust for the risk-free return component.

To study the impact of trading volume on the day-of-the-week effect, the daily trading volume for each index, OMXSSCPI, OMXSMCPI, and OMXSLCPI, was gathered for the same period, January 07th, 2014 to January 12th, 2024. Due to the non-public nature of the volume data for these indexes, it was obtained through a contact at Nasdaq Stockholm. Data scraping was used to remove values denoted by "-" decreasing each dataset to 2510 observations.

After combining the volume data with the datasets above, each consolidated dataset for the full-period and the respective subsamples include daily closing prices, excess returns, weekdays, and trading volumes for each index.

B. Descriptive Statistics

Perhaps the most striking finding from Table I is that contrary to the EMH, all capitalization sizes have a negative average return on Mondays, similar to Gibbons and Hess (1981) and the hypothesis suggested by Claesson (1987). Additionally, Fridays have the largest average return for small- and mid-capitalization stocks and the second-largest for large-capitalization stocks, aligning with Claesson's results. These patterns suggest potential regularities in stock returns linked to specific weekdays.

The daily average raw returns are 0,0504%, 0,0556%, and 0,0338% for small-, mid-, and large-capitalization stocks. Excess returns are slightly lower at 0,0497%, 0,0549%, and 0,0332% for the respective capitalization sizes. Surprisingly, the lowest daily average standard deviation is found in the small-capitalization index at 0,9982%, with the highest being 1,1550%, for large-capitalization firms. This does not coincide with typical theory, stating that small-capitalization firms tend to possess greater risk (Fama and French, 1992). Yet, in Table VI, the baseline variance is shown to be the highest for small-capitalization stocks, followed by mid-capitalization stocks and then large-capitalization stocks, which is consistent with the findings of Fama and French (1992).

Hence, this analysis indicates that while the daily standard deviation might suggest a

Table I

Table I presents the daily mean, standard deviation, minimum, maximum values, and the number of observations for each weekday, categorized by small-, mid-, and large- capitalization sizes. These statistics are detailed for both the raw returns in Section A and the excess returns in Section B. The weekdays are designated to show data specific to each day, while "All" compiles the results for the entire dataset across all capitalization sizes.

Descriptive Statistics

Weekday	Mean	SD	Min	Max	Obs.
Panel A: Raw Returns					
			Small-capitalization Stocks		
All	0,0504%	0,9982%	-12,2896%	4,9670%	2511
Monday	-0,0061%	1,2298%	-8,2106%	3,2634%	498
Tuesday	0,0814%	0,9292%	-2,9704%	4,9670%	513
Wednesday	0,0816%	0,8737%	-5,2573%	3,3853%	513
Thursday	-0,0293%	1,0457%	-12,2896%	3,1210%	499
Friday	0,1243%	0,8635%	-3,7413%	3,4571%	488
			Mid-capitalization Stocks		
All	0,0556%	1,0580%	-11,3118%	6,3985%	2511
Monday	-0,0205%	1,2565%	-6,9764%	4,2772%	498
Tuesday	0,0885%	1,0060%	-3,1060%	6,3985%	513
Wednesday	0,0694%	0,9721%	-4,5757%	4,6477%	513
Thursday	0,0087%	1,0875%	-11,3118%	3,0842%	499
Friday	0,1323%	0,9355%	-3,0760%	3,9844%	488
			Large-capitalization Stocks		
All	0,0338%	1,1550%	-11,1025%	7,3579%	2511
Monday	-0,0051%	1,2936%	-8,0254%	4,5944%	498
Tuesday	0,1087%	1,0867%	-2,8719%	7,3579%	513
Wednesday	0,0489%	1,0635%	-3,8670%	4,4207%	513
Thursday	-0,0440%	1,1976%	-11,1025%	4,3016%	499
Friday	0,0587%	1,1208%	-3,4378%	5,3727%	488
Panel B: Excess Returns					
			Small-capitalization Stocks		
All	0,0497%	0,9983%	-12,2890%	4,9676%	2511
Monday	-0,0067%	1,2300%	-8,2100%	3,2643%	498
Tuesday	0,0807%	0,9294%	-2,9696%	4,9676%	513
Wednesday	0,0810%	0,8742%	-5,2569%	3,3863%	513
Thursday	-0,0300%	1,0456%	-12,2890%	3,1227%	499
Friday	0,1236%	0,8638%	-3,7397%	3,4577%	488
			Mid-capitalization Stocks		
All	0,0549%	1,0580%	-11,3112%	6,3991%	2511
Monday	-0,0212%	1,2566%	-6,9758%	4,2778%	498
Tuesday	0,0878%	1,0062%	-3,1084%	6,3991%	513
Wednesday	0,0687%	0,9726%	-4,5751%	4,6482%	513
Thursday	0,0080%	1,0872%	-11,3112%	3,0683%	499
Friday	0,1317%	0,9353%	-3,0754%	3,9839%	488
			Large-capitalization Stocks		
All	0,0332%	1,1550%	-11,1019%	7,3585%	2511
Monday	-0,0058%	1,2935%	-8,0229%	4,5948%	498
Tuesday	0,1080%	1,0868%	-2,8713%	7,3585%	513
Wednesday	0,0481%	1,0637%	-3,8794%	4,4217%	513
Thursday	-0,0447%	1,1975%	-11,1019%	4,2906%	499
Friday	0,0580%	1,1207%	-3,4362%	5,3660%	488

different risk profile, the baseline variance confirms the established theory of higher risk in smaller firms. The lowest daily raw returns for each market size were observed on Thursday, March 12th, 2020, with declines of -12.28%, -11,31%, and -11,1% for small-, mid-, and large-capitalization stocks, making it one of the largest decreases in the Swedish stock market in history. Conversely, the highest daily returns in the dataset occurred on Tuesday, March 24th, 2020, just 12 days following the crash, with gains of 4,97%, 6,40%, and 7,36% for small-, mid-, and large-capitalization stocks. These abnormal returns could skew the results, potentially limiting the study.

For 1962-1993, it was suggested that there was a decline in the Monday effect for large-capitalization stocks due to heightened Monday investor trading (Kamara 1997). However, this was questioned in 2001, stating a reversal of the Monday effect decline post-1987 (Mehidian and Perry, 2001). This aligns with the findings in Table II, as the Monday effect seems to remain present. Moreover, coinciding with the research by Cross (1971), the average Monday and Friday returns tend to differ considerably. The difference in raw returns between Monday and Friday is 0,1304%, 0,1528%, and 0,0638% for the respective capitalization sizes. Although the difference is considerable, it is the second largest difference between two days of the week in the sample data. Instead, the largest difference is between Thursday and Friday, being 0,1536%, 0,1237%, and 0,1027% for small-, mid-, and large-capitalization stocks. The variation in the number of observations for each weekday arises since certain weekdays are more frequently designated as non-bank days. While this causes the sample sizes for each weekday to differ slightly, it is unlikely to impact the findings considerably.

C. Subsample Statistics

Table I shows that the full-period average returns are negative for Mondays. However, in Table II, the results vary across the subsamples. Specifically, in subsample 1 for small- and mid-capitalization stocks, and in subsamples 2 and 3 for large-capitalization stocks. Monday's returns are positive, challenging the consistency and predictability of Monday's performance. Furthermore, the standard deviation for Mondays is generally higher, suggesting more variable outcomes than other weekdays, coinciding with the findings of Claesson (1987). Table II consistently shows positive average returns on Fridays for all groups except large-capitalization stocks during COVID-19.

Tuesdays consistently show positive average returns across all subsamples and market sizes, diverging from Claesson's findings. Wednesday's returns are less consistent between the subsamples but generally positive across all indexes before and during the COVID-19 pandemic. In subsample 3, Wednesday's returns are negative for small- and mid-capitalization stocks but remain positive for large-capitalization stocks. Lastly, Thursdays are negative for all capitalization sizes during COVID-19, possibly due to the large crash on Thursday, 2020-03-12, potentially skewing the results as five of the remaining six subsamples have positive Thursdays.

D. Volume Statistics

Table III reveals that Friday's volume values are slightly lower than the remaining days of the week for the small-capitalization stocks across all columns. In contrast, Tuesdays, Wednesdays, and Thursdays show the largest averages in the dataset. The Friday mean value

Table II

Table II is an extension of Table I and presents the mean stock return for each weekday across all three subsamples to compare the daily return between weekdays and the size index. Moreover, Table II lists the standard deviation, minimum and maximum values, and the number of observations in the respective subsample and index.

Descriptive Statistics for the Subsamples

	Small-capitalization Stocks					Mid-capitalization Stocks					Large-capitalization Stocks				
	Subsample 1 (Pre)					**Subsample 1 (Pre)**					**Subsample 1 (Pre)**				
	Mean	SD	Min	Max	Obs.	Mean	SD	Min	Max	Obs.	Mean	SD	Min	Max	Obs.
All	0,00063965	0,00784839	−0,04760008	0,03931409	1522	0,0006202382	0,008076461	−0,05387691	0,03984443	1522	0,0003411788	0,009659155	−0,08025478	0,03714710	1522
Monday	0,00045615	0,00941146	−0,04760008	0,01864381	302	0,0002460259	0,009650526	−0,05387691	0,02399962	302	−0,0000780421	0,011010776	−0,08025478	0,03533354	302
Tuesday	0,00045098	0,00778019	−0,02419858	0,03931409	309	0,0007018700	0,007614291	−0,02943349	0,03241266	309	0,0005752403	0,009093501	−0,02485581	0,03714710	309
Wednesday	0,00077517	0,00728430	−0,03260613	0,02704310	309	0,0007502497	0,007512759	−0,02707017	0,03134082	309	0,0003223482	0,009111268	−0,03040391	0,03371036	309
Thursday	0,00009995	0,00761193	−0,03291627	0,03120981	304	0,0001943932	0,007575803	−0,02426691	0,02114951	304	−0,0000342139	0,009573153	−0,02911662	0,02909669	304
Friday	0,00143123	0,00691049	−0,02991476	0,02708620	298	0,0012144370	0,007858113	−0,02937452	0,03984443	298	0,0009258021	0,00942715	−0,02594737	0,03554520	298
	Subsample 2 (During)					**Subsample 2 (During)**					**Subsample 2 (During)**				
	Mean	SD	Min	Max	Obs.	Mean	SD	Min	Max	Obs.	Mean	SD	Min	Max	Obs.
All	0,000460729	0,01346864	−0,12289571	0,04967009	816	0,000468875	0,01428685	−0,113117590	0,063985260	816	0,0003380491	0,01481515	−0,11102494	0,07357883	816
Monday	−0,000654043	0,01699366	−0,08210590	0,03263697	162	−0,000884675	0,01728760	−0,069763920	0,042771790	162	0,0001153173	0,01682650	−0,05617366	0,04594401	162
Tuesday	0,001604811	0,01174261	−0,02970358	0,04967009	170	0,001321995	0,01327743	−0,031063300	0,063985260	170	0,0021434736	0,01351346	−0,02871850	0,07357883	170
Wednesday	0,001303572	0,01130091	−0,05257529	0,03385284	169	0,001083411	0,01310981	−0,045756710	0,046476560	169	0,0010094175	0,01339039	−0,03866937	0,04420713	169
Thursday	−0,001120307	0,01484501	−0,12289571	0,02807142	159	−0,000399795	0,01537221	−0,113117590	0,030358110	159	−0,0013175525	0,01582683	−0,11102494	0,04301609	159
Friday	0,001069982	0,01157674	−0,03741266	0,03457104	156	0,001164432	0,01179220	−0,030759790	0,036724190	156	−0,0004379777	0,01427142	−0,03437805	0,05372688	156
	Subsample 3 (Post)					**Subsample 3 (Post)**					**Subsample 3 (Post)**				
	Mean	SD	Min	Max	Obs.	Mean	SD	Min	Max	Obs.	Mean	SD	Min	Max	Obs.
All	−0,00048097	0,00696531	−0,02601542	0,020499888	173	0,000406142	0,009447535	−0,022605070	0,030623450	173	0,000314638	0,009040063	−0,02313211	0,03386746	173
Monday	−0,00183116	0,00733319	−0,02601542	0,016004356	34	−0,000978473	0,008082754	−0,016916970	0,015523740	34	0,000607173	0,005720798	−0,01582188	0,01260578	34
Tuesday	0,00015184	0,00797486	−0,01631794	0,020499888	34	0,000357483	0,011180677	−0,014216430	0,030623450	34	0,000457602	0,010803298	−0,01305839	0,03386746	34
Wednesday	−0,00116547	0,00570842	−0,02043877	0,009883498	35	−0,001678243	0,007482988	−0,017540080	0,010559240	35	0,000558883	0,007898125	−0,02313211	0,01303230	35
Thursday	0,00004054	0,00740573	−0,01375948	0,017039567	36	0,001330412	0,010783156	−0,017742060	0,030842170	36	0,000009435	0,010554468	−0,01895853	0,02942488	36
Friday	0,00038887	0,00631577	−0,01091678	0,010183443	34	0,003006465	0,008909240	−0,022605070	0,019243620	34	0,002315854	0,009389227	−0,01847502	0,02183039	34

of 180,931,899 shares transacted daily is 8,05% lower than the average of the remaining days of the business week (196,769,397). As the Friday volatility is also the lowest in the small-capitalization sample, it contradicts the research by Berument and Kiymaz (2003), who suggested that high volatility would be accompanied by low trading volume since liquidity traders are unwilling to trade in periods of high stock market volatility. For the mid- and large-capitalization stocks, Friday is no longer an outlier, being close to the aggregate average in both cases. Instead, Monday has the lowest average amount of transactions, 6,4% and 11,05% lower than the average of the remaining days of the business week (1,369,399,855 and 16,324,021,304) for the mid- and large-capitalization indexes. Additionally, for the mid-capitalization index, the results align with the findings of Berument and Kiymaz (2003), where Monday possesses the greatest volatility while having the lowest average trading volume.

Table III

Table III presents the volume statistics for each day of the week for the small-, mid-, and large-capitalization index on the Swedish stock market, along with the totals for the respective indexes. Volume is measured by the number of shares transacted each day. If A sells 100 shares to B, the volume is 100. The data includes the mean, standard deviation, min value, max value, and number of observations for each day of the week and the aggregated values for the respective index.

Volume Statistics

Weekday	Mean	SD	Min	Max	Obs.
			Small-capitalization Stocks		
All	193 690 257	126 587 744	25 218 007	2 218 035 812	2510
Monday	192 596 382	112 027 953	45 835 626	971 194 138	498
Tuesday	198 034 077	136 383 173	46 430 466	1 453 346 345	510
Wednesday	197 384 902	149 019 037	46 871 424	2 218 035 812	510
Thursday	199 062 227	130 164 227	37 336 406	1 012 855 811	502
Friday	180 931 899	96 961 654	25 218 007	773 552 549	490
			Mid-capitalization Stocks		
All	1 352 151 801	837 151 029	269 960 380	16 240 110 538	2510
Monday	1 281 312 454	1 007 550 878	316 329 535	16 240 110 538	498
Tuesday	1 361 439 994	780 806 176	396 892 230	5 820 937 447	510
Wednesday	1 385 442 834	830 124 122	357 005 391	8 848 861 982	510
Thursday	1 403 837 173	830 048 630	269 960 380	7 149 826 706	502
Friday	1 326 879 417	704 666 617	348 886 052	4 654 262 423	490
			Large-capitalization Stocks		
All	15 965 493 247	5 316 917 959	2 799 848 639	51 693 491 805	2510
Monday	14 519 852 416	4 947 242 322	4 782 953 555	42 560 572 110	498
Tuesday	16 102 644 608	5 212 182 249	4 894 372 211	51 693 491 805	510
Wednesday	16 318 974 749	5 257 906 672	5 691 830 101	47 730 015 364	510
Thursday	16 582 283 565	5 288 106 422	5 006 383 922	45 778 215 777	502
Friday	16 292 182 294	5 629 570 347	2 799 848 639	41 542 776 432	490

III. Methodology

A. OLS Regression

Following previous literature, the OLS regression is frequently used when analyzing the day-of-the-week effect. The model analyzes the relationship between a dependent

variable, i.e., the daily change in stock returns, and multiple independent variables, i.e., the days of the week. The model will regress daily stock returns on a set of dummy variables representing each day of the week, allowing us to estimate the average return for each weekday and test for statistically significant differences (Brooks 2008).

Equation (3) is the mathematical expression of the model used to estimate the average return for each day of the week.

$$R_t = \beta_1 D_{1t} + \beta_2 D_{2t} + \beta_3 D_{3t} + \beta_4 D_{4t} + \beta_5 D_{5t} + \varepsilon_t \quad (3)$$

Where R_t denotes the dependent variable, the stock index return on a day *t*. The model consists of five dummy variables D_{it}, each representing one day of the week ranging from Monday to Friday. Each dummy variable takes the value 1 if the examined day corresponds to the actual weekday at time *t*, and 0 otherwise. For instance, D_{1t} represents Monday at time *t* and D_{5t} represents Friday at time *t*. Lastly, the model is concluded with an error term ε_t, denoting the difference between the observed value and the regression's predicted value at time *t*.

When investigating time series, the residuals are likely to be correlated. We applied Newey West standard errors to our model to address the common issues of autocorrelation and heteroscedasticity in our data. Newey-West standard errors adjust for these characteristics by incorporating information about the correlation structure and allowing standard errors to vary. This provides more accurate estimates and ensures that the standard errors reflect the true variability of the coefficients (Newey and West, 1987).

The estimated coefficients β_i are interpreted as the average value of the dependent variable for each day, which in this context refers to the mean stock returns for each specific trading day of the week. To investigate whether or not the day-of-the-week effect exists in the sample, the null hypothesis states that the coefficients are equal to zero. The alternative hypothesis states that there is a significant difference between one or more of the coefficients from zero. This would imply that β_i for the investigated day is unique. As a result, if the probability value is less than the significance level (i.e., one, five, or ten percent), the null hypothesis is rejected, suggesting that the day-of-the-week effect is present in the sample.

B. Size Effect - Welch T-Test

The Welch t-test method investigates whether the differences in each mean are related to the size across stock indexes. Based on previous literature examining abnormalities in the stock market, Fama and French's (2008) method includes testing the mean difference. This model compares the small-, mid-, and large-capitalization stocks to investigate the mean across the same weekday in different samples. It is correctly done by comparing them separately, small to mid, small to large, and mid to large, for each weekday. The Welch test is a two-sided independent-samples t-test (i.e. unpaired t-test) assuming that the two sample variances are unequal. The aim is to use the model to determine if there are inconsistencies in the mean between the samples.

The null hypothesis in the Welch t-test states that the mean of the three independent samples should have no significant difference between the respective days of the week. This implies that if the probability value is less than the chosen significance level (i.e., one, five, or ten percent), the null hypothesis is rejected, implying that the means differ between samples (Welch 1947).

When examining the day-of-the-week effect, it is essential to include a size effect component in the analysis to account for the varying impacts of trading behavior, liquidities,

and volatilities across companies with different market capitalizations. Small-capitalization stocks, in particular, tend to exhibit higher volatility and lower liquidity compared to large-capitalization stocks, leading to more profound price movements in response to market activities (Fama and French, 1992). Such movements may not be evenly distributed throughout the week. Market dynamics, such as trading volumes and liquidity, often fluctuate due to periodic financial disclosures, macroeconomic announcements, or systematic market shifts, disproportionately impacting smaller firms. Additionally, investor behavior, which may differ between small-, mid-, and large-capitalization markets, can influence the day-of-the-week effect. Hence, incorporating the size effect allows us to refine our analysis of the day-of-the-week effect, providing a more detailed understanding of daily performance patterns across different market sizes. This approach facilitates our understanding of how small-, mid-, and large-capitalization stocks react differently to external factors and investor actions.

$$T = \frac{\bar{x}_i - \bar{x}_j}{\sqrt{(s_i^2 \div n_i) - (s_j^2 \div n_j)}} \tag{4}$$

Equation (4) presents the Welch t-test, which is used to investigate the presence of size effect across the days of the week between the different indexes. In the equation, $\bar{x}_i$ and $\bar{x}_j$ denote the means of the tested independent samples, s_i and s_j represent the respective standard deviation and, n_i and n_j are the number of observations.

C. Volatility Clustering - GARCH

The GARCH model predicts the volatility of returns on financial assets. It was first developed by Bollerslevin (1986), following the work on the ARCH (Autoregressive Conditional Heteroskedasticity) model by Engle (1982). The GARCH model covers volatility clustering, a phenomenon where a series of previous volatility affects the current volatility. High volatility series are followed by high volatility, and low volatility series are followed by low volatility, clustering periods based on their volatility. The null hypothesis for the model is that the data exhibits no volatility clustering.

The GARCH(1,1) model, which is one of the simplest forms of the GARCH model, can be represented by Equation (5) and (6):

Conditional mean equation:

$$R_t = \mu + \varepsilon_t \tag{5}$$

Where R_t denotes the return at time *t*, μ (mu) represents the constant term in the mean equation of the GARCH model. It can be interpreted as the average return of the series, assuming the mean equation only includes a constant and ε_t is the error term at time *t.*

Conditional Variance Equation of the GARCH Model:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{6}$$

Where σ_t^2 denotes the forecasted variance at time *t*, ω (Omega) is the constant term representing the baseline variance without any previous shocks or volatility clustering. Lower values suggest less inherent variance. ε_{t-1}^2 denotes the residual from the mean at time *t-1*. Additionally, α (alpha1) measures the reaction of the conditional variance to the squared residuals from the previous period. It captures the impact of the shock from the previous period on the current variance. A higher alpha indicates that recent shocks substantially affect current volatility, contributing to volatility clustering. β (beta1) measures the persistence of past variance in the current variance. A high beta, close to 1, suggests that volatilities are highly persistent over time, meaning that the effect of a volatility shock decreases slowly. Lastly, σ_{t-1}^2 denotes the variance from time *t-1*. The sum of α + β where α + β < 1 states the presence of volatility clustering. Values close to 1 indicate volatility clustering, while values close to 0 imply random volatility.

The Autoregressive (AR) part of the GARCH model captures the persistence of volatility over time by regressing the returns on their own lagged values over time. Conditional heteroscedasticity (CH) refers to the continuously changing variance over time. This implies that the residuals (the difference between the realized and predicted values) are not constant over time. In addition, the GARCH model includes a moving average, including the short-term effects on volatility. It covers how the variance of the current period's error term is influenced by the error terms from previous periods.

Identifying whether or not volatility clustering is present in the data is fundamental as it has considerable impacts on risk management. Since high volatility signals risk, many investors will adjust their strategies and risk assessments accordingly. This could involve changing the portfolio allocations, employing different financial instruments for hedging, or adjusting leverage, potentially affecting the day-of-the-week effect. To effectively utilize the GARCH model, the data must demonstrate stationarity, autocorrelation, and heteroscedasticity. Three statistical tests are employed to evaluate these properties: the Augmented Dickey-Fuller (ADF) test for stationarity, the Box-Ljung (BL) test for autocorrelation, and the Breusch-Pagan (BP) test for heteroscedasticity (Bollerslevin, 1986). The results, detailed in Appendixes A, B, and C, allow for rejecting the null hypothesis for each capitalization size, confirming the dataset's appropriateness for GARCH modeling.

D. Risk-Adjusted Values - Sharpe Ratio

Risk-adjusted values are generally more relevant to investors than expected returns as they account for reward and risk, allowing for better investment comparisons. For our analysis, this helps us identify which days of the week offer the best performance when considering both returns and volatility, leading to a more informed conclusion. The Sharpe ratio, a method used to compare risk-adjusted returns between investments, is presented in Equation (7).

$$SR = \frac{E(R_t - R_{rf})}{\sigma_t} \tag{7}$$

Roy (1952) was the first to propose the reward-to-risk ratio to determine the performance of an investment. Sharpe (1966) later introduced the Sharpe ratio, a measurement used to rate the performance of mutual funds concerning risk and return. Moreover, Bailey and Lopez de Prado (2012) state that the calculation of the Sharpe ratio has become one of the best-known performance evaluation metrics.

The most optimal investment has the highest Sharpe ratio, which provides the most considerable reward per unit of volatility of any investment available. However, this

statement only applies to the assumption that investors are mean-return optimizers. If other factors and preferences are considered, such as investment goals, time horizon, and risk tolerance, the Sharpe ratio is no longer sufficient for evaluating performance (Berk and DeMarzo, 2019). For our paper, the average Sharpe ratio is expected to be the same for each day of the week. Hence, significant differences between the weekdays suggest a day-of-the-week effect.

IV. Results

Section IV is divided into two parts: the full-period results are in part A, and the subsample results are in part B.

A.1 The Presence of the Day-of-the-Week Effect on the Swedish Stock Market

Table IV presents significant findings for small-, mid-, and large-capitalization stocks. Specifically, Tuesday's returns for these stock categories are significantly higher than on other weekdays, with significance levels at 10%, 10%, and 5%, respectively. Additionally, small-capitalization stocks show a positive return estimate on Wednesdays at a 5% significance level. These patterns persist in both raw and excess returns, though the latter's significance is slightly diminished due to the risk-free rate adjustment. The most notable results occur on Friday for small- and mid-capitalization stocks, where the null hypothesis is rejected at a 99% confidence level, coinciding with the findings of Claesson (1987). However, compared to Claesson's work, which suggested that Tuesdays generally yielded the lowest returns, Table IV shows the opposite effect. This is increasingly evident for large-capitalization stocks. Moreover, the results align with the findings of Abraham and Ikenberry (1994), suggesting that the day-of-the-week effect is stronger for small- and mid-capitalization stocks.

Despite the insignificance of Monday returns across all capitalization sizes, the estimates are negative, aligning with Gibbons and Hess (1981). Similar to Claesson (1987), our result suggests a day-of-the-week effect still exists in the Swedish stock market. However, there has been a shift in which days significantly deviate from the mean return. Friday's returns remain the highest, albeit not at a significant level for large-capitalization stocks. Tuesdays, the lowest previous performer, show no such significance anymore and has shifted to a significantly positive average for the large-capitalization index (5% significance level). The Monday average return, theoretically expected by Claesson (1987) to be the lowest, aligns somewhat with the findings in Table IV, although it lacks statistical significance. This contrasts with Claesson's results, where Monday returns were the second highest.

A.2 Implications of Capitalization Size on the Day-of-the-Week Effect

The results in Table V indicate a size effect in the sample data between small- and large-capitalization stocks and between mid- and large-capitalization stocks. However, for small- and mid-capitalization stocks, the data suggests no significant size effect. When comparing small- and large-capitalization stocks, the null hypothesis that Friday returns are equal can be rejected at a 10% significance level. The mean difference between the paired observations is 0,0656464%, supporting the theory of inconsistencies across capitalization sizes. The size effect is more profound between mid- and large-capitalization stocks. On Thursdays, the mean return difference is 0,0527%, rejecting the null hypothesis at a 5% significance level. On Fridays, the mean return difference is 0,07366%, leading to a rejection of the null hypothesis at a 1% significance level. Hence, Table V suggests that the size effect

Table IV

Table IV presents the output for raw returns gathered from Nasdaq Stockholm. The excess returns are calculated by subtracting the daily risk-free rate, gathered from The Swedish Central Bank, from the daily raw returns. Each data sample of small-, mid-, and large-capitalization stocks is run by an OLS regression, investigating if the estimated mean return for each weekday differs significantly from zero. An independent dummy variable represents each day of the week. "Estimate" is the model's prediction of that specific weekday's contribution to the stock price change (i.e. the dependent variable). Furthermore, Table IV provides a standard error ("Std. Error") and a probability value denoted as "Pr(>|t|)". *, **, and *** denote the statistical significance of the output data at a 10%, 5%, or 1% level.

OLS Regression Results

Panel A: Raw Returns

	Small-capitalization Stocks			Mid-capitalization Stocks			Large-capitalization Stocks		
	Estimate	Std. Error	Pr(>|t|)	Estimate	Std. Error	Pr(>|t|)	Estimate	Std. Error	Pr(>|t|)
Monday	-6,116e-05	5,8542e-04	0,9168	-2,0539e-04	5,7354e-04	0,72029	-5,1267e-05	5,7709e-04	0,92922
Tuesday	8,135e-04	4,1934e-04	0,05249*	8,8455e-04	4,4887e-04	0,048878**	1,0871e-03	4,7736e-04	0,02285**
Wednesday	8,168e-04	4,0146e-04	0,04199**	6,9432e-04	4,2565e-04	0,102978	4,8857e-04	4,6136-04	0,28971
Thursday	-2,931e-04	4,9538e-04	0,55406	8,7020e-05	4,9701e-04	0,861027	-4,3998e-04	5,4599e-04	0,42041
Friday	1,243e-03	3,7798e-04	0,00102***	1,3233e-03	4,2211e-04	0,001739***	5,8669e-04	5,0372e-04	0,24425

Panel B: Excess Returns

	Small-capitalization Stocks			Mid-capitalization Stocks			Large-capitalization Stocks		
	Estimate	Std. Error	Pr(>|t|)	Estimate	Std. Error	Pr(>|t|)	Estimate	Std. Error	Pr(>|t|)
Monday	-6,7456e-05	5,8561e-04	0,908305	-2,1169e-04	5,7614e-04	0,713332	-5,7564e-05	5,7697e-04	0,92054
Tuesday	8,0664e-04	4,1954e-04	0,054635*	8,7767e-04	4,4933e-04	0,050898*	1,0803e-03	4,7738e-04	0,02373**
Wednesday	8,0975e-04	4,0206e-04	0,044118**	6,8722e-04	4,2599e-04	0,106819	4,8147e-04	4,6163e-04	0,29705
Thursday	-3,0019e-04	4,9521e-04	0,544449	7,9987e-05	4,9810e-04	0,872434	-4,4702e-04	5,4589e-04	0,41293
Friday	1,2364e-03	3,7841e-04	0,001101***	1,3165e-03	4,2293e-04	0,001874***	5,7989e-04	5,0364e-04	0,24968

is more profound for small- and mid-capitalization stocks in the sample data, consistent with Abraham and Ikenberry's (1994) findings. A limitation of the t-test is that the returns have not been adjusted for risk. Therefore, a risk-adjusted comparison is provided in Table VII.

Table V

Table V provides the difference in mean between weekdays, the probability value, and the t-statistic for each weekday in respective capitalization size. The statistical result from the Welch t-test explains whether there is a significant difference in mean between the market capitalizations for each weekday. Meaning, the mean return for Monday - small-capitalization is compared with Monday mid-capitalization and large-capitalization stocks. *, **, and *** denote statistical significance at the 10%, 5%, or 1% level, respectivly.

T-test for Difference in Means Between Capitalization Indexes

	Difference in means	Probability Value	T-statistic
	Small and Mid-capitalization Stocks		
Monday	0,0001442335	0,59290	0,53494
Tuesday	-7,103152e-05	0,77510	−0,28590
Wednesday	0,0001225258	0,64170	0,46561
Thursday	−0,0003801741	0,14880	−1,44610
Friday	-8,015451e-05	0,75520	−0,31192
	Small and Large-capitalization Stocks		
Monday	-9,891939e-06	0,97890	−0,02646
Tuesday	−0,0002736180	0,39450	−0,85229
Wednesday	0,0003282741	0,32850	0,97816
Thursday	0,0001468303	0,67200	0,42371
Friday	0,0006564640	0,06658*	1,83860
	Mid and Large-capitalization Stocks		
Monday	−0,0001541254	0,60590	−0,51633
Tuesday	−0,0002025865	0,41830	−0,81005
Wednesday	0,0002057482	0,44910	0,75753
Thursday	0,0005270043	0,03262**	2,14270
Friday	0,0007366185	0,006137***	2,75240

A.3 The Presence of Volatility Clustering

Table VI showcases the statistics gathered from the GARCH model. Mu is the largest for mid-capitalization stocks and the lowest for large-capitalization stocks, corresponding to the descriptive statistics seen in Table I. However, the difference between small- and mid-capitalization stocks is more profound in the GARCH estimates. Omega is the smallest for large-capitalization stocks, followed by the mid-capitalization stocks, while the small-capitalization stocks have the largest. Interestingly, this is the opposite of the realized volatility in Table I. Hence, the GARCH model suggests that additional factors contribute to the increased volatility of large-capitalization stocks rather than being more inherently risky. This aligns with the findings of Zaremba and Shemer (2017), stating that small-capitalization stocks are more risky. The sum of alpha1 and beta1 yields 0,957, 0,985, and 0,985 for the respective indexes. As the values are near 1, it implies that volatility clustering exists for each capitalization size. This is further implied by doing the ARCH (Autoregressive Conditional Heteroskedasticity) test, where the null hypothesis is that there is no volatility clustering. The

P-values for the ARCH test are all above the 99% significance level seen in Appendix D. The clustering is further visualized in Appendixes E-G for respective capitalization size.

Table VI

Table VI presents the results of the GARCH model for all three indexes. The model uses four parameters to explain the different characteristics of the respective time series. Mu, a constant term, represents the estimated return. Omega represents the baseline variance. Alpha1 represents the reaction of the conditional variance to the squared residuals from the previous period. Beta1 measures the persistence of past variance in the current variance.

GARCH Statistics

	Small-capitalization Stocks	Mid-capitalization Stocks	Large-capitalization Stocks
mu	7.803574e-04	9.125638e-04	7.126750e-04
omega	4.487578e-06	2.940835e-06	2.566452e-06
alpha1	1.564039e-01	1.856003e-01	1.225121e-01
beta1	8.001727e-01	7.996193e-01	8.627023e-01

The presence of volatility clustering does not inherently contradict the EMH. However, it does introduce complexities in understanding market dynamics, suggesting that investment risks vary over time. This variability in risk levels can influence investor behavior, indicating that reactions to information and market adjustments may not be as immediate or rational as the EMH assumes. Such patterns highlight the nuanced ways information is absorbed and reflected in market prices, potentially leading to periods of higher uncertainty that affect investment strategies and decision-making. These insights are essential as they provide a more detailed framework for assessing market efficiency and understanding the psychological factors in the day-of-the-week effect.

A.4 Consequences of Risk Adjustments for the Day-of-the-Week Effect

Table VII

Table VII includes the average Sharpe ratio for each day of the week across all capitalization indexes. The daily Sharpe ratio is calculated by dividing the daily excess return (daily raw return - daily excess return) by the daily expected standard deviation estimated by the GARCH model.

Average Sharpe Ratio

	Small-capitalization Stocks	Mid-capitalization Stocks	Large-capitalization Stocks
	Sharpe Ratio	Sharpe Ratio	Sharpe Ratio
Monday	0,095234	0,099194	0,068131
Tuesday	0,106032	0,126032	0,128878
Wednesday	0,114824	0,105430	0,058074
Thursday	0,029192	0,085433	0,031382
Friday	0,194515	0,211284	0,110929

Table VII suggests that the overall highest risk-adjusted return occurs on Friday. Fridays have the highest risk-adjusted return for small- and mid-capitalization stocks and are the second highest for large-capitalization stocks. The lowest Sharpe ratio was found for Thursdays across all indexes, followed by Monday, which was the second lowest for both

small- and mid-capitalization stocks, and the third lowest was for large-capitalization stocks. The considerable differences in Sharpe ratios between the days of the week further suggest the presence of a day-of-the-week effect, as the abnormally high Friday return cannot be explained by an increase in volatility.

A.5 Days with the Highest and Lowest Returns of the Week Annually

Table VIII

Table VIII summarizes the times each weekday has the lowest or highest average returns annually from 2014-2024.

Highest and Lowest average return for each year

	Small-capitalization Stocks	
	Lowest	**Highest**
Monday	3	1
Tuesday	3	3
Wednesday	1	2
Thursday	3	2
Friday	0	2
	Mid-capitalization Stocks	
	Lowest	**Highest**
Monday	4	0
Tuesday	1	3
Wednesday	1	0
Thursday	4	3
Friday	0	4
	Large-capitalization Stocks	
	Lowest	**Highest**
Monday	1	0
Tuesday	1	4
Wednesday	1	1
Thursday	6	3
Friday	1	2

We take a similar approach to Claesson's investigation of the Swedish stock market, the results of which are shown in Table VIII. The findings show that Monday has had the lowest return for small-capitalization stocks in three out of the ten years and the highest in one year. Contrastingly, Friday never had the lowest return across the entire decade and twice the highest. The high Friday and low Monday returns remain consistent across the other capitalization sizes. Friday never had the lowest stock return and the highest four times for mid-capitalization stocks. At the same time, Monday had the lowest return in four out of ten years and never the highest. The large-capitalization index suggests less of a day-of-the-week effect when comparing Monday and Friday. Friday was the highest twice and lowest once, while Monday was the lowest once and is not the highest for any year. Moreover, the remaining days, Tuesdays, Wednesdays, and Thursdays, across all indexes, indicate varying results, making it difficult to suggest any day-of-the-week effect. These results differ from the

findings of Claesson (1987), who found low-performing Tuesdays. However, the persistence of well-performing Fridays seems to have been consistent over time. More detailed and descriptive statistics of the highest and lowest returns for each year are presented in Appendix H-J.

Looking at the aggregate results across all indexes, Monday had the lowest return eight times while only having the largest one year across all capitalization sizes. On the other hand, Fridays had the highest return eight times and the lowest only once. Once again, this indicates a considerable difference between Friday's and Monday's average returns, suggesting a day-of-the-week effect.

B. Day-of-the-Week Effect Across Periods

Table IX investigates the persistence of the day-of-the-week effect over time. In subsample 1, small-capitalization stocks show the highest stock return with a significance level of 1% on Friday. Furthermore, a smaller stock return was yet at a significant level of 10% on Wednesday. In the second subsample, representing the period during COVID-19, the Friday returns are no longer significantly different. On the other hand, Tuesdays yield the highest return at a significance level of 10%. The third subsample of the daily stock returns for small-capitalization stocks does not provide significant results for any weekday.

Moreover, subsample 1 for mid-capitalization stocks investigating stock returns before the COVID-19 pandemic shows similar results to small-capitalization stocks. The highest stock return had the lowest significance level of 1% on Friday, and a smaller stock return yet at a significant level of 10% on Wednesday. During COVID-19, results for subsample 2 of the OLS regression suggest no significant results for any weekday. In subsample 3 for the mid-capitalization index, Fridays again show significance at 5%.

Lastly, for large-capitalization stocks in subsample 1, the OLS regression suggests that Fridays yield the highest, most significant stock return at a significance level of 10%. In subsample 2, the results are shifted, where Tuesday is the weekday with the highest return at a significance level of 5%, while Friday's estimate becomes negative. Lastly, no regression estimates are significant for the large-capitalization stocks in subsample 3.

Table IX

Table IX is an extension of Table IV. It presents an OLS regression on the observations divided into three subsamples based on the period before, during, and after COVID-19 to explore if there are inconsistencies over time. As in previous OLS, Newey West adjustments for standard error concerning autocorrelation and heteroscedasticity are added to the model. Furthermore, for the simplicity of the analysis, only raw returns have been analyzed, as the excess returns yield nearly identical results for all tests. The OLS regression is presented through estimates of the return for each weekday, standard error, and the probability value denoted as Pr(>|t|). *, **, and *** denote statistical significance at the 10%, 5%, or 1% level, respectively.

OLS Regression Results for the Subsamples

	Small-capitalization Stocks			Mid-capitalization Stocks			Large-capitalization Stocks		
	Subsample 1			**Subsample 1**			**Subsample 1**		
	Estimate	Std. Error	Pr(>|t|)	Estimate	Std. Error	Pr(>|t|)	Estimate	Std. Error	Pr(>|t|)
Monday	4.5615e-04	5.4054e-04	0.3988705	2.4603e-04	5.4987e-04	0.654634	-7.8042e-05	5.5619e-04	0.8884
Tuesday	4.5098e-04	4.4149e-04	0.3071845	7.0187e-04	4.3261e-04	0.104928	5.7524e-04	4.5387e-04	0.2052
Wednesday	7.7517e-04	4.1524e-04	0.0621239 *	7.5025e-04	4.3056e-04	0.081625 *	3.2235e-04	5.1361e-04	0.5304
Thursday	9.9953e-05	4.4027e-04	0.8204330	1.9439e-04	4.4098e-04	0.659408	-3.4214e-05	5.8289e-04	0.9532
Friday	1.4313e-03	4.0397e-04	0.0004076 ***	1.2144e-03	4.5875e-04	0.008198 ***	9.2580e-04	5.3646e-04	0.0846 *
	Subsample 2			**Subsample 2**			**Subsample 2**		
	Estimate	Std. Error	Pr(>|t|)	Estimate	Std. Error	Pr(>|t|)	Estimate	Std. Error	Pr(>|t|)
Monday	-6.5404e-04	1.45240e-03	0.65260	-8.8468e-04	1.4506e-03	0.5449	1.1532e-04	1.3413e-03	0.93151
Tuesday	1.6048e-03	9.5860e-04	0.09449 *	1.3220e-03	1.0601e-03	0.2127	2.1435e-03	1.0663e-03	0.04474 **
Wednesday	1.3036e-03	8.8217e-04	0.13988	1.0834e-03	9.6638e-04	0.2625	1.0094e-03	1.0124e-03	0.31905
Thursday	-1.1203e-03	1.2190e-03	0.35834	-3.9979e-04	1.2383e-03	0.7469	-1.3176e-03	1.2523e-03	0.29306
Friday	1.0700e-03	8.7018e-04	0.21920	1.1644e-03	9.5260e-04	0.2219	-4.3798e-04	1.1339e-03	0.69941
	Subsample 3			**Subsample 3**			**Subsample 3**		
	Estimate	Std. Error	Pr(>|t|)	Estimate	Std. Error	Pr(>|t|)	Estimate	Std. Error	Pr(>|t|)
Monday	-1.8312e-03	1.2565e-03	0.1469	-9.7847e-04	1.3656e-03	0.47468	-6.0717e-04	9.6627e-04	0.5306
Tuesday	1.5184e-04	1.3841e-03	0.9128	3.5748e-04	1.8898e-03	0.85019	4.5760e-04	1.8261e-03	0.8024
Wednesday	-1.1655e-03	1.0078e-03	0.2491	-1.6782e-03	1.2468e-03	0.18011	-5.5888e-04	1.3162e-03	0.6717
Thursday	4.0535e-05	1.1927e-03	0.9729	1.3304e-03	1.7691e-03	0.45309	9.4354e-06	1.7365e-03	0.9957
Friday	3.8887e-04	1.0673e-03	0.7161	3.0065e-03	1.4438e-03	0.03883 **	2.3159e-03	1.5639e-03	0.1405

IV. Discussion

The analysis of the Swedish stock market from 2014 to 2024 reveals patterns in stock returns dependent on the day of the week, which may contradict the EMH. These findings align with previous studies by Kohers and Patel (1996), Yamori and Kurihara (2004), and Claesson (1987), which reported similar day-of-the-week effects in various markets. The patterns of stock returns peaking on specific weekdays suggest that information asymmetry or investor behavior could influence stock prices beyond what EMH would predict.

Additionally, the results suggest a size effect as small- and mid-capitalization stocks have a greater relative difference between the days of the week than the large-capitalization firms, aligning with the findings of Zaremba and Shemer (2017). Table IV shows that the results are most significant for Fridays, corresponding with several previous papers, most notably, the findings of Claesson (1987), who also looked at the Swedish market.

The findings challenge the weak form of EMH, suggesting that historical price data (in this case, the day of the week) can predict future returns. This could indicate that the Swedish stock market is inefficient, as prices reflect more than random information distributions. The findings suggest that investors, especially active traders, could enhance their strategies by accounting for the day-of-the-week effect. The evidence of the day-of-the-week effect might necessitate closer monitoring of trading practices that could exploit these inefficiencies, potentially destabilizing the market. Regulatory bodies might need to consider whether current market practices allow for fair trading. Portfolio managers might use this information to time their transactions more effectively or to manage risk, based on the variability in returns associated with the days of the week. Furthermore, due to volatility clustering in the Swedish stock market, investors might employ certain risk management strategies based on their risk appetite. However, as Claesson (1987) discussed, despite its importance in theory, it could be argued whether the day-of-the-week effect has any practical significance.

Table IX suggests inconsistencies depending on the timeframe in which each dataset is investigated. Pre-COVID-19, the Friday returns were especially significant for small- and mid-capitalization stocks while having some statistical significance for large-capitalization stocks. However, during the COVID-19 pandemic, the Swedish stock weekday returns deviated less profoundly. This resulted in the full-period analysis not being as statistically significant regarding the day-of-the-week effect, which is especially true for the small capitalization index. These findings could potentially indicate that external shocks might diminish the effect, corresponding with the findings of Högholm and Knif (2009), showing that the day-of-the-week effect can be affected by macroeconomic events.

Behavioral finance explains why investors make irrational decisions, potentially impacting the day-of-the-week effect. Individuals possess behavioral biases that affect their perception of a situation, thus influencing their decision-making (Slovic 1972). For instance, the absence of self-control could lead to more impulsive buying behavior, as investors may be inclined to act on short-term gratification (O'Donoghue & Rabin, 1999). According to prospect theory, individuals tend to experience the pain of losses worse than the pleasure of gain, so-called loss aversion. Therefore, theory implies that investors who experience a loss earlier in the week tend to become more risk-averse. However, this caution may be overlooked by the attempt to recoup previous losses, and investors dare to take on additional risk. Fear of regret among investors might drive them to increase consumption during certain days of the week. The dissatisfaction of missing previous opportunities or underperformance during the week increases, which might increase the willingness to pay overprice on Fridays (Kahneman and Tversky 1979). Lyroudi K., et al. (2004), suggest that investors feel

pessimistic on Mondays as it is the first day of the trading week, resulting in a decrease. In contrast, they feel optimistic during Fridays, the last day of the trading week, increasing stock returns.

Besides the behavioral finance aspect of the day-of-the-week effect, previous research suggests ulterior reasons that correspond to our study's findings. As Claesson (1987) suggested, there is a two-day return premium when investing on Fridays, which increases the share price, followed by a return to normal on Mondays, resulting in a price decrease. This phenomenon is particularly evident in our findings for Fridays but also has implications for the observed Monday returns. Additionally, as seen in Michaely et al. (2016), firms tend to wait until after the market has closed on Fridays to release bad news, while good news is published promptly. Although this does not explain why the Friday price generally increases compared to other days of the week, it does suggest a decline in Monday returns, aligning with our findings. The payday effect implies increased returns on the payday, as seen by Ma and Pratt (2018) when analyzing the US market. In Sweden, paydays occur most often on Fridays compared to any other day of the week due to the inability to pay employees during weekends (PFC, 2023). Hence, the payday effect is more likely to occur on Fridays, potentially resulting in abnormally positive returns.

This study is constrained by its focus on the Swedish stock market alone, which may limit the generalizability of the findings to other markets with different trading dynamics and regulations. Potentially, different cultural, economic, and regulatory contexts could lead to different behaviors on the stock market. Although a 10-year sample of data is used to capture the current effect, it may not consider longer-term trends or cyclical implications that could affect future predictions of the day-of-the-week effect. Furthermore, COVID-19 could have event-specific effects, which are not typical in other periods, potentially yielding a skewed view of the full period results. To some extent, this is mitigated by dividing the data into subsamples. However, dividing the data into subsamples has further potential limitations as the sample sizes decrease. This can reduce the statistical power of the tests conducted and may increase the risk of Type II errors. Using OLS regressions and GARCH models provides a robust analysis but might not capture all nuances of market behavior. Future studies could employ more complex models incorporating more variables or non-linear relationships. Additionally, other unobserved factors such as macroeconomic changes, political events, or global market dynamics could influence the day-of-the-week effect but are not controlled for the study. The Sharpe ratio provides a risk-adjusted comparison between the weekdays and the respective capitalization sizes. However, it does not provide sufficient information to compare with other papers and does not show if the differences are significant, limiting the study. The GARCH model is not applied to the subsample statistics; this is not done because the subsample data is not large enough to apply the model effectively, limiting the study.

We find significant results for a day-of-the-week effect. Yet, mainly due to the limitations above, the results do not provide enough evidence to determine whether the effect will remain consistent. Further analysis into other markets and time frames could help determine whether these patterns are unique to Sweden or part of a broader phenomenon. Additionally, incorporating interdisciplinary approaches that blend finance with psychology could provide deeper insights into the causes of these market anomalies. Moreover, exploring the impact of digital transformation and the increasing use of algorithmic trading could also be worthwhile, as these factors might influence the traditional day-of-the-week effects observed in stock markets. In our analysis, we have observed a size effect. However, the study does not consider why it has occurred, which opens the potential for continued investigation. Additionally, the effects of COVID-19 on the day-of-the-week is an unexplored topic. Further research could explore how other markets have been affected by the pandemic.

Interestingly, despite the high Friday returns, the trading volume is not high compared to other days of the week for any indexes. For small-capitalization stocks, the trading volume is surprisingly the lowest across all weekdays. Since Friday returns are generally higher, one could expect that investors would increase the trading volume, as seen in Kamara (1997). This area of the day-of-the-week effect would be interesting for future research to explore, if the volume relative to the returns is persistent across markets. Apart from investigating the impacts of volume statistics, further research could analyze more thoroughly why the day-of-the-week effect occurred in the Swedish stock market between 2014 and 2024, potentially investigating if some of the suggested reasons from other studies, are true, such as the news release timing, the payday effect or behavioral finance aspects. Our analysis shows that Thursday's average and risk-adjusted returns are the lowest for the different weekdays, rarely mentioned in historical literature. Additional studies could explore why this has happened and if it is expected to persist.

V. Conclusion

This study explored the day-of-the-week effect on the Swedish stock market from 2014 to 2024, aiming to understand how stock returns vary across different weekdays and under different market conditions. Our findings reveal a significant day-of-the-week effect, particularly seen in small- and mid-capitalization stocks, which challenges the Efficient Market Hypothesis (EMH).

The results suggest that Fridays consistently yield higher returns, while Mondays show lower, aligning with behavioral finance theories suggesting investor optimism at the end of the week and pessimism at the start. Apart from positive Tuesdays, our results align with previous findings of the Swedish stock market. Furthermore, our results suggest a size effect, with smaller stocks exhibiting more profound anomalies. Additionally, the period during the COVID-19 pandemic differed from Pre-COVID-19, where the significance of the day-of-the-week effect during the crisis period was diminished. Potentially indicating that macroeconomic fluctuations impact the day-of-the-week effect.

While this study contributes to further understand market anomalies, it is limited by its focus on the Swedish market and data division into subsamples, reducing statistical power. Continued studies could extend this analysis to other markets and investigate potential reasons for the effect.

References

Abraham, A., and D.L. Ikenberry, 1994, The Individual Investor and the Weekend Effect, Journal of Financial and Quantitative Analysis 29, 263-277.

Apolinario, R.M.C., A.R. Caro, L.J. Sales, and O.M. Santana, 2006, Day of the Week Effect on European Stock Markets, International Research Journal of Finance and Economics 2, 53-70.

Bailey, D.H., and M. Lopez de Prado, 2012, The Sharpe Ratio Efficient Frontier, Journal of Risk 15, 3-44.

Berk, J., and P. DeMarzo, 2019, Corporate Finance (5th Edition), Pearson Press.

Berument, Hakan, and Halil Kiymaz, 2001, The Day of the Week Effect on Stock Market Volatility, Journal of Economics and Finance 25, 181-193.

Berument, Hakan, and Halil Kiymaz, 2003, The day of the week effect on stock market volatility and volume: International evidence, Review of financial economics 12, 363-380.

Bollerslevin, Tim, 1986, Generalized autoregressive conditional heteroskedasticity, Journal of Econometrics 31, 307-327.

Brooks, C., 2008, Introductory Econometrics for Finance (2nd Edition), Cambridge University Press.

Carlucci, F. V., T. P. Junior, and F. G. Lima, 2013, A Study on the Day of the Week Effect in the Four major Capitals Markets of the Americas, Journal of International Finance & Economics 13, 11-20.

Chusanachoti, J., and R. Kamath, 2002, Market Conditions, Return Distributions, and the Day-of-the-Week Effects in Thailand: The Experience of the 1990s, American Business Review 20, 6-14.

Cinko, M., E. Avci, A. Aybars, and M. Öner, 2015, Analyzing the Existence of the Day of the Week Effect in Selected Developed Country Stock Exchange, International Journal of Economics and Finance 7, 33-43.

Claesson, Kerstin, 1987, Effektiviteten på Stockholms fondbörs, Ekonomiska forskningsinstitutet vid Handelshögskolan i Stockholm.

Cross, F., 1971, The Behavior of Stock Prices on Fridays and Mondays, Financial Analysts Journal 29, 67-69.

Engle, Robert, 1982, Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation, Econometrica 50, 987-1007.

Fama, F.E., 1965, The Behavior of Stock Market Prices. Journal of Business 38, 34-105.

Fama, F. Eugene, and Kenneth R. French, 2008, Dissecting Anomalies, The Journal of Finance 63, 1653-1678.

Fama, F. Eugene, and Kenneth R. French, 1992, The Cross-Section of Expected Stock Returns, The Journal of Finance 47, 427-465.

Folkhälsomyndigheten, 2023, När hände vad under pandemin?, Available Online: https://www.folkhalsomyndigheten.se/smittskydd-beredskap/utbrott/aktuella-utbrott/covid-19/nar-hande-vad-under-pandemin/, Accessed: 14 May 2024.

French, K. R., 1980, Stock Returns and the Weekend Effect, Journal of Financial Economics 8, 55-69.

Gibbons, M.R., and P. Hess, 1981, Day of the Week Effects and Asset Returns, The Journal of Business 54, 579-596.

Gonzalez-Perez, M.T., and D. E. Guerrero, 2013, Day-of-the-week Effect on the VIX: A Parsimonious Representation, North American Journal of Economics and Finance 25, 243-260.

Groth, John C., Wilbur G Lewellen, Gary G Schlarbaum, and Ronald C Lease, 1979, An analysis of brokerage house securities recommendations, Financial Analysts Journal 35, 32-40.

Guidi, F., 2010, Day-of-the-week Effect and Market Efficiency in the Italian Stock Market: an Empirical Analysis, The IUP Journal of Applied Finance 16, 5-51.

Högholm, K., and J. Knif, 2009, The impact of portfolio aggregation on day-of-the-week effect: Evidence from Finland, Global Finance Journal 20, 67-79.

Kahneman, Daniel, and Amos Tversky, 1979, Prospect Theory: An Analysis of Decision under Risk, Econometrica 47, 263-292.

Kamara, A., 1997, New evidence on the Monday Seasonal in Stock Returns, Journal of Business 70, 63-84.

Kohers, Theodor, and Jayen B. Patel, 1996, An Examination of the Day-Of-The-Week' Effect in Junk Bond Returns over Business Cycles, Review of Financial Economics 5, 31-46.

Lux, Thomas, 1995, Herd Behaviour, Bubbles and Crashes, The Economic Journal 105, 881-896.

Lyroudi, K., A. Dasilas, P.G. Patev, and N.K. Kanaryan, 2004, Day of the Week Effect in the Central and Eastern European Transition Stock Markets and Higher Moments of Security Returns, SSRN Electronic Journal.

Ma, Aixin J., and William R. Pratt, 2018, Payday Anomaly, Oklahoma City University.

Mehdian, Seyed, and Mark J. Perry, 2001, The Reversal of the Monday Effect: New Evidence from US Equity Markets, Journal of Business Finance & Accounting 28, 1043-1065.

Michaely, Roni, Amir Rubin, and Alexander Vedrashko, 2016, Further evidence on the strategic timing of earnings news: Joint analysis of weekdays and times of day, Journal of Accounting and Economics 62, 24-45.

Nasdaq, 2021, Rules & Regulations, Nasdaq Stockholm (Stockholmsbörsen), Available Online: https://www.nasdaq.com/market-regulation/nordic/stockholm, Accsessed: 14 May 2024.

Nasdaq Nordics, 2024, Historical prices NOMXSCSEPI, NASDAQ OMX Small Cap Sweden PI, (SE0002896373), Available Online: https://www.nasdaqomxnordic.com/indexes/historical_prices?Instrument=SE0002896373, Accessed: 20 January 2024.

Nasdaq Nordics, 2024, Historical prices OMXSLCPI, OMX_Stockholm_Large_Cap_PI, (SE0001775784), Available Online: https://www.nasdaqomxnordic.com/indexes/historical_prices?Instrument=SE0001775784, Accessed: 20 January 2024.

Nasdaq Nordics, 2024, Historical prices OMXSMCPI, OMX_Stockholm_Mid_Cap_PI, (SE0001775800), Availabe Online: https://www.nasdaqomxnordic.com/indexes/historical_prices?Instrument=SE0001775800, Accessed: 20 January 2024.

Newey, Whitney K., and Kenneth D. West, 1987, A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, Econometrica 55, 703-708.

O'Donoghue, Ted, and Matthew Rabin, 1999, Doing It Now or Later, The American Economic Review 89, 103-124.

Personal Finance Co. (P.F.C), 2023, Pay day, Available Online: https://www.getpfc.com/articles/payday-2022-2023, Accessed: 14 May 2024.

Puja, P., 2010, Days-of-the-Week-Effect and Stock Return Volatility: Theory and Empirical Evidence, Advances in Management 3, 14-21.

Riksbank, 2024, Sök räntor och valutakurser, Svenska stadsskuldsväxlar (SE SSVX) 3 månader, Available Online: https://www.riksbank.se/sv/statistik/sok-rantor--valutakurser/?g6-SETB3MBENCH=on&from=2019-04-27&to=2019-05-27&f=Day&c=cAverage&s=Comma, Accessed: 5 February 2024.

Rogalski, Richard J., 1984, New Findings Regarding Day-of-the-Week Returns over Trading and Non-Trading Periods: A Note, The Journal of Finance 39, 1603-1614.

Roy, A., 1952, Safety First and the Holding of Assets, Econometrica 20, 431-449.

Sharpe, William F., 1966, Mutual Fund Performance, Journal of Business 39, 119–138.

Shefrin, Hersh, and Meir Statman, 1985, The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence, The Journal of Finance 40, 777-790.

Slovic, P., 1972, Psychological Study of Human Judgment: Implications for Investment Decision Making, Journal of Finance 27, 779-799.

Smirlock, Michael, and Laura Starks, 1986, Day-of-the-week and intraday effects in stock return, Journal of Financial Economics 17, 197-210.

Welch, B.L., 1947, The Generalization of 'Student's' Problem When Several Different Population Variances are Involved, Biometrika 34, 28-35.

World Health Organization (WHO), 2023, Statement on the Fifteenth Meeting of the International Health Regulations (2005) Emergency Committee regarding the Coronavirus Disease (COVID-19) Pandemic, Available Online: https://www.who.int/news/item/05-05-2023-statement-on-the-fifteenth-meeting-of-the-international-health-regulations-(2005)-emergency-committee-regarding-the-coronavirus-disease-(covid-19)-pandemic, Accessed: May 14 2024.

Xiao, B., 2016, The Monthly Effect and the Day of the Week Effect in the American Stock Market, International Journal of Financial Research 7, 11-17.

Yamori, Nobuyoshi, and Yutaka Kurihara, 2004, The day-of-the-week effect in foreign exchange markets: multi-currency evidence, Research in international business and finance 18, 51-57.

Zaremba, A., and J. Shemer, 2017, Country Asset Allocation (1st Edition), Palgrave Macmillan.

Appendix

Appendix A

Augmented Dickey-Fuller Test

Null Hypothesis: The Data is Non-Stationary			
Stock Size	Small-capitalization	Mid-capitalization	Large-capitalization
P-Value	0.01***	0.01***	0.01***
Dickey-Fuller	-13.657	-13.137	-13.989
Lag Order	13	13	13
Conclusion	Reject H0	Reject H0	Reject H0
*** p<0.01, ** p<0.05, * p<0.1			

Appendix B

Box-Ljung Test

Null Hypothesis: The Data has no Autocorrelation			
Stock Size	Small-capitalization	Mid-capitalization	Large-capitalization
P-Value	5.236e-09***	5.726e-12***	1.75e-11***
X-squared	34.1	47.421	45.232
Conclusion	Reject H0	Reject H0	Reject H0
*** p<0.01, ** p<0.05, * p<0.1			

Appendix C

Breusch-Pagan Test

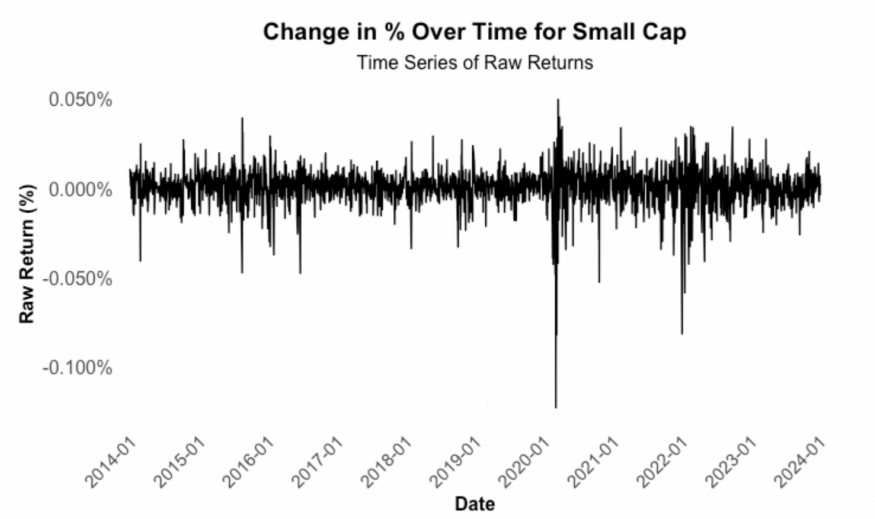
Null Hypothesis: The Data is Homoskedastic			
Stock Size	Small-capitalization	Mid-capitalization	Large-capitalization
P-Value	0.01625**	0.01351**	4.417e-04***
BP	5.7754	6.1012	12.347
Conclusion	Reject H0	Reject H0	Reject H0
*** p<0.01, ** p<0.05, * p<0.1			

Appendix D

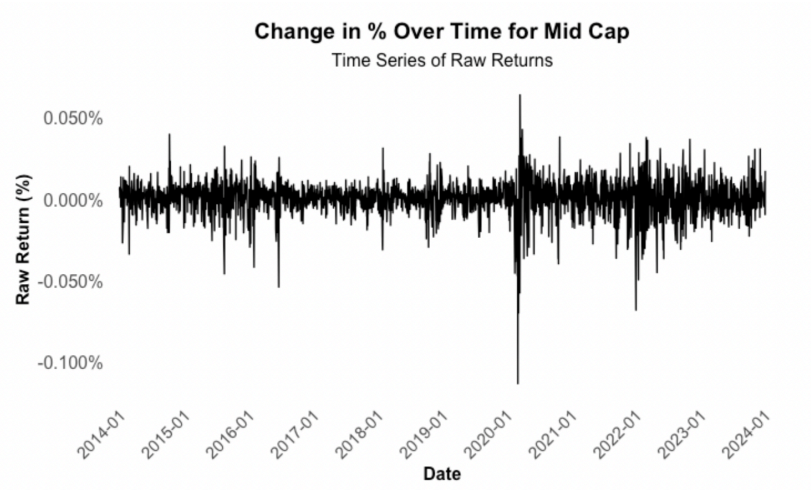
ARCH LM-test

Null Hypothesis: no ARCH effects			
Stock Size	Small-capitalization	Mid-capitalization	Large-capitalization
P-Value	5.382e-09***	5.933e-12***	1.814e-11***
Chi-Squared	34.046	47.351	45.162
Conclusion	Reject H0	Reject H0	Reject H0
*** p<0.01, ** p<0.05, * p<0.1			

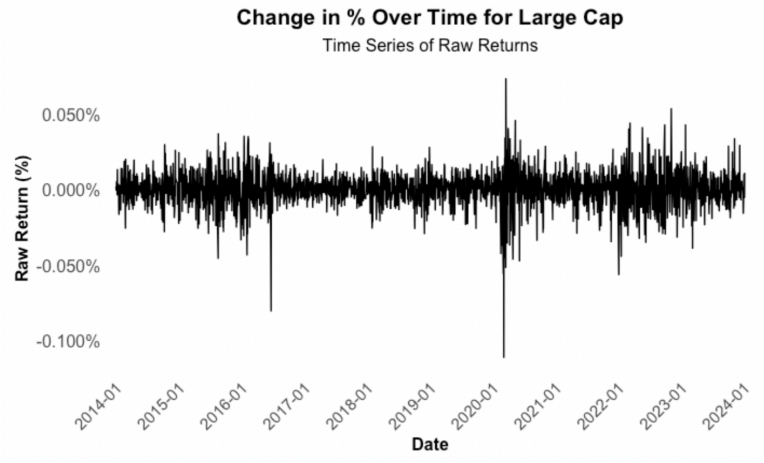
Appendix E



Appendix F



Appendix G



Appendix H

Mean, SD, Min and Max for Large-Capitalisation Stock, Across All Years and Weekdays

Year	Weekday	Mean_Large	SD_Large	Min_Large	Max_Large	Observations
2014	1	7.743013e-04	140737.31.00	−423443.00.00	320981.57.00	50
2014	2	1.901279e-03	144189.58.00	−356330.33.00	406632.52.00	52
2014	3	-1.747122e-04	133248.33.00	−462229.16.00	225225.14.00	50
2014	4	-4.499426e-04	147156.37.00	−332060.01.00	435944.08.00	48
2014	5	3.227146e-04	145232.12.00	−306091.13.00	499375.47.00	47
2015	1	4.052755e-04	220194.34.00	−756501.11.00	522270.10.00	51
2015	2	-1.780065e-03	215257.39.00	−414263.29.00	619118.23.00	51
2015	3	7.971151e-04	195142.45.00	−424762.08.00	359438.43.00	52
2015	4	2.293230e-03	195142.13.00	−461365.05.00	484944.49.00	49
2015	5	-6.384773e-04	185681.17.00	−421357.34.00	428619.43.00	48
2016	1	-1.511683e-03	287007.50.00	−1337579.37.00	588892.16.00	49
2016	2	7.609599e-04	168468.43.00	−290759.31.00	387298.39.00	52
2016	3	6.955824e-04	187845.22.00	−506731.46.00	561839.17.00	51
2016	4	-8.416826e-04	178434.39.00	−485276.59.00	373006.33.00	51
2016	5	2.239505e-03	200824.53.00	−432456.12.00	592420.02.00	50
2017	1	2.581295e-04	113280.11.00	−189757.22.00	334308.49.00	49
2017	2	8.087699e-04	102199.30.00	−280833.08.00	199407.00.00	50
2017	3	3.757388e-04	97184.02.00	−245581.28.00	287509.38.00	52
2017	4	-3.540135e-04	93984.00.00	−220828.12.00	184150.38.00	51
2017	5	2.386511e-04	102831.22.00	−192260.45.00	179912.05.00	49
2018	1	-4.488547e-04	143174.04.00	−423087.39.00	246545.12.00	49
2018	2	1.116231e-04	142809.24.00	−352393.13.00	347109.14.00	50
2018	3	5.967071e-05	152287.29.00	−337883.14.00	475832.42.00	50
2018	4	-1.310121e-03	187169.12.00	−483426.52.00	361453.21.00	51
2018	5	1.092862e-04	140232.55.00	−328581.32.00	309220.48.00	50
2019	1	3.787362e-04	142049.16.00	−380408.56.00	283188.39.00	51
2019	2	1.438600e-03	111058.37.00	−271810.27.00	233493.27.00	50
2019	3	2.577161e-04	134131.52.00	−426091.38.00	265036.16.00	50
2019	4	9.760871e-05	127418.01.00	−335262.46.00	281277.28.00	49
2019	5	3.154396e-03	147740.03.00	−381913.28.00	469109.35.00	50
2020	1	8.234836e-04	369211.06.00	−926636.42.00	765733.26.00	50
2020	2	5.760911e-03	260588.10.00	−452200.11.00	1226313.54.00	52
2020	3	1.162028e-03	253532.01.00	−609314.47.00	713778.15.00	52
2020	4	-4.073232e-03	346146.57.00	−1850415.37.00	571335.18.00	50
2020	5	-1.198201e-03	207310.46.00	−556497.46.00	563262.39.00	48
2021	1	2.789100e-04	155602.34.00	−447157.27.00	382166.32.00	51
2021	2	1.278314e-03	178121.29.00	−478641.44.00	448567.50.00	52
2021	3	1.089404e-03	147629.28.00	−320938.28.00	416467.24.00	51
2021	4	3.745418e-03	134541.25.00	−276026.38.00	303486.40.00	51
2021	5	-3.646775e-04	163256.52.00	−572967.34.00	264857.12.00	48
2022	1	-2.763725e-03	293038.38.00	−936227.39.00	571919.01.00	48
2022	2	2.776408e-04	235162.55.00	−401235.57.00	716854.50.00	52
2022	3	1.471144e-03	250941.02.00	−367993.22.00	736785.28.00	52
2022	4	-5.542291e-03	242912.34.00	−580042.51.00	385401.33.00	46
2022	5	1.042748e-03	316808.13.00	−503558.40.00	895447.57.00	49
2023	1	9.453403e-04	145739.34.00	−313529.23.00	420700.47.00	49
2023	2	3.951764e-04	172808.29.00	−290998.48.00	564457.40.00	50
2023	3	-8.502012e-04	163621.22.00	−644489.28.00	288983.31.00	52
2023	4	1.974979e-03	198199.06.00	−413564.56.00	716934.50.00	51
2023	5	8.328177e-04	181038.30.00	−399456.25.00	363839.55.00	47

Appendix I

Mean, SD, Min and Max for Mid-Capitalisation Stock, Across All Years and Weekdays

Year	Weekday	Mean_Mid	SD_Mid	Min_Mid	Max_Mid	Observations
2014	1	-2.355728e-04	151032.40.00	−561729.23.00	275964.18.00	50
2014	2	2.306506e-03	138152.35.00	−340923.33.00	392621.41.00	52
2014	3	7.552586e-04	114545.52.00	−339821.12.00	228152.52.00	50
2014	4	7.060197e-05	116690.59.00	−295683.43.00	330780.58.00	48
2014	5	5.740637e-05	162755.53.00	−446194.14.00	664073.54.00	47
2015	1	1.671936e-03	193258.09.00	−763401.31.00	399993.38.00	51
2015	2	2.047341e-04	168388.06.00	−366732.24.00	540211.00.00	51
2015	3	1.345577e-03	164447.12.00	−412483.48.00	311256.09.00	52
2015	4	3.025153e-03	143372.58.00	−347542.36.00	352491.46.00	49
2015	5	4.966538e-04	144390.08.00	−439186.19.00	272709.00.00	48
2016	1	-1.863401e-04	216322.01.00	−897948.31.00	391390.35.00	49
2016	2	5.580210e-04	118686.16.00	−272252.25.00	238902.48.00	52
2016	3	7.899279e-04	139586.53.00	−451169.31.00	426519.22.00	51
2016	4	-1.603328e-04	124369.33.00	−341395.20.00	271408.37.00	51
2016	5	1.293024e-03	154726.20.00	−489575.17.00	432621.55.00	50
2017	1	-7.370339e-05	93947.48.00	−268522.23.00	166773.04.00	49
2017	2	6.713828e-04	93856.10.00	−199763.52.00	170336.25.00	50
2017	3	7.461189e-04	79985.29.00	−159997.02.00	197899.13.00	52
2017	4	-4.997646e-04	108620.08.00	−313630.59.00	228842.40.00	51
2017	5	5.617652e-04	87246.28.00	−261411.55.00	187744.42.00	49
2018	1	-5.331062e-04	158377.21.00	−517142.19.00	383543.27.00	49
2018	2	-8.169941e-04	138720.02.00	−490558.10.00	246848.36.00	50
2018	3	6.270604e-04	141228.06.00	−185420.00.00	522347.05.00	50
2018	4	-1.081108e-03	147782.05.00	−404448.32.00	214634.56.00	51
2018	5	1.273325e-03	112540.49.00	−203715.31.00	375859.50.00	50
2019	1	9.639327e-04	122861.43.00	−390210.18.00	220634.18.00	51
2019	2	1.490518e-03	83616.53.00	−125867.46.00	339270.34.00	50
2019	3	1.777336e-04	101929.21.00	−339599.58.00	220732.58.00	50
2019	4	-3.482463e-04	90143.41.00	−203355.10.00	209276.02.00	49
2019	5	3.402728e-03	109426.31.00	−202597.40.00	309263.41.00	50
2020	1	4.074635e-04	361631.58.00	−1162732.05.00	712863.08.00	50
2020	2	4.908580e-03	242000.52.00	−236238.04.00	1066420.59.00	52
2020	3	1.990471e-03	271381.42.00	−762611.51.00	774609.20.00	52
2020	4	-2.776649e-03	343649.16.00	−1885293.13.00	444597.31.00	50
2020	5	2.252881e-03	171196.09.00	−512663.12.00	425983.44.00	48
2021	1	1.972097e-04	186138.04.00	−602983.45.00	402712.37.00	51
2021	2	8.143727e-04	205652.40.00	−511377.35.00	569157.34.00	52
2021	3	8.676415e-04	162494.19.00	−300915.35.00	469991.40.00	51
2021	4	4.160732e-03	161150.54.00	−404563.47.00	341590.36.00	51
2021	5	3.873517e-04	156563.47.00	−493868.48.00	279560.14.00	48
2022	1	-4.682873e-03	313985.59.00	−1133609.08.00	384294.04.00	48
2022	2	-1.472870e-03	225331.27.00	−517721.36.00	505990.17.00	52
2022	3	1.507182e-03	223013.19.00	−401587.16.00	630822.35.00	52
2022	4	-4.134770e-03	220031.02.00	−606790.10.00	300534.15.00	46
2022	5	1.794216e-03	255326.50.00	−425723.28.00	612069.53.00	49
2023	1	-5.521032e-05	146224.15.00	−281949.30.00	315113.42.00	49
2023	2	8.445743e-05	170100.28.00	−236940.26.00	510390.50.00	50
2023	3	-1.833944e-03	131382.57.00	−430797.10.00	180853.59.00	52
2023	4	2.506710e-03	189155.40.00	−295701.01.00	514036.08.00	51
2023	5	1.397581e-03	149561.49.00	−376751.08.00	320726.59.00	47

Appendix J

Mean, SD, Min and Max for Large-Capitalisation Stock, Across All Years and Weekdays

Year	Weekday	Mean_Large	SD_Large	Min_Large	Max_Large	Observations
2014	1	7.743013e-04	140737.31.00	−423443.00.00	320981.57.00	50
2014	2	1.901279e-03	144189.58.00	−356330.33.00	406632.52.00	52
2014	3	-1.747122e-04	133248.33.00	−462229.16.00	225225.14.00	50
2014	4	-4.499426e-04	147156.37.00	−332060.01.00	435944.08.00	48
2014	5	3.227146e-04	145232.12.00	−306091.13.00	499375.47.00	47
2015	1	4.052755e-04	220194.34.00	−756501.11.00	522270.10.00	51
2015	2	-1.780065e-03	215257.39.00	−414263.29.00	619118.23.00	51
2015	3	7.971151e-04	195142.45.00	−424762.08.00	359438.43.00	52
2015	4	2.293230e-03	195142.13.00	−461365.05.00	484944.49.00	49
2015	5	-6.384773e-04	185681.17.00	−421357.34.00	428619.43.00	48
2016	1	-1.511683e-03	287007.50.00	−1337579.37.00	588892.16.00	49
2016	2	7.609599e-04	168468.43.00	−290759.31.00	387298.39.00	52
2016	3	6.955824e-04	187845.22.00	−506731.46.00	561839.17.00	51
2016	4	-8.416826e-04	178434.39.00	−485276.59.00	373006.33.00	51
2016	5	2.239505e-03	200824.53.00	−432456.12.00	592420.02.00	50
2017	1	2.581295e-04	113280.11.00	−189757.22.00	334308.49.00	49
2017	2	8.087699e-04	102199.30.00	−280833.08.00	199407.00.00	50
2017	3	3.757388e-04	97184.02.00	−245581.28.00	287509.38.00	52
2017	4	-3.540135e-04	93984.00.00	−220828.12.00	184150.38.00	51
2017	5	2.386511e-04	102831.22.00	−192260.45.00	179912.05.00	49
2018	1	-4.488547e-04	143174.04.00	−423087.39.00	246545.12.00	49
2018	2	1.116231e-04	142809.24.00	−352393.13.00	347109.14.00	50
2018	3	5.967071e-05	152287.29.00	−337883.14.00	475832.42.00	50
2018	4	-1.310121e-03	187169.12.00	−483426.52.00	361453.21.00	51
2018	5	1.092862e-04	140232.55.00	−328581.32.00	309220.48.00	50
2019	1	3.787362e-04	142049.16.00	−380408.56.00	283188.39.00	51
2019	2	1.438600e-03	111058.37.00	−271810.27.00	233493.27.00	50
2019	3	2.577161e-04	134131.52.00	−426091.38.00	265036.16.00	50
2019	4	9.760871e-05	127418.01.00	−335262.46.00	281277.28.00	49
2019	5	3.154396e-03	147740.03.00	−381913.28.00	469109.35.00	50
2020	1	8.234836e-04	369211.06.00	−926636.42.00	765733.26.00	50
2020	2	5.760911e-03	260588.10.00	−452200.11.00	1226313.54.00	52
2020	3	1.162028e-03	253532.01.00	−609314.47.00	713778.15.00	52
2020	4	-4.073232e-03	346146.57.00	−1850415.37.00	571335.18.00	50
2020	5	-1.198201e-03	207310.46.00	−556497.46.00	563262.39.00	48
2021	1	2.789100e-04	155602.34.00	−447157.27.00	382166.32.00	51
2021	2	1.278314e-03	178121.29.00	−478641.44.00	448567.50.00	52
2021	3	1.089404e-03	147629.28.00	−320938.28.00	416467.24.00	51
2021	4	3.745418e-03	134541.25.00	−276026.38.00	303486.40.00	51
2021	5	-3.646775e-04	163256.52.00	−572967.34.00	264857.12.00	48
2022	1	-2.763725e-03	293038.38.00	−936227.39.00	571919.01.00	48
2022	2	2.776408e-04	235162.55.00	−401235.57.00	716854.50.00	52
2022	3	1.471144e-03	250941.02.00	−367993.22.00	736785.28.00	52
2022	4	-5.542291e-03	242912.34.00	−580042.51.00	385401.33.00	46
2022	5	1.042748e-03	316808.13.00	−503558.40.00	895447.57.00	49
2023	1	9.453403e-04	145739.34.00	−313529.23.00	420700.47.00	49
2023	2	3.951764e-04	172808.29.00	−290998.48.00	564457.40.00	50
2023	3	-8.502012e-04	163621.22.00	−644489.28.00	288983.31.00	52
2023	4	1.974979e-03	198199.06.00	−413564.56.00	716934.50.00	51
2023	5	8.328177e-04	181038.30.00	−399456.25.00	363839.55.00	47

Appendix H-J: The tables above present the Mean, SD, Min-value, Max-value, and total observations for each separate day of the week across all examined years. Excluding 2024 the small number of observations.

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AI Appendix

The AI tools Chat GPT 4 and Grammarly have been used to improve the quality of the writing in this bachelor's thesis in order to refine the viewer's readability. The tools have not been used to write any parts of the thesis or provide any results. All of the data collection, theoretical framework, findings, and conclusions have been done by the thesis authors.