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Monday Effect: Trading Patterns of Individual Investors

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This is to certify that the doctoral dissertation by

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Abstract

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by

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MS, Massachusetts Institute of Technology, 2003

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MS, Tuskegee University, 1978

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Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

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Abstract

The efficient market hypothesis (EMH) has served as the central theory in modern finance for more than half a century. The Monday effect, in which returns and trading volumes on Mondays are generally lower than other days of the week, is one of the anomalies of the EMH. Researchers postulated the different investment patterns of individual investors as an explanation for the Monday effect. The purpose of this comparative study is to examine the role of individual investors on the Monday effect in the United States stock market. This study involved using actual individual investor data from the New York Stock Exchange from May 2006 to April 2016. The study design is based on a non-experimental, quantitative, and comparative design and builds upon Fama's EMH theory. The focus is to compare investors' average daily returns, individual investor average daily trade percentages, and trading patterns on Monday with other weekdays. Using results from one-way ANOVA, study results demonstrated day of the week was not a factor in terms of average daily returns and individual investor daily trade percentages on Monday did not significantly differ from those on Tuesday, Wednesday, and Thursday. However, the percentage of individual investor trades on Fridays was significantly lower than individual investor trades on other weekdays. Days of the week had no effect on individual investor trading patterns. Results of this study may lead to positive social change by understanding individual investor trading behaviors, reducing information asymmetry, and increasing stock market liquidity.

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Dedication

I dedicate this dissertation to my mother Ponnamma Gopinathan. She has been an inspiration throughout my academic pursuits. She has inspired two generations of men and women in our family and circle of friends to pursue their dreams through her constant support, encouragement, and nudging.

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I would like to thank Dr. Holly Rick for her guidance, support, and encouragement through the dissertation process. I also want to thank Dr. Aridaman Jain and Dr. David Bouvin for their insight, advice, and encouragement. Their feedback and suggestions helped to shape this dissertation. I also want to thank my family and friends who stood by me, believed in me, and supported me throughout my doctoral journey.

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Chapter 1: Introduction to the Study

Fama (1970) said efficient market hypothesis (EMH) is the phenomenon in which prices of the stock in the market at a given time always and fully reflect all available information about that stock at that time. The Monday effect has been one of the anomalies of EMH. The Monday effect implies that returns and trading volumes on Mondays are generally lower than other days of the week (Bishal et al., 2019; Richards & Willows, 2019; Ulku & Rogers, 2018). One plausible explanation for the Monday effect is different investment patterns of institutional investors and individual investors (Abraham & Ikenberry, 1994; Bishal et al., 2019; Chan et al., 2004; Lu & Gao, 2016; Morse et al., 2014; Ulku & Rogers, 2018). The general management problem is that no one understands individual investors' trading behavior in terms of day of the week and time of the day on the Monday effect. Few researchers have evaluated individual investors' trading behavior in this regard and this research filled this gap. The results of this study may benefit individual investors, financial advisers, market administrators, and policymakers.

Chapter 1 includes a description of the background of the study, the research problem, and gap in current research literature. This chapter also includes the purpose of the study, research questions and hypotheses, theoretical foundation of the study, and nature of the study, including independent and dependent variables. I also summarize the methodology, introduce definitions and assumptions, and describe limitations of the study. Finally, I describe the significance of the study in advancing theory and practice and influencing positive social change.

Background of the Study

The EMH has served as the central theory in modern finance for more than half a century. Many stock markets have shown a variety of calendar anomalies such as the Monday effect, Turn of the Month effect, Month of the Year effect, January effect, Holiday effect, and Halloween effect (Anjum, 2020; Hirshleifer et al., 2020; Lu & Gao, 2016; Kumar, 2016; Kumar & Muneer, 2015).

Returns on the stock market are consistently low on Mondays (Aharon & Qudan, 2019; Arman & Lestari, 2018; Cross, 1973; Chukwuogor-Ndu, 2020; French, 1980; Lu & Gao, 2016; Tadepalli & Jain, 2018). In this study, I add to extant literature by analyzing returns on Mondays in the New York Stock Exchange (NYSE).

While many studies have concluded the existence of the Monday effect, researchers have not come to a consensus about the reasons for it (Bishal et al., 2019; Birru, 2018; Ulku & Rogers, 2018). There are many possible reasons for the Monday effect. Negative Monday returns are most probably due to less trading by institutional investors (Lakonishok and Maberly 1990; Ulku & Rogers, 2018). The trading behavior of individual investors drive this anomaly (Birru, 2018; Breaban & Noussair, 2018; Hirshleifer et al., 2020; Lu & Gao, 2016; Richards & Willow, 2018). However, no comprehensive study has been carried out using actual individual investor data showing the day of the week and time of day in the U.S. stock market. Most studies thus far mainly employed indirect approaches such as using proxies for individual investor data. Understanding the influence of the individual investors on the Monday effect requires gathering and analyzing the actual trading data of investors. Some attempts were made in the 1990s to understand the role of individual investors. However, actual individual trading data was not available during that time, and hence results are unreliable. This study aimed to fill this gap by using actual individual investor data including day of the week and time of day from the NYSE from 2006 to 2016.

Past studies have used proxies such as odd lots and small size investments to represent the individual investor trades. The validity of such proxies has significantly changed during the last two decades. Early 2000 witnessed the decimalization of stock prices where prices are represented in decimals. During this period, institutional investors also started computerized trading algorithms for order splitting. These two practices have led to a dramatic decrease in the average trade size. Consequently, trade size would not be an effective proxy for trades by the individual investor for the last 2 decades (Wang & Zhang, 2015). Secondly, individual investor trade behavior has also changed in the last two decades. Prior to 2000, most individual investors traded in odd lots that included any number of shares between 1 and 100. This pattern has changed in the last two decades, and individual investors now trade in round lots that include any number of shares that can be evenly divided by 100. Thus, using odd lot trading data as a proxy for individual investor trading does not correctly represent their trading patterns (Bishal et al., 2019).

Individual investor trading data used in this study is accurate since they are electronically gathered from the NYSE. The NYSE compiled the dataset using transaction records of purchases and sales in their centralized stock market. Thus, results of this study represent the actual behavior of individual investors and the impact of the

Monday effect. Past studies using proxies and other methods to represent individual investor behavior probably are not reliable because their data is not representative of individual investors.

Specifically, I used the comprehensive actual individual investor trading data, the NYSE ReTrac End of Day. This dataset includes all individual investors selling and purchasing records on the NYSE. Data used in this study covered a recent sample period (from May 2006 to April 2016) and hence was the most comprehensive assessment of individual investors' influence on the Monday effect.

This is the first study to quantitatively analyze the Monday effect on the U.S. stock exchange using data that covered the periods before, during, and after the financial crisis of 2008-2009 using actual individual investor data including day of the week and time of day information. This study involved using various statistical techniques such as descriptive statistics, analysis of variance (ANOVA), and a post hoc test to evaluate the influence of individual investor behavior and the Monday effect on the U.S. stock market.

Problem Statement

The EMH is one of the central theories of modern finance. In general, the market is said to be efficient if it adjusts quickly and accurately to new information. However, Monday effect is an intriguing anomaly of EMF.

One plausible explanation for the Monday effect is different investment patterns of institutional investors and individual investors. The general management problem is that no one understands individual investors' trading behavior regarding day of the week and time of day in terms of the Monday effect. Few researchers have evaluated individual investor' trading behavior in this regard, and this research filled this gap. The specific goal was to understand the impact of individual investor trading behavior and the Monday effect. The results of this study may benefit individual investors, financial advisers, market administrators, and financial policy makers.

Purpose of the Study

The purpose of this comparative study was to test the theory of the EMH and test the role of the individual investor and the Monday effect. The study was designed to compare individual investors' average returns, trade percentages, and trading patterns on Monday with other weekdays. The independent variable was day of the week. The dependent variables were average daily return, percentage of individual investor trade compared to the total trade, and number of individual investor trades in 30-minute intervals within a day. I used publicly available data from the NYSE from 2006 to 2016.

Research Questions and Hypotheses

RQ1: Are there statistically significant differences in investor average returns between Monday and other weekdays?

$H_0 1$: There are no statistically significant differences in investor average returns between Monday and other weekdays.

$H_a 1$: There are statistically significant differences in investor average returns between Monday and other weekdays.

RQ2: Are there statistically significant differences in individual investor trade percentages between Monday and other weekdays?

$H_0$2: There are no statistically significant differences in individual investor trade percentages between Monday and other weekdays.

H_a2: There are statistically significant differences in individual investor trade percentages between Monday and other weekdays.

RQ3: Are there statistically significant differences in individual investor trading patterns between Monday and other weekdays?

$H_0$3: There are no statistically significant differences in individual investor trading patterns between Monday and other weekdays.

H_a3: There are statistically significant differences in individual investor trading patterns between Monday and other weekdays.

Theoretical Foundation

The theoretical base for this study was Fama's 1970 theory of EMH. This theory implies that an investor cannot do better than the market, on a risk adjusted and consistent basis, because only new information can change the market price. The Monday effect implies that returns and the trading volumes on Mondays are generally lower than other days of the week (French, 1980; Rodriguez, 2012). One plausible explanation for the Monday effect is different investment patterns of institutional and individual investors (Bishal et al., 2019). However, few researchers have evaluated individual investors' trading behavior regarding the day of the week and time of the day. This theoretical framework was the best for my dissertation because the study evaluates an established theory in finance and assesses one of the anomalies of the theory.

Nature of the Study

In this study, I used the quantitative methodology. Chelaa (2017) described quantitative research as the study method that involves collecting and analyzing data using statistics. The quantitative method is the best approach to answer research questions requiring numerical data and generalizing results to a larger population. Accordingly, this methodology was consistent with the purpose of this study. The quantitative method usually builds upon existing theories and its results can be predictive, explanatory, or confirming (Williams, 2007). Researchers have used the quantitative methodology to study calendar anomalies. The quantitative method is normally used to answer questions relating to relationships between variables, either to establish or validate relationships. The quantitative research process normally consists of developing a problem statement and corresponding hypothesis. It is followed by an exhaustive literature review and data analysis. The study was based on a nonexperimental quantitative comparative design. The basic purpose of the comparative design is to evaluate relationships between variables (Cantrell, 2011).

I used secondary historical data archived by the NYSE. Secondary data is data collected by someone else for another primary purpose (Johnson, 2017). The dataset from the NYSE has all information regarding trades executed by individual investors. I used data from 2006 to 2016. For statistical analysis, I used descriptive statistics to measure trading patterns. I also used other statistical analyses such as ANOVA and a post hoc test to compare individual investors' mean returns and trade percentages between Monday and other weekdays.

Definitions

Anomaly: Behaviors or events that evolve to defy an established theory, model, or hypothesis without any logical explanation of why it happens (Kahneman & Tversky, 1979).

Calendar effect: Seasonal anomalies in the financial market, including the January effect, Monday effect, Islamic calendar effect, turn of the month effect, half and time of the month effect, month of the year effect, holiday effect, and Halloween effect.

Disposition effect: A bias that shows investors have a propensity to sell stocks that are gaining in value quickly and hold on to stocks that are losing value for a longer period (Richards et al., 2017).

Efficient market hypothesis (EMH): The phenomenon where the prices of the stock in the market at a given time always and fully reflect all available information about that stock at that time (Fama, 1970).

Information processing hypothesis: Individuals are more inclined to process information during the weekend (Abraham & Ikenberry, 1994).

Information release hypothesis: Corporations have a tendency to release positive financial information during weekdays and negative financial information during the weekend to mitigate panic selling and allow investors a few days to absorb negative news (French, 1980).

Investor's psychology hypothesis: Investors are more likely to purchase securities as holidays approach due general feelings of good fellowship and holiday excitement (Hirshleifer, 2001; Wachtel, 1942).

Monday effect: Returns and trading volumes on Mondays are generally lower than other days of the week (Afrilianto & Daryanto, 2019; Arman & Lestari, 2018; Rita et al., 2018).

Random walk hypothesis: Stock market price changes are unpredictable and evolve randomly (Fama, 1970).

Settlement regime hypothesis: The period between the trade date and settlement date creates an opportunity for an interest-free loan until the settlement (Lakonishok & Levi, 1982).

Weekend effect: Returns on Fridays are generally higher than other days of the week (Afrilianto & Daryanto, 2019; Tadepalli & Jain, 2018).

Assumptions

Assumptions are certain conditions that researchers assume are true but have no way to prove and are outside their control. There were three basic assumptions in this study. The first assumption involved the secondary dataset since it was not originally intended for this study. The dataset used in this study was archived data from the NYSE. I assumed that data collection was accurate and done in an ethical manner. The second assumption was that a statistical analysis of data provided insight regarding trading behaviors of individual investors.

Scope and Delimitations

In this section, I describe specific aspects of the research problem that are addressed in the study. I also explain populations that were included in the study and theories that were excluded from the study. The scope of this study involved testing the theory of the EMH, the Monday effect anomaly, and the role of individual investors on the Monday effect. The purpose of the study did not include the evaluation of other factors influencing the Monday effect such as institutional investors. I used archived data from the NYSE in the U.S. and did not include any data from investors from other countries. The dependent variables used in this study were average daily returns, percentages of individual investor trade compared to total trade, and number of individual investor trades.

I assumed all market participants were rational actors. I did not address mood and emotional aspects of participants when analyzing the impact of individual investor behavior on the Monday effect. As such, theories supporting behavioral economics were excluded from this study.

Limitations

In this section, I describe limitations of the study related to its design and methodological weaknesses. There are a few methodological weaknesses when using existing data to investigate new research questions and generate new knowledge. The first limitation of using the secondary data analysis method approach is that data were collected for another purpose and may not be ideal for this study. Some specific information pertaining to the study may be missing or information may have been collected in a different geographic region. Another disadvantage of using secondary data is that I did not participate in the data collection process and did not know exactly how it was conducted. Consequently, I was unaware of any potential problems during data collection in terms of how well it was performed.

Significance of the Study

This study may make significant contributions to advance theories on finance. It may also advance practices in finance. Additionally, it could contribute to positive social change by making the capital market more efficient.

Significance to Theory

This study may make significant contributions to advance theories regarding the EMH and Monday effect. However, most research on the Monday effect have primarily focused on institutional investments because individual investors make up only a small percentage of total investments. Results of this study may help advance knowledge of the individual investor's role on the Monday effect.

This study added to existing knowledge in financial literature. First, I investigated whether the Monday effect is still present in the U.S. market. Second, I analyzed individual investor behavior and its impact on the Monday effect. Finally, I covered a sample period (from May 2006 to April 2016) to provide the most comprehensive assessment of individual investors' influence on the Monday effect in a developed market since most recent studies mainly focused on emerging markets.

The study contributes to current literature regarding individual investor trading behaviors. Many past studies have treated individual investors as irrational and have labeled them as noise traders. These studies have largely focused on problems associated with individual investor trading behaviors compared to more informed and sophisticated institutional investors. Many earlier studies considered individual investors as uninformed participants and discounted their impact on the Monday effect. However, individual investors are in fact informed participants and contribute to stock market liquidity and information transparency (Wang & Zhang, 2015). This study was meant to provide the most comprehensive assessment of individual investors' influence on the Monday effect in a developed market.

This study also contributed to literature because of the dataset which contained actual individual investor trading information. Individual investor trading data used in this proposed study were accurate because they were electronically gathered from the NYSE. The NYSE compiled the dataset using transaction records of purchases and sales in their centralized stock market. Thus, results of this study represented actual behaviors of individual investors and the resulting impact on the Monday effect. Past studies using proxies and other methods to represent individual investor behavior probably are not reliable because their data is not representative of individual investors.

Significance to Practice

The study may help to advances practices for individual investors, financial advisers, market administrators, and policy makers. Results of the study may help individual investors understand patterns and biases involving their investment behavior and enable them to adjust their strategies to maximize their returns. It may also help financial advisers better tailor their services to help their customers.

One of the practical benefits of this study may be that it informs individual investors and financial advisors about behaviors of investors during days of the week and times of day. Results of the study showed which days and what time of day individual investors are more likely to trade stocks. This information in turn may help individual investors make right choices before they invest. Individual investors and financial advisors can use this information to optimize their investment decisions. They may be able to develop investment strategies to buy stocks on days and times of day when prices are typically low and sell stocks on a day and time when prices are typically high.

Significance to Social Change

The findings of this study may lead to positive social change. Understanding individual investment patterns and their influence on the market could help market administrators design markets in an efficient manner. Results of the study may also enable investment policy makers to develop policies and practices to protect individual investors while enhancing market efficiencies. An efficient market enables information transparency and market liquidity. Transparent financial markets enhance investor confidence, which could lead to more trading activities by more investors. Trading by individual investors can reduce information asymmetry and thus increase stock market liquidity (Wang & Zhang, 2015). Results of this study may help to understand individual investor behavior and thus can reduce information asymmetry and increase stock market liquidity.

Summary and Transition

This chapter included a description of the background of the study, research problem, and gap in current research. It also included the purpose of the study, research questions and hypotheses, theoretical foundation of the study, and nature of the study, including independent and dependent variables. Finally, I described the significance of the study in terms of advancing theory and practice and influencing positive social change. Chapter 2 includes descriptions of sources of theories and major theories in detail. I also provide an exhaustive review of current literature, including a review and synthesis of studies related to the research questions.

Chapter 2: Literature Review

The EMH is one of the central theories of modern finance. Fama (1970) said it is the phenomenon where prices of the stock in the market at a given time always and fully reflect all available information about that stock at that time. In general, the market is said to be efficient if the market adjusts quickly and accurately to new information in the market.

The Monday effect means that returns and trading volumes on Mondays are generally lower than other days of the week (Chan et al., 2004; French, 1980; Rodriguez, 2012). One plausible explanation for the Monday effect is the different investment patterns of institutional investors and individual investors (Abraham & Ikenberry, 1994; Bishal et al., 2019; Chan et al., 2004; Morse et al., 2014). The general management problem is that no one understands individual investors' trading behaviors regarding day of the week and time of day in relation to the Monday effect. Few researchers have evaluated individual investors' trading behavior in this regard and this research will fill this gap. The specific goal was to understand the impact of individual investors' trading behavior in relation to the Monday effect. The results of this study will benefit individual investors, financial advisers, market administrators, and financial policy makers.

The purpose of this comparative study was to test the theory of the EMH and role of individual investors in relation to the Monday effect. The study was designed to compare individual investors' average returns, trade percentages, and trading patterns between Monday and other weekdays. The independent variable was day of the week. The dependent variables were average daily returns, percentages of individual investor trade compared to total trade, and number of individual investor trades in 30-minute intervals within a day. I used publicly available data from the NYSE from 2006 to 2016 in this study.

This chapter contains the literature search strategy used for this study. In this chapter, I also describe the theoretical foundation and conceptual framework used for the study. Finally, the literature review section includes an exhaustive review of current literature used in this study.

Literature Search Strategy

The main theories used in the study are the EMH and Monday effect. I used several databases to find literature for this study, including EBSCOHost, Thoreau, Summons Multi-Database, ProQuest, Business Source Complete, Dissertation & Theses Q Walden University, Open Research Online, JSTOR, SAGE Premier/Journals, and Google Scholar. Keywords used, alone or in combination, to search for journals and articles were *efficient market hypothesis*, *Monday effect*, *weekend effect*, *day-of-the-week effect*, and *trading patterns*. In addition, the following keywords were used to search for seminal literature and other pertinent literature: *behavioral economics*, *disposition effect*, *prospect theory,* and *emotion regulation*. The literature search for contemporary articles focused on peer-reviewed journal articles published between 2016 and 2020. In addition, the literature review also includes several articles published since 1930 regarding the Monday effect. I specifically searched for seminal articles to find out about origins of theories used in the study. The literature review includes a large number of journal articles and other resources that are related to the topic and methodology and are consistent with the scope of the study. The literature review covers publications from 1930 to 2020.

Theoretical Foundation

The EMH implies that an investor cannot do better than the market on a risk adjusted and consistent basis, because only new information can change the market price. However, few researchers have evaluated individual investors' trading behavior regarding day of the week and time of day. This theoretical framework was the best for my dissertation because the study evaluates an established theory in finance and assesses one of the anomalies of the theory.

Literature Review

EMH

The market is said to be efficient if it adjusts quickly and accurately to new information. The EMH theory assumes that variations in prices are independent of one another and represent random behaviors, and the actual price of a stock at any given time is equal to the actual estimated value of that stock. In this context, participants cannot make excessive profits in an efficient market.

There are three categories of an EMH depending on level of information: weak, semi-strong, and strong (Fama, 1970). Fama tested these three categories to identify levels of information at which point the EMH fails. The first is called weak-form EMH. In this category, current prices of a stock are set at their historical prices. Results of tests of this form of EMH support the fair-game efficient market model. This form of EMH is characterized by the random movement of stock prices and is aligned with the random walk hypothesis.

The second type is called semi-strong-form EMH. In this form, current stock prices fully reflect historical information about prices as well as publicly available information in the market such as annual earnings and stock splits (Fama, 1970). Investors are unable to develop investment strategies based on basic analysis of balance sheets, income statements, and dividend changes to acquire excessive profit because such information is already public.

The third type is called strong-form EMH. In this form, the current price of the stock fully reflects historical information about the stock price, publicly available information in the market, and all pertinent information about the company, including private information (Fama, 1970). This category involves concerns that some individuals are privy to inside information compared with the general public, which can lead to excess profits. Fama (1970) said the strong form is not strictly consistent with the EMH because officers of corporations can use inside information. However, the practice of using private information to generate excess profit is not common in the investment community.

The EMH implies that investors cannot make excessive profits consistently because a stock's price movement has no usable patterns (Afrilianto & Daryanto, 2019). Thus, uninformed investors with a diversified portfolio can make same rates of return in the market as experts. As such, there is no possibility for an investor to earn above average market returns when security prices reflect all available information.

Average market performance is the most efficient in the long run and investors cannot outperform the market. This implies that returns on each day of the week are identical to returns on all other days (Sharif, 2019). Nevertheless, many studies have shown the presence of calendar anomalies in the marketplace and argued that investors have an opportunity to make excessive profits and outperform the market during certain periods.

Stock market price changes can be predicted because returns are influenced by seasonality (Afrilianto & Daryanto, 2019; Anjun, 2020; Hirshleifer et al., 2020; Kumar, 2016). Calendar anomalies pose the biggest threat to the EMH. Because of them, stock prices change depending on day of the week, month in the year, and time of day. These stock price behaviors are not consistent with the EMH. A shrewd investor can take advantage of these inconsistencies to earn excessive profits from the stock market (Karanovic & Karanovic, 2018). One of the most prominent calendar anomalies is the Monday effect.

Market Anomalies

Stock price changes that cannot be explained by established financial theories are normally termed financial market anomalies (Afrilianto & Daryanto, 2019). This is a general term used to describe behaviors or events that evolve to defy an established theory, model, or hypothesis without any logical explanation of why it happens. Anomalies usually have a consistent pattern and cannot be overlooked as random errors (Kahneman &Tversky, 1979). In the context of financial markets, calendar anomalies challenge the validity of the EMH and random walk theories. Once studied and exposed, some anomalies disappear while others persist.

Many authors have studied the existence of financial anomalies in developed and emerging markets. Similarly, there are many studies that show the existence of financial anomalies in different market sectors, including foreign currency exchanges, derivatives, bitcoin, interest rates, and treasury bills. Calendar anomalies include the January effect, day-of-the-week effect, Islamic calendar effect, turn-of-the-month effect, half-of-the-month effect, time-of-the-month effect, 4 month-of-the-year effect, holiday effect, and Halloween effect.

One of the seasonal anomalies is the January effect. The January effect is characterized by higher mean returns during the month of January compared those on other months of the year (Patel, 2016). The successive one-period returns of a stock are independent and follow a random path, and thus should not show any consistent variance in monthly stock returns over time. This implies that the January effect in stock market returns is an anomaly. Wachtel (1942) examined the Dow Jones Industrial Average from I927 to 1942 and said the index displayed frequent bullish tendencies from December to January. Many studies have also shown the presence of the January effect in different markets. One possible reason for the January effect is the window dressing hypothesis. Many investment managers sold their losing stocks in December to take advantage of tax rules and reduce their burdens (Lakonishok & Smidt, 1988). The selling trend depressed the stock price in December. Many investors bought back those stocks again in January, which in turn increased the stock price. This cycle of selling and buying back explains higher returns in January (Caporale & Zakirova, 2017).

The turn-of-the-month effect anomaly results in the average stock returns for the last and first 3 days of the month at a higher rate than returns during the rest of the days of the month. Since its discovery, many researchers have found this abnormality in different equity markets. Researchers have posited many reasons for the turn-of-the-month effect. Some researchers have linked it to the turn-of-the-year effect. Similar to the turn-of-the-year effect, investment managers dress up their portfolio at the end of each quarter in accordance with the window dressing hypothesis. Jebran and Chen (2017) said the turn-of-the-month effect in the U.S. market is driven by the timing of dividend payments on equity and the interest payments on debt.

The month-of-the-year effect involves changes in returns depending on the month of the year. The January effect is one example of this phenomenon. Another example is the Mark Twain effect, which shows stock returns at a lower rate in October compared to other months (Caporale & Zakirova, 2017).

that the half-of-the-month effect means returns on equity during the first half of the month are higher than returns during the second half of the month. Similar to the turn-of-the-month effect, many researchers have found this anomaly in different equity markets since its discovery.

The time of the month effect is a phenomenon where returns on equity are different during each third of the month. The first third of the month has the highest return, followed by returns during the second third, with the lowest rate of return during the last third of the month. Many researchers have identified this anomaly in different markets around the world.

The holiday effect means that preholiday returns on equity are generally higher than postholiday returns on equity. Seif et al. (2017) said argued that the holiday effect was a global phenomenon and did not depend on a specific country's capital market. The preholiday rate of return is many times larger than the normal daily rate of return (Caporale & Zakirova, 2017). Lakonishok and Smidt (1988) analyzed 90 years of data from the Dow Jones Industrial Average index and concluded pre-holiday rates of return were 23 times larger than normal daily rates of return. Bergsma and Jiang (2016) used data from 11 major international markets celebrating six cultural New Year holidays that do not occur on January 1 and found that stock markets tend to outperform during days surrounding a cultural New Year. Bergsma and Jiang attributed this effect to positive holiday moods and common cash infusions before a cultural New Year.

The Halloween effect shows that the rate of return on equity during months between November to April is higher than during other time periods. Investors commonly sell their assets in May and then buy them back in September (Caporale & Zakirova, 2017). Investors may be able to use this strategy to achieve higher returns than the market average.

Ramadan effect is part of the holy day effect. During Islamic calendar anomalies, return on equity is higher during holy days than other days. From the Islamic perspective, the Ramadan effect is the most significant. Different seasonal patterns of stock returns are documented in the Islamic calendar. The month of Ramadan is a holy month for all

Muslims around the world. The rate of return is higher during the month of Ramadan compared to other months (Jebran & Chen, 2017).

Day of the Week (DOW) Effect

The DOW effect has been one of the most studied anomalies of the EMH in financial literature. This effect consists of two types of anomalies: the Monday effect and the weekend effect. Several studies have evaluated the validity of the Monday effect (Bihal et al., 2019; Gayakar et al., 2020; Richards & Willows, 2019; Tadepalli & Jain, 2018; Tilica, 2018; Ulku & Rogers, 2018). The Monday effect states that returns and trading volumes on Mondays are generally lower than those on other days of the week (Afrilianto & Daryanto, 2019; Arman & Lestari, 2018; Rita et al., 2018). Many researchers have studied and documented this phenomenon extensively (Karanovic & Karanovic, 2018). Studies have shown that returns on the stock market are consistently low on Mondays (Aharon & Qudan, 2019; Arman & Lestari, 2018; Cross, 1973; Chukwuogor-Ndu, 2020; French, 1980; Lu & Gao, 2016; Tadepalli & Jain, 2018). The weekend effect suggests that the returns on Fridays are generally higher than on other days of the week. Xiao (2016) and others argued that the DOW effect was present in many markets around the world, including different sectors of the market, and influenced return on investments, specifically on Mondays and Fridays. Studies have shown that the DOW effect extends beyond the U.S. equity market and are present in many international markets (Afrilianto & Daryanto, 2019; Gayakar et al., 2020; Khan et al., 2018; Lu & Gao, 2016; Tadepalli & Jain, 2018). DOW effect is also present in other financial sectors such as real estate, bitcoin, derivatives, and interest rate. futures market, treasury bill market, currency exchange market, and bond market (Anjum, 2020; Arman & Lestari, 2018; Decourt et al., 2019; Faizan et al., 2018; Kumar 2016).

The weekend effect states that the returns on Fridays are generally higher than other days of the week and the returns on Monday are smaller than the rest of the week. (Afrilianto & Daryanto, 2019; Tadepalli & Jain, 2018). For more than half a century, researchers across the globe have quantitatively analyzed weekend effect (Abraham & Ikenberry, 1994; Anjum, 2020; Caporale & Plastun (2017); Fields, 1931; French, 1980; Keim & Stambaugh, 1984; Khan et al., 2018; Miss et al., 2019; Richards & Willows, 2019). Some of the recent studies argued that the weekend effect has disappeared in developed markets.

In 1930, Fred C. Kelly documented the Monday effect in his book Why You Win or Lose, arguing that individual investors tend to sell their stocks on Mondays, causing stock prices to decline that day. The author studied stock markets as a way to understand crowd behavior. Even though it was not a scientific study, he observed that the chances of losing in the market is greatest on Mondays. He also observed that the prices of the stocks are at their lowest point around 1:00 pm every day. Furthermore, he noticed that investors have a tendency to sell their good stocks and hold on to poor stocks. He concluded that human psychology played a bigger role in deciding whether investors win or lose rather than the economic conditions. Vanity and greed are the biggest reasons why individual investors lose in stock market. Confirmation bias caused investors to hold on to poor stocks, hoping they will advance in time. Mood also played significant role in individual investor behavior.

Fields (1931) empirically examined the hypothesis that investors had a tendency to sell their stocks the day before a stock exchange holiday. Because the stock market was open on Saturdays during that period and closed on Sundays, the hypothesis suggested a decline in prices and consequently a lower closing stock prices on Saturday than the prices on Friday and Monday because of more sell than buy orders. The study compared the Saturday index with the average of the Friday and Monday indexes for each week from the Dow Jones Industrial Average for period of 16 years from 1915 to 1930. The results of the study debunked the hypothesis and proved that the index for Saturday is sometimes higher and sometimes lower than the same indexes for Friday and Monday.

In the seminal work on the periodic structure in the Brownian motion of stock prices, Osborne (1962) argued that one can find a sample of stock for which the probable value of the expected change in $\log_e$ is slightly different than zero. While not in conflict with the elementary properties of the Brownian motion, Osborne asserted there was evidence of periodic structure corresponding to intervals of days, weeks, quarters, and years. The author suggested this phenomenon simply reflected the cycles of human attention span. The author also observed evidence of clustered activity.

Cross (1973) documented non-random movements in stock prices and the weekend effect in the U.S. stock market. The author quantitatively analyzed the distribution of price changes on Fridays and Mondays and the relationship between price changes on those two days. The study consisted of secondary data from 844 sets of Fridays and following Mondays from January 1953 to December 1970 in the Standard &

Poor's composite stock index. The study documented stock prices consistently rose on Fridays more often than on any other day of the week. The study also documented that stock prices rose the least on Mondays. The study concluded that the relationship between price changes on Friday and Monday was significantly different from the relationship between price changes on other successive business days.

French (1980) also studied the Monday effect using secondary data containing the daily returns of Standard and Poor’s composite portfolio from 1953 through 1977. To evaluate the change in the Monday effect over a long period of time, the author divided the 25-year study period into five smaller subperiods of 5 years each. The study confirmed that the average returns for Monday were significantly negative during all 5-year subperiods. However, the study found the average returns for the other 4 days of the week were positive. Gibbons and Hess (1981) further quantitatively studied the Monday effect and confirmed that daily returns on Mondays were unusually negative for 30 individual stocks of the Dow Jones Industrial Index. Keim & Stambaugh (1984) conducted the next major investigation of the Monday effect. The authors expanded the study data for a period to 55 years. The study results confirmed the Monday effect for the whole period. Similar to French, Lakonishok and Maberly (1990) also conducted a study using secondary data containing the daily returns of the NYSE listed common stocks for 25 years covering the period from 1962-86. Their study also confirmed the existence of the Monday effect in the U.S. market. They also found that retail investors trade relatively more than institutional investors on Mondays and argued the individual investor behavior was the main driver for the Monday effect. Additionally, Abraham and

Ikenberry (1994) conducted a similar study using secondary data from 1963 to 1991 to investigate the causes for the Monday effect. Their study found strong relationship between Fridays and Mondays return and concluded that Monday return are negative most of the time when the preceding Fridays return are negative.

More recently, Bishal et al. (2019) analyzed the DOW trading patterns to ascertain the individual investors' influence on the Monday effect in the U.S. market. They used secondary data of the NYSE-listed firms between March 2004 and June 2013. Consistent with the Monday effect, the authors found that Monday stock returns were generally lower than those of other weekdays and were negative on average. They also found that trading activity of individual investors on Mondays was lower than had been previously documented. Similarly, Birru (2018) documented the DOW effect in the cross-section of stock returns in the U.S. equity market. The study contained stock return data from NYSE, Amex, and Nasdaq common stocks from July 1963 through December 2013. The study showed that speculative stocks earned low returns on Mondays and high returns on Fridays. Similarly, Xiao (2016) found that the DOW effect persisted in the American stock market from 2010 to 2015. The author argued that daily returns were the lowest on Mondays and built up to a peak on Fridays. Chatterjee and Hubble (2017) evaluated the DOW effect in the biotechnology stocks using daily returns from the NASDAQ Biotechnology Index from 2002 to 2015. The results of the study concluded that DOW effect remained significant in biotechnology stocks in the U.S.

Several studies have recently contradicted the presence of the weekend effect in the U.S. market. Some such studies have suggested that the weekend effect has become less important over the years (Plastun et al., 2019). For example, Robins and Smith (2016) reported in their study that the weekend effect disappeared after 1975 and argued that it was no longer an anomaly in the U.S. stock market. The authors used data from daily weekday returns on the Center for Research in Security Prices market portfolios of the NYSE stocks that included daily log returns on the small minus big and high minus low from July 1926 to 10 December 2014. These dates span the 1953–1977 sample period in French (1980) and the 1962–1978 sample period in Gibbons and Hess (1981) studies. Similarly, Zica (2017) analyzed the DOW effect in three 18-year subperiods: from 1953 to 1970; from 1971 to 1988; and from 1989 to 2006. The results showed that the DOW had declined over a period of time with the last sub-period showing no effect at all. Additionally, Plastun et al. (2020) asserted that seasonal anomalies were common during the middle of the 20th century, but has disappeared in recent years from major global markets.

International Evidence

There are several studies that investigated the presence of seasonal anomalies in the international market with varying results. Chiah and Zhong (2019) quantitatively examined the day of the week effect in 24 international equity markets. In particular, they studied the difference between speculative and non-speculative stock returns. Their findings supported the presence of the DOW effect around the world. Similarly, Zhang et al. (2017) investigate the DOW effects in 28 markets from 25 countries around the world. The study results concluded the existence of DOW effects in both emerging and developed stock markets. Campanella et al. (2016) analyzed the EMH in European financial markets. The authors used secondary data from 1,708 manufacturing and service businesses and found the financial market in Europe was not consistent with semi-strong EMH. The authors conjectured the findings of the study supported theories of behavioral finance such as the irrational conduct of investors in financial markets and the tendency to take excessive risks associated with a particular stock. Similarly, Chukwuogor-Ndu (2020) examined the DOW stock return patterns and the volatility of returns of ten East Asian stock markets (China, India, Japan, Indonesia, Malaysia, Philippines, Singapore, South Korea, Thailand, and Taiwan) to provide empirical evidence in the post 1997 Asian financial crisis period. The study used data from daily closing market indices from 1998 to 2003. The authors concluded the DOW effect was still present in the ten Asian stock markets, even though the days with negative or positive returns have wandered to other days in some countries.

Anjum (2020) investigated the presence of the day of the week effect, weekend effect and month of the year effect in the stock exchanges in Pakistan. The secondary data used for the study consisted of monthly, daily and weekly returns of two stock exchanges. The data for one of the stock exchanges was from January 2004 to January 2016, while the data for the other was from January 2016 to April 2019. The study concluded the DOW effect was persistent in the Pakistan stock market. Similarly, Jebran and Chen (2017) investigated the presence of seasonal anomalies in an Islamic equity market of Pakistan. The study included daily data from September 2008 to June 2015. The results of the study indicated significant DOW effect, turn-of-the-month effect, time-of-the-month effect, and half-of-the-month effect in the Islamic index. Ulla et al. (2016)

also evaluated the presence of the January effect in the Karachi stock market. They used secondary data from the Karachi stock exchange 100 index for the period from January 2004 to December 2014. The results revealed the presence of the January effect in the Karachi market. Al Barghouthi and Ehsan (2017) studied five Jordanian indices and concluded the investors can outperform the market and make abnormal profits, and therefore was inefficiency at the weak form level. Cengiz et al. (2017) evaluated DOW effect in Borsa Istanbul Index and found the stock market inefficient. However, Öncü et al. (2017) found Borsa Istanbul Index to be consistent with EMH.

There are several studies conducted in the Indonesian market, albeit sometimes with conflicting results. For example, Afrilianto and Daryanto (2019) conducted a study using the stock of 22 companies listed in the Indonesian stock market. The authors used secondary data during the period from January 2013 to December 2018. The study result showed the DOW effect was present in all twenty-two stock returns during the study period. The authors concluded the DOW effect existed in the Indonesia Stock Exchange. Other studies supported this finding (Faisal & Majid, 2016; Hendrawaty & Huzaimah, 2019). Similarly, Arief (2020) used data from the Indonesia Stock Exchange from 2000 to 2019 to study the wandering weekday effect. The results of the study concluded there was a negative wandering Monday effect when the market is falling. Rita et al. (2018) tested the weekday pattern in Indonesian stock market during the period from August 2016 to January 2017. The results showed the lowest and highest return are observed on Mondays and Wednesdays respectively. Juniarwoko et al. (2017) investigated the DOW anomaly in the Indonesian stock market. The data contained information about 58 stocks that represented large, medium, and small cap stocks. The study concluded the DOW effect is present in the Indonesian stock market. Hambayanti and Budileksmana (2016) investigated the presence of the Monday effect in the Jakarta stock market. The secondary data consisted of stock market index at Jakarta Stock Exchange from 1999 to 2005. The results of the study concluded Monday returns are significantly negative and are lower than returns during the rest of the week. Another study (Bagaskara & Khairunnisa, 2019) also found similar results during the period from 2013 to 2017. Furthermore, Dian et al. (2018) analyzed market anomalies including the Monday effect and the January effect in Indonesia. The study used secondary data from 2016 to 2017. However, the study results concluded that the Monday effect was not present in the Indonesian stock market, but the January effect was present. Another study conducted by Arman and Lestari (2018) quantitatively researched Monday effect in the banking sector in the Indonesian stock exchange. They used secondary data of monthly closing prices of stocks from 2014 to 2017. The results of the study concluded the Monday effect is absent in banking stocks on the Indonesia Stock Exchange except during the months of April and June. Similar studies confirmed the absence of the DOW effect on Indonesian stock market (Nuroniyah & Ady, 2018; Suryanto, 2019).

There were a few studies on the Thailand stock market to evaluate the existence of the DOW effect with mixed results. Khanthavit and Chaowalerd (2016) evaluated the DOW effect in the Stock Exchange of Thailand using daily return data on three index portfolios from September 2002 to August 2015. The study found the DOW effect on two of the index portfolios, but not the third one.

Richards and Willows (2019) investigated the individual investor behavior and its impact on the Monday effect in the United Kingdom (UK). They used data from trading activity for 7200 UK investors from July 2006 to December 2009. The study results showed individual investors preferred trading on Mondays and traded in a W-shaped intraday pattern. Sharif (2019) examined whether the Weekend effect anomaly existed in the Australian Financial Exchange. The author used secondary data from January 1994 to September 2018 for the study and confirmed the presence of weekend Australian stock market. However, the author observed that the weekend effect had shifted from smaller stocks to larger stocks. Rossi & Gunardi (2018) examined seasonal anomalies in France, Germany, Italy and Spain from 2001 to 2010 and did not find strong evidence for their presence.

Razia and Yuvraj (2019) studied the DOW anomaly in India. They used data from 2001 to 2018. The researchers analyzed daily purchasing, selling, and net investing activities during this period. The conclusion of the study was the DOW effect was present in the Indian market and hence was inconsistent with the EMH. Similarly, Tadepalli and Jain (2018) studied stock exchanges in India to determine the presence of the DOW effect. They used secondary data from daily stock market returns of 11 market capital-based indices and 22 sectoral indices in two of the stock exchanges in India. They used the data from the start of the respective stocks to December 2017. The results of the study confirmed the presence of the DOW effect in both Indian stock exchanges. Chawla (2018) also examined the DOW effect in Indian stock markets. The study used data of 17 indices for the sample period from April 2009 to June 2018. The results concluded the

DOW effect existed in the Indian stock markets, and hence markets were inefficient. Kumar and Jawa (2017) studied the efficiency in Indian stock markets. The study included data from daily and monthly returns from January 1995 to December 2015 and confirmed the presence of the DOW effects in Indian stock markets. Kothari et al. (2017) evaluated DOW effects on the returns and volatility of the Bombay Stock Exchange and National Stock Exchange indices for the period from 2005 to 2014, validating its presence.

Obalade and Muzindusti (2019) investigated the behavior of the DOW effect under different bull and bear market conditions in African stock markets. The study used daily stock market return indices of the major stock markets in Africa (Nigeria, South Africa, Mauritius, Morocco, and Tunisia) for a period from 1998 to 2017. The findings of the study showed that active investors were able to make excessive profits in most African markets during bearish conditions, which was not consistent with the EMH. Using secondary data from 1995 to 2016, Toit et al, (2018) also investigated the presence of a DOW effect in the Johannesburg Stock Exchange indices. Their findings also supported the DOW effect in the South African markets.

Several quantitative studies tested the DOW effect in the Balkan countries. Tilica (2018) analyzed the evolution of the Bucharest stock exchange to understand the existence of the DOW effect and time-of-the-month effect in Romania. The study included secondary data from January 2000 to December 2017. The results showed both DOW effect and time-of-the-month effect impacted the Romanian stock market. In a similar study, Avdalović (2018) quantitatively analyzed the data from the stock exchanges in the Balkan region during the period from 2008 to 2014 to study the impact of the DOW effect. The results of the study confirmed the effect of the DOW on all stock markets in the region, except for Bulgaria. Similarly, Svrtinov et al. (2017) examined seasonal anomalies on the Macedonian stock market's daily returns during the period from 2006 to 2016. The results of the study provided evidence for the existence of the Monday effect and the January effect. Similarly, Caporale et al. (2016) found the Ukrainian stock market inefficient.

Winkelried and Iberico (2018) evaluated the influence of the DOW effect in six major Latin American markets. The secondary dataset used for the study consisted of representative indices for the Latin American stock markets derived from the Bloomberg database from 1995 to 2014. The study concluded Monday returns were the lowest and negative in all six markets, whereas Friday returns are the highest and positive in five cases. The results confirmed the DOW effect in major Latin American markets.

Novotna and Zeng (2017) tested the impact of the DOW effect in two Chinese stock markets. The authors used secondary data from the Shanghai Stock Exchange Composite Index and Shenzhen Composite Index during the period from 2000 to 2013. The overall results indicated that both indexes were impacted by the DOW effect.

Akbalik & Ozkan (2017) studied day of the DOW effect in Brazil, India, Indonesia, Turkey, and South Africa during 2007 to 2008. They found the DOW anomaly was absent in emerging markets, except Indonesia where there was significantly negative first trading day returns and positive Wednesday returns. A similar quantitative study by Khanna and Mittal (2016) of the stock markets in Brazil, Russia, India, China and South

Africa during 2001 to 2014 period showed the existence of the DOW effect in Indian and Chinese stock markets only.

Khan et al. (2018) evaluated the performance of Islamic stock indices for the presence of Islamic calendar anomaly. The study included daily data from January 2010 to September 2017 of the Shariah index consisting of funds from 22 emerging economies. The study showed mixed results with the effect of Ramadan both significant and insignificant depending on the year.

Presence of DOW Effect in Other Financial Sectors

Various other market segments are also susceptible to the DOW effect (Anjum, 2020; Arman & Lestari, 2018; Decourt et al., 2019; Faizan et al., 2018; Kumar 2016). Gayaker et al. (2020) investigated the relationship between the DOW effect and the interest rate in Turkey's financial market. They used secondary data of the daily interest rate and the daily return in Borsa Istanbul for the period from 1990 to 2017. The study argued the DOW effect decreased as the return in overnight interest rates decreased. They concluded there was a positive relationship between the expected relative returns on Monday to Friday and overnight interest rates. Similarly, Mangenis and Mike (2018) used daily data for futures prices from May 2010 to the end of December 2014 to study the existence of the DOW effect on the Ukrainian stock market. They observed abnormal positive returns on Fridays and concluded the Ukrainian stock market was inefficient. Mamende and Malaquias (2017) conducted research to analyze the Monday effect in Brazilian hedge funds that do not have redemption restrictions. The authors used daily returns from 2162 hedge funds, consisting of a total of 2,689,791 observations from

January 2005 to March 2014. The results of the study confirmed the existence of DOW effect in the Brazilian market.

Studies have shown that there is a negative correlation between stock market index and the corresponding volatility index. Akhtar et al. (2017) explored the DOW effect in the volatility index and its underlying stock index in India for a period from 2009 to 2016 and found positive Monday effect in the volatility index of India, but not in the stock index. In a slightly different study, Batrinca et al. (2018) used quantitative analysis to investigate the drivers affecting the trading volume in pan-European stock market. The study consisted of secondary data for the period between January 2000 and May 2015 comprising 2,353 stocks from different countries. Results of the study showed less trading activity on Mondays, and thus confirmed the DOW effect on trading volumes.

Bampinas et al. (2016) performed a quantitative study to evaluate the DOW effect in the securitized real estate market indices in Europe using data from 1990 to 2010. The results of the study reinforced the argument that DOW effect is not present in the European market. Bush and Stephens (2016) empirically examined the EUR/USD currency pair over six different periods from 1999 to 2014 to study the Monday effect on European currency. Based on the result, the authors postulated that the Monday effect existed in the EUR/USD currency pair, but was influenced by the relative strength or weakness of the EUR. In a similar study, Kumar (2016) examined the DOW effects on 12 currency markets of advanced and emerging currencies from 1985 to 2014. The study used secondary data from Board of Governors of the Federal Reserve System. The results showed that DOW effect was present on the currency market, with stronger effects on the emerging markets and effect almost vanishing for advanced currencies in later years. In a similar study, Dao et al. (2016) evaluated the spot foreign exchange markets of 8 major and 9 emerging currencies in the world and concluded that currency markets are weak-form inefficient.

Even though still young and volatile, the cryptocurrency market has attracted much attention in analyzing the DOW effect with varying results. Caporale and Plastun (2019) examined secondary data from four cryptocurrencies (BitCoin, LiteCoin, Ripple, and Dash) during the period from 2013 to 2017. The study found that most cryptocurrencies, except BitCoin, did not show the DOW effect. Further analysis indicated positive correlation between past and future values of cryptocurrencies which provided an opportunity to exploit its behavior to generate abnormal profits in the cryptocurrency market (Caporale et al., 2018). Ma and Tanizaki (2019) conducted a similar quantitative study using secondary data from 2013 to 2018 on BitCoin and found the DOW effect along with high volatility on Mondays and Thursdays in the market. Similarly, Mbanga (2019) quantitatively studied the DOW effect on price clustering in Bitcoin. The study contained secondary data from 2011 to 2018. The results proved that the clustering around whole numbers is stronger on Fridays and weaker on Mondays. proving the DOW effect in Bitcoin price clustering. A similar study conducted by Robiyanto et al. (2019) using secondary data from 2014 to 2018 to assess the DOW effect on Bitcoin and Litecoin confirmed its presence in the cryptocurrency market. Thus, the results showed the cryptocurrency market is not consistent with EMH. However, other studies did not find DOW effect on BitCoin, but the results found lower trading activities during evening hours and on weekends (Baur et al., 2019; Kaiser, 2019; Kinateder & Papavassiliou, 2019). Similarly, Long et al. (2020) investigated the cross-sectional seasonality anomaly in cryptocurrency markets and found significant seasonal pattern.

Possible Reasons for DOW Effect

Researchers have conjectured several reasons for the DOW effect during the past half century. However, there has been no consensus on any of the reasons. One argument for the DOW effect is the settlement date. The reasoning behind this argument was the Settlement Regime Hypothesis that states that the period between the trade date and the settlement date creates an opportunity for an interest-free loan until the settlement (Lakonishok & Levi, 1982). Weekends afforded an investor an extra two days to use the money in other markets (such as interest-bearing bank deposits). Gayaker et al. (2020) provided empirical evidence from Turkey that confirmed the DOW effect decreased as the overnight interest rates decreased.

Another hypothesis for the DOW effect is the timing of corporate financial announcements. French (1980) posited the information release hypothesis which argued corporations have a tendency to release positive financial information during weekdays and negative financial information on the weekend to mitigate panic selling and allowing investors a few days to absorb the negative news. A similar study by Abraham & Ikenberry (1994) confirmed this hypothesis and suggested corporations release good news during regular trading days and postpone the release of bad news until the weekend.

This pattern of news releases caused lower stock prices on Mondays and higher stock prices on Fridays.

A growing number of studies pointed to behavioral economics to explain the weekend effect and investor psychology. In general, these studies are predicated on investor psychology. These studies are rooted in the hypothesis that mood increases from Thursday to Friday, decreases on Monday. As a result, people were prone to evaluate future prospects more optimistically when they are in a good mood than when they are in a bad mood. Thus, investor mood influenced their investment decisions (Birru, 2018). This investment behavior contradicts with one of the basic assumptions of EMH which assumes all market participants are rational actors. Obalade & Muzindutsi, (2019) explained that individual investors act irrationally at times, making some decisions quickly and with insufficient information or time. Individual characteristics such as pessimism, optimism, fear, and mood play a critical role in investment decisions. Similarly, other patterns of behavior such as overconfidence and overreaction also influence investment decisions (Da et al., 2015; Daniel & Hirshleifer, 2015; Hao et al., 2018). Chhaochharia et al. (2019) also supported the behavioral economic theory and argued that mood of small business managers impacted their economic expectations.

The investor's psychology hypothesis states investors are more likely to purchase securities as holidays approach due to the general feeling of good fellowship and holiday excitement (Hirshleifer, 2001; Wachtel, 1942). Confirming this hypothesis, Rystrom and Benson (1989) found that individual investor selling activity followed a weekday patterns of psychological well-being. They argued the people are generally less optimistic on

Mondays and the lower Monday return is an example of investor's psychology hypothesis. Similarly, Thaler (1987) argued happier people believed in more positive outcomes and traded more profusely. In this context, investor's emotions impacted their investment decisions, and they could act irrationally. Birru (2018) argued that investor psychology was a major factor in deciding whether to buy or sell stocks. The author asserted investors were in good moods on Fridays and poor moods on Mondays. This dichotomy in emotion resulted in highest returns on Fridays and lowest on Mondays. Birru's conclusion is supported by findings from Chiah and Zhong (2019). Their study used data from 24 countries and empirically demonstrated investors' pessimism and optimism in assessing the company's future prospects translated to negative returns on Mondays and positive returns on Fridays. Richards et al. (2018) also supported the behavioral economic theories and argued that investors held stocks at a loss longer than stocks at a gain. The authors called this pattern of behavior as disposition effect and suggested that less experienced and less sophisticated investors are more prone to this behavior. Similarly, Richards and Willows (2018) identified individual investor characteristics such as propensity to trade frequently, reluctance to sell losses, and eagerness to sell gains as enabling the Monday effect.

Abraham and Ikenberry (1994) argued that the relationship between Friday and Monday was stronger than that of any other pair of consecutive trading days in the U.S. stock market. As an example, the authors proved that Monday returns were negative most of the time when Friday's return is negative. They also proved that Monday returns were positive only about 10% of the time when previous Friday returns were positive. The authors suggested the trading behavior of individual investors was one factor contributing to this pattern because they are more active sellers of stock on Mondays.

Some studies suggested institutional investors drove the Monday effect (Ali & Ulku, 2019). Several studies argued institutional investors were less active on Mondays because of the fear of possible private information flows over the weekend (Sias & Starks, 1995). More recently, Ulku & Rogers (2018) used data from daily trading with investor type identification from three major Asian stock markets (Korea, Taiwan, and Thailand) and concluded institutional investor trading was responsible for the Monday effect, not individual investor trading. The authors observed individual investors were net buyers when the preceding Friday returns were negative, thus mitigating the Monday effect. They conjured that institutional investor needed time to analyze large trades and hence were less active on Mondays. The results of the study pointed to a close relationship between the presence of the Monday effect and overall higher movement in price of institutional ownership. Similarly, Ulku and Andonov (2016) found that institutional investor trading was lowest on Mondays and individual investor trading was highest on Mondays.

Individual Investors

Many studies pointed to individual investors as the reason for the day of the week effect. Some studies suggested individual investors had a tendency to sell more stocks on Mondays and thus caused the decrease in stock price on that day. Osborne (1962) was the first person to suggest individual investment pattern is responsible for the weekend effect. The author speculated individual investors had more time to spend on financial decisions during the weekend and executed their decisions on Mondays. The author argued Mondays are usually planning days for institutional investors and hence were less active on that day. Lakonishok and Maberly (1990) also conducted a study using the dataset containing the daily returns of NYSE listed common stocks for 25 years covering the period from 1962-86. Their study also confirmed the existence of Monday effect in the U.S. market. They also found that retail investors trade relatively more than institutional investors on Mondays and argued individual investor behavior was the main driver for the Monday effect. Individual investors trade as percentage of the total trade was the highest on Mondays and the individual investors performed more sales transactions than buy transactions, resulting in lower returns on Mondays. The authors conjectured that the individual investors are mostly working people, have more time to analyze their financial portfolio during the weekend, and thus sell more profusely on Mondays. However, the institutional investors mostly use Mondays as a planning day and thus are less active.

Abraham and Ikenberry (1994) said individual investors participated more on Monday trades. Lakonishok and Maberly (1990) study agreed with this finding. Participation was higher if the stock market had bad news the previous week. The results of the study were based on U.S. market and argued that trading strategy of individual investors was one of the causes for the weekend trend. The authors argued that it is more costly for individual investors to gather accurate information about securities during weekdays because they typically have daytime jobs or are involved in other activities. These investors normally have opportunities to gather information during the weekend and reach investment decisions. The authors conjured this pattern of behavior as the reason for the active participation of individual investors on Mondays. However, the individual investors have a propensity to sell rather than buy on Mondays. The information these investors receive from the brokerage community during weekdays is normally skewed towards buy decisions. Thus, investors make more sell decisions during the weekend to balance out the buy-sell ratio or to cash out some securities. This phenomenon is known as the information processing hypothesis.

Summary and Conclusions

This chapter described the major themes in the literature as they pertained to this study. The main theory used in this study is the EMH which is one of the central theories of modern finance (Lekovic, 2018; Toit et al., 2018). Monday effect has been one of the most intriguing anomalies of EMH (Ulku & Rogers, 2018). While many studies have concluded the existence of the Monday effect, researchers have not come to a consensus about the reasons for it (Bishal et al., 2019). Some studies suggested that the trading behavior of individual investors drive this anomaly (Birru, 2018; Breaban & Noussair, 2018; Hirshleifer et al., 2020). However, no comprehensive study has been carried out using actual individual investor data showing the day of the week and time of the day in the US stock market. Understanding the influence of the individual investors on the Monday effect requires gathering and analyzing the actual trading data of investors. This study aims to fill this gap by using actual individual investor data including the day of the week and time of the day from 2006 to 2016.

This chapter included a description of the literature review, giving a synopsis of current literature that established the relevance to the problem of the study. It also explained the literature search strategy I used and the theoretical foundation for the study. Finally, it provided an exhaustive review of the current literature including studies related to the seasonal anomalies using quantitative methodology.

Chapter 3 includes the description of the research design rationale including the study variables. It provides a detailed description of the methodology and the data used in the study. This chapter also provides an explanation of data sorting and organizing procedures used in this study. Further, it includes threats to validity and ethical procedures used in the study.

Chapter 3: Research Method

The purpose of this comparative study was to test the EMH theory which is defined as the phenomenon where prices of the stock in the market at a given time always and fully reflect all available information about that stock at that time. I also tested the role of the individual investor on the Monday effect. The study was designed to compare individual investors' average returns, trade percentages, and trading patterns on Monday with other weekdays. The independent variable was day of the week. The dependent variables were average daily returns, percentages of individual investor trades compared to total trades, and number of individual investor trades in 30-minute intervals within a day. I used publicly available data from the NYSE from 2006 to 2016.

Chapter 3 includes a synopsis of the purpose of the study and descriptions of the research design rationale, including study variables. I also provide a detailed description of the methodology and data used in the study. This chapter includes an explanation of data sorting and organizing procedures used in this study. Additionally, Chapter 3 contains research questions and hypotheses as well as threats to validity and ethical procedures used in the study.

Research Design and Rationale

The research design for studies is a general plan that can help researchers answer research questions. It includes plans and strategies to analyze data and information (Cantrell, 2011). This study was based on a nonexperimental quantitative comparative design. The basic purpose of the design is to evaluate relationships between variables. The comparative design was best for this study because I was evaluating the relationship between variables to test the theory of the EMH and the role of individual investors on the Monday effect.

Methodology

There are three types of research methods: quantitative, qualitative, and mixed methods approaches. I evaluated these three methods to ascertain the method most suitable to answer research questions in this study. Most researchers choose the quantitative method to answer research questions requiring numerical data. Accordingly, I selected the quantitative methodology for this study. The qualitative method usually involves textual data, while mixed methods involves a combination of numerical and textual data (Williams, 2007). The qualitative method was not suited to address relationships between variables. The mixed methods approach has the characteristics of both quantitative and qualitative methods and is normally used when these two methods are not sufficient to address the research problem. The present study involved testing hypotheses based on the EMH, and qualitative data were not used. Consequently, the qualitative and the mixed methods approaches were not appropriate for this study.

The present study involved using the quantitative methodology. Chelaa (2017) described quantitative research as the study method that involves collecting and analyzing data using statistics. The quantitative method was the best approach to answer research questions requiring numerical data and generalize results to a larger population. Accordingly, this methodology was consistent with the purpose of this study, which was to compare individual investors' average returns, trade percentages, and trading patterns between Monday and other weekdays. Quantitative methods usually build upon existing theories, and results can be predictive, explanatory, or confirming (Williams, 2007). The quantitative method is normally used to answer questions related to relationships between variables, either to establish or validate relationships. The quantitative research process normally consists of developing a problem statement and corresponding hypothesis. It is followed by an exhaustive literature review and data analysis.

Population

Population selection is important in a quantitative study, and it must align with research questions. There are several factors that determine the efficacy of the research design, including quality of the data and selected population. The purpose of this comparative study was to test the EMH. I used publicly available secondary data from the NYSE during the period from 2006 to 2016. The NYSE is the largest stock exchange in the world, with a market capitalization of its listed companies at over USD 26 trillion.

There are two primary methods of collecting samples: probabilistic and non-probabilistic sampling. Almost all researchers evaluating calendar anomalies during the past 50 years have used non-probabilistic purposive sampling. Accordingly, the purposive sample data used for this study included all transactions on the NYSE from 2006 to 2016. Using archived data as the sample for this study was appropriate because it was suited to answer the research questions by evaluating the historical relationship between variables.

Archival Data

The present study involved publicly available secondary data from the NYSE. Individual investor trading data used in this study were accurate because they were electronically gathered from the NYSE. The NYSE compiled data using transaction records of purchases and sales in their centralized stock market.

Specifically, I used comprehensive actual individual investor trading data, the NYSE ReTrac End of Day. This dataset included all individual investors selling and purchasing records on the NYSE. It contains summaries of all stock activities during the day and includes the volume of retail buy and sell shares executed on the NYSE. Data used in this study covered a sample period from May 2006 to April 2016 and provided the most up to date assessment of individual investors' influence on the Monday effect.

Secondary data analysis involved data collected by a third party for another primary purpose. Government agencies such as the U.S. Census Bureau and Centers for Disease Control and Prevention collect data for their internal studies. Similarly, private companies such as Yahoo! and Bloomberg collect data on businesses. Researchers can use these types of data as secondary sources to conduct their studies. Secondary data analysis involves proper methods and procedures to evaluate data. Use of such data helps to complete the study faster with limited resources. Secondary data analysis involves the same basic research principles as studies using primary data, and researchers can apply theoretical knowledge and conceptual skills to address research questions.

There are several advantages to using secondary data. First, it is cost effective and convenient. Researchers do not have to invest time and money to collect data because it is already available (Johnson, 2017). Second, secondary data enables researchers to complete studies on an efficient timeline, bypassing the most time-consuming step of data collection. Third, secondary data also tends to be high quality with larger samples, because they are normally collected by funded or large organizations. Use of larger samples adds to the validity of results and helps to generalize findings. Fourth, access to high-quality secondary data enables many researchers who otherwise may be unable to afford to collect data to contribute to knowledge, thus equalizing opportunities for all and building a capacity for research. Finally, secondary data analysis enables research through replication and reinterpretation of existing research.

There are a few methodological weaknesses when using secondary data to investigate new research questions and generate new knowledge. The first limitation of using secondary data is it was collected for another purpose and may not be ideal for this study (Johnson, 2017). In this regard, I used programming scripts to extract the data used for this study. Another disadvantage of using secondary data is I did not participate in the data collection process and did not know exactly how it was conducted. I was unaware of any potential problems during data collection or whether all ethical procedures were followed.

Data Analysis Plan

Data analysis involves inspecting, cleansing, transforming, and modeling data. Through this process, raw data are converted into useful information for decision-making. There are many approaches and techniques in data analysis that are used in different business and research settings. This section includes approaches and techniques in data analysis used in this study. I also describe software used for data analysis. Furthermore, I explain data cleansing and screening procedures that were used in the study.

The purpose of this comparative study was to test the EMH and role of the individual investor on Monday effect. The study was designed to compare individual investors' average return, trade percentages, and trading patterns on Monday with other weekdays. Research questions and hypotheses were:

RQ1: Are there statistically significant differences in investor average returns between Monday and other weekdays?

$H_0 1$: There are no statistically significant differences in investor average returns between Monday and other weekdays.

$H_a 1$: There are statistically significant differences in investor average returns between Monday and other weekdays.

RQ2: Are there statistically significant differences in individual investor trade percentages between Monday and other weekdays?

$H_0 2$: There are no statistically significant differences in individual investor trade percentages between Monday and other weekdays.

$H_a 2$: There are statistically significant differences in individual investor trade percentages between Monday and other weekdays.

RQ3: Are there statistically significant differences in individual investor trading patterns between Monday and other weekdays?

$H_0 3$: There are no statistically significant differences in individual investor trading patterns between Monday and other weekdays.

$H_a 3$: There are statistically significant differences in individual investor trading patterns between Monday and other weekdays.

Statistical Package for the Social Science (SPSS) software was the primary tool used for data analysis in this study. The software can compute various descriptive statistics as well as create a comparative study to assess relationships between independent and dependent variables.

The present study involved using various statistical techniques, such as descriptive statistics, ANOVA, and a post hoc test to evaluate the influence of the individual investor behavior on the Monday effect for the U.S. stock market. The ANOVA test was used in this study to evaluate the influence of the independent variable on the dependent variables. A post hoc test was used when the ANOVA found statistically significant differences in the means of the dependent variables. It was used to identify sources of differences in the means of the dependent variables.

I used Microsoft Excel spreadsheets to enable the cleansing and screening process for data. The NYSE ReTrac End of Day database contains all transactions for individual investors selling and purchasing records on the NYSE on a continuous basis. One of the dependent variables was the number of individual investor trades in 30-minute intervals within a day. Raw data from the NYSE ReTrac End of Day database was processed using the Excel spreadsheet so that all individual trade data were accumulated and recorded in 30-minute time intervals. This processed data was then input into SPSS for statistical analysis.

Threats to Validity

Research findings are useful when results are true for similar individuals or subjects outside the study. The concept of validity applies to all types of research.

Additionally, it refers to accuracy of measurements used in the research. In this regard, the researcher must choose the right instruments to evaluate relationships between independent and dependent variables. There are three kinds of threats to validity in research: external validity, internal validity, and construct validity.

Archived secondary data from the NYSE was used for the study. Consequently, there was no direct or indirect interaction between me and subjects during the data collection process. This method of using secondary archived data minimized common threats to validity.

External Validity

External validity refers to issues with the study design. It involves the validity of applying conclusions from a study outside the context of that study. It also involves measuring generalizability of empirical findings to the general population. External validity is essential in most scientific research.

The dataset I used for the study was a large, archived dataset from the NYSE. Individual investor trading data used in this study were accurate because they were electronically gathered by the NYSE. The NYSE is the largest stock exchange in the world with a market capitalization of its listed companies of over USD 26 trillion. The NYSE compiled the dataset using transaction records of purchases and sales in their centralized stock market. Because the dataset was exceptionally large and represented individual investors' trading data from most of the U.S., results of this study can be generalized to the whole population.

Internal Validity

Internal validity refers to issues with subject selection. Internal validity measures the accuracy of conclusions drawn within the context of a particular study. It is needed to ensure that the observed results truly represent the behavior of the population and are not a result of methodological errors (Brewer, 2000).

I used SPSS software as the primary tool for data analysis in the present study. This software is widely used for statistical analysis by educational institutions and businesses worldwide. I also used publicly available secondary data from the NYSE. The use of secondary data from a reputable source and the widely used SPSS software minimized any threat to internal validity in this study.

Construct Validity

Construct validity measures the appropriateness of inferences made based on observations or measurements. It evaluates whether a test measures the intended construct (Peter, 1981). Construct validity in a research is necessary to ascertain the overall validity of the test. The tests used in this research such as descriptive statistics, ANOVA, and a post hoc test have been used in the past by several researchers in evaluating the calendar effect. Past successful use of the tests for similar studies and its acceptance by the scientific community minimized any threat to construct validity in this study.

Ethical Procedures

Farrimond (2012) defined ethical research as studies following the current practices of ethical norms, codes, and regulations generally accepted by the scientific community. Accordingly, researchers must use methodologies that demonstrate the trustworthiness and credibility of their study. Walden University has instituted several processes and procedures to ensure that researchers follow strict ethical procedures. Like most universities, Walden has an IRB. IRB ensures that Walden University research complies with all U.S. federal regulations and the university's internal ethical standards. Researchers have to go through an Institutional Review Board ethics review and approval process before they can start data collection or have dataset access.

The NYSE electronically gathered the data used in this study from May 2006 to April 2016. Consequently, the data is nearly 5 years old, and there was no direct or indirect interaction between me, as the researcher, and the subjects or the data collection process. This process minimized any ethical procedure violation.

Summary

The purpose of this comparative study was to test the theory of EMH and the role of the individual investor on the Monday effect. The study was designed to compare the individual investor's average return, trade percentage, and trading patterns on Monday with other weekdays. After evaluating the three methodologies, I selected the quantitative methodology for this study. It was the best method to answer research questions requiring numerical data and to apply the results to a larger population. Additionally, this method was consistent with the purpose of this study. The study used publicly available secondary data from the NYSE and used SPSS software as the primary tool for data analysis.

This chapter provided an explanation of the data sorting and organizing procedures used in this study. It also stated the research questions and hypotheses. Additionally, it included threats to validity and the ethical procedures used in the study.

Chapter 4 contains the study results and transitional material from the findings of the study. Chapter 5 contains a detailed interpretation of the findings. Additionally, Chapter 5 contains the limitations of the study and recommendations for future research. It will conclude with the implications of the study in regard to social change.

Chapter 4: Results

The purpose of this comparative study was to test the theory of the EMH. I also tested the role of the individual investor on the Monday effect. The study was designed to compare individual investors' average returns, trade percentages, and trading patterns on Monday with other weekdays. The independent variable was day of the week. The dependent variables were average daily returns, percentages of individual investor trade compared to the total trade, and number of individual investor trades in 30-minute intervals within a day. I used publicly available data from the NYSE from 2006 to 2016.

Research questions and hypotheses were as follows:

RQ1: Are there statistically significant differences in investor average returns between Monday and other weekdays?

$H_0$1: There are no statistically significant differences in investor average returns between Monday and other weekdays.

H_a1: There are statistically significant differences in investor average returns between Monday and other weekdays.

RQ2: Are there statistically significant differences in individual investor trade percentages between Monday and other weekdays?

$H_0$2: There are no statistically significant differences in individual investor trade percentages between Monday and other weekdays.

H_a2: There are statistically significant differences in individual investor trade percentages between Monday and other weekdays.

RQ3: Are there statistically significant differences in individual investor trading patterns between Monday and other weekdays?

$H_0$3: There are no statistically significant differences in individual investor trading patterns between Monday and other weekdays.

H_a3: There are statistically significant differences in individual investor trading patterns between Monday and other weekdays.

Chapter 4 includes a brief review of the purpose, research questions, and hypotheses. Additionally, I describe data compared to the larger population. Finally, this chapter contains study results including statistical analysis findings organized by research question.

Data Collection

I used publicly available secondary data from the NYSE during the period from 2006 to 2016. Individual investor trading data used in this study are accurate because it is electronically gathered from the NYSE. The NYSE compiled data using transaction records of purchases and sales in their centralized stock market.

I used a dataset from the NYSE named NYSE ReTrac End of Day. This dataset includes all individual investors selling and purchasing records on the NYSE. It contains summaries of all stock activities during the day and includes volume of retail buy and sell shares executed on the NYSE. The first dataset comprised daily trade volume of individual investors and the second dataset comprised total daily trade of all investors in NYSE from May 2006 to April 2016. The NYSE recorded this data electronically every millisecond. I chose this 10-year period because it is the latest period during which data were available, and the NYSE stopped collecting this data starting May 2016.

The third dataset comprised closing prices of the NYSE Composite Index from 2006 to 2016. While more recent data were available in 2021, I used data from 2006 to 2016 to be consistent with the study period. I accessed this data from the *Wall Street Journal* web site. I used this data as a proxy to calculate average daily returns of investors. Individual investors, collectively, invest in diversified portfolios. Consequently, their average daily returns are similar to that of the NYSE Composite Index. As such, the NYSE Composite Index tracks price movements of over 2400 common company stocks listed in that exchange.

The NYSE is the largest stock exchange in the world with a market capitalization of its listed companies of over USD 26 trillion as of 2021 (NYSE, n.d.). Many of the biggest corporations including over 80% of the S&P 500 benchmark index companies are traded on the NYSE. The average trading volume in NYSE is between 2 billion and 6 billion (NYSE, n.d.). The NYSE represents more than one third of the entire global stock market value and more than two thirds of U.S. stock market value. Because the dataset is exceptionally large and represents individual investors' trading data from most of the U.S., results of this study can be generalized to the whole population.

Study Results

The NYSE historical dataset contains two sets of data. The first dataset, called the NYSE Trade Program, contained all trade transactions per day listed by every millisecond. Adding up all trade volumes in a day accounted for the total number of trades. The second dataset, called NYSE Trade Retail, contains individual investor trade transactions per day listed by every millisecond. Adding up all trade volumes in a day in this dataset accounted for the number of individual investor trades. This dataset was also used to calculate individual investor trade volume in 30-minute intervals. The formula used to calculate daily individual investor trade percentage is:

$$\textit{Daily Percentage of Individual Investor Trade} = \frac{T2}{T1}$$

In this equation, T_1 is the total number of trades and T_2 is the number of individual investor trades.

The dataset retrieved from the *Wall Street Journal* web site contains daily closing prices of the NYSE Composite Index. The formula used to calculate individual investor average daily return is:

$$\textit{Individual Investor Average Daily Return} = \frac{P2-}{P1}$$

In this equation, P_1 is the closing price of the NYSE Composite Index on a given day and P_2 is the closing price of the NYSE Composite Index on the next trading day.

Tests for Assumptions

I conducted a one-way ANOVA to determine whether there were any statistically significant differences between means of individual investor average daily returns between Monday and other weekdays in order to answer RQ1. Similarly, I conducted a one-way ANOVA to determine whether there were any statistically significant differences between means of percentages of individual investor trades between Monday and other weekdays in order to answer RQ2. Finally, I plotted average 30-minute interval trade volumes of individual investors from Monday through Friday for each year and visually compared trading patterns between Monday and other weekdays to answer RQ3.

I analyzed data to ensure it met assumptions that are required for a one-way ANOVA to give valid results. Data met the assumption of measurement at ratio level for independent variables because all dependent variables are measured at that level. Data satisfied the assumption of categorical measurement for the independent variable because the days of the week are measured in that level. The assumption of independence of observations is also met because individual investor data were from different days.

I tested the assumption of normality by evaluating the normal probability plot. I concluded that there were no major violations of this assumption. If data points deviated too much from normal distribution, I transformed data and drew histogram and P-P plots. I tested for the final assumption of homogeneity of variances using Levene's test. Results showed that variances are not significant ($p >. 05$) for both average daily returns and percentage of individual investor trade, concluding that the data did not violate the assumption of homogeneity of variance.

Research Question(s) and Hypotheses

RQ1: Are there statistically significant differences in investor average returns between Monday and other weekdays?

Figure 1

RQ1 Histogram: Frequency Versus Magnitude for Average Daily Return

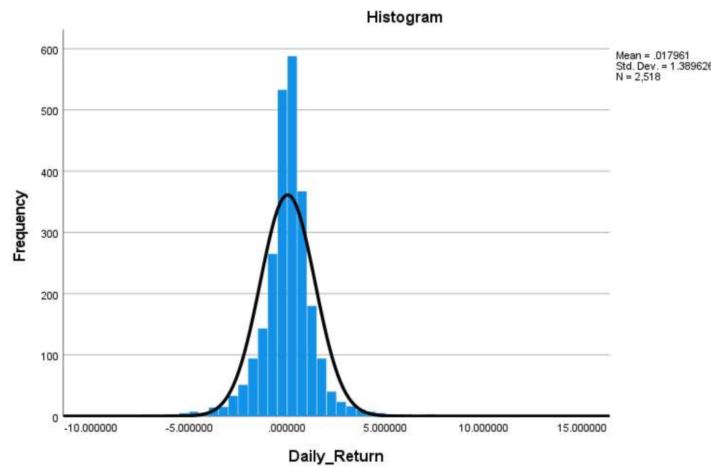
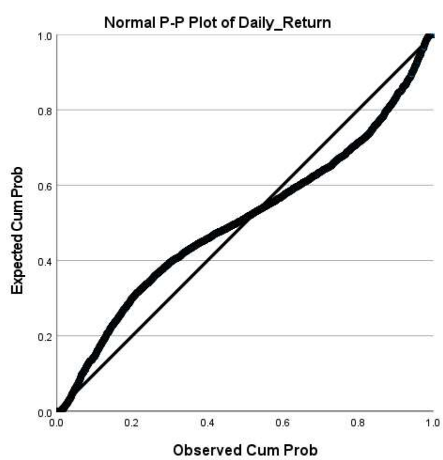


Figure 2

RQ1 P-P Plot: Expected Cumulative Probability Versus Observed Cumulative Probability for Average Daily Return



I used histogram and P-P plots to evaluate the assumption of normality for the data. Figure 1 shows the histogram plot of frequency versus magnitude for the dependent variable of average daily return. The histogram is more peaked than the standard bell curve. For expediency, I assumed that normal distribution is a reasonable fit for the purpose of carrying out the hypothesis tests.

Figure 2 shows differences between expected and observed cumulative probability for the dependent variable of average daily return. The P-P plot curve was a line diagonal from the bottom left to the top right with the plotted line above and then below the normal distribution line. As such, points do not lie on the normal straight line. However, they are not too far from the straight line, and I assumed that normal distribution is a reasonable fit for the purpose of carrying out hypothesis tests.

Table 1

Descriptive Statistics for Average Daily Returns

	N	Mean	SD	95% CI for Mean	
				Lower Bound	Upper Bound
Monday	475	-.0712	1.5820	-.2138	.0714
Tuesday	515	.0948	1.4260	-.0287	.2182
Wednesday	518	.0035	1.3404	-.1122	.1191
Thursday	507	.0358	1.4183	-.0879	.1596
Friday	503	.0204	1.1597	-.0811	.1220
Total	2518	.0180	1.3896	-.0363	.0723

Table 2

Tests of Homogeneity of Variances for Average Daily Returns

	Lavene Statistic	df1	df2	Sig.
Based on Mean	1.437	4	2513	.219
Based on Median	1.466	4	2513	.210
Based on Median with adjusted df	1.466	4	2342.938	.210
Based on trimmed mean	1.432	4	2513	.224

Table 3

ANOVA for Average Daily Returns

	Sum of Squres	df	Mean Square	F	Sig.
Between Groups	7.088	4	1.772	.917	.453
Within Groups	4853.391	2513	1.931		
Total	4860.479	2517			

Descriptive statistics associated with average returns of weekdays are reported in Table 1. Results showed Monday had the numerically smallest mean level of average daily returns (M = -.07) and Tuesday was associated with the highest mean (M = .09). In order to test the hypothesis that there are no statistically significant differences in individual investor average returns between Monday and other weekdays, I performed a one-way ANOVA. Prior to conducting the AVOVA, I tested the assumption of homogeneity of variances using Levene's F test as shown in Table 2. Based on the test results $F(4, 2513)=1.44$, $p=.219$, I concluded that the assumption of homogeneity of variances was satisfied. The one-way ANOVA results, as shown in Table 3, yielded a statistically insignificant effect, with $F(2, 2513)= .917$, $p= .453$. Thus, the null hypothesis that there are no statistically significant differences in individual investor average returns between Monday and other weekdays was accepted. Taken together, results of the study indicated that day of the week had no effect on the average daily returns.

RQ2: Are there statistically significant differences in individual investor trade percentages between Monday and other weekdays?

Figure 3

RQ2 Histogram: Frequency Versus Magnitude for Investor Trade Percentages Using Original Data

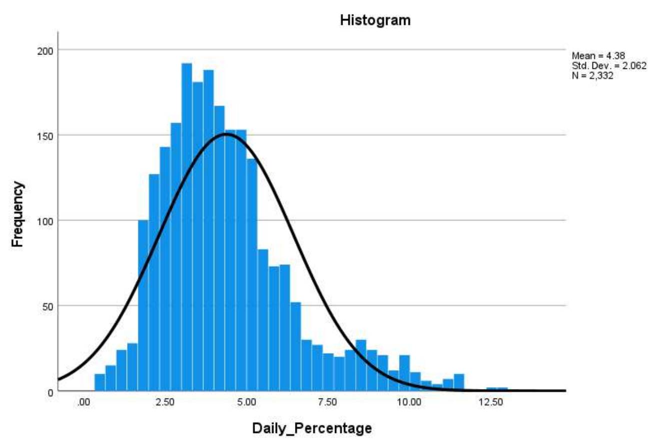


Figure 4

RQ2 P-P Plot: Expected Cumulative Probability Versus Observed Cumulative Probability for Individual Investor Trade Percentage Using Original Data

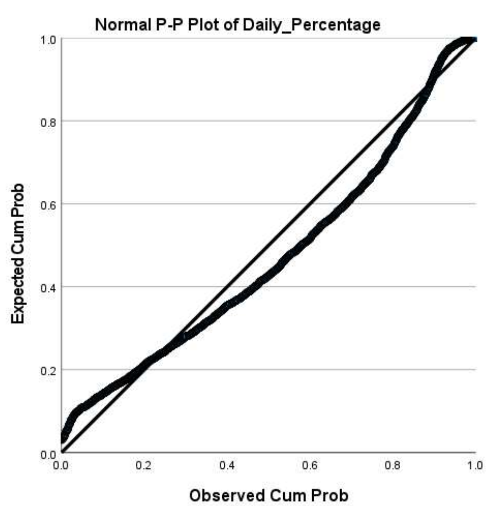


Table 4

Descriptive Statistics for Individual Investor Daily Percentages Using Original Data

	N	Mean	SD	95% CI for Mean	
				Lower Bound	Upper Bound
Monday	467	4.5823	2.0430	4.3966	4.7681
Tuesday	466	4.5022	2.0373	4.3167	4.6876
Wednesday	466	4.5392	2.0175	4.3555	4.7229
Thursday	466	4.5200	2.0392	4.3343	4.7056
Friday	467	3.7373	2.0574	3.5502	3.9243
Total	2332	4.3760	2.0623	4.2923	4.4597

Table 5

Tests of Homogeneity of Variances for Individual Investor Daily Percentages

	Lavene Statistic	df1	df2	Sig.
Based on Mean	.180	4	2327	.949
Based on Median	.162	4	2327	.958
Based on Median with adjusted df	.162	4	2325.249	.958
Based on trimmed mean	.199	4	2327	.939

The descriptive statistics associated with the percentage of individual investor trade on all weekdays are reported in Table 4. In order to test the hypothesis that there are no statistically significant differences in the individual investor daily percentage between Monday and other weekdays, I performed a one-way ANOVA. Prior to conducting the AVOVA, I tested the assumption of homogeneity of variances using Levene's *F* test as shown in Table 5. Based on the test results $F(4, 2327)=.18$, $p=.949$, I concluded that the assumption of homogeneity of variances was satisfied.

Similar to the previous analysis, I used histogram and P-P plot to evaluate the assumption of normality for the data. Figure 3 shows the histogram plot of frequency versus magnitude for the dependent variable of individual investor trade percentage. The histogram showed a skewed distribution towards the larger values. Figure 4 shows the P-P Plot of the expected cumulative probability versus observed cumulative probability for the dependent variable of individual investor trade percentage. This plot displays the expected cumulative probability straight line and the observed cumulative probability. The P-P plot curve was a line diagonal from the bottom left to the top right with the plotted line above and then below the normal distribution line, and finally slightly above the normal distribution line. As such, the points do not lie on the normal straight line. In order to reduce the deviation from the normal distribution, I performed a transformation of the daily percentage data to their square root values. Transforming data that are not normally distributed is a common technique used so that the transformed data is normally distributed (Transforming Data in SPSS Statistics, n.d.).

Figure 5

RQ2 Histogram: Frequency Versus Magnitude Using the Squre Root Transformed Values for Individual Investor Trade Percentages

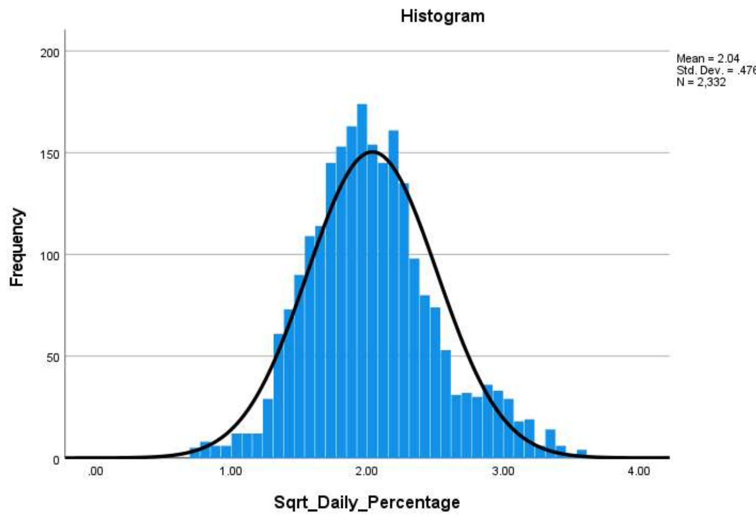


Figure 6

RQ2 P-P Plot: Expected Versus Observed Cumulative Probability Using Squre Root Transformed Values for Individual Investor Trade Percentages

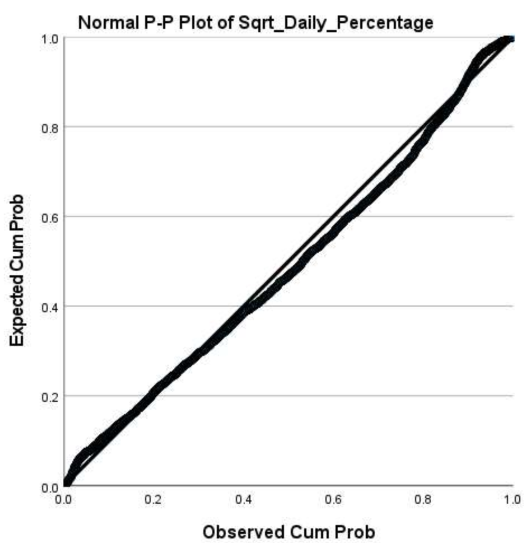


Table 6

Descriptive Statistics for Individual Investor Daily Percentages Using Square Root Transformed Values

	N	Mean	SD	95% CI for Mean	
				Lower Bound	Upper Bound
Monday	467	2.0923	.4529	2.0511	2.1335
Tuesday	466	2.0729	.4534	2.0317	2.1142
Wednesday	466	2.0832	.4471	2.0425	2.1239
Thursday	466	2.0762	.4580	2.0345	2.1179
Friday	467	1.8611	.5236	1.8135	1.9087
Total	2332	2.0371	.4758	2.0178	2.0564

Figure 5 shows the histogram plot of frequency versus magnitude for the dependent variable using the squre root transformed values of individual investor trade percentage. Figure 6 shows the P-P Plot of the expected cumulative probability versus observed cumulative probability using the squre root transformed values for the dependent variable of individual investor trade percentage. While these two plots are better than the two previous plots using the original values, they are not the best fit for a normally distributed data. In order to further reduce the deviation from the normal distribution, I performed a transformation of the daily percentage data to their logarithmic values to the base of 10. The logarithmic transformation is the most used technique to change skewed data to conform with normal distribution (Feng et al., 2014).

Figure 7

RQ2 Histogram: Frequency Versus Magnitude Using Logarithemic Transformed Values for Individual Investor Trade Percentages

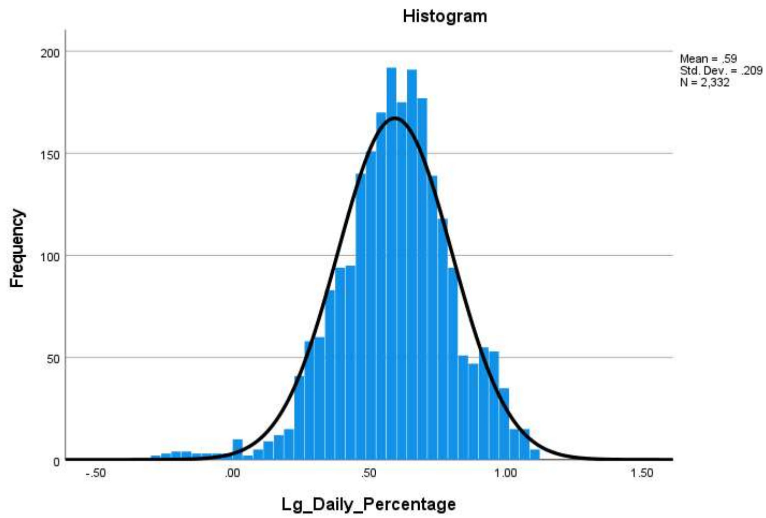


Figure 8

RQ2 P-P Plot: Expected Versus Observed Cumulative Probability Using Logarithemic Transformed Values for Individual Investor Trade Percentages

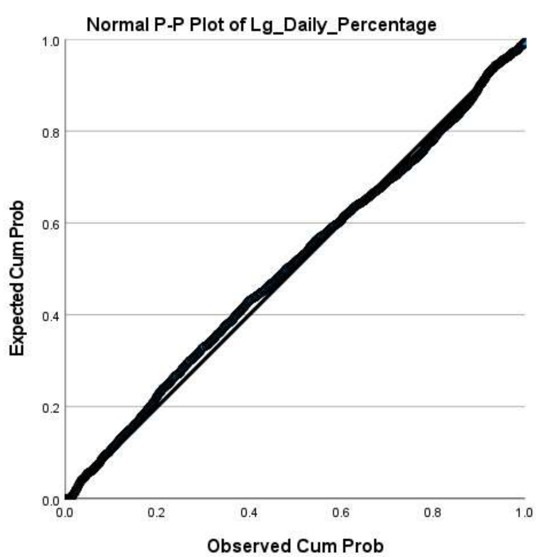


Table 7

Descriptive Statistics for Individual Investor Daily Percentage using Logarithemic Transformed Values

	N	Mean	SD	95% CI for Mean	
				Lower Bound	Upper Bound
Monday	467	.6215	.1849	.6047	.6383
Tuesday	466	.6130	.1876	.5959	.6300
Wednesday	466	.6181	.1831	.6014	.6348
Thursday	466	.6138	.1905	.5964	.6311
Friday	467	.5026	.2614	.4788	.5263
Total	2332	.5938	.2086	.5853	.6022

Figure 7 shows the histogram of the frequency versus magnitude of the logarithemic transformed values for the dependent variable of individual investor trade percentage**.** This histogram is generally symmetrical with a peak slighly higher than the standard bell curve. Figure 8 shows the P-P Plot of the expected cumulative probability and the observed cumulative probability of the logarithmic transformed values for the dependent variable of individual investor trade percentage. This P-P plot curve is a reasonably straight-line diagonal from the bottom left to the top right. This plot supports that normal distribution is a good fit on the log scale for the purpose of carrying out the hypothesis tests.

Table 8

ANOVA for Individual Investor Daily Percentage using Logarithemic Transformed Values

	Sum of Squres	df	Mean Square	F	Sig.
Between Groups	4.876	4	1.219	29.368	.000
Within Groups	96.593	2327	.042		
Total	101.469	2331			

Table 9

Post Hoc Tests for Individual Investor Daily Percentage Using Logarithemic Transformed Values – Multiple Comparisons

Days of the week (I)	Days of the Week (J)	Mean Difference (I-J)	Sig.	95% CI	
				Lower Bound	Upper Bound
Monday	Tuesday	.00855	.968	-.0279	.0450
	Wednesday	.00341	.999	-.0330	.0398
	Thursday	.00775	.978	-.0287	.0442
	Friday	.11893*	.000	.0825	.1553
Tuesday	Monday	-.00855	.968	-.0450	.0279
	Wednesday	-.00515	.995	-.0416	.0313
	Thursday	-.00080	1.000	-.0372	.0356
	Friday	.11038*	.000	.0740	.1468
Wednesday	Monday	-.00341	.999	-.0398	.0330
	Tuesday	.00515	.995	-.0313	.0416
	Thursday	.00434	.998	-.0321	.0408
	Friday	.11552*	.000	.0791	.1519
Thursday	Monday	-.00775	.978	-.0442	.0287
	Tuesday	.00080	1.000	-.0356	.0372
	Wednesday	-.00434	.998	-.0408	.0321
	Friday	.11118*	.000	.0748	.1476
Friday	Monday	-.11893*	.000	-.1553	-.0825
	Tuesday	-.11038*	.000	-.1468	-.0740
	Wednesday	-.11552*	.000	-.1519	-.0791
	Thursday	-.11118*	.000	-.1476	-.0748

The one-way ANOVA results are shown in Table 8. There was a significant difference in the individual investor trade percentage between weekdays at the $p<.05$ level $F(4, 2327) = 29.37$, $p = .000$. Thus, there was sufficient evidence to reject the null hypothesis that there are no statistically significant differences in the individual investor trade percentage between Monday and other weekdays was rejected. I conducted post hoc comparisons using the Tukey HSD test which indicated that the mean score for individual investor percentage (M=.5938, SD=.2086) was significantly different than the Friday percentage (M=.5026, SD=.2614). However, the Monday percentage (M=.6215, SD=.1849) did not significantly differ from the individual investor percentages on Tuesday, Wednesday, and Thursday. Taken together, the results of the study indicated that the percentage of individual investor trades on Fridays were significantly lower than the individual investor trades on other weekdays.

Table 10

Comparison of Descriptive Statistics for Individual Investor Daily Percentage: Original Data Versus Square Root Transformed Data Versus Logarithmic Transformed Data

Days of the Week	N	Mean			95% CI for Mean					
		Original Data	Square Root Trans. Data	Log. Trans. Data	Original Data		Square Root Transformed Data		Logarithmic Transformed Data	
					Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound
Monday	467	4.5823	2.0923	.6215	4.3966	4.7681	2.0511	2.1335	.6047	.6383
Tuesday	466	4.5022	2.0729	.6130	4.3167	4.6876	2.0317	2.1142	.5959	.6300
Wednesday	466	4.5392	2.0832	.6181	4.3555	4.7229	2.0425	2.1239	.6014	.6348
Thursday	466	4.5200	2.0762	.6138	4.3343	4.7056	2.0345	2.1179	.5964	.6311
Friday	467	3.7373	1.8611	.5026	3.5502	3.9243	1.8135	1.9087	.4788	.5263
Total	2332	4.3760	2.0371	.5938	4.2923	4.4597	2.0178	2.0564	.5853	.6022

Table 11

Comparison of Descriptive Statistics for Individual Investor Daily Percentage on the Original Scale Based on Square Root and Logarithmic Transformed Data

Days of the Week	N	Mean			95% CI for Mean					
		Original Data	Values in Original Scale from Sq. Rt. Data	Values in Original Scale from Log. Trans. Data	Original Data		Values in Original Scale from Square Root Transformed Data		Values in Original Scale from Logarithmic Transformed Data	
					Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound
Monday	467	4.5823	4.3777	4.1831	4.3966	4.7681	4.2070	4.5518	4.0244	4.3481
Tuesday	466	4.5022	4.2969	4.1020	4.3167	4.6876	4.1278	4.4698	3.9437	4.2658
Wednesday	466	4.5392	4.3397	4.1505	4.3555	4.7229	4.1778	4.5110	3.9939	4.3132
Thursday	466	4.5200	4.3106	4.1096	4.3343	4.7056	4.1392	4.4855	3.9482	4.2766
Friday	467	3.7373	3.4637	3.1813	3.5502	3.9243	3.2888	3.6431	3.0116	3.3597
Total	2332	4.3760	4.1498	3.9246	4.2923	4.4597	4.0715	4.2288	3.8486	4.0013

Table 10 shows the comparison among the descriptive statistics for the individual investor daily percentage for the original data, square root transformed data, and logarithmic transformed data. It shows that the mean value and the confidence intervals are on three different scales, therefore, they are not comparable.

Table 11 shows the comparison of descriptive statistics for individual investor daily percentage on the original scale, based on square root transformed data and logarithmic transformed data. The mean of the transformed values on the original scale based on square root transformed data is smaller than the original data. Similarly, the upper bound and the lower bound at the 95% confidence interval of the transformed values on the original scale based on square root transformed data are also lower than the original data. Further it shows all mean values of the transformed values on the original scale based on logarithmic transformed data are even lower. Since the logarithmic transformed data are much closer to a Normal distribution than the original data, the corresponding 95% confidence intervals are more valid than those for the original data. Moreover, the 95% confidence intervals for the logarithmic transformed data are shorter than those for the original data.

RQ3: Are there statistically significant differences in individual investor trading patterns between Monday and other weekdays?

I used descriptive statistics and heuristic techniques to answer this research question. Specifically, I plotted the individual investor trade volume for every 30-minute interval and visually compared the trading pattern between Monday and other weekdays to evaluate the difference. First, I calculated the average trade volume for every 30-

minute interval for each day, Monday through Friday, for each year. Next, I plotted a line graph of the average trade volume for every 30-minute interval for each day for every year on a single plot. As an example, the formula used to calculate average trade volume for the T_i 30-minute interval on Monday of a year is shown below:

$$\textit{Average Trade Volume for the } T_i \textit{ 30-Minute Interval on Monday} = \frac{\sum_{n=1}^{N} Tin}{N}$$

In this equation, T_i is the average trade volume for the i^{th} 30-minute interval on Monday and *N* is the total number of Mondays that year.

Figures 9–13 show the plots for the individual investor 30-minute interval trading pattern for years 2007, 2008, 2009, 2014, and 2015. For brevity, these five years are used to illustrate the trading pattern before the financial crisis (year 2007), during the financial crisis (years 2008 and 2009), and after the financial crisis (years 2014 and 2015).

Figure 9

Individual Investor 30-Minute Interval Trading Pattern for 2007

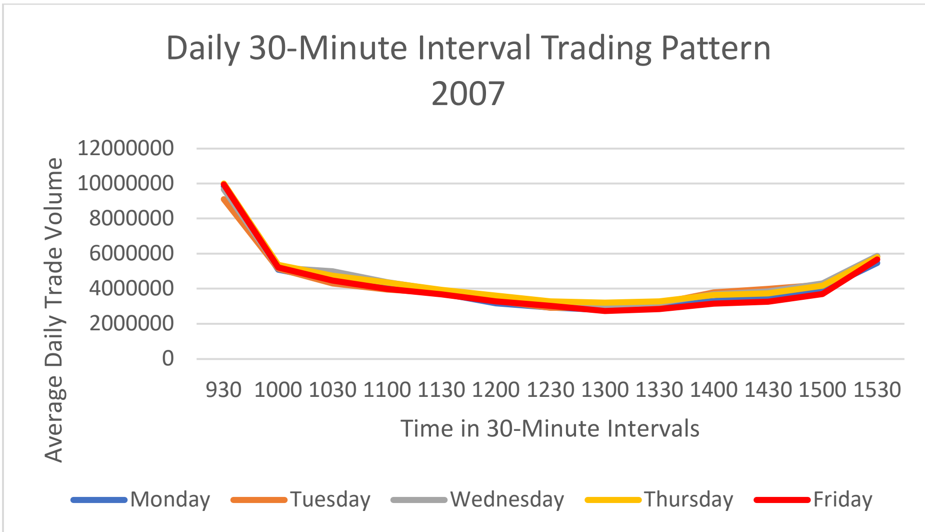


Figure 10

Individual Investor 30-Minute Interval Trading Pattern for 2008

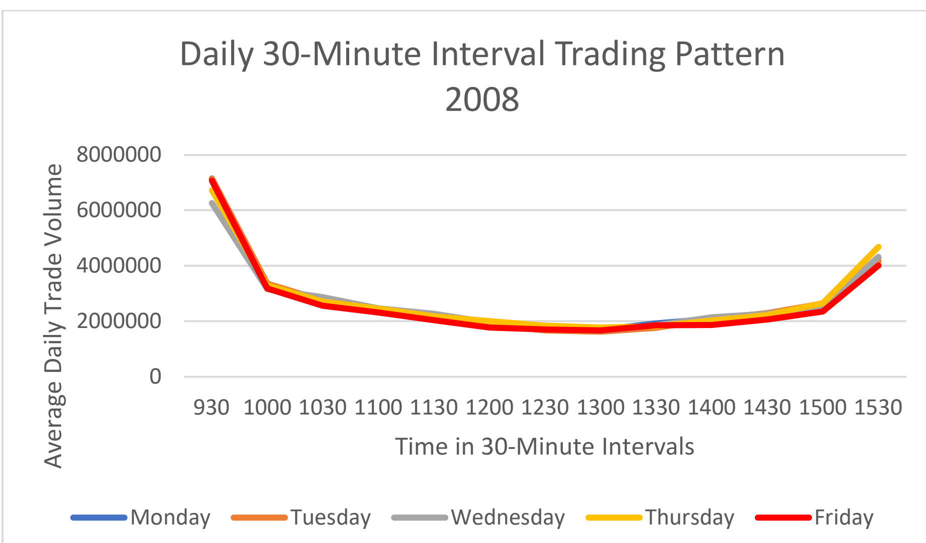


Figure 11

Individual Investor 30-Minute Interval Trading Pattern for 2009

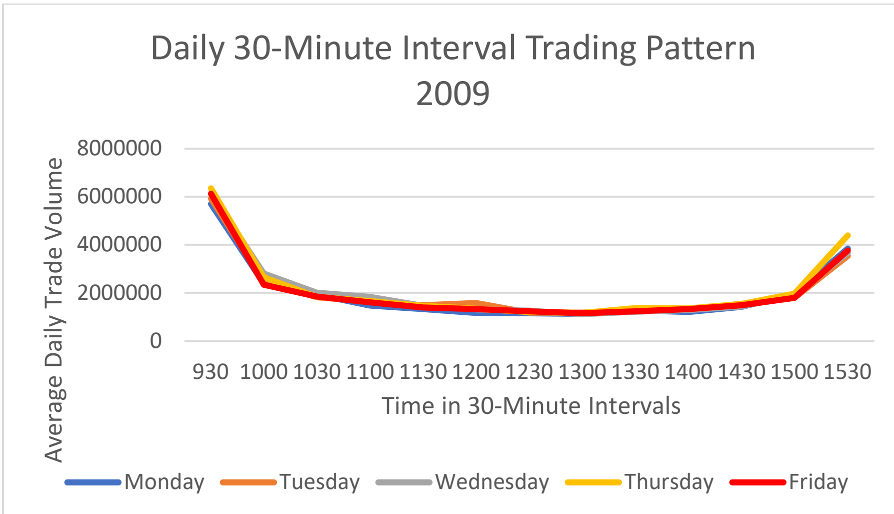


Figure 12

Individual Investor 30-Minute Interval Trading Pattern for 2014

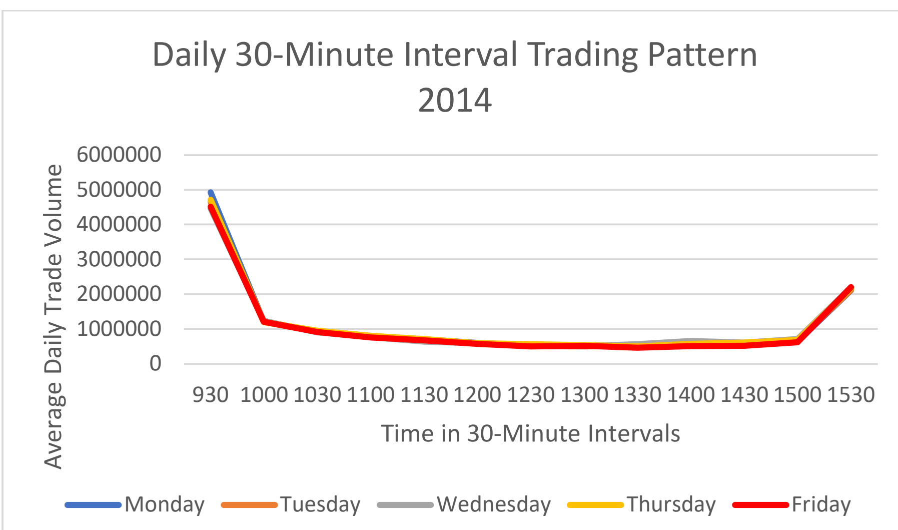
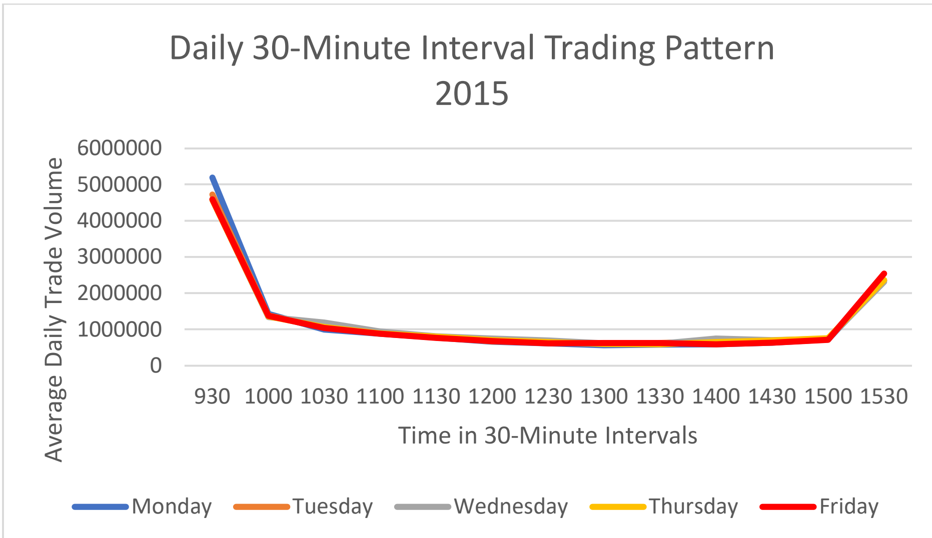


Figure 13

Individual Investor 30-Minute Interval Trading Pattern for 2015



Visual comparisons of plots in Figures 9 -13 shows the 30-minute interval average daily trade volume plots for all weekdays were generally congruent. Accordingly, I concluded there are no significant differences in the individual investor trading pattern between Monday and other weekdays for all five years and I accepted the null hypothesis. The results of the study indicated that days of the week had no effect on the individual investor trading pattern between Monday and other weekdays.

The plots showed the 30-minute interval starting at 9:30 Eastern Time had the highest individual investor trade volume for all years and all days. The plots also showed that the 30-minute interval starting at 15:30 Eastern Time generally had the second highest individual investor trade volume. Finally, the plots showed that the 30-minute intervals during the middle of the day, from 12:00 until 13:30, generally had the lowest trade volumes.

Summary

In this study, I examined the theory of the EMH and Monday effect. The first research question aimed to evaluate the Monday effect and analyzed the difference in the individual investor average return between Monday and other weekdays. Using results from one-way ANOVA, I concluded that days of the week had no effect on the average daily returns. The findings revealed there is sufficient evidence to accept the null hypothesis that there are no statistically significant differences in the individual investor average return between Monday and other weekdays.

The second research question also evaluated the Monday effect by analyzing the difference in the individual investor trade percentage between Monday and other weekdays. Using results from one-way ANOVA and post hoc tests, I concluded that the Monday percentage did not significantly differ from the individual investor percentages on Tuesday, Wednesday, and Thursday. However, the study results showed the percentage of individual investor trades on Fridays were significantly lower than the individual investor trades on other weekdays.

Finally, based on the study results, I concluded the days of the week have no effect on the individual investor trading pattern between Monday and other weekdays. However, the findings displayed the 30-minute interval starting at 9:30 Eastern Time had the highest individual investor trade volume and the interval starting at 15:30 Eastern Time generally had the second highest individual investor trade volume. Further, the results of the study indicated that the 30-minute intervals during the middle of the day, from12:00 until 13:30, generally had the lowest trade volumes.

In the next chapter, I will interpret the findings of this study and describe the ways they extend knowledge regarding Monday effect. I will also describe the limitations, validity, and generalizability of the results in the next chapter. Further, the chapter will include recommendations for further research associated with the findings that could advance the theories on finance. Finally, the chapter will conclude describing the implications of the results on the significance to theory, practice, and social change.

Chapter 5: Discussion, Conclusions, and Recommendations

The EMH has served as the central theory in modern finance for more than half a century. It is defined as the phenomenon where prices of the stock in the market at a given time always and fully reflect all available information about that stock at that time (Fama, 1970). However, stock markets have shown a variety of calendar anomalies such as the Monday effect. The Monday effect means that returns and trading volumes on Mondays are generally lower than other days of the week (Bishal et al., 2019). Returns on the stock market are consistently low on Mondays. One plausible explanation for the Monday effect is different investment patterns of institutional and individual investors (Ulku & Rogers, 2018). The purpose of this comparative study was to test the theory of the EMH. I also tested the role of the individual investor on the Monday effect. The study was designed to compare individual investors' average returns, trade percentages, and trading patterns on Monday with other weekdays. In this study, I added to extant literature by analyzing returns on Mondays compared to other weekdays using publicly available data from the NYSE from 2006 to 2016.

Chapter 4 contains a brief review of the purpose, research questions, and study results including statistical analysis. Results of this study yielded important findings regarding the EMH and the role of individual investors on the Monday effect. Results revealed there were no statistically significant differences in terms of individual investor average returns between Monday and other weekdays. In this context, this study's findings aligned with some of the other recent studies, suggesting that the Monday effect has become less important over the years and was no longer an anomaly in the U.S. stock market (Plastun et al., 2019; Robins & Smith, 2016; Zica, 2017). Results also showed that individual investor trading activity on Monday did not significantly differ ($p > .05$) from other weekdays except Friday. In this regard, findings of this study contradicted other findings that suggested individual investors were most active on Mondays.

Using results from a one-way ANOVA, I concluded that day of the week had no effect on average daily returns. Results of the study showed there is sufficient evidence to accept the null hypothesis that there are no statistically significant differences in terms of individual investor average returns between Monday and other weekdays.

Using results from a one-way ANOVA and post hoc tests, I concluded that Monday percentages did not significantly differ from individual investor percentages on Tuesday, Wednesday, and Thursday. However, results of the study revealed percentages of individual investor trades on Fridays were significantly lower than percentages of individual investor trades on other weekdays.

Using descriptive statistics and heuristic analysis, I concluded day of the week had no effect on individual investor trading patterns between Monday and other weekdays. However, 30-minute intervals starting at the opening of the stock market at 9:30 Eastern Time had the highest individual investor trade volume, while the 30-minute interval at the closing of the stock market from 15:30 to 16:00 Eastern Time generally had the second highest individual investor trade volume. Further, study results revealed 30-minute intervals during the middle of the day, from 12:00 until 13:30, generally had the lowest trade volumes.

Interpretation of Findings

The theoretical framework for this study was Fama's 1970 theory of EMH. This implies that returns on each day of the week are identical to returns on all other days (Sharif, 2019). Nevertheless, many studies have shown the presence of calendar anomalies such as the Monday effect in the marketplace and argued that investors have opportunities to make excessive profits and outperform the market during certain periods. One plausible explanation for the Monday effect is different investment patterns of institutional and individual investors (Bishal et al., 2019). However, few researchers have evaluated individual investors' trading behavior regarding day of the week and time of day. This is the first study to quantitatively analyze the Monday effect on the U.S. stock exchange using data that covers periods before, during, and after the financial crisis of 2008-2009 using actual individual investor data, including day of the week and time of day.

RQ1 was about the Monday effect and differences in terms of investor average returns between Monday and other weekdays. Results showed that average returns were lowest on Mondays and had a negative value. Nevertheless, a one-way ANOVA analysis yielded a statistically insignificant effect, with $F(2, 2513) = .917$ and $p = .453$. Based on study results, I concluded day of the week had no effect on average daily returns. Results showed there is sufficient evidence to accept the null hypothesis that there were no statistically significant differences in terms of individual investor average returns between Monday and other weekdays.

Figure 14

Average Daily Returns of NYSE Composite Index from 2006 to 2016

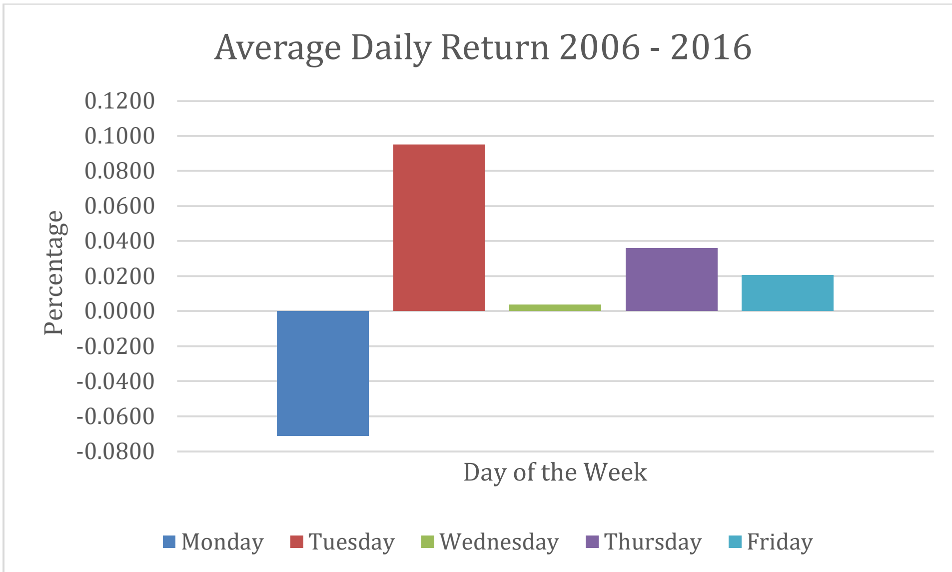


Figure 14 shows average daily returns of the NYSE Composite Index from May 2006 to April 2016. Monday mean returns were negative and associated with the numerically smallest mean level of average daily returns (M = -.07). However, a one-way ANOVA analysis did not yield statistically significant differences in mean returns on Monday compared to other weekdays using a 95% confidence interval.

RQ2 involved analyzing differences in individual investor trade percentages between Monday and other weekdays. Using results from one-way ANOVA and post hoc tests, I concluded Monday percentages did not significantly differ from individual investor percentages on Tuesday, Wednesday, and Thursday. However, study findings indicated percentages of individual investor trades on Fridays were significantly lower ($p < .05$) compared to individual investor trades on other weekdays.

Figure 15

Individual Investor Trade as a Percentage of Total Trade 2006 to 2016

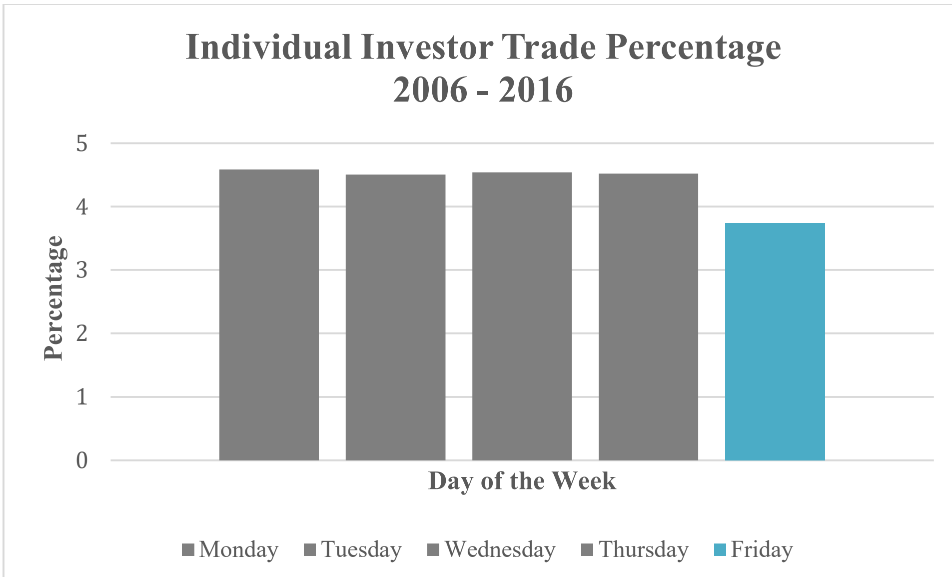


Figure 15 shows individual investor trade as a percentage of total trade from May 2006 to April 2016. Monday was associated with the numerically highest mean level of daily percentages ($M = 4.58$) and Friday was associated with the smallest mean ($M = 3.74$). Results of the analysis revealed statistically significant differences in terms of individual investor trade percentages on Friday compared to other weekdays using a 95% confidence interval. In this regard, results of the study supported other recent findings that individual investors are least active on Fridays. I recommend additional research in this area to determine reasons why individual investors trade less frequently on Fridays compared to other weekdays.

Figure 16

Mean Annual Percentage of Individual Investor Trade Volume from 2006 to 2016

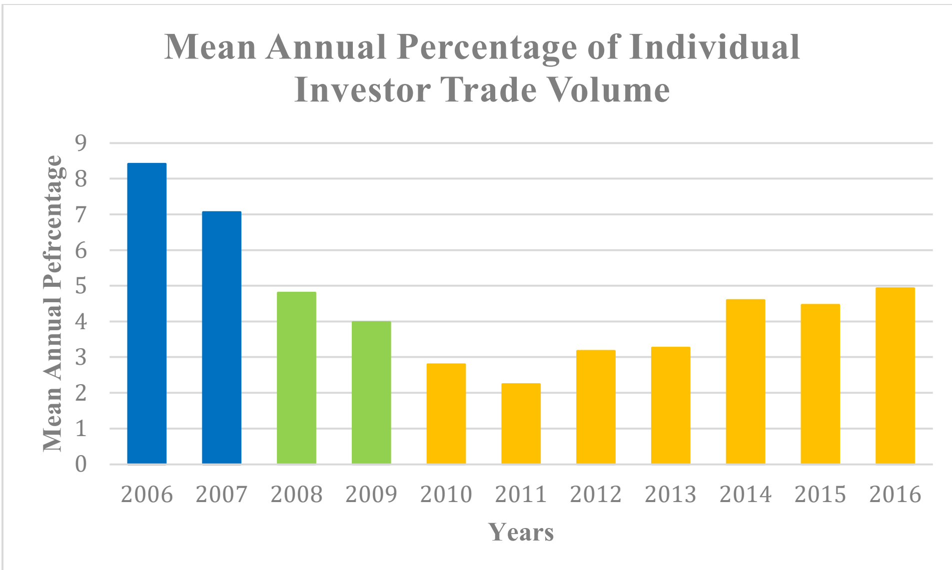


Figure 16 shows the mean annual percentage of individual investor trade volume was in the 7.1-8.4% range during the 2006 and 2007 period before the financial crisis of 2008-2009. It steadily decreased during the financial crisis and continued to decrease after the crisis reaching a low of 2.25% in 2011. 2012 and 2013 saw modest increase in this percentage to approximately 3.2%. Finally, the mean annual percentage of individual investor trade volume seem to settle at a value approximately 4.7% during 2014, 2015, and 2016, albeit well below the pre financial crisis level. The timeline of the mean annual percentage of individual investor trade volume patterns during the post-financial crisis period seemed to resemble recovery of other financial indicators. For example, it took the Dow Jones Industrial Average until March 2013 to break its 2007 high. Similarly, unemployment did not reach its prerecession level of 5% until 2015. I recommend further research in this area to ascertain the relationship, if any, between mean annual percentages of individual investor trade volume patterns and other financial market recovery indicators before, during, and after the financial crisis.

Finally, study results showed day of the week had no effect on individual investor trading patterns between Monday and other weekdays. However, findings showed the 30-minute interval starting at the opening of the stock market at 9:30 Eastern Time had the highest individual investor trade volume, while the interval at the closing of the stock market from 15:30 to 16:00 Eastern Time generally had the second highest individual investor trade volume. Further, study results showed 30-minute intervals during the middle of the day, from 12:00 until 13:30, generally had the lowest trade volumes. Richards and Willows (2019) said individual investors preferred trading on Mondays and traded in a W-shaped intraday pattern. Individual investors had the highest trade volumes during the beginning of the day, followed by the second highest trading volume in the middle of the day starting at 13:00, and finally the third highest volume during the closing 30-minute period. Further research is needed to evaluate differences between behaviors of individual investors in the United Kingdom and U.S.

Limitations of the Study

The main weakness of this study involves use of secondary data. The first limitation of using secondary data is they were collected for another purpose and may not be ideal for this study. In this regard, I had to use programming scripts to extract data for this study. Another disadvantage of using secondary data was that I did not participate in the data collection process. Consequently, I was not aware of potential problems during data collection or whether all ethical procedures were followed in the process.

There are a couple of limitations involving generalization of results of the study across regions and cultures. First, data for the study are primarily from a population consisting of individual investors in the U.S., which may not accurately represent other individual investors across the world. Consequently, results of this study may not be relevant to other countries which are economically, socially, and culturally different from the U.S. Second, use purposive sampling rather than probabilistic sampling undermines generalizing results. I mitigated this limitation by using an extremely large dataset from the NYSE that represents more than one third of the entire global stock market value and more than two thirds of U.S. stock market value.

A final limitation of the study was that I used daily returns of the NYSE Composite Index as a proxy for individual investor daily returns. The NYSE Composite Index is a good measure of stock market performance because it tracks price movements of over 2400 company common stocks listed in that exchange. Nevertheless, individual investor daily returns may not exactly mimic the NYSE Composite Index.

Recommendations

There are a few recommendations for additional research that emerged from results of this study. The first recommendation is associated with the finding that percentages of individual investor trades on Fridays were significantly lower than individual investor trades on other weekdays. Study results showed that Friday was associated with the smallest mean level of daily percentages (*M* = 3.74). Results of analysis revealed statistically significant differences in terms of individual investor trade percentages on Friday compared to other weekdays using a 95% confidence interval. Further research is needed to determine reasons why individual investors trade less frequently on Fridays compared to other weekdays.

The second recommendation is associated with findings related o mean annual percentages of individual investor trade volumes before, during, and after the financial crisis of 2008-2009. As Figure 16 shows, it steadily decreased during the financial crisis and continued to decrease after the crisis, reaching a low of 2.25% in 2011. Figure 16 also shows that 2012 and 2013 saw a modest increase in this percentage to approximately 3.2%. Finally, the mean annual percentage of individual investor trade volume seem to settle at a value approximately 4.7% during 2014, 2015, and 2016. However, the percentage was still well below the pre financial crisis level. As stated before, the timeline of changes in the mean annual percentage of individual investor trade seems to resemble the recovery timeline of other financial indicators. Further research is needed to ascertain relationships and patterns, if any, between the mean annual percentage of individual investor trade volume and other financial market indicator patterns before, during, and after the financial crisis.

Third, further research is needed to find reasons for individual investor intraday behavior. While the results of this study indicated the days of the week had no effect on the individual investor trading pattern between Monday and other weekdays, the findings revealed individual investors in the NYSE traded in a bathtub shaped intraday pattern. Specifically, the study results displayed the 30-minute interval starting at the opening of the stock market at 9:30 Eastern Time had the highest individual investor trade volume and the interval at the closing of the stock market from 15:30 to 16:00 Eastern Time generally had the second highest individual investor trade volume. The study results also displayed the 30-minute intervals during the middle of the day, from 12:00 until 13:30, generally had the lowest trade volumes. A similar study conducted in the United Kingdom by Richards & Willows (2019) based on 7200 investors found individual investors preferred trading on Mondays and traded in a W-shaped intraday pattern. Further research is needed to evaluate the differences in the behaviors of individual investors in the United Kingdom and the U.S.

Finally, a broader study into the intraday pattern of all trades including the institutional investor will help further the knowledge on intraday trade behavior. In this study, I primarily analyzed the individual investor intraday trade pattern. The trade volume data used in this study included both sales and purchase data. Additional studies splitting the trade volumes separately into sales and purchase volumes can shed light into the specific characteristics of individual and institutional investor trading behavior. From a behavioral economics perspective, such studies along with the present study can provide valuable insight into the behavior of the investors during the day of the week and time of the day.

Implications

The results of this study may make significant contributions to advance the theories on finance. It may also advance practices in finance. Additionally, it could contribute to positive social changes by helping market administrators to design the markets more efficiently.

Significance to Theory

This study added to the existing knowledge base in financial literature. First, the paper investigates whether the Monday effect reported in several literatures (Afrilianto & Daryanto, 2019; French, 1980; Lu & Gao, 2016; Jebran & Chen, 2017; Rodriguez, 2012) is still present in the U.S. market. Second, this paper analyzed the individual investor behavior and its impact on the Monday effect. Finally, the proposed study covered a longer and more recent sample period (from January 2006 to June 2016) and provided the most comprehensive assessment of individual investor's influence on the Monday effect in a developed market.

This study also contributed to the literature because the dataset used contained actual individual investor trading information. The individual investor trading data used in this study was accurate because it was electronically gathered from the NYSE. Past studies using proxies and other methods to represent individual investor behavior probably lack validity because the data used was not a representative sample of individual investors.

The findings of the study revealed individual investors in the NYSE traded in a bathtub shaped intraday pattern. This is the first study in the U.S. to analyze the intraday trading pattern of individual investors using actual individual investor data. The findings of this study can provide valuable insight into the behavior of the individual investors during the day of the week and time of the day and thus help to advance the literature on behavioral economics.

Significance to Practice

The results of this research provided valuable insight to individual investors and financial advisors regarding the behavior of the investors during the day of the week and time of the day. Results showed which days and what time of the day individual investors are more likely to trade stocks. This information, in turn, may help individual investors make the right choice before they invest. Individual investors and financial advisors can use this information to optimize their investment decision. They may be able to develop an investment strategy to buy the stocks on the days and time of the day when the prices are typically low and sell the stocks on a day and at a time when the prices are typically high.

Significance to Social Change

The findings of this study may make positive social change. Understanding the individual investment patterns and its influence on the market helps market administrators to design the markets more efficiently. An efficient market enables information transparency and market liquidity. Transparent financial markets enhance investor confidence which could lead to more trading activities by more investors. The results of this study may help to further understand the individual investor behavior, reduce information asymmetry, and increase the stock market liquidity.

Conclusions

This study primarily tested the theory of EMH and the associated calendar anomaly Monday effect. Past researchers had postulated the different investment patterns of institutional investors and individual investors as one plausible explanation for the Monday effect. Using actual individual investor data from the NYSE that covers the periods before, during, and after the financial crisis of 2008–2009, this study quantitatively analyzed the Monday effect on the U.S. stock exchange.

The first research question analyzed the difference in the investor average return between Monday and other weekdays. The study finding using one-way ANOVA analysis yielded a statistically insignificant effect. Thus, the findings of this study were consistent with some of the recent studies that argued the Monday effect was no longer an anomaly in the U.S. stock market.

The second research question was aimed to evaluate the difference in the individual investor trade percentage between Monday and other weekdays. The results showed that the Monday percentage did not significantly differ from the individual investor percentages on Tuesday, Wednesday, and Thursday. However, the study results showed the percentage of individual investor trades on Fridays was significantly lower than the individual investor trades on other weekdays.

Finally, the third research question compared the difference in the individual investor trading pattern between Monday and other weekdays. Using descriptive statistics and heuristic techniques, the study results displayed that the days of the week had no effect on the individual investor trading pattern between Monday and other weekdays.

The study results also revealed the individual investors traded in a bathtub shaped pattern during the day with the highest trade volume at the stock market opening 30-minute interval and the second highest trade volume at the stock market closing 30-minute interval.

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