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The day-of-the-week effect in Swedish stock returns

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Abstract

One implication of the Efficient Market Hypothesis (EMH) is that it is not possible to consistently and over time create abnormal returns without taking on additional risk. However, the hypothesis has become one of the most debated theories in financial economics. Numerous studies suggest that seasonal patterns exist in stock returns, so-called calendar effects, which violates the assumption of stock market efficiency. In contribution to this literature, the present study aims to investigate the day-of-the-week effect on the Swedish stock market in small, mid, and large-capitalization stocks. This study reports positive day-of-the-week effects among small and mid-capitalization stocks, both for raw returns and for risk-adjusted returns, but finds no such effects for large-capitalization stocks. However, the observed day-of-the-week effects do not prevail consistently over time, which indicates only weak evidence against the EMH.

Keywords: day-of-the-week effect, efficient market hypothesis, anomalies, size effect

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Table of Contents

1. Introduction

According to financial economics theory and the Efficient Market Hypothesis (EMH), stock prices fully reflect all available information regarding the intrinsic value of a stock. The EMH suggests that without taking on additional risk it is impossible to gain abnormal returns. Fama (1965) introduces the underlying assumption of the EMH and argues that stock price movements are random, which implies that only new information affects future stock prices. If future stock market fluctuations were predictable, all public and private information would not already be reflected in the fundamental stock value which violates the assumption of the efficient stock market (Bodie et al. 2014).

However, as opposed to the EMH, previous literature reports systematic patterns in average stock returns of days, weeks, months, and years, respectively. This seasonal phenomenon of stock returns, so-called stock market calendar effects, has become a prominent topic in the financial economics literature (Brooks 2008). Fama (1965) stresses that it is interesting to study calendar effects according to the underlying question of whether it is possible to predict future stock prices based on historical stock market patterns. If stock returns tend to follow systematic patterns, future stock prices might be predictable, which violated the assumption of the EMH. Several authors have documented stock market anomalies and one of the most extensively studied calendar effects is the day-of-the-week effect, which implies that the variation in stock returns are related to the specific weekday (Claesson 1987). Thenceforth, the day-of-the-week effect could be a potential explanation to the significantly higher, or lower, average stock returns documented in certain weekdays (Brooks 2008). For instance, numerous studies report significant abnormalities in stock returns on Mondays. A possible explanation is that Monday returns are calculated over the weekend, three calendar days, instead of over one calendar day (Fama 1965; Gibbons and Hess 1981; Smirlock and Starks 1985). Even though the majority of research focuses on the Friday to Monday effect, the day-of-the-week effect related to other specific weekdays also exists (Borges 2009; Cinko et al. 2015).

Consequently, seasonal patterns in stock markets contradict the assumption of EMH since calendar effects, and anomalies, create opportunities for investors to gain abnormal stock returns by taking advantage of inefficient stock markets. Moreover, stock markets can be more or less efficient, depending on its characteristics and the characteristics of the stocks.

For instance, the market for small-capitalization stocks tends to be more inefficient than the large-capitalization stock market (Brooks 2008). Zaremba and Shemer (2017) suggest that there might be a size effect in stock returns and that small-capitalization stocks tend to yield higher returns than large-capitalization stocks. Moreover, calendar effects of small and mid-capitalization stocks seem to be more prominent than calendar effects for large-capitalization stocks, and small-capitalization stocks tend to have greater risk-adjusted returns (Abraham and Ikenberry 1994; Banz 1981)

This study aims to examine the day-of-the-week effect on the Swedish stock market over the sample period from 6th October 2006 to 22th January 2019. The EMH usually divides into different forms of market efficiency, and according to Claesson (1987), the weak form of EMH is analysed using the information contained in historical stock prices. Investigating the day-of-the-week effect in Swedish stock returns is, therefore, one way of testing the weak form of EMH in the Swedish stock market. In general, researchers analyse calendar effects in financial markets by calculating daily stock returns. However, investors are typically not solely interested in the average return of a stock but also the risk-adjusted return of a stock. Because of that, this study examines the day-of-the-week effect on both raw returns and risk-adjusted returns. The realised risk-adjusted returns are calculated in the spirit of the Sharpe ratio which is a well-known financial risk-return ratio that was first applied by Sharpe (1966), and according to Bailey and Lopez de Prado (2012), it is today the 'gold standard' of evaluating the performance of an investment.

Moreover, this study attempts to determine if the day-of-the-week effect tends to differ between different stock sizes and therefore tests three indexes containing all small, mid, and large-capitalization stocks listed on the Nasdaq OMX Stockholm. To the best of my knowledge, only a few studies investigating the day-of-the-week effect have been performed on the Swedish stock market. Furthermore, there is a research gap in investigating the day-of-the-week effect on stocks with different market capitalizations. Another contribution to the literature is that this study focuses on the period during and after the financial crisis and thus the persistence of the day-of-the-week effect is tested by dividing the sample period into four subsamples, based on business cycle.

The two econometric approaches used in this study is the ordinary least squares (OLS) model and the generalized autoregressive conditional heteroscedasticity (GARCH) model. This study reports positive day-of-the-week effects among small and mid-capitalization stocks, both for raw returns and for risk-adjusted returns but finds no such effects for large-capitalization stocks. However, the observed day-of-the-week effects do not prevail consistently over time, which indicates only weak evidence against the EMH. Lastly, this study finds no relation between the day-of-the-week effects and the business cycle.

The remainder of this paper is structured as follows: the second chapter provides an overview of the theoretical framework. Chapter three reviews some of the most relevant previous literature investigating the day-of-the-week effect in the U.S. and the European market and introduces stock market size effects. Chapter four explains the research approach, including the data and the econometric model. The fifth chapter reports the empirical results, and chapter six gives the conclusion. Chapter seven presents some suggestions for future research based on the findings of this study.

2. Theoretical Framework

2.1. The Efficient Market Hypothesis

In order to examine stock market efficiency, the fundamental criteria is whether stock prices fully reflect all available information. The EMH suggests that today's stock prices do reflect all, public and (or) private, information about the future stock prices and stock market fluctuations; hence, investors are unable to gain abnormal stock returns (Rossi 2015). Fama (1965) introduces the term 'efficient markets', and if the market efficiency assumption holds, all new information is unpredictable and stock price movements follow a 'random walk'. Consequently, changes in stock prices are both random and unpredictable (Bodie et al. 2014; Fama 1970).

The EMH often divides into three forms of market efficiency based on the following information levels: the weak form of efficiency, the semi-strong form of efficiency, and the strong form of efficiency (Rossi 2015). The weak-form hypothesis asserts that stock prices already reflect all available information about historical stock prices, trading volumes, and short interests. According to the weak-form of the EMH, it is not possible to gain abnormal returns based on this publicly available information (Bodie et al. 2014). The semi-strong form of the EMH states that stock prices reflect all publicly available information about the firm, which means that stock prices adjust immediately when new information becomes public (Rossi 2015). Lastly, the strong form of the EMH declares that all available information, both public and private, is already reflected in stock market prices (Bodie et al. 2014).

However, the weak form of the EMH is challenged in the financial economics literature since some authors have observed that it might be possible to predict future stock returns, based on historical stock prices. Because the EMH suggests that investors are unable to detect mispricing in stock markets, many studies investigate if calendar effects, or anomalies, exist in financial markets. Calendar effects refer to the fact that stock returns tend to follow systematic patterns at specific days, weeks, months, or years. In other words, a calendar effect is an economic consequence related to the calendar (Brooks 2008; Rossi 2015). The most renowned calendar effects studied are the open-and-close-of-market effect, the January effect, the weekend effect, and the day-of-the-week effect (Brooks 2008). The phenomenon of calendar effects in financial markets contradicts the theoretical assumptions of the general stock market condition (i.e. efficient stock markets), and thus violates the EMH (Bodie et al. 2014).

On the other hand, calendar effects in daily stock returns do not necessarily imply that the stock market is inefficient since other, probably unknown, factors might as well influence stock returns and stock prices. For that reason, it might for instance be appropriate to control for the market risk premium (i.e. the excess return of the stock market return and the treasury bond yield) since abnormalities in daily stock returns could depend on the fluctuations in the stock market risk premium (Brooks 2008).

2.2. The Risk-return (Sharpe) Ratio

Investors are typically interested in the expected excess return that they can gain from replacing a less risky investment (i.e. T-bills) with a risky investment. The attraction of a portfolio, or the trade-off between risk and return, can be calculated by dividing the investment risk premium with the standard deviation of the excess return. The reward-to-risk ratio was first proposed by Roy (1952), with the purpose to determine the performance of an investment. The risk-return measure stated in Equation 1 (i.e. the Sharpe ratio) was later introduced by Sharpe (1966), as a measure of the performance of mutual funds. Today, according to Bailey and Lopez de Prado (2012), the 'gold standard' of evaluating the performance of an investment is to calculate the Sharpe ratio.

In general, the higher the Sharpe ratio the more attractive is the risk-adjusted return and thereby the investment (Bodie et al. 2014). The underlying assumption behind the Sharpe ratio is that investors are mean-variance optimizers, and hence are trading off excess return against variance. If investors have preferences for, or against, higher moments (e.g. skewness and kurtosis), and returns are not normally distributed, then the Sharpe ratio is no longer a fully adequate performance measure (Markowitz 1952).

$$SR = \frac{E(R_p - R_f)}{\sigma_p}, \tag{1}$$

The mathematical expression for the traditional Sharpe ratio is stated in Equation 1, where R_p denotes the rate of return of the investment, R_f denotes the risk-free rate of return, and σ_p denotes the standard deviation of the investment.

3. Literature Review

3.1. The Day-of-the-week Effect

A prominent topic in the financial economics literature is the impact of seasonality in stock returns, usually mentioned as calendar effects or calendar anomalies. Fama (1965) discusses the underlying question of the phenomenon, which regards to what extent it is possible to predict future stock market fluctuations based on the historical patterns of stock returns. The literature investigating calendar effects is extensive, and one of the most frequently studied calendar effects is the day-of-the-week effect. Generally, the underlying assumption of the distribution of stock returns is that it is independent of specific weekdays (Claesson 1987).

However, previous literature presents convincing evidence that the mean and variance of stock market returns statistically differ between weekdays (Cinko et al. 2015; Cross 1971; French 1980; Guidi 2010; Rogalski 1984; Smirlock and Starks 1986). On the other hand, some studies do not find a significant day-of-the-week effect (Steeley 2000; Apolinario et al. 2006).

The day-of-the-week effect in stock returns has been comprehensively dissected based on different econometric approaches, periods, frequencies, markets, and countries. One of the standard econometric methodologies is to run a standard OLS regression model, where the number of dummy variables included in the model depends on the frequency of the data (e.g. investigating the day-of-the-week effect using daily data means including one dummy variable for each weekday) (Gibbons and Hess 1981; Smirlock and Starks 1985). Another common approach is to use a GARCH (1,1) model or to combine several models in order to determine the persistence of the day-of-the-week effect (Berument and Kiymaz 2001; Guidi 2010).

Osborne (1962) was first to document the day-of-the-week effect in U.S. stock returns. The majority of the earliest research investigating the day-of-the-week effect focuses on the U.S. market. In general, the U.S. market is characterised by abnormally lower average returns on Monday, but higher average returns on Friday, compared to the other weekday returns. Cross (1971) investigates differences in stock market returns across weekdays by focusing on the Friday to Monday returns for the S&P500, covering the period from 1953 to 1970. The author reports that price changes on Monday and Friday are significantly different from other weekdays. Thenceforth, numerous studies present similar results of the day-of-the-week effect on the U.S. stock market. French (1980) investigates the weekend effect on the S&P500 from 1953 to 1977, based on the assumption of the calendar time hypothesis. This hypothesis states that Monday returns should be three times higher than other individual weekday returns since Monday returns are calculated over three calendar days, instead of one. The results presented by the author contradicts the hypothesis since the average return for Monday was significantly negative, while the average returns for all other weekdays were positive. The result was found to be persistent during all five subsample periods tested.

Similarly, Gibbons and Hess (1981) analyse the existence of the day-of-the-week effect on the U.S. stock market. This study uses daily observations of the S&P500 and the Dow Jones 30 for the period 1962 to 1978. The authors find persistent and robust evidence of negative average stock market returns on Monday. The Monday effect is documented by many authors investigating a similar period (Rogalski 1984; Smirlock and Starks 1986). However, some studies report that the Monday effect may not be as persistent in today's stock market. For instance, Kamara (1997) investigates the Monday effect over the period 1962 to 1993. He uses daily returns of the S&P500 and a small-capitalization index of the New York Stock Exchange (NYSE). The author finds that the Monday effect becomes weaker during the end of the sample period, but the Monday effect was found to persist for small-capitalization stocks. Berument and Kiymaz (2001) test the day-of-the-week effect on the S&P500 for the period 1983 to 1997. The authors find a day-of-the-week effect both in volatility and returns and the highest and lowest returns are documented on Wednesday and Monday, respectively. The volatility is found to be highest on Friday and lowest on Wednesday. However, the day-of-the-week effect tends to differ between subperiods, which means that the volatility between weekdays statistically differs. A study investigating the 20th century is performed by Xiao (2016) who examines the day-of-the-week effect in the U.S. stock market based on daily data from the Russell 3000 index over the period 2000 to 2015. The author conducts the study by dividing the sample period into several subsamples based on whether an economic recession or expansion characterised the specific period. The results presented do not suggest that the day-of-the-week effect still exists.

Not only the U.S. market is covered by previous literature. The day-of-the-week effect has also been examined in the European stock market, and the results presented are not consistent. While some of the authors do not find any effect, others do. Moreover, the effect tends to differ depending on the specific country and period investigated. Steeley (2000) investigates the day-of-the-week effect in the U.K. stock market. He reports that the weekday phenomenon has disappeared during the 1990s but suggests that the Monday and Friday returns significantly differ from the other weekdays. Similarly, Apolinario et al. (2006) analyse the day-of-the-week effect on several European market indexes during the period 1997 to 2004, and for most of the countries tested in this study, there is no significant day-of-the-week effect found. Borges (2009) tests the day-of-the-week effect in 17 European markets between 1994 and 2007. In contrast to Steeley (2000) and Apolinario et al. (2007), he finds negative Monday returns, positive Tuesday returns, and positive Friday returns for different countries. Significant positive Friday returns are found for two of the Nordic countries included in the study, Iceland and Norway. Another study investigating many European indexes is performed by Cinko et al. (2015). The authors aim to examine the day-of-the-week effect in several developed countries, mostly European, between 1999 to 2013. They present negative and positive returns on Monday and Friday, respectively for some of the indexes. Furthermore, negative Wednesday returns and positive Thursday returns are reported for a few indexes tested.

3.2. The Size Effect

Some authors investigate if calendar effects tend to be related to a size effect. For instance, Abraham and Ikenberry (1994) analyse the weekend effect in equal-weighted indexes on the NYSE. They report a stronger weekend effect for small and mid-capitalization stocks and discuss the impact of the individual investor behaviour on fluctuations in stock prices. The size effect is often referred to as the 'small-cap effect' motivated by the fact that small-capitalization stocks tend to beat large-capitalization stocks in terms of returns (Zaremba and Shemer 2017). The size effect is investigated in many stock markets, but the majority of studies cover the U.S. market, where the relationship between stock capitalization and stock returns was first discovered by Banz (1981). He investigates stock returns between 1936 to 1975 on the NYSE and reports that the risk-adjusted returns of small-capitalization stocks, on average, exceed the risk-adjusted returns of large-capitalization stocks. More specific, monthly stock returns of small-capitalization stocks were 0.4 percent greater than for large-capitalization stocks. According to previous research, the size premium in stock returns between small and large-capitalization stocks vary between stock markets. Doeswijk (1997) investigates the stock market in the Netherlands between 1973 to 1995 and report a size premium of 0.13 percent. A considerably more substantial monthly size premium of 0.76 percent is observed in Finland by Wahlroos and Berglund (1987).

Banz (1981) suggests that the outperformance of small-capitalization stocks over large-capitalization stocks indicates that there is misspecification of the Capital Asset Pricing

Model (CAPM).[1] Similarly, Fama and French (1993) argue that the extra premium for small-capitalization stocks is related to a risk that is not captured in the CAPM. Moreover, the size effect is not found to be persistent over time, and there is a seasonal pattern in the size effect. However, there is no theoretical explanation for the size effect or small-cap effect. For instance, Banz (1980) claims that it is unclear whether it is stock size affecting stock returns, or if it is another factor that correlates with stock size affecting stock returns.

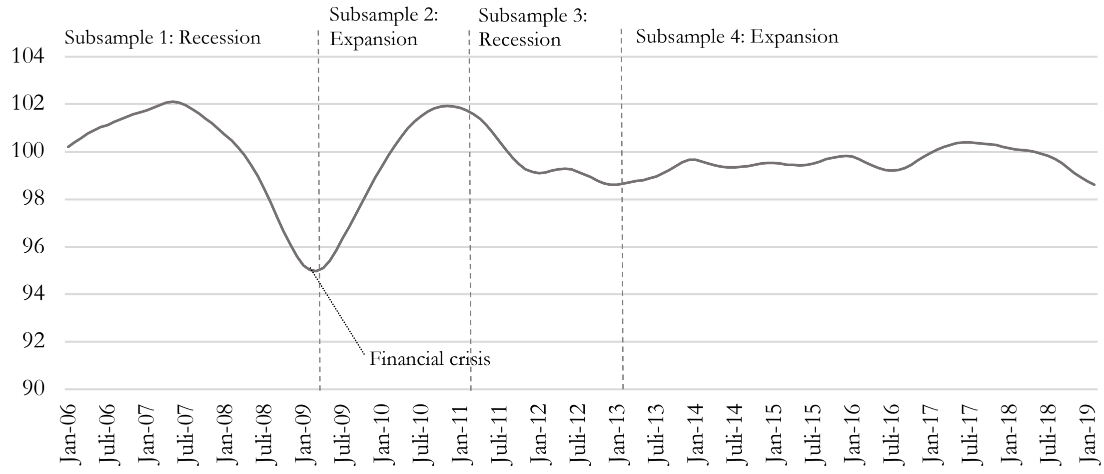
4. Research Approach

4.1. Data Description

Daily closing prices of the OMX Stockholm Small Capitalization PI (OMXSSCPI) index, OMX Stockholm Mid Capitalization PI (OMXSMCPI) index, and OMX Stockholm Large Capitalization PI (OMXSLCPI) index are collected from Nasdaq OMX Nordic (Nasdaq 2019). The index prices are calculated as price-weighted averages, and the OMXSSCPI, OMXSMCPI, and OMXSLCPI respectively consist of all small, mid and large-capitalization stocks listed on Nasdaq OMX Stockholm. The sample period ranges from 6th October 2006 to 22th January 2019, and the total sample contains 3,084 observations, for each index. Small stocks have a market capitalization of less than 150 million euro, and large stocks have a market capitalization equal to, or larger than, one billion euros. To calculate the market capitalization of a stock, the total number of all outstanding shares are multiplied with the daily closing prices (Nasdaq 2018).

The sample is further divided into four subsamples in order to test the persistence of the day-of-the-week effect in Swedish stock returns. Similar to Xiao (2016), the subsamples are divided based on economic business cycle fluctuations. The subsamples are therefore grouped according to the composite leading indicator for Sweden. Figure 1 displays the indicator which provides signals of turning points in business cycle fluctuations (OECD 2019). From Figure 1 it is then possible to determine periods of economic recession and expansion.

[1] The CAPM explains the relationship between expected return and the market risk of the asset (Sharpe 1964; Lintner 1965).



Source: OECD (2019)

FIGURE 1
The Composite Leading Indicator for Sweden

The final subsamples range from 6th October 2006 to 6th April 2009; 7th April 2009 to 7th February 2011; 8th February 2011 to 9th February 2013; and 10th February 2013 to 22th January 2019.

The index closing prices are used to calculate daily stock returns. The single period arithmetic return for day *t* is calculated according to Equation 2, where R_t denotes the percentage daily return at the *t*-th day, P_t denotes the index closing price at day *t*, and P_{t-1} denotes the daily closing price at the *t-1*-th day.

$$R_t = \left(\frac{P_t - P_{t-1}}{P_{t-1}}\right) * 100, \tag{2}$$

Risk-adjusted returns are calculated in the spirit of the Sharpe ratio, presented in Equation 1. To calculate the excess return, the daily risk-free rate is subtracted from each observation of daily returns in the sample. Daily data of three-months-treasury bills are collected from the Swedish central bank (Riksbank 2019), which is used as an approximation for the risk-free rate in calculating the risk-adjusted returns. Furthermore, the GARCH (1,1) model predicts the variances for each observation in the sample. The standard deviation is estimated by taking the square root of the predicted variances to calculate Sharpe ratios for each daily observation.

4.2. Descriptive Statistics

TABLE 1
The Highest and Lowest Weekday Returns

	Raw Returns			**Risk-adjusted Returns**		
	Small	Mid	Large	Small	Mid	Large
Lowest	Wednesday: -0.017 %	Monday: 0.005 %	Friday: -0.001 %	Wednesday: -0.055 %	Tuesday: 0.001 %	Wednesday: -0.002 %
Highest	Monday: 0.094 %	Friday: 0.084 %	Thursday: 0.050 %	Monday: 0.138 %	Friday: 0.113 %	Thursday: 0.033 %

Table 1 summarizes the lowest and highest average weekday returns for each separate index.

Table 2 reports descriptive statistics for the three indexes and describes the average daily raw returns in panel A and the risk-adjusted daily returns in panel B. Moreover, Table 2 lists the average return of each weekday in order to compare daily returns across weekdays, as well as between the indexes. Table 2 also presents the standard deviation, the minimum value, the maximum value and the number of observations for each sample.

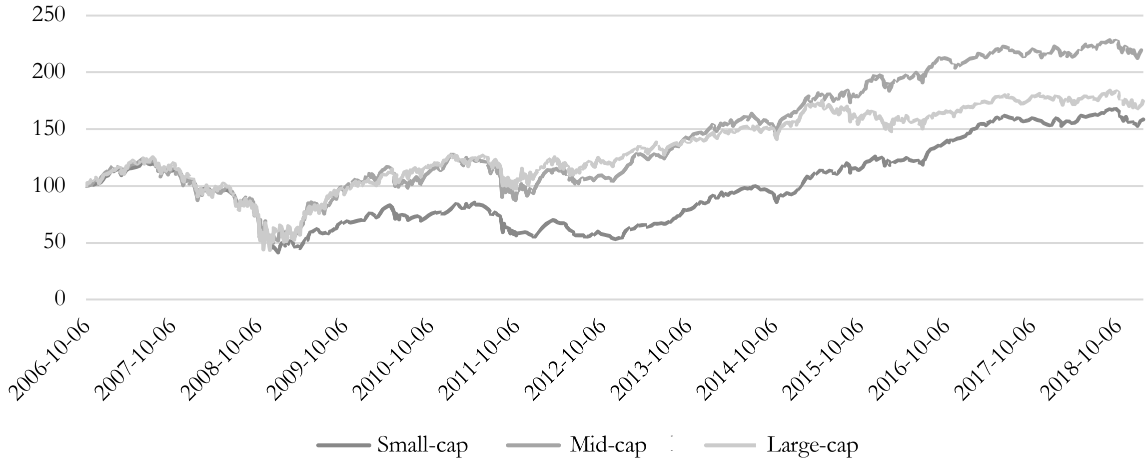
The mean returns presented in Table 2, panel A are 0.019, 0.039, and 0.024 percent for the small, mid, and large-capitalization index, respectively. The average risk-adjusted returns in Table 2, panel B, are 0.027, 0.044, and 0.011 percent for the small, mid, and large-capitalization index, respectively. In line with Banz (1981), the risk-adjusted daily returns for small-capitalization stocks (0.027 percent) exceed the risk-adjusted daily returns for large-capitalization stocks (0.011). Moreover, when adjusting the daily returns for the risk, the return increases for both small (from 0.019 percent to 0.027 percent) and mid-capitalization stocks (from 0.039 percent to 0.044 percent). However, for large-capitalization stocks, the returns decrease when adjusting for risk (from 0.024 percent to 0.011 percent). On average, mid-capitalization stocks yield the highest daily returns, both for raw and risk-adjusted returns. When comparing raw returns, small-capitalization stocks yield the lowest daily raw returns, on average. For the risk-adjusted returns, the large-capitalization stocks yield less return than the small-capitalization stocks.

Furthermore, the highest and lowest average daily raw returns for small-capitalization stocks are observed on Monday (0.094 percent) and Wednesday (-0.017 percent) respectively. According to the calendar time hypothesis, the higher Monday returns observed for small-capitalization stocks are reasonable since the return is calculated over three calendar days instead of one calendar day (French 1980) but according to the literature, Monday returns are usually negative (Rogalski 1984; Smirlock and Starks 1986). However, positive Monday returns strengthen the fact that the Monday effect becomes weaker or is no longer present in today's stock market (Kamara 1997; Xiao 2016). When the returns are adjusted for risk, Monday and Wednesday still yield the highest and lowest (0.139 percent and -0.055 percent) average returns respectively for small-capitalization stocks. In contrast, mid-capitalization stocks yield the highest and lowest average raw returns on Friday (0.084 percent) and Monday (0.005 percent respectively. The finding is consistent with previous literature suggesting than Monday and Friday returns are, on average, different (i.e. lower and higher respectively) compared to the other weekdays (Apolinario et al. 2006; Cinko et al. 2015; Steeley 2000) and that Monday returns are lower and Friday returns are higher, even though Monday returns for the mid-capitalization stocks are not negative in Table 2 (Kamara 1997; Xiao 2016). However, when the returns are risk-adjusted, Tuesday yields the lowest daily returns (0.001 percent), on average, but the average Monday returns are slightly above (0.0027 percent). Friday still yields the highest risk-adjusted return for mid-capitalization stocks (0.113 percent). Lastly, large-capitalization stocks yield the highest and lowest returns on Thursday (0.050 percent) and Friday (-0.001 percent) respectively. When adjusting for risk, the highest and lowest average returns are observed on Thursday and Wednesday, respectively (0.033 percent and -0.002 percent).

The average weekday returns for small, mid, and large-capitalization stocks are also displayed in bar charts in Appendix A. By looking at the bar charts, it is clear that the highest mean returns are observed on Monday, Friday, and Thursday for small, mid, and large-capitalization stocks respectively.

TABLE 2
Descriptive Statistics

Observations	Mean	Std.	Min	Max	Obs.
		Panel A: Raw Returns			
		Small-capitalization Stocks			
All	0.0191	0.6689	-4.9648	5.5747	3,084
Monday	0.0937	0.6345	-4.1522	3.6091	610
Tuesday	-0.0143	0.7895	-4.1636	5.5747	623
Wednesday	-0.0171	0.6564	-2.9023	3.9182	625
Thursday	0.0321	0.5996	-4.9648	2.1929	623
Friday	-0.0011	0.6439	-3.0253	2.8564	603
		Mid-capitalization Stocks			
All	0.0387	1.0777	-6.3404	9.9245	3,084
Monday	0.0052	1.2528	-5.8893	9.9245	610
Tuesday	0.0221	1.0208	-4.1008	4.9331	623
Wednesday	0.0664	1.0530	-6.2207	6.8260	625
Thursday	0.0170	1.0339	-4.8147	4.2490	623
Friday	0.0842	1.0133	-6.3404	5.7435	603
		Large-capitalization Stocks			
All	0.0243	1.3642	-8.0255	9.7172	3,084
Monday	0.0253	1.2808	-6.0813	8.5824	610
Tuesday	0.0185	1.5245	-8.0255	9.7173	623
Wednesday	0.0252	1.3455	-5.2066	6.9085	625
Thursday	0.0503	1.3293	-6.3814	6.0080	623
Friday	-0.0010	1.3293	-6.3918	5.0460	603
		Panel B: Risk-adjusted Returns			
		Small-capitalization Stocks			
All	0.0267	1.0060	-6.8219	5.4540	3,084
Monday	0.1381	0.9606	-6.2953	5.4540	610
Tuesday	-0.0329	1.1429	-6.8219	3.1249	623
Wednesday	-0.0551	0.9701	-5.0858	3.3013	625
Thursday	0.0542	0.8977	-3.6956	3.3066	623
Friday	0.0294	1.0314	-3.7335	4.6279	603
		Mid-capitalization Stocks			
All	0.0437	1.0231	-5.5497	9.3357	3,084
Monday	0.0027	1.1799	-5.5497	9.3358	610
Tuesday	0.0010	0.9588	-3.8034	3.1041	623
Wednesday	0.0675	0.9319	-3.0728	2.8461	625
Thursday	0.0367	1.0226	-3.9031	3.1903	623
Friday	0.1126	1.0059	-4.0728	5.0616	603
		Large-capitalization Stocks			
All	0.0109	0.9903	-6.4715	6.2501	3,084
Monday	0.0167	0.9343	-4.4417	6.2501	610
Tuesday	0.0061	1.0546	-6.4715	4.9969	623
Wednesday	-0.0021	1.0037	-4.2552	5.2649	625
Thursday	0.0332	0.9480	-4.9682	3.4854	623
Friday	-0.0013	1.0083	-4.6145	2.8229	603

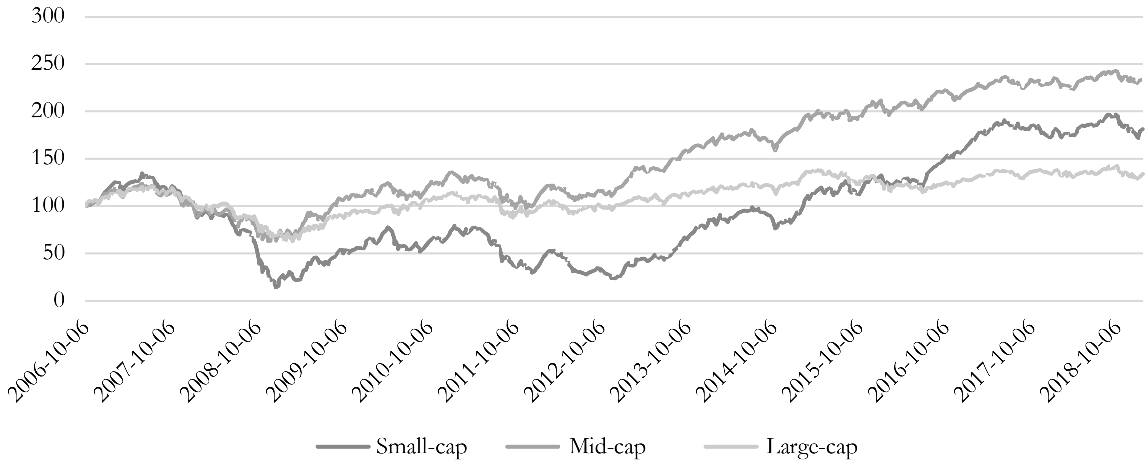


Source: Nasdaq OMX Nordic (2019)

FIGURE 2
Daily Raw Returns of the Small, Mid, and Large-capitalization Index

Figure 2 displays cumulative returns of the indexes (index value 2006=100) investing 100 SEK in the beginning of the sample period. The mid and large-capitalization stocks slightly differ during the sample period. However, after 2015, the gap between the indexes increases since the development of the large-capitalization stocks levels out. At the end of the sample period, the gap between the small and large-capitalization stocks decreases.

Figure 3 displays the risk-adjusted returns of the stocks (index value 2006=100). Compared to Figure 2, the returns of the small-capitalization stocks exceed the large-capitalization stocks after 2016. The mid-capitalization stocks tend to have the highest risk-adjusted returns over the sample period.



Source: Nasdaq OMX Nordic (2019)

FIGURE 3
Risk-adjusted Returns of the Small, Mid, and Large-capitalization Index

4.3. Model Specifications and Statistical Tests

4.3.1. The Welch's t-test

To examine if mean returns and the calendar variables differ across stocks with different sizes, Fama and French (2008) propose to test for differences in means. This study tests the small, mid, and a large-capitalization stocks using a two-sided independent-samples t-test (i.e. unpaired t-test), the so-called Welch's test. Welch's t-test is an inferential statistical test that determines whether two independent samples statistically differ in means, and the fundamental underlying assumption of this t-test is that the two sample variances are unequal.

Furthermore, the null hypothesis of the Welch t-test states that there is no difference in means between two independent samples. In other words, if the probability value of the Welch's t-test is less than the chosen level of significance (i.e. one, five or ten percent), the null hypothesis is rejected which implies that the sample means of the two different samples are unequal (Welch 1947).

4.3.2. The OLS Model

According to previous literature, one of the standard approaches used in examining stock market calendar effects is to run an OLS model. Because of that, this study first tests the day-of-the-week effect on the Swedish stock market by using the standard OLS regression approach, both for raw returns and for risk-adjusted returns. It is convenient to include dummy variables in the econometric model when analysing calendar effects of financial data on stock returns. The number of dummy variables included in the OLS regression model should equal the frequency of the data, which means five dummy variables if using daily data (Brooks 2008).

Equation 3 shows the mathematical expression of the day-of-the-week effects OLS model, where the dependent variable R_t is the daily returns of the index at time *t*.

$$R_t = \beta_1 D_{1t} + \beta_2 D_{2t} + \beta_3 D_{3t} + \beta_4 D_{4t} + \beta_5 D_{5t} + \epsilon_t, \tag{3}$$

The model further consists of five dummy variables, one dummy variable representing each weekday (i.e. Monday to Friday), and an error term ϵ_t. For instance, the dummy variable D_{1t} is the Monday dummy variable and takes value one if Monday at time *t*, and zero otherwise. The second dummy variable D_{2t} takes value one if Tuesday at time *t*, and zero otherwise, and so on.

In order to avoid the problem of perfect multicollinearity, the specified regression model does not consist of a constant term. Instead of running a regression without a constant, it is also possible to avoid multicollinearity by only including four dummy variables, and thereby allow the constant to capture the effect of the excluded fifth variable. According to the no-constant approach, the estimated coefficients of the dummy variables are interpreted as the average value of the dependent variable during each day. In other words, the coefficient estimates are interpreted as the mean stock returns for each specific trading weekday (i.e. Monday to Friday). If a day-of-the-week effect exists, the coefficients should be significantly different from zero (Brooks, 2008). The null hypothesis of testing the day-of-the-week effect is that the daily stock returns of each weekday are equal:

$$H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5$$

The alternative hypothesis states that there is a difference in daily returns between weekdays. This implies that if β_i is different from zero there is a day-of-the-week effect in the *i*th-day of the index. Consequently, if the probability value for β_i is less than the significance level (i.e. one, five, or ten percent) the null hypothesis is rejected. Not rejecting the null hypothesis means that there is not a day-of-the-week effect in the specific stock index.

4.3.3. The GARCH (1,1) Model

Using a standard OLS approach in modelling stock market returns has been questioned. The reason is that there are some drawbacks with using the OLS model in this context. One of the problems of using an OLS model is related to heteroscedasticity in stock returns data. Moreover, there is a problem because the error variances are non-constant over time, so-called volatility clustering, and the phenomenon should be stressed when modelling financial market returns (Guidi 2010).

Appendix B present time-series line plots of daily stock returns for small, mid, and large-capitalization stocks, respectively. The figures suggest that volatility clustering exists in the data, which is the standard and expected pattern for the financial market variance. Volatility clustering refers to the fact that large returns (positive or negative) are expected to be followed by large returns (positive or negative), and similar holds for small returns. The implication is that the current level of volatility has a positive correlation to the volatility of the most recent preceding periods (Brooks 2008). Since volatility clustering is present in financial market return data, it is reasonable to use an autoregressive conditional heteroscedasticity (ARCH) model, which was first introduced by Engle (1982). Unlike the OLS model, the ARCH model allows the conditional variance of the error term to depend on its previous own lags *q*. The number of lags included in the model determines how many lagged squared errors the conditional variance depends on. However, there are some well-known limitations with the ARCH(*q*) model and the more frequently used GARCH(*p,q*), first presented by Bollerslev (1986), has fewer limitations but still allows the conditional variance to depend on its lags. The GARCH (1,1) model is used as a compliment in this study to predict the day-of-the-week effect in stock returns. The GARCH model is only performed for the raw returns since the risk-adjusted returns are already adjusted for the variances.

Equation 4 and Equation 5 show the conditional mean equation and the conditional variance equation of the GARCH (1,1) model, where ω is the constant term, σ_t^2 is the conditional variance of the error term, ϵ_t, γ_i and α_i are coefficients and σ_{t-1}^2 is the lag of the conditional variance.

$$R_t = \beta_1 D_{1t} + \beta_2 D_{2t} + \beta_3 D_{3t} + \beta_4 D_{4t} + \beta_5 D_{5t} + \epsilon_t, \tag{4}$$

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \gamma\sigma_{t-1}^2, \tag{5}$$

The GARCH (1,1) model interprets the current fitted variance using a weighted function of the long-term average value, information regarding volatility in previous periods, and the model fitted variance. Moreover, even though robust standard errors correct for heteroscedasticity in an OLS regression model, there might still be problems related to volatility clustering. The GARCH (1,1) model might therefore be more appropriate to use. The conditional maximum likelihood method estimates the GARCH (1,1) model (Brooks 2008).

4.4. Model Criticism

In this study, the day-of-the-week effect is tested without adding any additional control variables to the model. What should be stressed is that there might be other variables affecting stock prices, for instance transaction costs, but there might also be other, unknown factors that affect small, mid, and large-capitalization stocks differently. Since these factors are not included in the empirical model, the day-of-the-week effect might be weaker, or more prominent, when adding these control variables. Moreover, the risk-adjusted returns are calculated in the spirit of the Sharpe ratio, using predicted variances. The measure is an approximation and using other risk-adjusted measures, or variances predicted by other time-series models, could give different results.

4.5. Model Diagnostics

When time-series data are used in regression analysis it is appropriate to control for stationary processes. If the processes are not stationary the results will be spurious, which means that a trend that does not exist are documented hence the coefficient estimates, and the statistical tests, will be both invalid and misleading (Verbeek 2004). The augmented Dickey-Fuller unit-root test detects non-stationary processes and tests if a variable follows a unit-root process. The null hypothesis is that a unit root is contained in the variable while the alternative hypothesis says that the variable was generated by a stationary process. The results of the test presented in Appendix C report that the null hypothesis is rejected due to the small probability values which implies that the processes are stationary.

Before running the regressions, the OLS model is tested for both autocorrelation and heteroscedasticity. If heteroscedasticity is present, the OLS estimate will provide unbiased estimates but not the best linear unbiased estimator; thus, the estimates will be inefficient. By inefficient estimates, the results of the coefficient estimates might be misleading. To test if the error terms in the OLS model are heteroscedastic the Breusch-Pagan LM test is performed, which is a Lagrange multiplier test. If rejecting the null hypothesis, heteroscedasticity is a problem since the null hypothesis states that the error terms are homoscedastic (Verbeek 2004). Appendix C reports the results of the Breusch-Pagan LM test.

Another problem related to the OLS model is autocorrelation since the data contains time series. If autocorrelation is present in the model, the estimates are inefficient as a consequence of biases within the standard errors. Consequently, it is necessary to test for autocorrelation of the error terms when using time-series data. By the Breusch-Godfrey LM test, it is possible to detect autocorrelation. The Breusch-Godfrey LM test is a general test of autocorrelation, where the null hypothesis states that there is no autocorrelation. If the probability value is less than the significance level, the null hypothesis is rejected. The drawback of the test is that it is difficult to determine the number of lagged residuals to include, but following econometric theory, the most appropriate is to choose the number of lags based on the frequency of the data. Because of that, the test is performed using five lags since the time-series observations used in this study consist of daily data (Brooks 2008). Appendix C presents the test results of the Breusch-Godfrey LM test.

According to the test results, both autocorrelation and heteroscedasticity are present in the OLS model. To correct for the problems, the robust standard errors are applied to the OLS and GARCH regression model. Moreover, the GARCH (1,1) model corrects for heteroscedasticity when investigating the day-of-the-week effect on raw stock returns.

5. Results

5.1. Difference in Means

Appendix D reports the results from Welch's t-test. The test results suggest that there is no difference in means between the returns of the small, mid, and large-capitalization stocks. Banz (1981) argues that risk-adjusted returns of small-capitalization stocks tend to exceed the risk-adjusted returns of large-capitalization stocks, and the Welch's t-test is therefore performed on risk-adjusted returns as well. The results show no difference in means of risk-adjusted returns between the stocks.

However, even though the indexes do not differ in means, the mean of each specific weekday return may differ. Because of that, it is relevant to test if there is a difference in mean returns across weekdays. In other words, the average Monday small-capitalization stock return is compared to the average Monday return of mid and large-capitalization stocks. Appendix D presents the results of the Welch's t-test. The results suggest that there is a difference in mean returns between small and mid-capitalization stocks for Wednesday and Friday, on a ten percent significance level.

Furthermore, a similar structure of the Welch's t-test is performed on risk-adjusted returns of specific weekdays in order to examine if adjusting for risk in daily returns will affect the specific weekday returns for the indexes. Appendix D shows that there is a difference in means between small and mid-capitalization stocks on Monday and Wednesday, which is statistically significant on a five percent significance level. Another finding is that small and large-capitalization stocks differ in means on Monday, statistically significant on a five percent significance level. Lastly, the mid and large-capitalization stocks differ in means on Friday on ten percent significance level. Consequently, the results from the Welch's t-test implies that adjusting for risk in weekday returns affect the overall result of comparing mean returns between indexes related to different stock sizes.

5.2. The Day-of-the-week Effect

The day-of-the-week effect in Swedish stock returns is examined by two different models: the standard OLS and the OLS-GARCH (1,1) model. Table 3 reports the day-of-the-week effect for small, mid, and large-capitalization stocks, respectively, both for raw returns and risk-adjusted returns. The results in Table 3 suggest that the coefficient estimates of raw returns are more efficient when using the OLS-GARCH (1,1) model since the standard errors are, most of the times, larger in the OLS model (see results for mid and large-capitalization stocks), which implies that the OLS-GARCH (1,1) is more appropriate to use.

The regression results for small-capitalization stocks suggest that there is a positive effect for Monday returns, statistically significant at one percent (see column 1 to column 3), which implies that average Monday returns of small-capitalization stocks tend to be significantly higher than the average returns of all other weekdays. According to the estimates of each weekday, Wednesday yields the lowest return among small-capitalization stocks. The positive Monday effect contradicts the findings of previous literature. For instance, Cross (1971) and French (1980) find negative Monday returns. Instead, the positive Monday returns support the calendar time hypothesis, which assumes that Monday returns on average should exceed other weekday returns since it is calculated over three calendar days instead of one (French 1980). Furthermore, the results show a weak Thursday effect for small-capitalization stocks, but only in the GARCH (1,1) model (see column 2).

The regression results for mid-capitalization stocks suggest lower returns at the beginning of the week, compared to the end of the week. The results report significant day-of-the-week effects for mid-capitalization stocks and show a positive effect for Friday (see column 4 to column 6), Thursday (see column 5), and Wednesday (see column 5 and column 6). The results of the mid-capitalization stocks differ from the results of the small-capitalization stocks. The results for mid-capitalization stocks are more in line with previous literature observing low and high Monday and Friday returns, respectively (Cross 1971; French 1980). Moreover, similarly, the Thursday effect was also documented by Cinko et al. (2015).

The results in Table 3 from the baseline regressions of small, mid, and large-capitalization stocks show day-of-the-week effects for small and mid-capitalization stocks, but not for large-capitalization stocks. The results in Table 3 support the argument of Abraham and Ikenberry (1994) suggesting that the day-of-the-week effect is stronger for small and mid-capitalization stocks.

TABLE 3
Regression Results

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Small-capitalization Stocks			**Mid-capitalization Stocks**			**Large-capitalization Stocks**		
	Raw Returns		Risk-adjusted Returns	Raw Returns		Risk-adjusted Returns	Raw Returns		Risk-adjusted Returns
Monday	0.0937***	0.146***	0.138***	0.00509	0.0699	0.00248	0.0253	0.0811	0.0167
	(0.0257)	(0.0299)	(0.0389)	(0.0507)	(0.0468)	(0.0478)	(0.0519)	(0.0531)	(0.0378)
Tuesday	-0.0143	0.0177	-0.0329	0.0221	0.0408	0.00104	0.0185	0.0189	0.00606
	(0.0317)	(0.0259)	(0.0458)	(0.0409)	(0.0368)	(0.0384)	(0.0611)	(0.0500)	(0.0423)
Wednesday	-0.0171	-0.0310	-0.0551	0.0664	0.106***	0.0675*	0.0252	0.0476	-0.00211
	(0.0263)	(0.0215)	(0.0389)	(0.0421)	(0.0337)	(0.0373)	(0.0538)	(0.0477)	(0.0401)
Thursday	0.0321	0.0414**	0.0542	0.0170	0.106***	0.0366	0.0503	0.0431	0.0332
	(0.0241)	(0.0209)	(0.0361)	(0.0414)	(0.0366)	(0.0410)	(0.0533)	(0.0425)	(0.0380)
Friday	0.000976	0.0269	0.0291	0.0842**	0.0979***	0.113***	-0.00103	0.00759	-0.00134
	(0.0262)	(0.0225)	(0.0420)	(0.0412)	(0.0317)	(0.0409)	(0.0541)	(0.0437)	(0.0410)
Lag 1 ARCH		0.260***			0.265***			0.238***	
		(0.0432)			(0.0438)			(0.0366)	
Lag 1 GARCH		0.642***			0.765***			0.886***	
		(0.0950)			(0.0730)			(0.0938)	
Constant		0.0330			-0.0701			-0.211*	
		(0.0282)			(0.0492)			(0.122)	
Observations	3,084	3,084	3,084	3,084	3,084	3,084	3,084	3,084	3,084

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.3. The Persistence of the Day-of-the-week Effect

In order to determine if the day-of-the-week effect is persistent over time, the sample is divided into four subsamples based on the specific period of the business cycle, economic recession or expansion. The day-of-the-week effect is then tested for all different subsamples across small, mid, and large-capitalization stocks.

Table 4 reports the subsample regression results for small-capitalization stocks. Comparing the subsample results, the day-of-the-week effect changes over time and across the subsamples. The regression results of the first subsample differ between the three models of raw and risk-adjusted returns (see column 1 to column 3). In the first regression model, the lowest and highest returns are observed on Friday and Monday, respectively, and a five percent negative significant day-of-the-week effect is observed on Friday (see column 1). The results of the second and third regression models are more consistent since the lowest and highest returns are observed on Tuesday and Monday, respectively (see column 2 to column 3).

The regression results of the second time period, for small-capitalization stocks, suggest positive Monday, Tuesday, and Friday effects and the effect is observed to be strongest on Monday and Tuesday (see column 4 to column 6). Moreover, positive returns are observed on all weekdays except on Wednesday, where the coefficient estimates are negative. For the third small-capitalization stocks subsample, the highest returns are observed on Monday (see column 8 and column 9) and Thursday (see column 7) while the lowest returns are observed on Tuesday (see column 7 and column 9) and Wednesday (see column 8). Negative Tuesday and Wednesday effects are observed on a five percent significance level, where the Tuesday effect slightly exceeds the Wednesday effect.

The regression results of the fourth subsample show a strong and positive Monday effect, that was also reported from Table 3 (see column 1 to column 3) and the regression results of the second subsample in Table 4 (see column 4 to column 6). During the second and the fourth subsample, where the Monday effect is present, it is an economic expansion. However, since the results of the other weekdays across the two subsamples largely differ, the positive Monday effect observed during economic expansions (see column 4 to column 6, and column 10 to column 12) should be interpreted with caution. Moreover, the results of subsample four report Thursday and Friday effects (see column 10 to column 12). Even though the regression results change between the models and time periods, Monday returns are often observed to be higher than the other weekday returns for small-capitalization stocks. According to Kamara (1997) the day-of-the-week effect is persistent over time for small-capitalization stocks. However, the results of the small-capitalization subsamples largely differ and because of that, the day-of-the-week effect of small-capitalization stocks do not prevail consistently over time.

Similar to small-capitalization stocks, the results of mid-capitalization stocks, presented in Table 5, suggest that the day-of-the-week effect differs between time periods. However, no day-of-the-week effect is observed testing the first subsample. The regression results of the second subsample report a positive Monday effect, on a five percent significance level (see column 4 to column 6). The positive Monday effect of the second subsample was also observed for small-capitalization stocks. The lowest weekday returns are observed on Friday (see column 4 to column 6). The third subsample regression results for mid-capitalization stocks are in line with evidence from previous literature documenting low Monday returns, since the lowest and highest returns are observed on Monday and Friday respectively (see column 7 to column 9). A positive Friday effect is observed on five percent significance level (see column 8 and column 9). The results for the fourth subsample are inconsistent to the other subsamples tested. The results suggest a positive Wednesday effect (see column 10 to column 12), a positive Friday effect (see column 10 to column 12), and a positive Thursday effect (see column 11).

According to the results in Table 6, large-capitalization stocks tend to have weaker and fewer day-of-the-week effects compared to the results of small and mid-capitalization stocks. No day-of-the-week effect is observed for large-capitalization stocks during the first subperiod. The second subperiod reports different results and a positive and significant Tuesday effect is observed (see column 4 to column 6). The Tuesday effect is also reported for the third subsample, but it is negative and weak (see column 8). The regression results for the fourth subsample do not suggest any significant day-of-the-week effect.

Consequently, the day-of-the-week effect tends to be more prominent in small and mid-capitalization stocks. This is in line with Abraham and Ikenberry (1994) who find that the calendar effect (i.e. weekend effect) is stronger for small and mid-capitalization stocks. However, the regression results of the subsamples across the stocks indicate that the day-of-the-week effect do not prevail consistently and over time.

TABLE 4
Regression Results Small-capitalization Stocks

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Subsample 1 2006-10-06 to 2009-04-06			**Subsample 2 2009-04-07 to 2011-02-07**			**Subsample 3 2011-02-08 to 2013-02-09**			**Subsample 4 2013-02-10 to 2019-01-22**		
	Raw Returns		Risk-adjusted Returns	Raw Returns		Risk-adjusted Returns	Raw Returns		Risk-adjusted Returns	Raw Returns		Risk-adjusted Returns
Monday	-0.0167	0.140	-0.0310	0.113*	0.140**	0.192*	0.0202	0.0489	0.0254	0.158***	0.192***	0.264***
	(0.0798)	(0.0941)	(0.0959)	(0.0659)	(0.0617)	(0.113)	(0.0646)	(0.0659)	(0.101)	(0.0283)	(0.0335)	(0.0472)
Tuesday	-0.0974	-0.0961	-0.166	0.139**	0.139**	0.196**	-0.150**	-0.103	-0.239**	0.0160	0.0546	0.0384
	(0.0898)	(0.0643)	(0.103)	(0.0675)	(0.0572)	(0.0963)	(0.0760)	(0.0650)	(0.108)	(0.0416)	(0.0351)	(0.0705)
Wednesday	-0.0758	-0.0482	-0.111	-0.0190	-0.0100	-0.0248	-0.0641	-0.112**	-0.149	0.0266	-0.00117	0.000211
	(0.0701)	(0.0548)	(0.0843)	(0.0589)	(0.0557)	(0.112)	(0.0621)	(0.0567)	(0.103)	(0.0364)	(0.0282)	(0.0541)
Thursday	-0.0855	0.0263	-0.0742	0.0687	0.0574	0.112	0.0267	-0.00802	0.0193	0.0732**	0.0686**	0.118**
	(0.0638)	(0.0492)	(0.0763)	(0.0648)	(0.0508)	(0.110)	(0.0552)	(0.0500)	(0.0858)	(0.0312)	(0.0287)	(0.0508)
Friday	-0.141**	-0.0317	-0.153	0.0885*	0.0826*	0.166*	-0.0357	-0.0222	-0.0516	0.0529	0.0654*	0.112*
	(0.0704)	(0.0505)	(0.0936)	(0.0525)	(0.0448)	(0.0885)	(0.0648)	(0.0540)	(0.101)	(0.0355)	(0.0334)	(0.0618)
Lag1 ARCH		0.332***			0.274**			0.232**			0.236***	
		(0.119)			(0.113)			(0.0926)			(0.0608)	
Lag1 GARCH		0.697***			0.383			0.648***			0.480***	
		(0.144)			(0.360)			(0.247)			(0.184)	
Constant		-0.0356			0.102			0.0379			0.0974*	
		(0.0453)			(0.0995)			(0.0749)			(0.0508)	
Observations	625	625	625	462	462	462	506	506	506	1,491	1,491	1,491

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE 5
Regression Results Mid-capitalization Stocks

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Subsample 1 2006-10-06 to 2009-04-06			**Subsample 2 2009-04-07 to 2011-02-07**			**Subsample 3 2011-02-08 to 2013-02-09**			**Subsample 4 2013-02-10 to 2019-01-22**		
	Raw Returns		Risk-adjusted Returns	Raw Returns		Risk-adjusted Returns	Raw Returns		Risk-adjusted Returns	Raw Returns		Risk-adjusted Returns
Monday	-0.0733	0.0641	-0.0561	0.239**	0.289**	0.227**	-0.180	-0.117	-0.157	0.0262	0.0626	0.0333
	(0.161)	(0.134)	(0.110)	(0.115)	(0.120)	(0.109)	(0.138)	(0.114)	(0.118)	(0.0552)	(0.0520)	(0.0688)
Tuesday	-0.124	-0.0873	-0.126	0.118	0.160	0.111	-0.0314	-0.0829	-0.0526	0.0713	0.0749*	0.0716
	(0.119)	(0.0966)	(0.0805)	(0.109)	(0.114)	(0.108)	(0.114)	(0.105)	(0.0969)	(0.0449)	(0.0417)	(0.0554)
Wednesday	-0.0279	0.0829	0.0322	0.115	0.124	0.0874	0.0853	0.0718	0.0542	0.0835*	0.0990**	0.0941*
	(0.132)	(0.0910)	(0.0831)	(0.121)	(0.113)	(0.116)	(0.105)	(0.0842)	(0.0857)	(0.0435)	(0.0392)	(0.0523)
Thursday	-0.102	0.0942	-0.0161	0.0879	0.100	0.0878	-0.0165	0.00642	-0.0286	0.0568	0.120***	0.0780
	(0.120)	(0.0944)	(0.0889)	(0.106)	(0.0967)	(0.101)	(0.120)	(0.0964)	(0.100)	(0.0452)	(0.0461)	(0.0609)
Friday	0.0523	0.0240	0.0265	0.0644	0.0725	0.0756	0.123	0.267***	0.226**	0.0908**	0.0765*	0.112**
	(0.129)	(0.0775)	(0.0937)	(0.101)	(0.0909)	(0.0992)	(0.106)	(0.0813)	(0.102)	(0.0447)	(0.0394)	(0.0559)
Lag1 ARCH		0.379***			0.114***			0.197***			0.280***	
		(0.123)			(0.0417)			(0.0599)			(0.0803)	
Lag1 GARCH		0.643***			1.112***			1.056***			0.537***	
		(0.125)			(0.210)			(0.152)			(0.129)	
Constant		-0.098			-0.285			-0.367***			0.109*	
		(0.111)			(0.192)			(0.142)				
Observations	625	625	625	462	462	462	506	506	506	1,491	1,491	1,491

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE 6
Regression Results Large-capitalization Stocks

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Subsample 1 2006-10-06 to 2009-04-06			**Subsample 2 2009-04-07 to 2011-02-07**			**Subsample 3 2011-02-08 to 2013-02-09**			**Subsample 4 2013-02-10 to 2019-01-22**		
	Raw Returns		Risk-adjusted Returns	Raw Returns		Risk-adjusted Returns	Raw Returns		Risk-adjusted Returns	Raw Returns		Risk-adjusted Returns
Monday	-0.196	-0.0266	-0.104	0.0677	0.0799	0.0496	0.146	0.170	0.0960	0.0645	0.0844	0.0670
	(0.169)	(0.181)	(0.0856)	(0.127)	(0.117)	(0.0949)	(0.134)	(0.117)	(0.0906)	(0.0542)	(0.0562)	(0.0558)
Tuesday	0.0458	0.0140	-0.00748	0.306**	0.334***	0.232**	-0.230	-0.234*	-0.158	0.00159	0.0252	0.00853
	(0.205)	(0.157)	(0.0972)	(0.141)	(0.116)	(0.0985)	(0.154)	(0.132)	(0.106)	(0.0623)	(0.0590)	(0.0641)
Wednesday	-0.0570	-0.0494	-0.0725	0.00692	0.0443	0.00208	0.0656	0.0838	0.0310	0.0514	0.0511	0.0357
	(0.177)	(0.166)	(0.0952)	(0.134)	(0.122)	(0.101)	(0.143)	(0.127)	(0.0982)	(0.0544)	(0.0501)	(0.0556)
Thursday	0.0784	0.129	0.0657	0.139	0.139	0.112	0.0399	-0.0199	-0.0007	0.0146	0.00908	-0.00378
	(0.167)	(0.143)	(0.0860)	(0.149)	(0.129)	(0.110)	(0.142)	(0.113)	(0.0899)	(0.0527)	(0.0470)	(0.0526)
Friday	-0.137	0.0128	-0.0474	0.0732	0.0134	0.0344	0.0498	0.00380	-0.00280	0.0184	0.00457	0.0113
	(0.159)	(0.136)	(0.0826)	(0.138)	(0.132)	(0.105)	(0.157)	(0.104)	(0.103)	(0.0575)	(0.0535)	(0.0611)
Lag1 ARCH		0.230**			0.175***			0.130***			0.137***	
		(0.108)			(0.0658)			(0.0490)			(0.0339)	
Lag1 GARCH		0.898***			0.972***			1.469***			0.988***	
		(0.289)			(0.228)			(0.374)			(0.174)	
Constant		-0.485			-0.211			-1.268*			-0.119	
		(0.796)			(0.325)			(0.701)			(0.133)	
Observations	625	625	625	462	462	462	506	506	506	1,491	1,491	1,491

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6. Conclusions

This study aims to examine the day-of-the-week effect in Swedish stock returns by investigating three different stock indexes. The three indexes contain all small, mid, and large-capitalization stocks listed on the Nasdaq OMX Stockholm. In total, the dataset consists of 3,084 daily observations of index closing prices over the period 6th October 2006 to 22th January 2019.

The baseline regressions results, from testing the whole sample period, suggest that the day-of-the-week effect tends to differ between small, mid, and large-capitalization stocks. More specifically, this study reports positive day-of-the-week effects among small and mid-capitalization stocks, both for raw returns and for risk-adjusted returns, but finds no such effects for large-capitalization stocks and thus there might be a size effect in the day-of-the-week effect. The results indicate positive Monday and Thursday effects for small-capitalization stocks, as well as positive Wednesday, Thursday, and Friday effects for mid-capitalization stocks. However, no explanation exists for the size effect, and the results of this study should therefore be interpreted with caution.

Furthermore, by dividing the sample into four different subsamples, it is possible to determine whether the day-of-the-week effect is persistent over time. However, the regression results from the subsamples show that the day-of-the-week effect do not prevail consistently and over time and hence this study reports only weak evidence against the weak form of the EMH.

Moreover, the results do not obviously show that the day-of-the-week effects, and the observed patterns in daily the stock returns, are related to specific business cycle periods (i.e. recession and expansion).

7. Future Research

Even though calendar effects are extensively studied, a number of extensions can be added to this research since there are still questions to answer. Based on previous research and the results reported from this study, the suggestion for future research is to focus on two questions: First mainly, is there a size effect? If not, what other unknown variables could explain the deviations between stocks with different stock market capitalizations? Second, are calendar anomalies related to the business cycle? If not, are there other factors affecting the pattern in stock market returns between small, mid, and large-capitalization stocks. In order to determine whether sock markets are efficient or not, it is crucial to examine the underlying factors of stock market anomalies and calendar effects. Moreover, future research should consider the size effect in the context of the day-of-the-week effect and other calendar effects.

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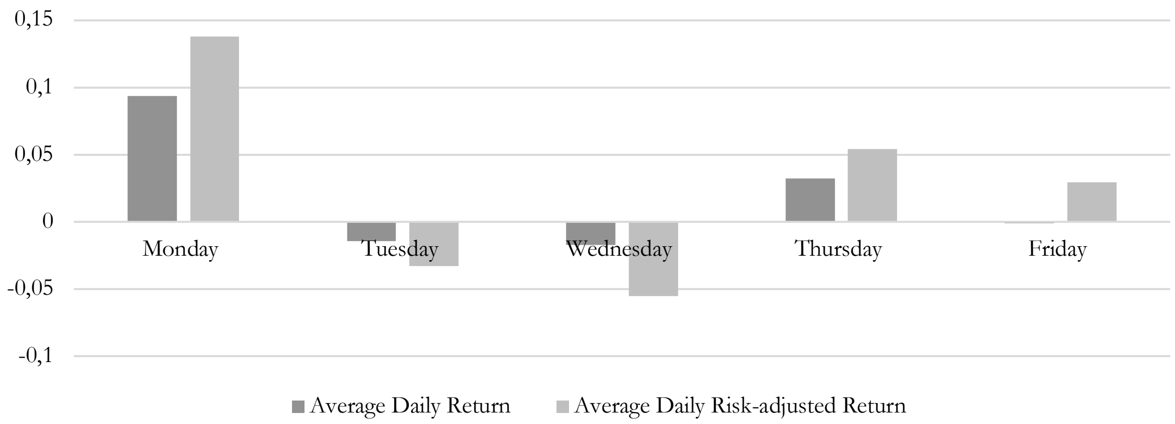
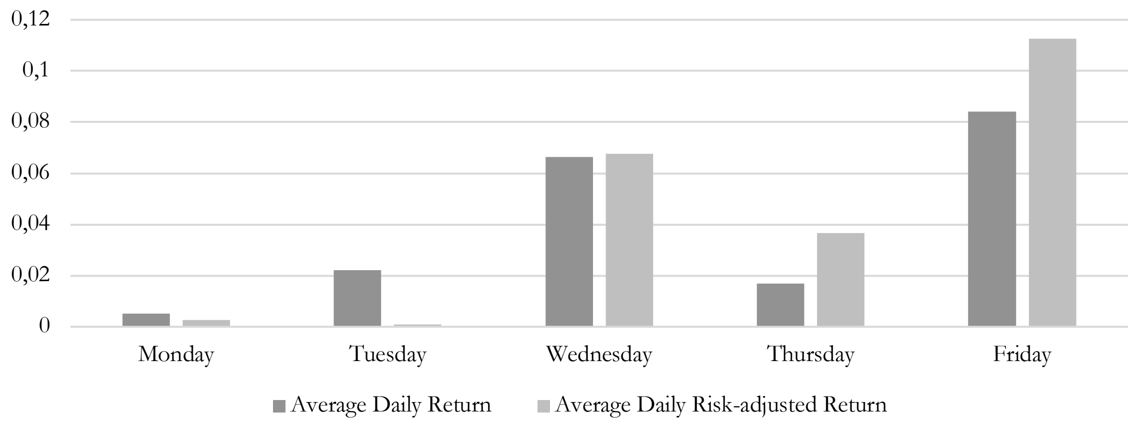
Appendix A

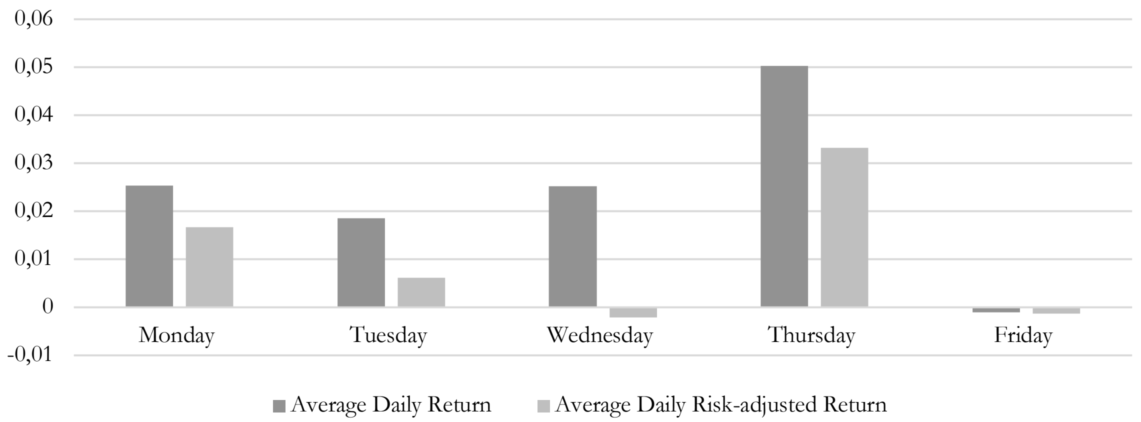
The bar charts show the average weekday returns (from Monday to Friday) for small, mid, and large-capitalization stocks.



Small-capitalization stocks



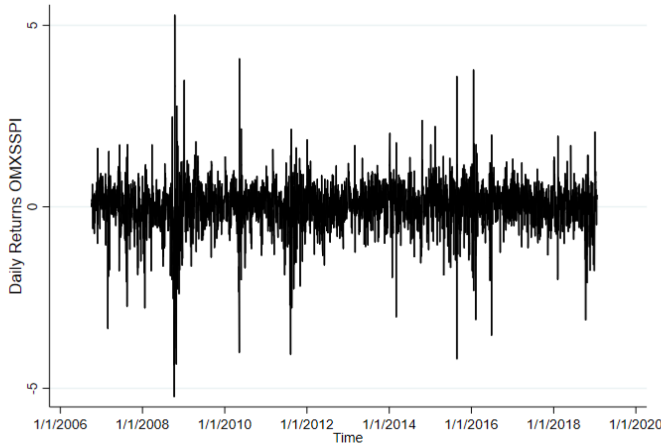
Mid-capitalization stocks



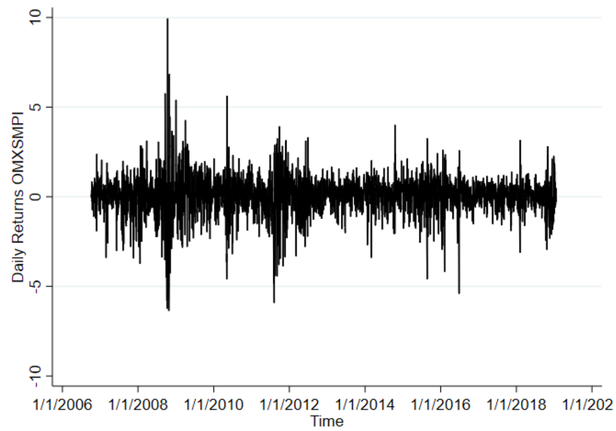
Large-capitalization stocks

Appendix B

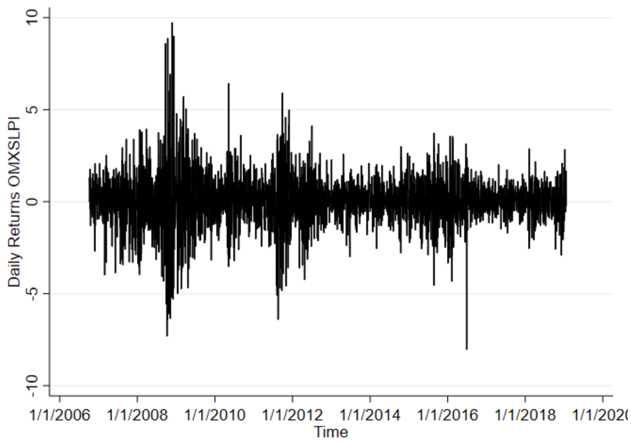
The graphs display time-series line plots of daily returns for small, mid, and large-capitalization stocks.



Small-capitalization Stocks



Mid-capitalization Stocks



Large-capitalization Stocks

Appendix C

The tables present the results from each of the statistical tests: the Breusch-Pagan LM test for heteroscedasticity, and the Breusch-Godfrey LM test for autocorrelation, and the augmented Dickey-Fuller unit-root test for stationarity.

Breusch-Pagan LM Test for Heteroscedasticity

	F-statistic	Probability Value
Small-capitalization Stocks		
Raw Returns	62.870	0.0000
Risk-adjusted Returns	100.01	0.0000
Mid-capitalization Stocks		
Raw Returns	73.070	0.0000
Risk-adjusted Returns	101.14	0.0000
Large-capitalization Stocks		
Raw Returns	86.530	0.0000
Risk-adjusted Returns	118.54	0.0000

H_0: Error variances are homoscedastic

Breusch-Godfrey LM Test for Autocorrelation

	X^2	Degrees of Freedom	Probability Value
Small-capitalization Stocks			
Raw Returns	91.300	5	0.0000
Risk-adjusted Returns	104.389	5	0.0000
Mid-capitalization Stocks			
Raw Returns	37.736	5	0.0000
Risk-adjusted Returns	33.680	5	0.0000
Large-capitalization Stocks			
Raw Returns	13.0166	5	0.0166
Risk-adjusted Returns	6.256	5	0.2821

H_0: No serial correlation of any order up to p

Dickey-Fuller Unit-root Test for Stationarity

	T-statistic	MacKinnon Approximate Probability Value
Small-capitalization Stocks		
Raw Returns	-41.991	0.0000
Risk-adjusted Returns	-41.400	0.0000
Mid-capitalization Stocks		
Raw Returns	-47.367	0.0000
Risk-adjusted Returns	-48.189	0.0000
Large-capitalization Stocks		
Raw Returns	-49.856	0.0000
Risk-adjusted Returns	-49.397	0.0000

H_0: The variable contains a unit root

Appendix D

The tables report the results from the Welch's t-test for difference in means between the different samples (i.e. small, mid, and large-capitalization mean stock returns), both for the whole sample and for each specific weekday.

Welch's t-test for Difference in Means

	Difference in means	Probability Value	T-statistic
Small and Mid-capitalization Stocks			
Raw Returns	-0.0196	0.3904	-0.8591
Risk-adjusted Returns	-0.0170	0.5104	-0.6582
Small and Large-capitalization Stocks			
Raw Returns	0.0144	0.6455	0.4601
Risk-adjusted Returns	0.0328	0.2005	1.2802
Mid and Large-capitalization Stocks			
Raw Returns	-0.0052	0.8488	-0.1907
Risk-adjusted Returns	0.0158	0.5338	0.6223

*** p<0.01, ** p<0.05, * p<0.1

Welch's t-test for Difference in Means, Weekdays, Raw Returns

	Difference in means	Probability Value	T-statistic
Small and Mid-capitalization Stocks			
Monday	0.0885	0.1200	1.5560
Tuesday	-0.0355	0.4927	-0.6863
Wednesday	-0.0846	0.0887*	-1.7037
Thursday	0.0208	0.6648	0.4335
Friday	-0.0831	0.0898*	-1.6983
Small and Large-capitalization Stocks			
Monday	0.0684	0.2377	1.1815
Tuesday	-0.0337	0.6250	-0.4889
Wednesday	-0.0418	0.4857	-0.6974
Thursday	-0.0174	0.7667	-0.2967
Friday	0.0019	0.9743	0.0322
Mid and Large-capitalization Stocks			
Monday	-0.0201	0.7818	-0.2771
Tuesday	0.0018	0.9799	0.0252
Wednesday	0.0428	0.5316	0.6258
Thursday	-0.0383	0.5727	0.0948
Friday	0.0850	0.2127	1.2470

*** p<0.01, ** p<0.05, * p<0.1

Welch's t-test for Difference in Means, Weekdays, Risk-adjusted Returns

	Difference in means	Probability Value	T-statistic
Small and Mid-capitalization Stocks			
Monday	0.1355	0.0281**	2.1990
Tuesday	-0.0332	0.5794	-0.5544
Wednesday	-0.1239	0.0217**	-2.2988
Thursday	0.0252	0.6449	0.4610
Friday	-0.0833	0.1568	-1.4167
Small and Large-capitalization Stocks			
Monday	0.1214	0.0254**	2.2377
Tuesday	-0.0396	0.5255	-0.6350
Wednesday	-0.0526	0.3472	-0.9404
Thursday	0.0217	0.6801	0.4124
Friday	0.6040	0.6040	0.5188
Mid and Large-capitalization Stocks			
Monday	-0.01406	0.8176	-0.2307
Tuesday	-0.0064	0.9104	-0.0064
Wednesday	0.0713	0.1941	1.2992
Thursday	-0.0035	0.9500	-0.0627
Friday	0.1138	0.0506*	1.9568

*** $p<0.01$, ** $p<0.05$, * $p<0.1$