# Halloween Effect and Equity Mutual Funds in Thailand

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# ผลกระทบฮาโลวีนและกองทุนรวมตราสารทุนในประเทศไทย

น.ส.ธันยพร วิริยะดี



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วิทยานิพนธ์นี้ศึกษาผลกระทบฮาโลวีนซึ่งเป็นหนึ่งในความผิดปกติตามฤดูกาลที่มีชื่อเสียงที่สุด จากข้อมูลจะสังเกตได้ว่าผลตอบแทนในช่วงเดือนพฤศจิกายนถึงเมษายนที่เรียกกันว่าช่วงฤดูหนาวมีแนวโน้วสูงกว่าช่วงเดือนพฤษภาคมถึงตุลาคมที่เรียกกันว่าช่วงฤดูร้อน จากตัวอย่างกองทุนรวมตราสารทุนหุ้นไทย 97 กองทุนในช่วงปี 2555-2564 การศึกษานี้ได้ขยายการวิจัยก่อนหน้าโดยเน้นที่ผลกระทบของวันฮาโลวีนในตลาดกองทุนรวม การวิจัยนี้ประกอบด้วยวัตถุประสงค์หลัก 3 ส่วน การศึกษาส่วนแรกจะตรวจสอบปรากฏการณ์ฮาโลวีนในกองทุนรวมหุ้นไทย ส่วนที่สองจะพิจารณาลักษณะต่างๆของกองทุนโดยจัดหมวดหมู่ตามฐานข้อมูลของ Morningstar เนื่องจากกองทุนประเภทต่างๆ อาจมีขนาดผลกระทบฮาโลวีนที่แตกต่างกัน การศึกษานี้จึงตรวจสอบเพิ่มเติมถึงการปรากฏตัวของผลกระทบฮาโลวีนใน 6 กลุ่มจาก 11 ลักษณะที่แตกต่างกัน แบ่งโดยมูลค่าหลักทรัพย์ตามราคาตลาด อัตราส่วนทางบัญชีต่อตลาด รูปแบบการลงทุนแบบเชิงรุกและเชิงรับ และอุตสาหกรรมต่างๆ วิจัยนี้ได้สร้างกลยุทธ์การลงทุนโดยพิจารณาจากขนาดผลกระทบฮาโลวีนโดยลงทุนในชนิดกองทุนที่มีผลกระทบฮาโลวีนสูงสุดในช่วงฤดูหนาวและลงทุนในชนิดกองทุนที่ไม่มีผลกระทบฮาโลวีนหรือมีน้อยกว่าในช่วงฤดูร้อน และเปรียบเทียบกับเกณฑ์มาตรฐานที่ใช้กลยุทธ์ซื้อถือระยะยาว การศึกษาส่วนที่สามจะสร้างกลยุทธ์โมเมนตัมที่ดัดแปรงโดยในฤดูหนาว ลงทุนในพอร์ตที่มีกลุ่มกองทุนรวมที่ผลตอบแทนต่ำและในฤดูร้อน ลงทุนในพอร์ตที่มีกลุ่มกองทุนรวมที่ผลตอบแทนสูงและขายชอร์ตพอร์ตที่มีกลุ่มกองทุนรวมที่มีผลตอบแทนต่ำเพื่อตรวจสอบว่ามีประสิทธิภาพเหนือกว่ากลยุทธ์โมเมนตัมทั่วไปหรือไม่

วิทยานิพนธ์นี้พบผลกระทบฮาโลวีนในกองทุนรวมตราสารทุนไทยและมีผลตอบแทนที่สูงในฤดูหนาวซึ่งสอดคล้องกับ Kenourgios และ Samios (2021) นอกจากนั้นผลกระทบฮาโลวีนปรากฏในทุกลักษณะยกเว้นกองทุนที่ลงทุนในหุ้นเติบโต การศึกษานี้แสดงให้เห็นขนาดของผลกระทบฮาโลวีนแตกต่างกันตามลักษณะต่างๆของกองทุนรวมซึ่งคล้ายกับผลของ Arendas et al (2018) และ Jacobsen & Visaltanachoti (2009) การศึกษาค้นพบขนาดผลกระทบฮาโลวีนสำหรับกองทุนเชิงรับมากกว่ากองทุนเชิงรุก เหตุผลนึงคือผู้จัดการกองทุนซึ่งรับรู้ปรากฏการณ์นี้สร้างกลยุทธ์ของตนเองว่าจะลงทุนอะไรในแต่ละช่วงเวลา Kenourgios และ Samios (2021) ชี้ให้เห็นว่าผู้จัดการกองทุนลงทุนในหุ้นเพิ่มช่วงเดือนพฤษภาคมถึงตุลาคม ยิ่งไปกว่านั้นกลยุทธ์ rotation และกลยุทธ์โมเมนตัมที่ดัดแปรงให้ผลตอบแทนดีกว่าเกณฑ์มาตรฐาน กลยุทธ์ rotationโดยลงทุนในกองทุนที่ลงทุนในหุ้นขนาดใหญ่และหุ้นคุณค่า/กองทุนที่ลงทุนในหุ้นขนาดกลางและเล็กและหุ้นคุณค่า และ กองทุนเชิงรับ/กองทุนเชิงรุกสามารถสร้างผลตอบแทนที่เป็นบวกอย่างมีนัยสำคัญ




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This paper investigates one of the most famous seasonal anomalies, namely Halloween effect. It is based on the observation that return during November to April so-called winter period tend to perform better than return during May to October so-called summer period. Using a sample of 97 Thailand equity funds during 2012-2021, we extend previous research by focusing on the Halloween effect in mutual funds market. Our research consists of three main objectives. First, we investigate the existence of Halloween effect in Thailand equity mutual funds. Second, we look into different characteristics of funds by categorizing based on categories from Morningstar database. As different types of funds may have different strengths of Halloween effect, we further examine the presence of Halloween effect in 6 groups of 11 different types of characteristics includes different market capitalization, book-to-market ratio, investment style of active and passive and sectors. Then, we create trading strategies which based on the different strength of Halloween effect by investing in a funds characteristic with the highest Halloween effect during winter and a funds characteristic with no or less Halloween effect during summer months and compare with the benchmark of buy-and-hold strategy. Third, we generate modified momentum strategy, which is to long loser portfolio in winter, and long winner portfolio and short loser portfolio in summer and investigate whether it outperforms conventional momentum long-short strategy.

Consistent with Kenourgios and Samios (2021), our results show that Halloween effect exists in equity mutual funds with significant positive winter months return. We provide evidence of a robust Halloween effect in every characteristic except for growth funds. Our findings also show that size of Halloween effect varies across different characteristics of mutual funds similar to Arendas et al. (2018) and Jacobsen and Visaltanachoti (2009). Halloween effect is stronger for passive funds than active funds. One possible explanation is fund manager who acknowledge this phenomenon create their own strategy of what to invest during each period. Kenourgios and Samios (2021) suggests that fund managers increase their equity exposure during May to October. We also show that the investment based on rotation strategy and modified momentum strategy is profitable and outperform their benchmark. The rotation strategy of investing largevalue/midsmallvalue funds and passive/active funds generate a positive and significant abnormal return.



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# CHAPTER 1

# Introduction

## 1.1 Background and Significance of the problem

Halloween effect is one of seasonal anomaly which based on the old market wisdom "Sell in May and go Away" from the oldest references in Financial Times dated back in 1935 (Zhang & Jacobsen, 2021). Because the markets tend to go down during summer, investors should sell their stocks in May. Some investors may know it as Halloween Indicator which suggest leaving the stock markets and come back after Halloween, 31 October.

Since then, Bouman and Jacobsen (2002) are the first to further investigated the validity of Sell in May in MSCI indices during 1970 to 1998 across 37 markets and identify the presence of Halloween Effect by comparing the 6-month period of winter period (November to April) and summer period (May to October). They found that winter returns give a substantially higher return than summer returns and exist in 35 out of 37 markets and the difference between average return between winter and summer months was statistically significant in 20 out of 35 countries. Their study causes a great doubt of the validity of EMH (Efficient Market Hypothesis) as these anomalies could predict the stock prices and investors can create investment strategy to time the market (Fama, 1970).

After the first publication, many researchers expand the analysis of this calendar anomaly in different markets with the most in stock indices in different countries to validify EMH. Plastun et al. (2020) suggests that Halloween effect first appear and become more pronounce in the middle of 20th century for US stock market. Bouman and Jacobsen (2002) claimed that Halloween effect is present in UK since 1694, which is more than 300 years. Consistently, Zhang and Jacobsen (2013) who investigate price index of GFD UK stock during 1693 to 2009 and found that Halloween effect is present in their full sample period. Carrazedo et al. (2016) looked into Nordic and Eurozone region by using 37 sector indices of Dow Jones Stoxx during 1992 to 2010 found that

Halloween effect exist in all indices with significant effect in two-thirds. Lean (2011) investigates 6 Asian countries, namely Malaysia, Japan, Hong Kong, Singapore, China and India during 1991 to 2008. Their result reveals that by using OLS regression model, Halloween effect is only significant in Malaysia and Singapore, but China, India and Japan become statistically significant after using GARCH models to account for time varying volatility. Zhang and Jacobsen (2021) who uses all available historical data of stock indices worldwide to verify the robustness of Halloween effect in many perspectives. They noted that surprisingly Halloween effect seems to not disappear or reverse itself even after publicly known of this market wisdom even before the first published paper by Bouman and Jacobsen (2002). In fact, many literatures (eg. Andrade et al. (2013) and Swinkels and Van Vliet (2012))' results are consistent with Bouman and Jacobsen (2002)'s out of sample test. Therefore, Halloween effect unlikely to be caused by data mining. Jacobsen et al. (2005) show that the Halloween effect is a market wide phenomenon and not relate to common anomalies, including size, book-to-market ratios and dividend yield. Jacobsen and Visaltanachoti (2009) investigate the Halloween effect among sectors in US stock market. They reveal that the effect is strongest in production related sectors.

Zhang and Jacobsen (2021) also investigate from another viewpoint whether excess return in summer is positive compared to risk free return. Sell in May suggests to leave the equity market at the beginning of May. However, it might be better for investors to stay in the equity market if summer return is greater than risk free return. Their result correspond with the market wisdom and in line with Bouman and Jacobsen (2002). Therefore, they conclude that Halloween effect does not only violate EMH, but also no risk return trade off. Kenourgios and Samios (2021) also found similar risk level in winter and summer months in their European equity mutual funds. However, their result still shows that winter returns are higher than summer returns. This conclude that high winter return is not due to higher risk.

As introduced earlier, there are ample literatures investigate Halloween effect in stock markets in a broad view. However, studies of Halloween effect in mutual fund market are relatively scare. Agrrawal and Skaves (2015) explore many seasonality including Halloween effect in US ETFs with underlying asset of US and international stocks, real estate, bond and gold and found the presence of a robust Halloween effect with the exceptions of the short and long-term US Treasuries. Kenourgios and Samios (2021) look at Halloween effect in large European equity funds (Asset under management (AuM) more than 5 billion Euros) and suggests that even after controlled for Turn of Year effect[1], their result still show a robust Halloween effect.

Motivated by the limited evidence of mutual funds and in Asia-Pacific, our paper will investigate Halloween effect in equity mutual funds in Thailand. Because mutual fund is an important investment vehicle for investors who wants to diversified their portfolio risks and provide access to the equities, money market instruments, bonds, derivatives and other securities, the popularity of mutual funds grow steadily. According to Charoenrook and Pavabutr (2020), during 1992 to 2018, mutual funds' NAV (Net Asset Value) to GDP ratio grew at 11.47% at a compound annual rate. Moreover, AuM, which signify the size of mutual funds industry has grown at an average of 18% annually and continue the upward trend during 2013 to 2018. Regarding to equity mutual funds in Thailand, AuM grews significantly during 2007 to 2019 at 21% which due to not only the increase in equity prices but also the funds flow. Even though fixed income fund remains the most dominant in Thai mutual fund industry, the growth rate during similar period is at 8.5% which is slower compared to equity funds (Charoenrook & Pavabutr, 2020). Referring to Global Investor Experience (GIE) report done by Morningstar (2017) stated that most markets impose no holding limits with what fund could invest, except from Thailand, China and India. For Thailand, the regulator impose overall equity holding limit, which allows no more than 15% in a single stock security or not more than the asset weight in benchmark index plus 5% to encourage for diversification. Charoenrook and Pavabutr (2020) revealed that the regulation of equity holding limits makes performance of equity funds to



[1] January effect refers to a positive abnormal mean returns of equity during the first week of January. This effect is one of the element of Turn of Year effect, which is a pattern of positive equity returns during last week of December and first half of January.

converge to the average market return or market weighted benchmark. Therefore, it would be interesting to investigate the presence of Halloween effect in this market.

## 1.2 Objectives

This research aims to investigate the Halloween effect in the Thai equity mutual funds market. This paper consists of three main objectives.

Evidence from Kenourgios and Samios (2021) found that there is an evidence of Halloween effect in the equity mutual funds by using sample of 118 equity funds with full pricing history between 2008 to 2017 and it is still robust even after control for Turn-of-Year effect. As the evidence of Halloween effect is extensive in stock markets after the first publish paper of Bouman and Jacobsen (2002), the first objective of this research will study the evidence of Halloween effect in equity mutual funds market in Thailand.

Furthermore, most papers focus on the Halloween effect in a macro level, we will further investigate this effect in a micro view by investigating different characteristic of mutual funds. This includes different market capitalization, book-to-market ratio, investment style of active and passive and sectors. Because different characteristics of equity mutual funds can have different strength of Halloween effect similar to January effect in which relates to size (Banz, 1981) and book-to-market effects (Fama & French, 1996), we will examine the existence of the Halloween effect in 6 groups of 11 different types of characteristics based on category from Morningstar database. If funds performance with different characteristics does show variation throughout the months, which is the higher average monthly return during the winter period of November to April compared to summer period of May to October means Halloween effect is present, then the result from this study will provide useful information of what months or periods are the best time to buy and sell mutual funds units for investors. Therefore, we will create trading strategy that exploit Halloween effect based on different characteristic by using the rotation strategy. Similar to Jacobsen and Visaltanachoti (2009)'s sector rotation strategy, this strategy will long a characteristic funds with highest significant of Halloween effect during winter months and long a characteristic funds with lowest or no significant during summer months.

Lastly, we will apply Halloween effect to momentum strategy. Bhootra (2019) shows that momentum winners and losers have higher return in winter months than summer months. While during most of winter months, momentum losers have high returns due to high January returns, they earn negative returns in most of summer months. Base from this findings, Bhootra (2019) creates the modified momentum strategy which is to long winner in winter months, and long winner and short losers in summer months. Followed their strategy with using equity funds sample, we will form momentum portfolio by identifying the portfolio of winner funds in winter months and loser funds in summer months. Then, we further investigate this strategy by comparing returns of modified momentum strategy with the conventional momentum strategy which is to long winners and short losers.

### 1.3 Scope of the study

This study will focus on open-end Thai equity mutual funds. The principal data of each fund can be collected from Morningstar. For the first objective, to study Halloween effect and its existence in equity mutual fund market, we collect total monthly return data of 97 funds with full history return during 2012-2021. We also collect same data and period for the second objective of examining Halloween effect in different characteristics, including active/passive funds, large/mid and small cap funds, value/growth funds and sector funds. The data includes 86 active funds, 6 passive funds, 80 large cap funds, 12 mid-small cap funds, 85 value funds, 1 growth funds, 48 largevalue funds, 33 midsmallvalue funds, 2 energy funds and 2 banking sector funds with full history return during 2012-2021. Then, to generate the rotation strategy based on different effect on different types of characteristics, we will use Single Index model, Fama French Three factor model and Carhart Four model to test its significance similar to Jacobsen and Visaltanachoti (2009). For the last objective, we incorporate Halloween effect with momentum strategy to compare average returns with the conventional momentum strategy, we will use CAPM, Fama French Three factor model and Carhart Four model to test for its significant.

### 1.4 Contribution

1. A large body of literature investigated the presence of Halloween effect of the stock markets; however, the evidence of the mutual fund market is still limited. Moreover, most of the papers provide the evidence of Halloween effect in a macro perspective, this paper will investigate the Halloween effect in micro level as well by looking at different characteristics of mutual funds, such as active/passive funds, large/mid and small cap funds, value/growth funds and sector funds. Therefore, to the best of our knowledge, this study will fill the research gap by providing new insights for Halloween effect in Mutual fund market.
2. Evidence of the Halloween effect in Thailand is found by Bouman and Jacobsen (2002), however, some papers reveal that it is insignificant and a January effect in disguise (eg. Friday and Bo (2015)). Our paper will be the first study to investigate Halloween effect in Thai equity mutual funds market. Due to the limited research in Asia-Pacific, our paper will provide additional evidence in this market.
3. As evidence from Bhootra (2019), momentum strategy with Halloween effect or the modified momentum strategy outperform conventional momentum strategy. Therefore, our paper will investigate momentum strategy with Halloween effect using Thai equity funds to form winners and losers portfolio and compare whether performance from this strategy will outperform the conventional momentum strategy.
4. Halloween effect is not cause from an extraordinary performance of a short period, but it continuously show a persistent trend of higher winter return than summer return over time. Moreover, Halloween effect does not suffer from Murphy's law, which means that this effect does not disappear over time or reverse itself (Plastun et al., 2020). By knowing that Halloween effect exists in the Thai equity mutual fund market and different strength of Halloween effect

in different characteristics, investors could do market timing of the best periods to buy or sell equity mutual funds. They could also use the extension of Halloween trading strategies from this research, namely rotation strategy and modified momentum strategy to gain higher returns and beat the market.

### 1.5 Research Hypothesis

**Hypothesis 1:** *Halloween effect is present in Thai equity mutual fund market*

Halloween effect can be inspected by the positive difference between average monthly return in winter period of November to April and summer period of May to October. Evidence from MSCI World stock index by Bouman and Jacobsen (2002) and Doeswijk (2008) shows that the pattern of Halloween effect is not due to an isolated performance of a month, but the phenomenon is the result of the whole six-month periods' behavior. Kenourgios and Samios (2021) who examine the occurrence of Halloween effect in equity mutual funds market in Europe by using sample of 118 funds with full pricing history between 2008 to 2017 found that there is an evidence of Halloween effect in the equity mutual funds.

If Halloween effect exists in Thai equity mutual funds, then we would assume that the excess return in winter months is positive and statistically significant.

**Hypothesis 2:** *There are difference size of Halloween effect in different characteristic of Thai equity funds.*

Many literatures focus on the Halloween effect on a macro level of whether this anomaly is presence or not, but very few focus on a micro perspective. Similar to January effect, Halloween effect could be related to other well known anomalies, such as size effect (Banz, 1981) and book-to-market effect (Loughran, 1997). Jacobsen et al. (2005) studied the Halloween effect in different firm characteristics in US stocks using Fama and French data. They create value and equally weighted portfolios formed on Size, Book-to-Market ratio (B/M), Earnings-Price ratio (E/P), Dividend Yields (D/Y) and Cash-Flow-to-Price ratio (CF/P). They reveal that unlike January effect, Halloween effect is a market wide phenomenon and not relate to the Size effect and Book-to-Market anomaly. They also found that size of Halloween effect does not relate to portfolios formed on Cash-Flow-to-Price ratio and Earnings-Price ratio. However, Arendas et al. (2018) who looked into individual stocks noted that Halloween effect was statistically significant in 18 out of 35 stocks, but significantly vary of Halloween effect strength from stock to stock. It could be that Halloween effect is concentrated in certain types of funds. Jacobsen and Visaltanachoti (2009) also conclude there is a different size of Halloween effect in among US sectors and industries.

**Hypothesis 2A**: *Halloween effect is more present in mid and small cap funds than large cap funds*

The first group of characteristics to investigate is size or market capitalization. Banz (1981) suggests that both return and risk-adjusted return, small stocks tend to outperform large stocks. Consistently, Fama and French (1992) conclude that smaller firms have higher average return. Dzhabarov and Ziemba (2010) investigated S&P 500 stock index as a proxy for large-cap stocks and Russell 2000 stock index as a proxy for small-cap stocks. Their result also reveals that small-cap stocks has stronger Halloween effect. However, Jacobsen et al. (2005) claimed that Halloween effect is unrelated to size.



If Halloween effect is more present in mid and small cap fund than large cap fund, then we would assume that the excess return in winter months is positive and statistically significant.

**Hypothesis 2B:** *Halloween effect is more present in value funds than growth funds*

The second group of characteristics to investigate is book-to-market. Fama and French (1992) suggests that low book-to-market firms tend to have lower average returns than firms with high book-to-market ratio. Consistently, O'Brien et al. (2010) found this positive relationship between average returns and book-to-market ratio in Australian stock market. Therefore, Halloween effect are more likely to present in funds with high book-to-market. However, Jacobsen et al. (2005) shows that book-to-market ratio is irrelevant to Halloween Effect after controlling January effect.

If Halloween effect is more present in value fund than growth fund, then we would assume that the excess return in winter months is positive and statistically significant.

**Hypothesis 2C:** *Halloween effect is more present in active funds than passive funds*

The third group of characteristics to investigate is investment style of active and passive. Active funds are professionally managed by fund managers who try to outperform the market. With the uses of Halloween strategy from Bouman and Jacobsen (2002) and extensive of Halloween strategy (e.g. Jacobsen and Visaltanachoti (2009)'s sector rotation strategy) that outperform buy-and-hold strategy of market portfolio, investors would get higher returns which outperform market indices. This signify that one would get better return if portfolio is actively managed. Therefore, active funds should present a more strength of Halloween effect. However, Kenourgios and Samios (2021) suggests that European fund manager pay no attention to Halloween effect as their evidence shows that 4 out of 5 funds remain unchanged or an increasing market performance of each fund during summer period.

If Halloween effect is more present in active than passive fund, then we would assume that the excess return in winter months is positive and statistically significant.

**Hypothesis 2D:** *Size of Halloween effect is different across sector funds*

The fourth group of characteristics to investigate is sectors. Evidence from Jacobsen and Visaltanachoti (2009) in US 17 sector and 49 industries stock indices reveal that defensive consumer-oriented sectors tend to have no strong Halloween effect and procyclical sectors includes raw material and production sectors tend to have a strong Halloween effect. Therefore, different sector funds might have different strengths of Halloween effect.

**<u>Hypothesis 2E:</u>** *Performance of rotation strategy based on different characteristics of funds outperform buy-and-hold strategy*

Jacobsen and Visaltanachoti (2009) shows that with large different in size of Halloween effect accross US sectors and industries, they could create sector rotation strategy[2] to outperform their benchmark of CRSP value-weighted US stock fund as a market index and one- month U.S. Treasury bill as a proxy of a risk-free investment. Similarly, with different strength of Halloween effect across different characteristics, namely market capitalization, book-to-market ratio, investment style of active and passive and sector funds, we could do rotation strategy that could outperform the buy-and-hold strategy of passive funds total return.

**<u>Hypothesis 3:</u>** *Performance of Halloween effect with momentum strategy or Modified momentum strategy outperform conventional momentum strategy*

To identify whether equity funds have similar pattern to momentum strategy of high return in winter and low returns in summer periods for winner funds and loser funds. Evidence from Bhootra (2019) show that both winner and loser momentum portfolios perform well in winter period of November to April than summer period of May to October. Their result shows that momentum losers' average monthly return is −0.46% during summer period, and 1.72% during winter period. Similarly, momentum winners's average monthly return is 0.77% during summer period, and 2.50% during winter period. From this evidence, the performance of modified momentum strategy is

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[2] Sector rotation strategy is to invest in an equally-weighted portfolio of five consumer industries during summer months and invest in an equally-weighted portfolio of five production industries during winter months (Jacobsen and Visaltanachoti, 2009)

investigated. The strategy is long in winners only during winter period, and long winners and short losers during summer period. Their findings reveal that it outperform the conventional long winners and short losers. Therefore, by using equity funds data, we would expect that the modified momentum strategy outperform conventional momentum strategy as well.

# CHAPTER 2

# Literature Review

## 2.1 Efficient Market Hypothesis

Efficient Market Hypothesis or EMH developed by Fama (1970) claims that all available information should be reflected in market prices and considers security prices adjustments with respect to three different types based on the nature of information. Weak-form test refers to the information on past prices and trading volume which is available to all investors. The semi-strong form includes all available information and the efficiency of the market to adjust prices when there are changes in the publicly available information. Examples consist of company's earnings reports announcement, new security issues, stock splits, etc. Strong-form test refers to all available information is accounted for in the market prices, including the information that only insiders traders have access to. Fama (1970) mentions that markets are efficient and all available information fully reflects in the market prices.

If markets are really efficient, excess returns should not be earned by investors. However, undervalued companies can still be found allowing investors to earn excess returns. Ying et al. (2019) investigated the possible explanations for the excess returns. Anomalies are irregularities in returns and are found by investors allowing them to earn excess returns. However, research shows that consistent with EMH, as soon as an anomaly is found in the market and documented in financial literature, which means becoming part of the public information, they seem to weaken or disappear. Ying et al. (2019) conclude that investors do not always act rational since they will make misjudgments and mistakes leading to opportunities for other investors to yield excess returns, both in short and long term.

Calendar anomalies are seasonal movements in stock prices that are related to a specific time period and were first reported by Wachtel (1942). Lo (2004) developed an alternative hypothesis, called the Adaptive Markets Hypothesis (AMH) on the basis of these calendar anomalies. This allows the degree of efficiency of the markets to vary over time. In order to see if pattern in the behavior of calendar anomalies can be connected to AMH, Urquhart and McGroarty (2014) tested many well-known calendar anomalies, including Monday effect, January effect, turn-of-the-month effect and the Halloween effect on Dow Jones Industrial Average since January 1900 to December 2013. Their study confirmed that consistent with the AMH, these market anomalies do vary over time and are more or less favorable depending on the market conditions. Urquhart and McGroarty (2014) also examined different trading strategies based on calendar anomalies, which also deviates in efficiency depending on market conditions. These findings are inconsistent with EMH.

## 2.2 Literature Review of Halloween Effect

After the first published paper by Bouman and Jacobsen (2002), many researchers expand their analysis to challenge the stock market efficiency and focused on the robustness of the Halloween effect across stock indices, countries, and time periods. They also test whether performance from a trading strategy based on this phenomenon are better.



### 2.2.1 Halloween Effect in Stock market

There are extensive research on the existence of the Halloween effect in the stock market by observing the returns of the stock index during the period November to April (winter months) compared to the period May to October (summer months). Many of them found that the average return in winter months is higher than summer months in both developed and emerging markets. With the same countries of Bouman and Jacobsen (2002), Andrade et al. (2013) check all 37 countries by using 6-month returns. They confirm the positive Halloween effect in all countries during 1998 to 2012 with significant for 13 cases. Zhang and Jacobsen (2013) shows that out of 109 price indices, Halloween effect is present in 82 countries. Their findings suggest that winter returns are higher than summer returns at 4.5% on average.

Jacobsen et al. (2005) studied the Halloween effect in equally and value weighted portfolios for the US stock market formed on earnings-price ratio, size, dividend yield, cashflow-to-price ratio and book-to-market ratio using Fama and French data. Their results reveal that Halloween effect is significantly present in all portfolios. They also found that the formed portfolio's anomalous behavior are unrelated to Halloween effect. Moreover, they show that the Halloween effect is different from the well-known January effect. Unlike, Halloween indicator which seems to be a market-wide phenomenon, January effect shows more presence in high book-to-market portfolios and smaller firms' portfolios. As a result, they conclude that Halloween effect is not related to other well-known anomalies.

As many research focused only on specific countries or time periods, Zhang and Jacobsen (2021) reexamined the Halloween effect by using all historical data available from all countries worldwide (114 stock markets in which stock indices exist) categorized by MSCI to avoid data mining, sample selection bias, outliers and statistical problems. Their result reveals that Halloween effect is stronger in developed and emerging markets than in frontier and rarely studied markets. Moreover, they found that Halloween effect is stronger in the last 50 years.

In Asian markets, Lean (2011) studied the Halloween effect in stock indices from 6 countries, including Malaysia, Japan, Hong Kong, Singapore, China and India from 1991 to 2008. He found that the Halloween effect is present in all countries except Hong Kong and significant for Malaysia and Singapore. Guo et al. (2014) studied in China using the GTA CSMAR index of Chinese A shares during 1997 to 2013 and found that the Halloween effect is significant and robust to other calendar effects. They also inspect the companies in 13 different industries. Their findings show that this effect occurs in all industries but only eight are significant. The real estate, culture and finance industries exhibit the weakest effect; transportation, hydroelectric and manufacturing show strongest. Positive summer returns are only shown in culture among all industries. Maberly and Pierce (2004) and Sakakibara et al. (2016) studied in Japan stock market shows that Halloween effect seems to be stronger in the bull market.

For evidence of the Halloween Effect in Thailand stock market. Bouman and Jacobsen (2002) showed that SET Index has higher average monthly return in winter months compared to summer months because of the combination of January and Halloween effect. They also found that over the same period 1988 to 1998, the Halloween effect did not have a significant impact. However, Friday and Bo (2015) found evidence of the Halloween effect in SET and SET50 Index but not statistically significant. While Haggard et al. (2015) reveal that outlier is not significant to the robustness of Halloween effect in Thai stock market. Tang-u-thaisuk et al. (2018) extend their research to selected stocks in SET Energy Index. Their result shows that the Halloween effect had no significant impact on mean monthly returns but exhibited significance on the volatility of returns.

### 2.2.2 Halloween effect in Mutual fund market



While there are many evidence on the Halloween Effect in the stock market both in developed and emerging markets, evidence of the Halloween effect in the mutual funds market is still limited. Kenourgios and Samios (2021) expand past research by studying the existence of the Halloween effect in large European equity mutual funds (AuM more than 0.5 billion Euro) during 2008 to 2017. With the regression based from Bouman and Jacobsen (2002), they found that more than 75% of the funds show the existence of a significant Halloween effect at 5% significance level and 90% of the funds at 10% significance level. Another study done by Agrrawal and Skaves (2015) examined seasonality including the Halloween effect in 10 highly liquid ETFs with underlying markets in bonds, gold, real estate and US and international stocks. Their result verified the existence of robust Halloween effects in the ETF, except short and long term US Treasuries.

## 2.3 Literature Review of Halloween Strategy

The Halloween effect also known as Sell in May effect is a simple strategy where investors have a position in stocks in the period November to April and sell in the period May to October or invest in risk free return proposed by Bouman and Jacobsen (2002). Many research suggests that Halloween Strategy outperforms the classic buy-and-hold strategy (Plastun et al. (2020); Carrazedo et al. (2016); Swinkels and Van Vliet (2012); Sakakibara et al. (2016); Guo et al. (2014)). Zhang and Jacobsen (2021)

Moreover, there are many new strategies to exploit the Halloween effect. For example,

Jacobsen and Visaltanachoti (2009) proposed a sector rotation strategy after they investigated US sectors and industries. Because defensive consumer-oriented sectors have no strong Halloween effect and procyclical sectors includes raw material and production sectors have a strong Halloween effect, the strategy works when investors hold portfolios focusing in production sectors, includes Machine, Steel and Construction in winter and invest in portfolios with focus on consumer-oriented sectors with short lifespans products, includes Utilities, Consumer and Food in summer. Their result also shows that sector rotation strategy significantly outperforms the Buy-and-hold strategy and Halloween strategy proposed by Bouman and Jacobsen (2002) since sector funds (Fidelity funds) are available in 1990. Moreover, they reveal that Bouman and Jacobsen (2002)'s strategy turns out to be inferior to the Buy-and-hold strategy.

Andrade et al. (2013) studied the Halloween effect in the US market by using SPDR S&P 500 ETF during 1994 to 2012 and proposed a leveraged Sell in May strategy in which investors reduce their exposure to stock beginning in May and leverage by using futures starting in November. Their result shows that in terms of

Sharpe ratios and raw returns, it is highly profitable and beats the Buy-and-Hold strategy.

Fiore and Saha (2015) studied the Halloween effect using CRSP market index during 1968 to 2012 and found that Halloween effect is weak for low-risk stocks and strong for high-risk stocks. They proposed a Halloween risk rotation strategy which have position in stock with low risks in summer and invest in riskier stocks in winter. On a return basis, this strategy significantly outperforms the classic Halloween strategy and the Buy-and-Hold strategy, but not on a risk-adjusted basis.

Bhootra (2019) shows that during winter months, the momentum loser and winter portfolios have higher return compared to summer months which is consistent with the Halloween effect by using monthly data for US stocks listed on AMEX, NASDAQ, and NYSE during 1963-2017. Therefore, he proposed a modified momentum strategy which is to long winner stocks in winter period of November to April, and long winner and short loser stocks in summer period of May to October. Comparing this strategy to the conventional momentum strategy which is to long winner stocks and short loser stocks, their result shows that modified momentum strategy give better return and Sharpe ratio.

**2.4 Explanation of Halloween effect**



The possible causes of Halloween effect have been investigated by many studies.

To find an explanation for the anomaly, many possible causes are considered by Bouman and Jacobsen (2002). These causes are the data mining, trading volume, changes in interest rates, January effect, vacations, risk and news. Their findings suggest that there is a relation between timing of summer vacations and trading volume, and countries with long summer vacations have the strongest effect. They also separate their data into southern and northern hemisphere. Summer vacations are at a different time for countries with southern-hemisphere relatively to northern-hemisphere countries. By looking at the returns in November - April or winter months of both hemispheres, they also find a higher returns for southern-hemisphere countries.

Bouman and Jacobsen (2002) left the seasonal anomaly unexplained in the end. Hong and Yu (2009) who investigated in 51 stock markets provide similar evidence of lower trading activity during vacation periods. Zhang (2014) also confirm that vacation periods has a negative impact on market returns for 34 countries. Kaustia and Rantapuska (2016) found that the investors' monthly trading patterns are consistent with the vacation hypothesis. By looking into data of stock trading from all Finnish investors, they observe that stocks are sold before vacation begins and traded less during vacation period.

After the Bouman and Jacobsen (2002)'s first publication, this started the debate around the anomaly. A possible explanation for Halloween effect proposed by Kamstra et al. (2003) is SAD or Seasonal Affective Disorder. They believe that investors are depress during the fall as hours of daylight decreases. Therefore, this leads to a higher risk aversion of investor and resulted in lower stock returns. Later, stock returns will recover after the increase of daylight and winter solstice. However, Jacobsen and Marquering (2008) note that the strong effects in countries close to the equator does not caused by SAD. They claim that the correlation between stock returns and weather are a result of data driven.

Doeswijk (2008) suggested that optimism cycle could be a reason for this effect. Their evidence shows Halloween strategy's abnormal return are economically significant. The optimism cycle hypothesis assumes investors start to anticipate for next calendar year in the 4th quarter of the year and usually are too optimistic about the economic outlook. As the year proceeds, investors become more pessimistic as their outlook reverses around summer break. Instead of the variation in outlook perceived for the earnings and economy during the year and twelve-month rolling forward period, this hypothesis assumes that investors think in calendar years. Therefore, investors should have more position in stocks during November through April and less during May through October.

Maberly and Pierce (2004) contended that Bouman and Jacobsen (2002) documentation. They believe that Halloween effect which is significant in the U.S. stock returns seems are driven by two outliers in the period of October 1987's world equity prices crashes, and the hedge fund Long-Term Capital Management collapse in the period of August 1998. Therefore, they re-examined this effect during April 1982 - April 2003 in the U.S. stock market. They found that after these outliers are adjusted, the Halloween effect disappeared. However, after estimating the Halloween effect by using three robust regression methods in the similar period, Witte (2010) who reported that the four largest outliers in addition to October 1987 and August 1998 suggested that outliers do not drive the result of Bouman and Jacobsen (2002). They conclude that Halloween effect would be enlarge by outliers.

Jacobsen and Visaltanachoti (2009) consider liquidity could be a reason for Halloween effect. They use liquidity captured from the measures of Pástor and Stambaugh (2003). However, their evidence shows that liquidity is unrelated to this seasonal effect.

Swinkels and Van Vliet (2012) studied CRSP value-weighted index's daily return during 1963 to 2008 for the interaction of the five calendar anomalies: weekend effect, Sell-in-May effect, turn-of-the-month effect, January effect and holiday effect. When testing without controlling other calendar effects, sell-in-may effect is significant at the 1% level. Their result still shows a significant sell-in-may effect at 5% level after controlled for the other calendar effects. Moreover, they found that this sell-in-may effect is still positive but turns insignificant in this test after removing days which relate to other calendar effects which is different compared to other calendar effects with same method of calculations.

As many previous debates shown that the behavioral changes of investors could be one of the causes, Carrazedo et al. (2016) argued that negative average returns in the summer months may related to Halloween effect rather than the significant positive average returns in the winter months. Moreover, they believe that the certain events could cause Halloween effect. For example, mutual funds flows can cause stock prices to be negative constantly in summer.

Lloyd et al. (2017) proposed a self-fulfilling prophecy as the cause of Halloween effect. When investors know that the presence of Halloween effect in market, they expect a decrease in price in the beginning of May and would eventually increase in November. Therefore, investors put downward pressure on the market by lower their portfolios exposure in May and come back in November. This will lead to an increase of stocks demand and will push price upwards. This pattern is expected to happen again and again, which lead to self-fulfilling prophecy.

Waggle and Agrrawal (2018) observed shown that the post-election in US stocks during November to April returns are significantly higher than in non-election years for both November to April and May to October. Therefore, they suggest performance of post-election makes higher returns significantly during November–April.

# CHAPTER 3

# Data

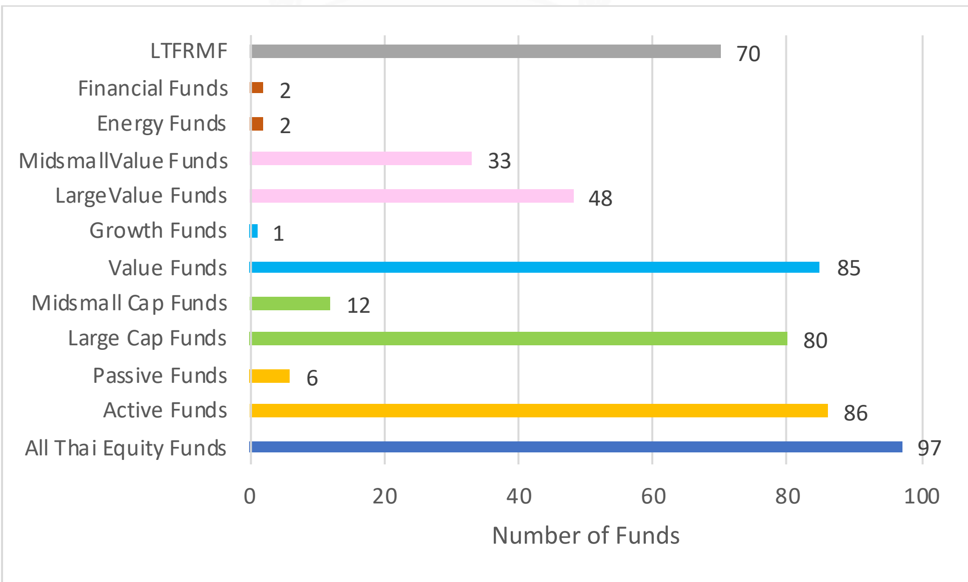
## 3.1 Observations

To test the first objective, which is the existence of Halloween effect in Thailand equity funds, we obtain data of open-end Thailand equity mutual funds from MorningStar Direct. Despite Zhang and Jacobsen (2013); (2021) suggests that even after include dividend in their sample, their result is unaffected, we will include dividend in our sample as dividend payments may have impact on the result. In order to include dividend, we collect total monthly return data of 97 funds with full history return during 2012-2021. Because the data used in this research need to have complete data during the investigated period, this could create survivorship bias because we exclude funds with not full history return and new funds that have total monthly return starting from February 2012. We also exclude tax saving funds as these funds invest in long term and specific requirements to get tax benefit.

In order to investigate the difference size of Halloween effect in different characteristics in mutual funds for second objective, the data of Thai equity funds will be separated into 6 groups of 11 characteristics, such as active funds/passive funds, large funds/mid and small cap funds, value funds/growth funds and sector funds (energy and financial). For the first 2 types of funds, we can categorize the funds into active funds and passive funds by using Index fund category. Next, by using MorningStar category, we can divide into different sizes of funds, large funds and mid/small cap funds and sector-focus funds. For value funds and growth funds, we can filter by using MorningStar's equity style box. Lastly, we also use equity style box to separate between largevalue funds and midsmallvalue funds. Similar to the first objective, we collect same type of data and in similar period for second objective. Figure 1 presents number of each fund characteristic used in this research. The data obtained from Morningstar includes 86 active funds, 6 passive funds, 80 large cap funds, 12 mid-small cap funds, 85 value funds, 1 growth funds, 48 largevalue funds, 33 midsmallvalue funds, 2 energy sector funds and 2 financial sector funds with full history return during 2012-2021. Then, we formulate the rotation strategy based on different size of Halloween effect in different characteristics which will later compared to buy-and-hold strategy of passive funds total return which obtain from Morningstar (Jacobsen and Visaltanachoti (2009). As mutual funds have expense ratio and other costs which SET Total Return Index does not have, we use passive funds total return which invest close to SET Total Return Index to be our benchmark.

For the third objective, which is to compare the average return of the extended version of Halloween strategy to the conventional momentum strategy and buy-and-hold strategy. For this strategy, modified momentum strategy and conventional momentum strategy, we will use the same data set of Thai equity funds as the first objective to rank the funds and construct portfolio of winner funds and loser funds.

**Figure 1** Number of funds in each characteristic
This figure presents the number of funds collected from Morningstar database. All Thailand equity mutual funds are categorized into each characteristic by using category provided by Morningstar. Index fund category is used to filter for active funds and passive funds. MorningStar category is used to filter for large cap funds, midsmall cap funds and sector-focus funds. MorningStar's equity style box is used to filter for value funds, growth funds, largevalue funds and midsmallvalue funds.



## 3.2 Measurement

In this section, we will discuss the method of identifying variables used for each objective.

### 3.2.1 Investigate Halloween Effect in Equity mutual funds

For the first objective, which is to test the existence of Halloween effect, we will first obtain the total return of equity mutual funds from Morningstar. The returns are calculated by:

$$r_t = \frac{NAV_t - NAV_{t-1} + DIV}{NAV_{t-1}} \quad (1)$$

where,

- $r_t$ is monthly return of fund on month t
- $NAV_t$ is net asset value of funds on last trading day of month t
- $NAV_{t-1}$ is net asset value of funds on last trading day of month t-1
- $DIV$ is dividends received during the period



### 3.2.2 Investigate Halloween Effect in Different characteristics of funds

Because different characteristics can have different strengths of Halloween effect, we further investigate the micro perspective of Halloween effect in equity mutual funds. In order to test for the second objective, we will calculate average monthly returns denoted as $r_t$ of 11 different characteristics of funds, including active funds, passive funds, large funds, mid and small cap funds, value funds, growth funds, largevalue funds, midsmallvalue funds, sector funds (energy and financials) and tax-saving funds similar to equation (1).

#### 3.2.2.1 Rotation Strategy

After we test for the different strengths of Halloween effect in different characteristics of equity mutual funds, within the same group of characteristics, we select a characteristic of funds with most significant in Halloween effect and long in winter period of November to April and long a characteristic of funds with no or least significant in summer period of October to May similar to sector rotation strategy by Jacobsen and Visaltanachoti (2009). The rotation strategy will be rebalanced every 6 month.

To compute variables used in Single Index Model, we need to collect data for risk-free rate, which will be Thailand 3-month Treasury Bill Total return from ThaiBMA during 2012 to 2021 (Zhang & Jacobsen, 2021). For the market return, we will use passive funds total return from Morningstar (Jacobsen and Visaltanachoti (2009).

### 3.2.3 Momentum Portfolio Formation

For third objective, to extend momentum strategy with Halloween effect by comparing returns between modified momentum strategy, which is to long losers in winter, and long winners and short losers in summer with the conventional momentum strategy, which is to long winners and short losers using equity funds sample. Therefore, we need to construct momentum portfolios. For the modified momentum portfolio, we need to construct long portfolios of winner funds and loser funds and a short portfolio of loser funds. Similarly, for the conventional momentum portfolio will construct a long portfolio of winner funds and a short portfolio of loser funds.



Follow Bhootra (2019)’s method, we first identify the winner and loser portfolio. The portfolios are formed equally-weighted and use similar approach done by Jegadeesh and Titman (1993) to calculate the returns.

Momentum portfolios are constructed using portfolio of Thai equity mutual funds and we calculate as the simple multi-period return over the past *J* months, which we can compute by:

$$r_{i,T}^{J} = \prod_{t=1}^{J}\left(1 + r_{i,T-(t-1)}\right) - 1\,, J = 3,6,12 \qquad (2)$$

where,

- $r_{i,T}^{J}$ is formation period return of each portfolio

To start with, we use the 6-month/6-month strategy as in 6-month formation/6-month holding period. This strategy is when the winner and loser portfolio are formed at the end of the 6 months and are held for 6 months. In formation period, the funds are ranked in descending order on the basis of their returns in the past 6 months at the beginning of each month t. Based on these ranking, funds in top 10 percent are calculating from cumulative returns over months t-6 to t-1 will be identified as the winner portfolios. Similarly, the loser portfolios are represented as funds in top 10 percent of cumulative returns over past 6 months. Over months *t* to *t* + 5, funds remain in these portfolios. The momentum strategy return is calculated by the difference in returns of equally weighted winner and loser portfolio. The strategy is zero-cost investment strategy and to maintain equal weights, the portfolio will rebalance every 6 months.



To test the significant of strategy return, we need to compute Fama French Three Factor Model[3], we will collect data for

- $SMB_t$ is size premium

  SMB is the difference between small market capitalization portfolio (small stock) minus big market capitalization portfolio (big stock). We can compute SMB by:

[3] See Fama and French (1993)

$$SMB = \frac{1}{3}(small\ value + small\ neutral + small\ growth) - \frac{1}{3}(big\ value + big\ neutral + big\ growth)$$

- $HML_t$ is value premium

  $HML$ is the difference between High BTM portfolios (value stock) minus Low BTM portfolios (growth stock). We can compute HML by:

$$HML = \frac{1}{2}(small\ value + big\ value) - \frac{1}{2}(small\ growth + big\ growth)$$

To test the significant of strategy return, we need to compute Carhart Four Factor Model (1997)

- $UMD_t$ is momentum factor

  $UMD$ is a portfolio formed from a long position in past winners and a short position in past losers.

Similar to the rotation strategy, risk-free rate to be used in models, including CAPM, Fama French Three factor model and Fama French Five factor model will be Thailand 3-month Treasury Bill Total Return from ThaiBMA during 2012 to 2021. For the market return, we will use passive funds total return from Morningstar in similar period.



### 3.3 Summary Statistics

Table 1 presents the data statistics of returns for all funds and each type of characteristics during January 2012 to December 2021. These observations are collected from Morningstar. We observe that some of our data is interesting. First, average monthly return for active funds performs better than passive funds with lower standard deviation. RActive is monthly return by averaging all active funds in month t. RPassive is monthly return by averaging all passive funds in month t. The average and standard deviation of funds' return (RActive) are 0.6623% (7.9473 per year) and 0.0445 (0.1541 per year). Compared to passive fund, the average and standard deviation of funds' return (RPassive) are 0.5718% (6.8610 per year) and 0.0486 (0.1534 per year). We can observe that the average return is higher for active funds than passive funds.

Second, average monthly return for large cap funds performs worse than midsmall cap funds with higher standard deviation. RLarge is monthly return by averaging all funds which invest in large cap stocks in month t. RMidsmall is monthly return by averaging all funds which invest in midsmall cap stocks in month t. The average and standard deviation of funds' return (RLarge) are 0.6487% (7.7842 per year) and 0.0446 (0.1545 per year). Compared to midsmall cap fund, the average and standard deviation of funds' return (RMidsmall) are 0.6846% (8.2152 per year) and 0.0449 (0.1554 per year). We can observe the average return is lower for large funds than midsmall funds. Third, average monthly return for value funds performs better than growth funds with lower standard deviation. RValue is monthly return by averaging all funds which invest in stocks with high book-to-market in month t. RGrowth is monthly return by averaging all funds that invest in stocks with low book-to-market in month t. The average and standard deviation of funds' return (RValue) are 0.6483% (7.7790 per year) and 0.0441 (0.1527 per year). Compared to growth fund, the average and standard deviation of funds' return (RGrowth) are 0.3845% (4.6144 per year) and 0.0526 (0.1823 per year). We observe that the average return is higher for value funds than growth funds.

Funds with mix characteristic of capitalization and book-to-market also provide an appealing observation. RLargeValue is monthly return by averaging all funds which invest in stocks with large capitalization and high book-to-market in month t. RMidsmallValue is monthly return by averaging all funds which invest in stocks with midsmall capitalization and high book-to-market in month t. We can observe that the average return is lower for largevalue funds than midsmallvalue funds. The average and standard deviation of funds' return (RLargeValue) are 0.6069% (7.2834 per year) and 0.0447 (0.1547 per year). Compared to midsmallvalue fund, the average and standard deviation of funds' return (RMidsmallValue) are 0.8298% (9.9574 per year) and 0.0435 (0.1506 per year).

Different sectors also show variations of returns and standard deviations. Energy sectors provide a lower return than financial sectors with higher standard deviations. REnergy is monthly return by averaging all funds which invest in energy stocks in month t. RFinancial is monthly return by averaging all funds which invest in financial stocks in month t. The average and standard deviation of funds' return (REnergy) are 0.5766% (6.9191 per year) and 0.0575 (0.1992 per year). Compared to financial fund, the average and standard deviation of funds' return (RFinancial) are 0.5776% (6.9308 per year) and 0.0562 (0.1945 per year). We observe that the average return is lower for energy funds than financial funds.

Winner portfolio performs better than loser portfolio with higher standard deviation. RWinner is monthly return by averaging all funds which selected to be in winner portfolio in month t. RLoser is monthly return by averaging all funds which selected to be in loser portfolio in month t. The average and standard deviation of portfolio return (RWinner) are 0.7369% (8.8431 per year) and 0.0459 (0.1591 per year). Compared to loser portfolio, the average and standard deviation of portfolio return (RLoser) are 0.6533% (7.8392 per year) and 0.0443 (0.1535 per year). We observe that the average return is higher for winner funds than loser funds.

**Table 1** Summary of Data statistics

This table shows the main variables used in this research. Return of each type of characteristics are calculated as average monthly return.

| Variable | N | Std. Dev | Mean | Min | Max | Median |
|---|---|---|---|---|---|---|
| RAll (%) | 120 | 4.45 | 0.6539 | -15.51 | 16.26 | 0.607 |
| (Per annum) | | (15.41) | (7.8465) | | | |
| RActive (%) | 120 | 4.43 | 0.6623 | -15.41 | 15.59 | 0.575 |
| (Per annum) | | (15.34) | (7.9473) | | | |
| RPassive (%) | 120 | 4.86 | 0.5718 | -16.41 | 22.82 | 0.642 |
| (Per annum) | | (16.84) | (6.8610) | | | |
| RLarge (%) | 120 | 4.46 | 0.6487 | -15.26 | 16.73 | 0.639 |
| (Per annum) | | (15.45) | (7.7842) | | | |
| RMidsmall (%) | 120 | 4.49 | 0.6846 | -16.95 | 15.57 | 0.960 |
| (Per annum) | | (15.54) | (8.2152) | | | |
| RValue (%) | 120 | 4.41 | 0.6483 | -15.13 | 16.04 | 0.551 |
| (Per annum) | | (15.27) | (7.7790) | | | |
| RGrowth (%) | 120 | 5.26 | 0.3845 | -21.89 | 25.05 | 1.206 |
| (Per annum) | | (18.23) | (4.6144) | | | |
| RLargeValue (%) | 120 | 4.47 | 0.6069 | -15.27 | 17.08 | 0.638 |
| (Per annum) | | (15.47) | (7.2834) | | | |
| RMidsmallValue (%) | 120 | 4.35 | 0.8298 | -14.85 | 14.71 | 0.743 |
| (Per annum) | | (15.06) | (9.9574) | | | |
| REnergy (%) | 120 | 5.75 | 0.5766 | -17.78 | 25.41 | 0.590 |
| (Per annum) | | (19.92) | (6.9191) | | | |
| RFinancial (%) | 120 | 5.62 | 0.5776 | -24.04 | 22.22 | 1.180 |
| (Per annum) | | (19.45) | (6.9308) | | | |
| RLtfrmf (%) | 120 | 4.25 | 0.5765 | -14.76 | 15.51 | 0.500 |
| (Per annum) | | (14.72) | (6.9184) | | | |
| RWinner (%) | 120 | 4.59 | 0.7369 | -16.12 | 16.25 | 0.800 |
| (Per annum) | | (15.91) | (8.8431) | | | |
| RLoser (%) | 120 | 4.43 | 0.6533 | -16.42 | 14.42 | 0.464 |
| (Per annum) | | (15.35) | (7.8392) | | | |

Table 2 present the return during summer period of May to October and return during winter period of November to April. All types of characteristics seem to have higher winter months return than summer months return. We could observe from the positive excess winter return which calculate by return during November to April minus return during May to October. Consistent with other studies which investigate this seasonal anomaly including Bouman and Jacobsen (2002), this indicates that Halloween effect is present in mutual funds market. Mean returns of Passive funds and energy funds during May to October is -0.01% and -0.17%. This indicates that Passive funds and energy funds are likely to have a large magnitude of Halloween effect.

Figure 2 and Figure 3 display return of each characteristic of funds in each month. It is interesting to observe that the highest average monthly return for every type of funds except financial funds is April. Every type of funds exhibits average return of more than 2.5% in April. People may have a high expectation for the quarter 1 performance and would like to receive dividend. Moreover, the lowest average monthly return for our data is May. Possible explanations can be that many stocks pay dividend during this month. Therefore, stock price decreases to reflect the dividend payout. Investors can also forecast the performance of remaining quarter, so trading volume becomes lower. It is also seeming that investors widely known this old market wisdom of Sell in May. They would expect this phenomenon to occur every year. This can create a self-fulfilling prophecy proposed by Lloyd et al. (2017) as the cause of Halloween effect. When investors know that the presence of Halloween effect in market, they expect a decrease in price in the beginning of May and would eventually increase in November. Therefore, investors put downward pressure on the market by lower their portfolios exposure in May and come back in November. This will lead to an increase of stocks demand and will push price upwards. This pattern is expected to happen again and again, which lead to self-fulfilling prophecy.

Similar pattern of negative return during December and a notable increased in January can be observed in every type of funds. This can be explained by the optimism cycle suggested by Doeswijk (2008) The optimism cycle hypothesis assumes investors start to anticipate for next calendar year in the 4th quarter of the year and usually are too optimistic about the economic outlook. As the year proceeds, investors become more pessimistic as their outlook reverses around summer break. The negative return in December can be explained by fund flows. Choi (2015) noted that the month with the smallest net cash flows is December and January is the month in which equity funds experience the largest net cash flows. The large net flows in January are attributed to increased purchases, and the small net flows in December are due to increased redemptions.

**Table 2** Summer return (May-October) to Winter return (November-April)

The table shows average monthly summer returns and winter returns of all equity mutual funds and each type of characteristics. Excess winter return is calculated by return during November to April minus return during May to October.

| Variable | May-October | | November-April | | Excess Winter |
|---|---|---|---|---|---|
| | Mean | Std. Dev | Mean | Std. Dev | |
| RAll | 0.14% | 3.81 | 1.18% | 4.99 | 1.04% |
| RActive | 0.15% | 3.81 | 1.18% | 4.95 | 1.03% |
| RPassive | -0.01% | 3.92 | 1.20% | 5.61 | 1.20% |
| RLarge | 0.12% | 3.80 | 1.19% | 5.01 | 1.07% |
| RMidsmall | 0.26% | 3.96 | 1.11% | 4.95 | 0.85% |
| RValue | 0.13% | 3.79 | 1.17% | 4.92 | 1.05% |
| RGrowth | 0.21% | 4.13 | 0.56% | 6.22 | 0.35% |
| RLargeValue | 0.07% | 3.81 | 1.15% | 5.01 | 1.08% |
| RMidsmallValue | 0.33% | 3.79 | 1.33% | 4.82 | 1.01% |
| REnergy | -0.17% | 4.52 | 1.32% | 6.72 | 1.49% |
| RFinancial | 0.05% | 4.87 | 1.10% | 6.27 | 1.05% |
| RLtfrmf | 0.08% | 3.64 | 1.07% | 4.76 | 0.99% |
| RWinner | 0.38% | 3.98 | 1.14% | 5.14 | 0.76% |
| RLoser | 0.16% | 3.89 | 1.17% | 4.90 | 1.00% |

**Figure 2** Average monthly returns of all equity funds in each month

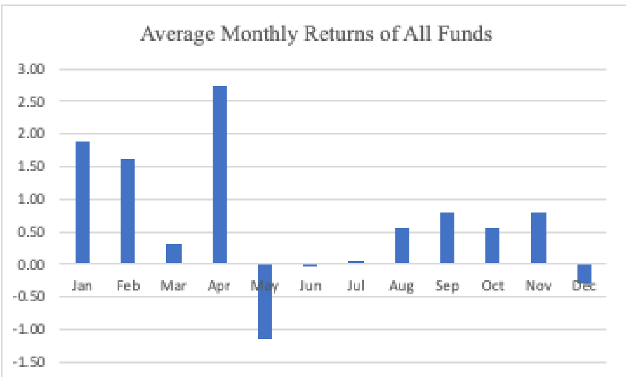
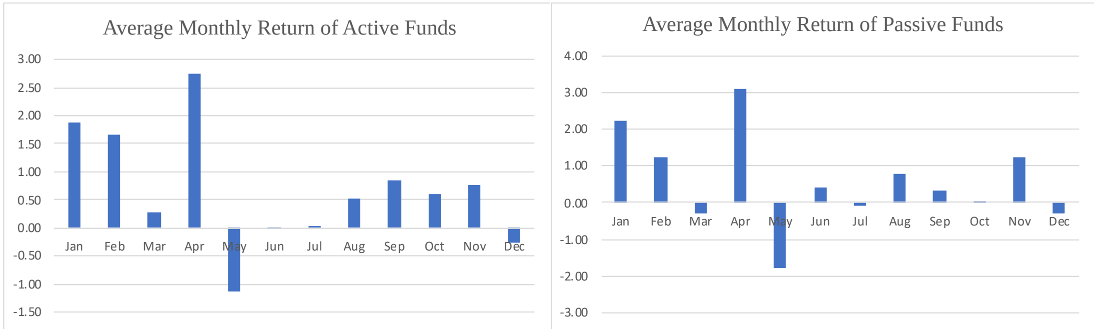
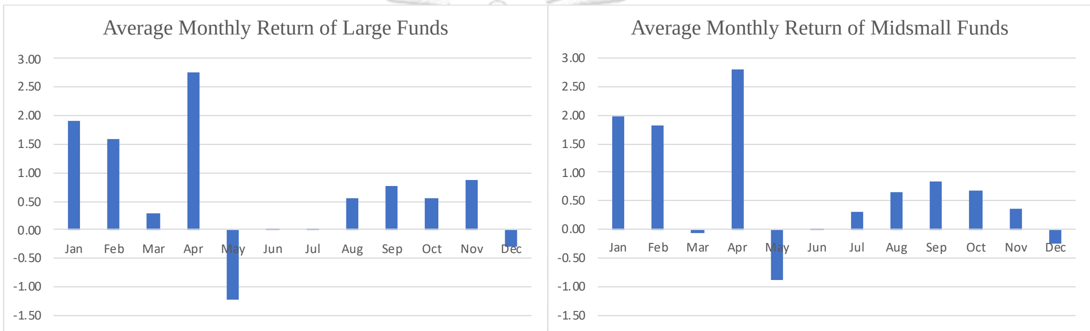


**Figure** 3 Average monthly returns of each funds' characteristic in each month

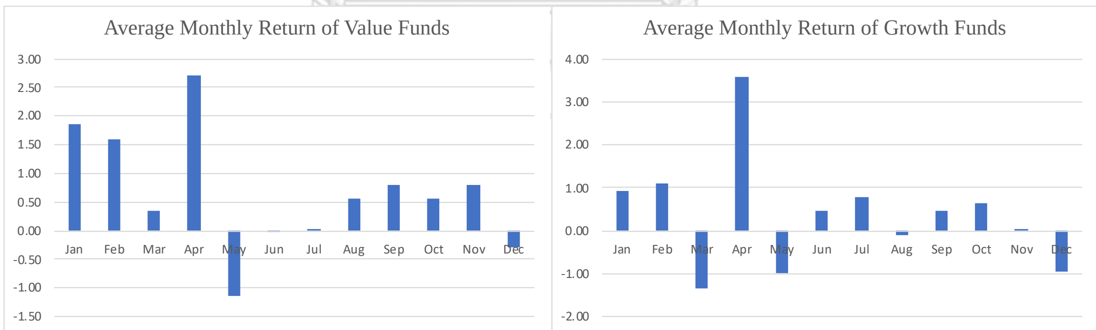
Panel A: Average monthly returns of Active funds and Passive funds



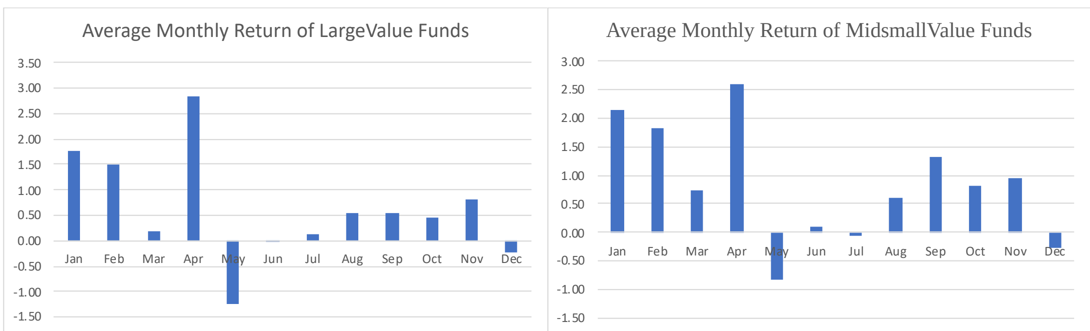

Panel B: Average monthly returns of Large funds and Midsmall funds



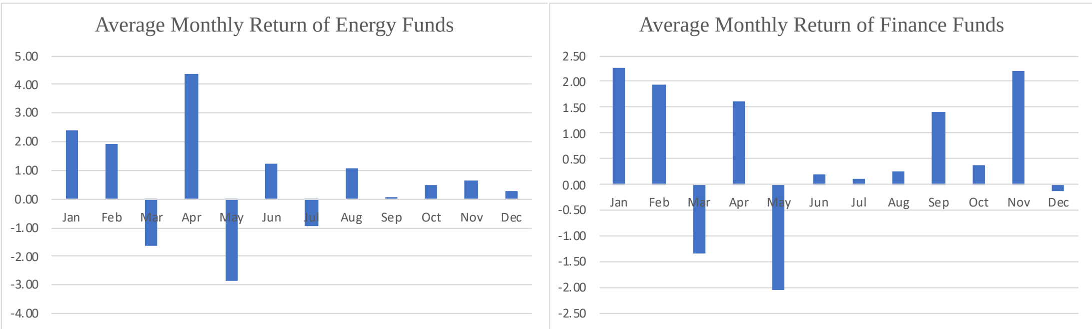

Panel C: Average monthly returns of Value funds and Growth funds



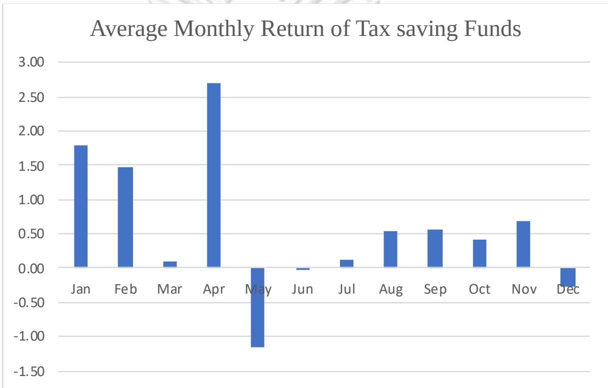

Panel D: Average monthly returns of Largevalue funds and Midsmallvalue funds



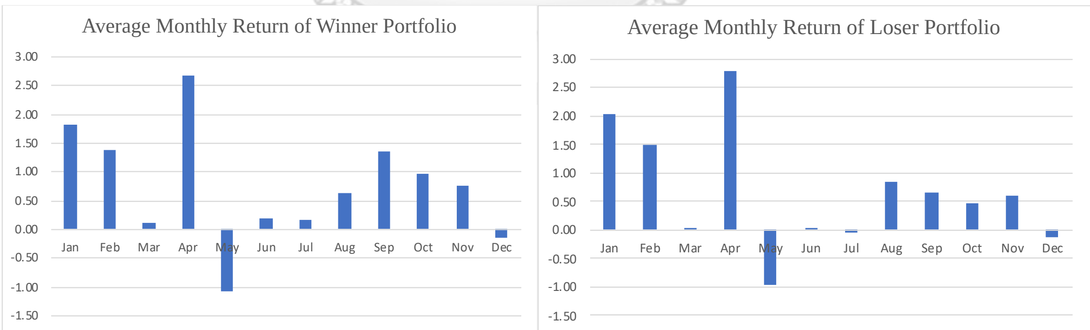
Panel E: Average monthly returns of Sector funds




Panel F: Average monthly returns of Tax saving funds




Panel G: Average monthly returns of Winner and Loser portfolio



In the first part of the analysis, tests for assessing weak form efficiency are carried out using a mix of parametric and non-parametric tests: for assessing whether the series is stationary, the Augmented Dickey Fuller (ADF) test and the Phillips Perron (PP) test. If stationarity is not seen at the level, then differences will be tested.

The ADF test is a parametric test for higher order correlation by assuming that the series (y) follows an AR(p) process with p lagged difference terms and an error term $v_t$. Under the null hypothesis, the series is assumed not to have a Unit Root.

$$\Delta y_t = \alpha y_{t-1} + \chi' \delta + \beta_1 \Delta y_{t-1} + \beta_2 \Delta y_{t-2} + \ldots + \beta_p \Delta y_{t-p} + v_t \qquad (3)$$

where,

- $\delta$ is a vector of deterministic terms (constant, trends)
- $\Delta y_{t-p}$ is used for approximate ARMA structure of errors

The Phillips Perron test (1988) is an alternative way of checking for a Unit Root and uses a non-parametric method of controlling for serial correlation. Under the null the series is assumed not to have a Unit Root.



From Table 3, we can conclude that all average monthly return have no unit root for both Augmented Dickey Fuller Test and Phillips Perron Test. The results show that the absolute value of test statistic of both test are higher than the absolute value of critical value at 5%. Null hypothesis can be rejected at level, which means the return of our variables are stationary. Therefore, we can use these data to analyse the existence of Halloween effect in Thailand equity mutual funds.

**Table 3** Unit Root Tests of ADF and PP

This table present the unit root test for average monthly return of all data samples by Augmented Dickey Fuller Test (ADF) and Philips Perron Test (PP). At level, test statistic of ADF and PP are shown in the table with their critical value at 5%.

| Variables | At Level | | | |
|---|---|---|---|---|
| | ADF | Critical Value 5% | PP | Critical Value 5% |
| RAll | -9.9066 | -3.448 | -9.8557 | -3.448 |
| RActive | -9.8151 | -3.448 | -9.7577 | -3.448 |
| RPassive | -3.9211 | -3.4504 | -10.6176 | -3.448 |
| RLarge | -9.9898 | -3.448 | -9.9459 | -3.448 |
| RMidsmall | -9.4281 | -3.448 | -9.3431 | -3.448 |
| RValue | -9.9071 | -3.448 | -9.8568 | -3.448 |
| RGrowth | -9.5782 | -3.448 | -9.4958 | -3.448 |
| RLargeValue | -10.1194 | -3.448 | -10.0867 | -3.448 |
| RMidsmallValue | -4.0798 | -3.4504 | -9.5597 | -3.448 |
| REnergy | -10.8056 | -3.448 | -11.1301 | -3.448 |
| RFinancial | -9.2385 | -3.448 | -9.2242 | -3.448 |
| RInfrastructure | -10.0290 | -3.448 | -10.0235 | -3.448 |
| RLtfrmf | -10.0408 | -3.448 | -10.0018 | -3.448 |

Table 4 reports the statistic data of market portfolio by using CAPM, Fama and French 3 factor model and Carhart 4 factor model. RMkt is the average passive fund total return from 2012 to 2021 which equals to 0.57% per month or 6.86% per annum. SMB is the size factor calculated by small portfolio minus big portfolio. The small portfolio refers to small market capitalization stock and big portfolio refers to large market capitalization stock which equals to 0% per month or 0.02% per annum. HML is the value factor calculated by high portfolio minus low portfolio which high portfolio refers to high book value to market capitalization stock and low portfolio refers to low book value to market capitalization stock. HML equals to -0.28% per month or -3.33% per annum. The conclusion from this statistic data indicates small portfolio performs better than big portfolio. It also indicates that low portfolio performs better than high portfolio. UMD is momentum factor which equals to 6.13% per month or 73.56% per annum. This means the momentum portfolio performs well by long past winners and short past losers.

**Table 4** Market Portfolio Return

The table reports the statistic data of market portfolio according to the Carhart 4 factor model. RMkt is passive funds total return from 2012 to 2021. SMB is size factor calculated by small portfolio which refers to small market capitalization stock minus big portfolio which refers to big market capitalization stock. HML is value factor calculated by high portfolio which refers to high book value to market stock minus low portfolio which refers to low book value to market stock. UMD is momentum factor which compute by up portfolio minus down portfolio. The portfolio formed from a long position in past winners and a short position in past losers.

| Variable | Std. Dev | Mean |
|---|---|---|
| RMkt | 0.049 | 0.57% |
| (Per annum) | 0.168 | 6.86% |
| SMB | 0.031 | 0.00% |
| (Per annum) | 0.107 | 0.02% |
| HML | 0.035 | -0.28% |
| (Per annum) | 0.120 | -3.33% |
| UMD | 0.049 | 6.13% |
| (Per annum) | 0.169 | 73.56% |

# CHAPTER 4

# Methodology

## 4.1 Halloween effect in Thai equity mutual funds

In order to test objective 1, we will first use Bouman and Jacobsen (2002)'s model using OLS regression similar to the mainstream researches to identify the occurrence of Halloween effect in Thai equity mutual funds. $r_t$ for objective 1 will be the average monthly return of all equity funds in the data sample. We also add $\mathrm{Covid_t}$ as a control variable during Covid period in which returns highly fluctuate from January to March 2020.

$$r_t = \mu + \alpha_1 Hal_t + \alpha_2 Covid_t + \varepsilon_t \quad (4)$$

where,

- $r_t$ is average monthly return of all equity funds in month t
- $\mu$ is average return for summer period (May to October)
- $\alpha_1$ is different of average returns for winter and summer months
- $Hal_t$ is Halloween dummy, equals to 1 during winter period of November to April, and equal to 0 during summer period of May to October
- $Covid_t$ is Covid dummy, equals to 1 during January to March 2020 and equal to 0 in other periods.

We will also use exponential GARCH (EGARCH) model proposed by Nelson (1991) for equation 4's residuals to allow for asymmetric shock to volatility (Lean (2011); Zhang and Jacobsen (2021). The conditional variance of future asset prices will not follow a changes in prices symmetrically. It can be described as the increase of the price X% has a different influence on future volatility to the decrease of the price X% today. Nelson (1991) shows that the volatility of the next day of the US stock market will be influenced more by a decrease in the market than an increase, with the same magnitude. Moreover, the forecasts of the conditional variance are guaranteed to be nonnegative, even if the parameters are negative. Therefore, there is no need to impose any non-negativity restrictions on the parameters. As documented by many studies that financial data shows asymmetric behavior which is bad news tend to contribute to the increase of volatility than good news in return of equity. This known as leverage effect, it implies that volatility is likely to fall as returns rise and vice versa. EGARCH (1,1) can be written as

$$r_t = \mu + \alpha_1 Hal_t + \alpha_2 Covid_t + \varepsilon_t$$

$$logh_t = \omega + \beta \left|\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right| + \alpha \frac{\epsilon_{t-1}}{\sigma_{t-1}} + \gamma \log(\sigma_{t-1}^2) + \delta Covid_t \qquad (5)$$

where $logh_t$ represents log of conditional variance. $\beta$ is arch term which shows the relationship between past and current variance in absolute term. $\alpha$ is leverage effect which exhibits relationship of past return volatility to future return volatility. The presence of leverage effects can be known by testing the hypothesis of $\alpha > 0$. If the result found to be $\alpha \neq 0$, the impact is asymmetric in the conditional volatility. If $\alpha < 0$ implies that bad news in the market will increase the volatility more than good news of an equal magnitude. $\gamma$ is garch term which displays the persistence of past volatility and whether it helps to predict future volatility.



In presence of Halloween effect in Thai equity mutual funds, the estimate of $\alpha_1$ should be statistically different to zero. $\alpha_1$ also represent the size of Halloween effect.

### 4.2 Halloween effect in different characteristic of Thai equity mutual funds

Due to the significant role of January effect in size and book-to-market anomaly documented by Jacobsen et al. (2005), we exclude January dummy and use Bouman and Jacobsen (2002)'s model. Because Halloween effect may concentrate in particular types of mutual funds' characteristics, we further investigate the micro perspective of this effect.

In order to test objective 2, we investigate the relationship between Halloween effect in 11 different characteristics, namely active funds, passive funds, value funds, growth funds, large-cap funds, mid and small-cap funds, largevalue funds, midsmallvalue funds, sector funds (energy and financial) and tax saving funds. We will use regression model (4) and (5) to test the presence of Halloween effect in different characteristic of mutual funds. $r_t$ in equation (4) and (5) for this objective will be defined as average monthly return of each fund characteristic in month t. Comparing the different in presence of Halloween effect, the estimate of $\alpha_1$ should be statistically different to zero. Also, we will look at the magnitude of $\alpha_1$. As $\alpha_1$ represents the size of Halloween effect, $\alpha_1$ should have a larger size for a characteristic of fund with more Halloween effect. For example, if Halloween effect is present more in midsmall than large-cap funds, we would expect bigger size of $\alpha_1$ in midsmall than large-cap fund. Similar to active more than passive funds, value than growth fund, we would expect bigger size of $\alpha_1$ in active than passive fund and value than growth fund. For different sectors, we would expect different size of $\alpha_1$. (Hypothesis 2A,B,C,D)

**4.2.1 Rotation Strategy**

With large different in summer and winter returns across US sectors and industries, Jacobsen and Visaltanachoti (2009)'s sector rotation strategy works when investors hold portfolios which focus on production-related sectors (*Construction, Steel* and *Machine*) in winter and invest in portfolios consumer-oriented sectors focused with short lifespans products (*Food*, *Consumer,* and *Utilities*) in summer. Their evidence of US sectors and industries shown that defensive consumer-oriented sectors have no strong Halloween effect and procyclical sectors includes production and raw material have a strong effect. Specifically, during summer period, consumer-oriented sectors outperform the market index and production-related sectors beat market index in winter.

Similarly, if occurrence of Halloween effect varies across mutual funds' characteristics, we can create rotation strategy which will based on different characteristics of within the same group switch in and out between winter and summer months. This strategy is when investor have a position in a fund characteristic with most significant in Halloween effect during winter months from November to April and invest in a fund characteristic with no or least significant during summer months from May to October. (Hypothesis 2E)

We test the significant of Halloween effect by using Single Index model. However, due to similar reasons of the strong relation between January effect and size and book-to-market effect, we do not assign January to be the control variable of Halloween effect.

$$r_t^s - r_t^f = \mu + \beta\left(r_t^m - r_t^f\right) + \varepsilon_t \qquad (6)$$

where,

- $r_t^s - r_t^f$ is excess strategy return
- $r_t^m - r_t^f$ is excess market return



Fama French Three factor model[4]:

$$r_t^s - r_t^f = \mu + \beta\left(r_t^m - r_t^f\right) + sSMB_t + hHML_t + \varepsilon_t^s \qquad (7)$$

where,

- $SMB_t$ is size premium sorted by market capitalization
  SMB is the difference between small market capitalization portfolio (small stock) minus big market capitalization portfolio (big stock).
- $HML_t$ is value premium

[4] See Fama and French (1993)

$HML$ is the difference between High BTM portfolio (value stock) minus Low BTM portfolio (growth stock).

Carhart Four factor Model:

$$r_t^s - r_t^f = \mu + \beta\left(r_t^m - r_t^f\right) + sSMB_t + hHML_t + uUMD_t + \varepsilon_t^s \quad (8)$$

- $UMD_t$ is momentum factor

$UMD$ is a portfolio formed from a long position in past winners and a short position in past losers.

### 4.2.2 Buy-and-Hold Strategy

Buy-and Hold Strategy is when investors buy the portfolio benchmark and hold their equity position from 2012 until the end of investment period in 2021. The portfolio benchmark used in this study will be Passive funds Total Return.

## 4.3 Extension of Halloween strategy compared to Conventional Momentum Strategy



### 4.3.1 Modified Momentum Strategy



In this section, we extend the conventional long-short momentum strategy and incoperate with Halloween effect to enhance the performance of the strategy. If modified momentum strategy do outperform conventional momentum strategy, investors could follow this strategy and do market timing of the best periods to buy or sell equity mutual funds and get a better return to beat the market. Evidence from Bhootra (2019)'s finding reveals that modified momentum strategy give better return and and sharpe ratio comparing this strategy to the conventional momentum strategy. They proposed a modified momentum strategy which is to long winner stocks in winter, and long winner and short loser stocks in summer. They found that both winner and loser momentum portfolios from US stock market perform well in winter period of November to April than summer period of May to October. Specifically, momentum winners and losers have higher return in winter months than summer months, but momentum losers earn negative returns in most of summer months.

Therefore, for objective 3, we will investigate modified momentum strategy whether it beats the conventional momentum strategy by using all Thai equity funds data. Similar to Bhootra (2019), the winner portfolio are identified as funds in top 10 percent of cumulative returns over months $t$-6 to $t$-1 at the beginning of each month $t$ and the loser portfolios are identified as funds in bottom 10 percent of cumulative returns. For the modified momentum portfolio, we construct a long portfolio of winner funds and a short portfolio of loser funds and compare returns of each portfolio during winter period of November to April and during summer period of May to October. We test the significant of Halloween effect of winner portfolio, loser portfolio and winner-loser portfolio's return with equation (4) and (5). In this case, $r_t$ will be portfolio return. In presence of Halloween effect in winner portfolio, loser portfolio and winner-loser portfolio, the estimate of $\alpha_1$ should be statistically different to zero. (Hypothesis 3)

In order to know whether the significant of return will be different after include Fama French 2 factors, SMB and HML and after include another factor, UMD. Therefore, we test the significant of the winner and loser portfolio returns by these three models: CAPM, Fama French Three factor model, Carhart Four factor model (Bhootra, 2019).

CAPM model:

$$r_t^p - r_t^f = \mu + \beta_p\left(r_t^m - r_t^f\right) + \varepsilon_t^p \quad (9)$$

where,

- $r_t^p$ is return of momentum portfolio in month t

- $r_t^f$ is risk free rate in month t
- $\beta_p$ is beta of the portfolio
- $r_t^m - r_t^f$ is market risk premium

For modified momentum strategy portfolio, $r_t^p$ will be a portfolio return of modified momentum strategy, which is to long portfolio of winner funds in winter, and long portfolio of winners and short portfolio of loser funds in summer. To compute the portfolio return, we average the excess return to winner portfolio during winter months, and winner-loser portfolio return during summer months. For its benchmark, conventional momentum strategy, $r_t^p$ will be portfolio return of conventional momentum strategy, which is to long winners portfolio and short losers portfolio. The return to the conventional long-short momentum strategy will be winner-loser portfolio.

Fama French Three factor model[5]:

$$r_t^p - r_t^f = \mu + \beta\left(r_t^m - r_t^f\right) + sSMB_t + hHML_t + \varepsilon_t^p \qquad (10)$$

where,

- $SMB_t$ is size premium sorted by market capitalization
  SMB is the difference between small market capitalization portfolio (small stock) minus big market capitalization portfolio (big stock).
- $HML_t$ is value premium
  $HML$ is the difference between High BTM portfolio (value stock) minus Low BTM portfolio (growth stock).

Carhart Four factor Model (1997):

[5] See Fama and French (1993)

$$r_t^p - r_t^f = \mu + \beta\left(r_t^m - r_t^f\right) + sSMB_t + hHML_t + uUMD_t + \varepsilon_t^p \quad (11)$$

where,

- $UMD_t$ is momentum factor

$UMD$ is a portfolio formed from a long position in past winners and a short position in past losers.

### 4.3.2 Conventional Momentum Strategy

In order to test for the third objective of whether modified momentum strategy outperform conventional momentum strategy, we construct a long portfolio of winner funds and a short portfolio of loser funds follow Bhootra (2019)'s method. To compare performance with modified momentum strategy, conventional momentum strategy, as a benchmark strategy is to long winner and short losers in similar period. Then, we will test its significance using CAPM (equation 9), Fama French Three factor model (equation 10) and Carhart four factor model (equation 11).

# CHAPTER 5

# Result

## 5.1 Empirical results for Halloween effect in Thai equity mutual funds

The estimation results of Halloween effect are represented in Table 5 by running regression model (4) and (5). If Halloween effect exists in Thailand equity mutual funds, we should see the positive coefficient of Halloween Dummy. With OLS model, result shows that average monthly return of all funds exhibit a positive coefficient $\mathrm{Hal_t}$ of 0.0164 with 10% significance level. This implies that Halloween effect exist in all equity funds in data sample. Moreover, we observe winter return during November to April is higher than summer return during May to October. $\alpha_1$ which denoted as excess winter return is positive. The result is in line with Table 2 which show the positive excess return for winter period 1.04%. Similarly, coefficient of $\mathrm{Hal_t}$ are reported as positive of 0.0128 with 10% significant level using EGARCH model. Compared to OLS model, we observe that $\alpha_1$ is lower by using EGARCH model. Our result is consistent with Kenourgios and Samios (2021) who examine the occurrence of Halloween effect in equity mutual funds market in Europe by using sample of 118 funds with full pricing history between 2008 to 2017. In addition, we could observe the coefficient of $Covid_t$ for both model is statistically significant. This implies that the huge drop in return during the Covid period of January to March 2020 does have a large effect on the return in data sample. Moreover, the variance equation of EGARCH model shows that all types of characteristics seems to have an asymmetric behavior or leverage effect. A negative leverage effect term ($\alpha_k$) implies the existence of the leverage effect in stock returns. In other word, a bad news in the market increases volatility more than an equal magnitude of good news. One possible explanation can be the excess fund flow in winter months. Documented by Wagner et al. (2018), their result show that the Sell in May effect is positive (negative) in years when fund flows during the winter months are higher (lower) than those during the summer months.

**Table 5** Regression result of Halloween effect for all Thailand equity mutual funds

This table presents the result of coefficient of Halloween effect by running ordinary least square (OLS) model

$$r_t = \mu + \alpha_1 Hal_t + \alpha_2 Covid_t + \varepsilon_t$$

and exponential GARCH (EGARCH) model. The regression model are as follow:

$$r_t = \mu + \alpha_1 Hal_t + \alpha_2 Covid_t + \varepsilon_t$$

$$logh_t = \omega + \beta\left|\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right| + \alpha\frac{\epsilon_{t-1}}{\sigma_{t-1}} + \gamma\log(\sigma_{t-1}^2) + \delta Covid_t$$

This model, we use data from all equity mutual funds in Thailand. We defined the dependent variable by returns of all funds and dummy variable represent the Halloween effect. $r_t$ is average monthly return of all funds. $Hal_t$ is equal to 1 during winter period of November to April and equal to 0 during summer period of May to October. In addition, we added $Covid_t$ as control variables during high return fluctuation during crisis during January until March 2020. For OLS model's error term, we utilise Newey and West (1987) autocorrelation and heteroscedasticity consistent standard errors. For EGARCH variables, $\beta_i$ is size effect which shows relationship between past variance and current variance in absolute term. $\alpha_k$is sign effect or leverage effect which shows relationship of past return volatility to future return volatility. $\gamma_i$ is garch term. Value in parenthesis indicates t-value of coefficient. Significant level at 1%, 5% and 10% are denoted as ***,** and * respectively.

| | Variable | OLS | EGARCH |
|---|---|---|---|
| **All** | $\mu$ | 0.0013 | 0.0025 |
| | | (0.2581) | (0.5076) |
| | $Hal_t$ | 0.0164* | 0.0128* |
| | | (1.8768) | (1.8052) |
| | $Covid_t$ | -0.1185*** | -0.0947** |
| | | (-6.1520) | (-2.0062) |
| | $\omega$ | | -3.2331 |
| | | | (-1.594) |
| | $\beta$ | | 0.1238 |
| | | | (0.4576) |
| | $\alpha$ | | -0.2582* |
| | | | (-1.8753) |
| | $\gamma$ | | 0.5241* |
| | | | (1.7987) |
| | $Covid_t$ | | 0.69 |
| | | | (0.6759) |
| | Observations | 120 | 120 |
| | R-squared | 0.1838 | 0.1762 |

## 5.2 Empirical results for Halloween effect in different characteristic of Thai equity mutual funds

We further investigate the different magnitude of Halloween effect by looking into different type of characteristics, namely active funds, passive funds, value funds, growth funds, large-cap funds, mid and small-cap funds and sector funds (energy and financial). Similarly, if Halloween effect exist in different types of characteristics, we should observe a positive coefficient of Halloween dummy. If size of Halloween effect varies across different characteristics of mutual funds, we should observe a positive and significant with different magnitude of coefficient.

Table 6-11 present regression result of Halloween effect in different characteristics. We observe the variation of coefficient $Hal_t$ in different characteristics with some are statistically significant in both OLS and EGARCH model. Result from Table 6 shows that large-cap funds and midsmall-cap funds exhibit a positive coefficient for both OLS and EGARCH model. $\alpha_1$ for large-cap funds and midsmall-cap funds is 0.0167 and 0.015 using OLS model. They both report positive coefficient $Hal_t$ at 10% significant level. However, only large-cap funds exhibit a positive Halloween dummy coefficient of 0.0132 with 10% significance level for EGARCH model. This means that Halloween effect appears in both funds in OLS model. We also observe magnitude of Halloween effect is larger in large funds than midsmall funds. The result are inconsistent with Dzhabarov and Ziemba (2010) who investigated S&P 500 stock index as a proxy for large-cap stocks and Russell 2000 stock index as a proxy for small-cap stocks. However, Wagner et al. (2018) claimed a strong winter-summer seasonality in mutual fund flows that is present across all investment styles. In line with Table 2, excess winter return for large cap funds is higher than midsmall cap funds of 0.22%. We can explain by liquidity of different capitalizations in each type of funds. As midsmall cap stocks have lower liquidity than large cap stocks, large cap funds return can be affected by the effect of Halloween more than midsmall cap funds.

**Table 6** Regression result of Halloween effect for Large cap funds and Midsmall cap funds

This table presents the result of coefficient of Halloween effect by running ordinary least square (OLS) model

$$r_t = \mu + \alpha_1 Hal_t + \alpha_2 Covid_t + \varepsilon_t$$

and exponential GARCH (EGARCH) model. The regression model are as follow:

$$r_t = \mu + \alpha_1 Hal_t + \alpha_2 Covid_t + \varepsilon_t$$

$$logh_t = \omega + \beta \left|\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right| + \alpha \frac{\epsilon_{t-1}}{\sigma_{t-1}} + \gamma \log(\sigma_{t-1}^2) + \delta Covid_t$$

This model, we use data from all equity mutual funds and separate into different capitalization in Thailand. We defined the dependent variable by returns of large and midsmall cap funds and dummy variable represent the Halloween effect. $r_t$ is average monthly return of each type of funds. $Hal_t$ is equal to 1 during winter period of November to April and equal to 0 during summer period of May to October. In addition, we added $Covid_t$ as control variables during high return fluctuation during crisis during January until March 2020. For OLS model's error term, we utilise Newey and West (1987) autocorrelation and heteroscedasticity consistent standard errors. For EGARCH variables, $\beta_i$ is size effect which shows relationship between past variance and current variance in absolute term. $\alpha_k$is sign effect or leverage effect which shows relationship of past return volatility to future return volatility. $\gamma_i$ is garch term. Value in parenthesis indicates t-value of coefficient. Significant level at 1%, 5% and 10% are denoted as ***,** and * respectively.

| Variable | Large | | Midsmall | |
|---|---|---|---|---|
| | OLS | EGARCH | OLS | EGARCH |
| $\mu$ | 0.0011 | 0.0022 | 0.0024 | 0.0035 |
| | (0.2196) | (0.4393) | (0.4686) | (0.7436) |
| $Hal_t$ | 0.0167* | 0.0132* | 0.015* | 0.0117 |
| | (1.8935) | (1.8673) | (1.7290) | (1.6302) |
| $Covid_t$ | -0.1177*** | -0.0951** | -0.1232*** | -0.0957 |
| | (-6.1641) | (-2.1067) | (-6.0400) | (-1.4635) |
| | | | | |
| $\omega$ | | -3.2841 | | -2.8275 |
| | | (-1.5935) | | (-1.6076) |
| $\beta$ | | 0.1165 | | 0.1364 |
| | | (0.4395) | | (0.4841) |
| $\alpha$ | | -0.2663* | | -0.2035* |
| | | (-1.8914) | | (-1.6812) |
| $\gamma$ | | 0.5147* | | 0.5879** |
| | | (1.7329) | | (2.3223) |
| $Covid_t$ | | 0.6485 | | 0.8839 |
| | | (0.6243) | | (0.9406) |
| | | | | |
| Observations | 120 | 120 | 120 | 120 |
| R-squared | 0.1815 | 0.1747 | 0.1904 | 0.1809 |

The result of OLS and EGARCH regression model for value funds and growth funds are displayed in Table 7. $\alpha_1$ signify the excess winter return. Coefficient of Halloween effect ($\alpha_1$) for funds that invested in high book-to-market stocks is 0.0163 for OLS model and 0.0121 for EGARCH model. In line with Table 2, we observe return during November to April is higher than return during May to October. While value funds exhibit a positive coefficient with 10% significance level respectively, growth funds are not statistically significant in both model. Our result are consistent with O'Brien et al. (2010) who found this positive relationship between average returns and book-to-market ratio in Australian stock market. Value funds also has a larger size of Halloween effect than growth funds. One of the possible reasons is dividend payment. While value stocks tend to be mature firms which payout dividend, growth stocks tend to utilize their profit as reinvestment for future projects. Therefore, investors who hold mutual fund unit in value funds may decrease their holdings during the ex-dividend month. However, for those who do not want dividend, they tend to invest in growth stocks and profit from capital gain only. Therefore, investors tend to continue to have position for funds that invest in growth stocks for a long period. Choi (2015) also suggests that if investors decide to buy or sell mutual funds, following stock market performance, the seasonal patterns in cash flows to mutual funds are simply a reflection of the seasonal patterns in stock market returns.

**Table 7** Regression result of Halloween effect for Value funds and Growth funds

This table presents the result of coefficient of Halloween effect by running ordinary least square (OLS) model

$$r_t = \mu + \alpha_1 Hal_t + \alpha_2 Covid_t + \varepsilon_t$$

and exponential GARCH (EGARCH) model. The regression model are as follow:

$$r_t = \mu + \alpha_1 Hal_t + \alpha_2 Covid_t + \varepsilon_t$$

$$logh_t = \omega + \beta \left|\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right| + \alpha \frac{\epsilon_{t-1}}{\sigma_{t-1}} + \gamma \log(\sigma_{t-1}^2) + \delta Covid_t$$

This model, we use data from all equity mutual funds and separate into different book-to-market in Thailand. We defined the dependent variable by returns of value and growth funds and dummy variable represent the Halloween effect. $r_t$ is average monthly return of each type of funds. $Hal_t$ is equal to 1 during winter period of November to April and equal to 0 during summer period of May to October. In addition, we added $Covid_t$ as control variables during high return fluctuation during crisis during January until March 2020. For OLS model's error term, we utilise Newey and West (1987) autocorrelation and heteroscedasticity consistent standard errors. For EGARCH variables, $\beta_i$ is size effect which shows relationship between past variance and current variance in absolute term. $\alpha_k$is sign effect or leverage effect which shows relationship of past return volatility to future return volatility. $\gamma_i$ is garch term. Value in parenthesis indicates t-value of coefficient. Significant level at 1%, 5% and 10% are denoted as ***,** and * respectively.

| Variable | Value | | Growth | |
|---|---|---|---|---|
| | OLS | EGARCH | OLS | EGARCH |
| $\mu$ | 0.0013 | 0.0026 | 0.0021 | 0.0005 |
| | (0.2517) | (0.5252) | (0.4163) | (0.0927) |
| $Hal_t$ | 0.0163* | 0.0121* | 0.0115 | 0.0109 |
| | (1.8638) | (1.6654) | (1.2495) | (1.2110) |
| $Covid_t$ | -0.1163*** | -0.0920** | -0.1593*** | -0.1425 |
| | (-6.1922) | (-2.0008) | (-7.1346) | (-1.538) |
| $\omega$ | | -3.1588 | | -6.775*** |
| | | (-1.5248) | | (-3.6383) |
| $\beta$ | | 0.1582 | | 0.4328* |
| | | (0.5884) | | (1.7293) |
| $\alpha$ | | -0.2413* | | -0.2466* |
| | | (-1.7625) | | (-1.3371) |
| $\gamma$ | | 0.5402* | | -0.0216 |
| | | (1.8183) | | (-0.0717) |
| $Covid_t$ | | 0.6674 | | -0.3015 |
| | | (0.6572) | | (-0.0963) |
| Observations | 120 | 120 | 120 | 120 |
| R-squared | 0.181 | 0.1725 | 0.2204 | 0.2173 |

Table 8 presents regression result for Halloween effect in mix characteristics of capitalization and book-to-market. We detect this phenomenon in both funds which invest in stocks with the characteristics of large cap and value and stocks with the characteristics of midsmall cap and value. Result shows that $\alpha_1$ are positive for both OLS and EGARCH model. $\alpha_1$ indicates the excess return during winter months (November to April) compared to summer months (May to October). $\alpha_1$ for largevalue funds and midsmallvalue funds is 0.0166 and 0.0158 in OLS model. In line with Table 2, average monthly return of largevalue funds is higher than midsmallvalue funds of 0.07%. Moreover, coefficient $Hal_t$ of largevalue and midsmallvalue funds are positive and significant at 10% level in OLS model. This implies that Halloween effect exist in both largevalue and midsmallvalue funds. By looking at the magnitude of coefficient $Hal_t$, we observe that Halloween effect are stronger in largevalue than midsmallvalue funds.

**Table 8** Regression result of Halloween effect for Largevalue funds and Midsmallvalue funds

This table presents the result of coefficient of Halloween effect by running ordinary least square (OLS) model

$$r_t = \mu + \alpha_1 Hal_t + \alpha_2 Covid_t + \varepsilon_t$$

and exponential GARCH (EGARCH) model. The regression model are as follow:

$$r_t = \mu + \alpha_1 Hal_t + \alpha_2 Covid_t + \varepsilon_t$$

$$logh_t = \omega + \beta \left|\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right| + \alpha \frac{\epsilon_{t-1}}{\sigma_{t-1}} + \gamma \log(\sigma_{t-1}^2) + \delta Covid_t$$

This model, we use data from all equity mutual funds and separate into different capitalization and book-to-market. We defined the dependent variable by returns of value and growth funds and dummy variable represent the Halloween effect. $r_t$ is average monthly return of each type of funds. $Hal_t$ is equal to 1 during winter period of November to April and equal to 0 during summer period of May to October. In addition, we added $Covid_t$ as control variables during high return fluctuation during crisis during January until March 2020. For OLS model's error term, we utilise Newey and West (1987) autocorrelation and heteroscedasticity consistent standard errors. For EGARCH variables, $\beta_i$ is size effect which shows relationship between past variance and current variance in absolute term. $\alpha_k$is sign effect or leverage effect which shows relationship of past return volatility to future return volatility. $\gamma_i$ is garch term. Value in parenthesis indicates t-value of coefficient. Significant level at 1%, 5% and 10% are denoted as ***,** and * respectively.

| Variable | LargeValue | | MidsmallValue | |
|---|---|---|---|---|
| | OLS | EGARCH | OLS | EGARCH |
| $\mu$ | 0.0007 | 0.0034 | 0.0033 | 0.005 |
| | (0.1411) | (0.6748) | (0.6390) | (1.1676) |
| $Hal_t$ | 0.0166* | 0.0088 | 0.0158* | 0.0051 |
| | (1.9018) | (1.2481) | (1.8001) | (0.7563) |
| $Covid_t$ | -0.1180*** | -0.0923** | -0.1139*** | -0.0823** |
| | (-6.3203) | (-2.5541) | (-5.9412) | (-2.1593) |
| $\omega$ | | -3.3951* | | -0.3498 |
| | | (-1.9107) | | (-1.1121) |
| $\beta$ | | 0.1341 | | 0.0895 |
| | | (0.5237) | | (0.8272) |
| $\alpha$ | | -0.3396** | | 0.0217 |
| | | (-2.2001) | | (0.3032) |
| $\gamma$ | | 0.5027** | | 0.9612*** |
| | | (1.9736) | | (24.4245) |
| $Covid_t$ | | 0.5727 | | 0.7120** |
| | | (0.5496) | | (2.3657) |
| Observations | 116 | 120 | 120 | 120 |
| R-squared | 0.1817 | 0.1659 | 0.178 | 0.1516 |

The occurrence of Halloween effect in active and passive funds are displayed in Table 9. Both coefficient $Hal_t$ ($\alpha_1$) for both OLS and EGARCH model. $\alpha_1$ indicates the excess return during winter months (November to April) compared to summer months (May to October). $\alpha_1$ for active funds and passive funds is 0.0121 and 0.0138 in EGARCH model. In line with Table 2, average monthly return of active funds is lower than passive funds of 0.17%. While Active funds exhibit a positive coefficient with 10% significance level, passive fund exhibit a positive coefficient with 1% significance level in EGARCH model. This implies that Halloween effect exist in both active and passive fund. Lower mean average return during summer ($\mu_t$) than winter periods ($Hal_t$) in passive funds return can signify that investors who have position in passive funds which invest close to Stock Exchange of Thailand (SET) Index also take this effect into consideration. As announcement of dividend payment, this results in stock market slump from first week of May.

By looking at the magnitude of coefficient of $Hal_t$ ($\alpha_1$) , we found that passive funds have a stronger Halloween effect than active funds. By comparing the summer months return, we could observe that active funds have a higher return than passive funds. Fund managers that actively managed equity mutual funds in Thailand may take caution of Halloween effect. However, they have their investment strategy to generate a good performance during summer months. Kenourgios and Samios (2021) suggests that European fund manager pay no attention to Halloween effect. Their findings show that 4 out of 5 funds remain unchanged or an increasing market performance of each funds during summer period. Therefore, those who invest in active funds are not as worry about Halloween effect than those who invest in passive funds. As passive funds' investors acknowledge that Halloween effect occur during May to October in SET, they decrease their position to avoid the slump in stock return which would effect the return of passive funds. Therefore, Halloween effect is stronger in passive funds.

**Table 9** Regression result of Halloween effect for Active funds and Passive funds

This table presents the result of coefficient of Halloween effect by running ordinary least square (OLS) model

$$r_t = \mu + \alpha_1 Hal_t + \alpha_2 Covid_t + \varepsilon_t$$

and exponential GARCH (EGARCH) model. The regression model are as follow:

$$r_t = \mu + \alpha_1 Hal_t + \alpha_2 Covid_t + \varepsilon_t$$

$$logh_t = \omega + \beta \left|\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right| + \alpha \frac{\epsilon_{t-1}}{\sigma_{t-1}} + \gamma \log(\sigma_{t-1}^2) + \delta Covid_t$$

This model, we use data from all equity mutual funds and separate into different investment style. We defined the dependent variable by returns of active and passive funds and dummy variable represent the Halloween effect. $r_t$ is average monthly return of each type of funds. $Hal_t$ is equal to 1 during winter period of November to April and equal to 0 during summer period of May to October. In addition, we added $Covid_t$ as control variables during high return fluctuation during crisis during January until March 2020. For OLS model's error term, we utilise Newey and West (1987) autocorrelation and heteroscedasticity consistent standard errors. For EGARCH variables, $\beta_i$ is size effect which shows relationship between past variance and current variance in absolute term. $\alpha_k$is sign effect or leverage effect which shows relationship of past return volatility to future return volatility. $\gamma_i$ is garch term. Value in parenthesis indicates t-value of coefficient. Significant level at 1%, 5% and 10% are denoted as ***,** and * respectively.

| Variable | Active | | Passive | |
|---|---|---|---|---|
| | OLS | EGARCH | OLS | EGARCH |
| $\mu$ | 0.0015 | 0.0028 | -0.0006 | -0.0005 |
| | (0.2944) | (0.5597) | (-0.1141) | (-0.1037) |
| $Hal_t$ | 0.0162* | 0.0121* | 0.019** | 0.0138*** |
| | (1.8404) | (1.6475) | (2.0981) | (2.6867) |
| $Covid_t$ | -0.1175*** | -0.0921* | -0.1279*** | -0.1133* |
| | (-6.1209) | (-1.9329) | (-6.3847) | (-1.7585) |
| $\omega$ | | -3.198 | | -2.0537 |
| | | (-1.5405) | | (-1.6364) |
| $\beta$ | | 0.1649 | | -0.2053 |
| | | (0.6114) | | (-1.0178) |
| $\alpha$ | | -0.2321* | | -0.3628*** |
| | | (-1.7046) | | (-3.5086) |
| $\gamma$ | | 0.5344* | | 0.6605*** |
| | | (1.7909) | | (3.6344) |
| $Covid_t$ | | 0.706 | | 0.5993 |
| | | (0.6868) | | (0.8341) |
| Observations | 120 | 120 | 120 | 120 |
| R-squared | 0.1822 | 0.1732 | 0.1826 | 0.1763 |

Table 10 present regression result of Halloween effect in sector focused funds, namely energy and financial funds. We detect this phenomenon in both funds. Result shows that $\alpha_1$ are positive for both OLS and EGARCH model. $\alpha_1$ indicates the excess return during winter months (November to April) compared to summer months (May to October). $\alpha_1$ for energy funds and financial funds is 0.0214 and 0.0136 in OLS model. In line with Table 2, average monthly return of energy funds is higher than financial funds of 0.44%. Moreover, coefficient $Hal_t$ of energy funds and financial funds are positive and significant at 5% level and 10%level in OLS model. This implies that Halloween effect exist in both energy and financial funds. By looking at the magnitude of coefficient $Hal_t$, we observe that Halloween effect are stronger in energy than financial funds. Our results are consistent with evidence from Jacobsen and Visaltanachoti (2009) in US 17 sector and 49 industries stock indices reveal that different sector funds might have different strength of Halloween effect.

**Table 10** Regression result of Halloween effect for Sector funds

This table presents the result of coefficient of Halloween effect by running ordinary least square (OLS) model

$$r_t = \mu + \alpha_1 Hal_t + \alpha_2 Covid_t + \varepsilon_t$$

and exponential GARCH (EGARCH) model. The regression model are as follow:

$$r_t = \mu + \alpha_1 Hal_t + \alpha_2 Covid_t + \varepsilon_t$$

$$logh_t = \omega + \beta \left|\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right| + \alpha \frac{\epsilon_{t-1}}{\sigma_{t-1}} + \gamma \log(\sigma_{t-1}^2) + \delta Covid_t$$

This model, we use data from sector focused funds. We defined the dependent variable by returns of energy and financial funds and dummy variable represent the Halloween effect. $r_t$ is average monthly return of each type of funds. $Hal_t$ is equal to 1 during winter period of November to April and equal to 0 during summer period of May to October. In addition, we added $Covid_t$ as control variables during high return fluctuation during crisis during January until March 2020. For OLS model's error term, we utilise Newey and West (1987) autocorrelation and heteroscedasticity consistent standard errors. For EGARCH variables, $\beta_i$ is size effect which shows relationship between past variance and current variance in absolute term. $\alpha_k$is sign effect or leverage effect which shows relationship of past return volatility to future return volatility. $\gamma_i$ is garch term. Value in parenthesis indicates t-value of coefficient. Significant level at 1%, 5% and 10% are denoted as ***,** and * respectively.

| Variable | Energy | | Financial | |
|---|---|---|---|---|
| | OLS | EGARCH | OLS | EGARCH |
| $\mu$ | -0.0017 | -0.0002 | 0.0005 | 0.0011 |
| | (-0.2968) | (-0.036) | (0.0839) | (0.2078) |
| $Hal_t$ | 0.0214** | 0.0136 | 0.0187* | 0.0083 |
| | (2.0891) | (1.6245) | (1.7210) | (1.0779) |
| $Covid_t$ | -0.1303*** | -0.0879** | -0.1645*** | -0.1279*** |
| | (-5.0962) | (-2.0514) | (-6.2047) | (-3.0569) |
| $\omega$ | | -2.9977*** | | -0.0461 |
| | | (-2.6735) | | (-0.4125) |
| $\beta$ | | 0.2124 | | -0.1514 |
| | | (0.8809) | | (-1.2827) |
| $\alpha$ | | -0.4187** | | 0.0101 |
| | | (-2.4580) | | (0.1654) |
| $\gamma$ | | 0.5351*** | | 0.9732*** |
| | | (3.1309) | | (7.59) |
| $Covid_t$ | | 0.6645 | | 0.4801* |
| | | (0.3801) | | (1.6912) |
| Observations | 120 | 120 | 120 | 120 |
| R-squared | 0.1399 | 0.1237 | 0.2144 | 0.1936 |

Table 11 shows that Halloween effect exist in tax saving funds which includes LTF and RMF. Coefficient $Hal_t$ are positive with 10% significant level. Result shows that $\alpha_1$ are positive for both OLS and EGARCH model. $\alpha_1$ indicates the excess return during winter months (November to April) compared to summer months (May to October). $\alpha_1$ for LTFRMF funds is 0.0156 and 0.0124 in OLS and EGARCH model. One of reasons can be tax benefit. In Thailand, policy requires investors to hold their mutual fund units for a long period and need to invest yearly to be able. People would normally invest at the end or start of the year. Therefore, this could be a reason why average winter return period during November to April for LTF and RMF is higher than summer period. Consistent with Choi (2015), equity funds receive the highest net cash flows in January and the lowest in December. The large net flows in January are attributed to increased purchases, and the small net flows in December are due to increased redemptions. D'Mello et al. (2003) suggests the tax-loss selling hypothesis that there is abnormal selling pressure prior to the year-end for stocks that have experienced large capital losses in the current and prior years. In addition, investors delay realizing capital gain by postponing the sale of capital gain stocks until after the new year.

**Table** 11 Regression result of Halloween effect for Tax saving funds

This table presents the result of coefficient of Halloween effect by running ordinary least square (OLS) model

$$r_t = \mu + \alpha_1 Hal_t + \alpha_2 Covid_t + \varepsilon_t$$

and exponential GARCH (EGARCH) model. The regression model are as follow:

$$r_t = \mu + \alpha_1 Hal_t + \alpha_2 Covid_t + \varepsilon_t$$

$$logh_t = \omega + \beta \left|\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right| + \alpha \frac{\epsilon_{t-1}}{\sigma_{t-1}} + \gamma \log(\sigma_{t-1}^2) + \delta Covid_t$$

This model, we use data from tax saving funds. We defined the dependent variable by returns of Long Term Funds (LTF) and Retirement Mutual Funds (RMF) funds and dummy variable represent the Halloween effect. $r_t$ is average monthly return of LTFRMF funds. $Hal_t$ is equal to 1 during winter period of November to April and equal to 0 during summer period of May to October. In addition, we added $Covid_t$ as control variables during high return fluctuation during crisis during January until March 2020. For OLS model's error term, we utilise Newey and West (1987) autocorrelation and heteroscedasticity consistent standard errors. For EGARCH variables, $\beta_i$ is size effect which shows relationship between past variance and current variance in absolute term. $\alpha_k$is sign effect or leverage effect which shows relationship of past return volatility to future return volatility. $\gamma_i$ is garch term. Value in parenthesis indicates t-value of coefficient. Significant level at 1%, 5% and 10% are denoted as ***,** and * respectively.

| Variable | LTFRMF | |
|---|---|---|
| | OLS | EGARCH |
| $\mu$ | 0.0008 | 0.0017 |
| | (0.1732) | (0.3570) |
| $Hal_t$ | 0.0156* | 0.0124* |
| | (1.8893) | (1.8994) |
| $Covid_t$ | -0.1131*** | -0.0919* |
| | (-6.1194) | (-1.7782) |
| $\omega$ | | -3.1339 |
| | | (-1.4797) |
| $\beta$ | | 0.08 |
| | | (0.31034) |
| $\alpha$ | | -0.2499* |
| | | (-1.9137) |
| $\gamma$ | | 0.5399* |
| | | (1.7881) |
| $Covid_t$ | | 0.7385 |
| | | (0.7332) |
| Observations | 120 | 120 |
| R-squared | 0.1836 | 0.1778 |

### 5.2.1 Empirical results for Rotation Strategy

We create strategy which exploit the different strength of Halloween effect in different type of characteristics. Rotation strategy is formed by choosing the characteristics with the most Halloween effect by comparing at the magnitude of coefficients $Hal_t$ in winter and select the one with lowest or no Halloween effect to invest in summer. Referring to the result from Hypothesis 2A-E, we can conclude that Halloween effect is stronger for passive funds, large-cap funds, value funds, largevalue funds and energy funds. Therefore, we formulate 5 strategies from different type of characteristics as follow.

i. Invest in Passive funds in winter period and Active funds in summer periods.
ii. Invest in Large-cap funds in winter period and Midsmall-cap funds in summer periods.
iii. Invest in Value funds in winter period and Growth funds in summer periods.
iv. Invest in LargeValue funds in winter period and MidsmallValue funds in summer periods.
v. Invest in Energy funds in winter period and Financial funds in summer periods.



According to cumulative returns in Figure 4, we observe that strategy of investing in Large Value funds in winter and investing in Midsmall Value Funds in summer provides the best return among other strategies. In December 2021, the rotation strategy iv generate 2.14% equate to the benchmark portfolio of 1.73%. Compared to the benchmark of passive funds with buy-and-hold strategy, all rotation strategies provide better return. Performance of all rotation strategies are displayed in Table 12. The result shows that rotation strategy of long a fund with characteristics of large-cap and high book-to-market in winter and long a fund with characteristics of midsmall-cap and high book-to-market in summer give the highest return of 0.7352% (or 8.8223% per annum) and lowest standard deviation of 4.4464% (or 15.4026% per annum). We observe that the risk adjusted return for this strategy calculated by Sharpe ratio is the highest of 0.4450 per annum. All rotation strategies also perform better than the benchmark of buy-and-hold strategy with average monthly return of 0.5718% (or 6.8610 per annum) and standard deviation of 4.86% (or 16.84% per annum). This is consistent with cumulative return shown in Figure 4. At the end of the investigated period, on December 2021, the rotation strategy of largevalue/midsmall value give the highest cumulative return compared to other strategies and all rotation strategies outperform the benchmark.

**Figure 4** cumulative returns of rotation strategies compared to the benchmark of buy-and-hold strategy

**Table 12** Rotation Strategies Performance

This table presents the average monthly return, standard deviation and sharpe ratio of rotation strategies. The rotation strategy is to long a fund characteristic with the highest magnitude of Halloween effect in winter and long the one with lowest or no Halloween effect to invest in summer. 5 rotation strategies are shown in this table. i) Active/Passive: invest in passive funds in winter period and active funds in summer periods. ii) Value/Growth: invest in large-cap funds in winter period and midsmall-cap funds in summer periods. iii) Large/Midsmall: invest in value funds in winter period and growth funds in summer periods. iv) LargeValue/MidsmallValue: invest in largevalue funds in winter period and midsmallvalue funds in summer periods. v) Sectors: invest in energy funds in winter period and financial funds in summer periods. The benchmark is buy-and-hold strategy of market portfolio in similar period. The market portfolio is passive funds.

| | | **Average (%)** | **SD (%)** | **Sharpe Ratio** |
|---|---|---|---|---|
| Rotation Strategy | Active / Passive | 0.6743 | 4.8059 | 0.1062 |
| | (Per annum) | 8.0919 | 16.6480 | 0.3679 |
| | Value / Growth | 0.6900 | 4.5519 | 0.1156 |
| | (Per annum) | 8.2796 | 15.7681 | 0.4003 |
| | Large / Midsmall | 0.7164 | 4.5203 | 0.1222 |
| | (Per annum) | 8.5964 | 15.6587 | 0.4233 |
| | LargeValue / MidsmallValue | 0.7352 | 4.4464 | 0.1285 |
| | (Per annum) | 8.8223 | 15.4026 | 0.4450 |
| | Sectors | 0.6876 | 5.8805 | 0.0891 |
| | (Per annum) | 8.2517 | 20.3707 | 0.3085 |
| Buy-and-Hold Strategy | Market Portfolio | 0.5718 | 4.86 | 0.0839 |
| | (Per annum) | 6.8610 | 16.84 | 0.2907 |

Then, we test the excess return of all strategies by CAPM, Fama and French 3 factor model and Carhart 4 factor model. Table 13-15 presents regression result of CAPM. Table 13 shows that all strategy except active/passive and sectors have a positive alpha. Excess return of rotation strategy of LargeValue funds and MidsmallValue funds is 0.008 and statistically significant at 5% level. This implies that this strategy generates abnormal return compared to the market portfolio. This is consistent with the cumulative return in Figure 4 in which the cumulative return of the strategy beat the benchmark. Even though excess return from other strategies is not statistically significant, these strategies still generate a positive abnormal return except for rotation strategy of active/passive and sectors. Regression result of Fama and French 3 factor model from Table 14 shows that excess return of rotation strategy of LargeValue funds and MidsmallValue funds is statistically significant at 5%. The excess return of this strategy is 0.0009. This implies that even after control for value and size effect, this strategy still gives abnormal return. Even though excess return from other strategies is not statistically significant, they still generate a positive abnormal return. Regression result of Carhart 4 factor model from Table 15 shows that excess return of rotation strategy of Large Value funds and Midsmall Value funds is statistically significant at 10%. The excess return of this strategy is 0.0034. Rotation strategy of different investment style of passive and active funds is statistically significant at 5%. The excess return of this strategy is 0.001. This could signify that even after control for excess market return, value effect, size effect and momentum effect, Rotation strategy of Active Passive funds and Large Value Midsmall value still generate abnormal return.

**Table 13** Regression result of Rotation Strategy by CAPM

This table presents the result of rotation strategies by running the ordinary least square regression model. Abnormal returns are estimated using CAPM.

$$r_t^s - r_t^f = \mu + \beta\left(r_t^m - r_t^f\right) + \varepsilon_t$$

$r_t^s$ is the strategy return. $r_t^m$ is the market portfolio which represent by passive funds. Value in parenthesis indicates t-value of coefficient. Significant level at 1%, 5% and 10% are denoted as ***,** and * respectively.

| Variable | Rotation Strategy (CAPM) | | | | |
|---|---|---|---|---|---|
| | **Active / Passive** | **Value / Growth** | **Large / Midsmall** | **LargeValue / MidsmallValue** | **Sectors** |
| Constant | $-7.34 \times 10^{-5}$ | 0.0005 | 0.0006 | 0.0008** | -0.0005 |
| | (-0.0753) | (0.3836) | (1.1031) | (2.3734) | (-0.1852) |
| Market Premium | 1.0542*** | 0.972*** | 1.0079*** | 0.9955*** | 1.1604*** |
| | (48.2326) | (32.9496) | (84.7942) | (125.9442) | (19.7857) |
| Observations | 120 | 120 | 120 | 120 | 120 |
| R-squared | 0.9517 | 0.902 | 0.9839 | 0.9926 | 0.7684 |

**Table 14** Regression result of Rotation Strategy by Fama and French 3 Factor Model
This table presents the result of rotation strategies by running the ordinary least square regression model. Abnormal returns are estimated using Fama and French 3 factor model.

$$r_t^s - r_t^f = \mu + \beta\left(r_t^m - r_t^f\right) + sSMB_t + hHML_t + \varepsilon_t^s$$

$r_t^s$ is the strategy return. $r_t^m$ is the market portfolio which represent by passive funds. Value in parenthesis indicates t-value of coefficient. Significant level at 1%, 5% and 10% are denoted as ***,** and * respectively.

| Variable | Rotation Strategy (Fama and French 3 Factor Model) | | | | |
|---|---|---|---|---|---|
| | **Active / Passive** | **Value / Growth** | **Large / Midsmall** | **LargeValue / MidsmallValue** | **Sectors** |
| Constant | 0.0004 | 0.0002 | 0.0006 | 0.0009** | 0.0008 |
| | (0.4093) | (0.1335) | (1.1214) | (2.5227) | (0.3030) |
| Market Premium | 1.0487*** | 0.9779*** | 1.0071*** | 0.9959*** | 1.1463*** |
| | (49.5183) | (32.8707) | (82.8649) | (124.6234) | (20.2237) |
| SMB | -0.1315*** | 0.1105 | -0.0103 | -0.0074 | -0.3484*** |
| | (-2.7426) | (1.6408) | (-0.3753) | (-0.4072) | (-2.7142) |
| HML | 0.1540*** | -0.1069* | 0.0057 | 0.0215 | 0.4211*** |
| | (3.6523) | (-1.8046) | (0.2356) | (1.3483) | (3.7317) |
| Observations | 120 | 120 | 120 | 120 | 120 |
| R-squared | 0.9567 | 0.9048 | 0.9839 | 0.9928 | 0.7933 |

**Table 15** Regression result of Rotation Strategy by Carhart 4 Factor Model
This table presents the result of rotation strategies by running the ordinary least square regression model. Abnormal returns are estimated using Carhart 4 factor model.

$$r_t^s - r_t^f = \mu + \beta\left(r_t^m - r_t^f\right) + sSMB_t + hHML_t + uUMD_t + \varepsilon_t^s$$

$r_t^s$ is the strategy return. $r_t^m$ is the market portfolio which represent by passive funds. Value in parenthesis indicates t-value of coefficient. Significant level at 1%, 5% and 10% are denoted as ***,** and * respectively.

| Variable | Rotation Strategy (Carhart 4 Factor Model) | | | | |
|---|---|---|---|---|---|
| | **Active / Passive** | **Value / Growth** | **Large / Midsmall** | **LargeValue / MidsmallValue** | **Sectors** |
| Constant | 0.0034** | 0.0004 | 0.0007 | 0.001* | 0.0042 |
| | (2.2634) | (0.1865) | (0.7525) | (1.6898) | (1.0140) |
| Market Premium | 1.0453*** | 0.9776*** | 1.0071*** | 0.9958*** | 1.1425*** |
| | (50.4027) | (32.6553) | (82.3340) | (123.8361) | (20.1234) |
| SMB | -0.1059** | 0.1125 | -0.0098 | -0.0066 | -0.3195** |
| | (-2.2097) | (1.6253) | (-0.3475) | (-0.3572) | (-2.4344) |
| HML | 0.1186*** | -0.1096* | 0.005 | 0.0204 | 0.3812*** |
| | (2.7279) | (-1.7451) | (0.1952) | (1.2124) | (3.2016) |
| UMD | -0.0502** | -0.0038 | -0.001 | -0.0014 | -0.0568 |
| | (-2.5416) | (-0.133) | (-0.0848) | (-0.1868) | (-1.0489) |
| Observations | 120 | 120 | 120 | 120 | 120 |
| R-squared | 0.959 | 0.9048 | 0.9839 | 0.9928 | 0.7953 |

### 5.3 Empirical results for Extension of Halloween strategy compared to Conventional Momentum strategy

Our last objective is to investigate modified momentum strategy to conventional long-short momentum strategy whether it outperforms. We create winner portfolio and loser portfolio and examine for the presence of Halloween effect. In formation period, the portfolios are ranked in descending order on the basis of their returns in the past 6 months at the beginning of each month t. Based on these ranking, funds in top 10 percent are calculating from cumulative returns over months t-6 to t-1 will be identified as the winner portfolios. Funds in bottom 10 percent are calculating from cumulative returns over months t-6 to t-1 will be identified as the loser portfolios.

We observe the Halloween effect by running Bouman (2002)'s OLS model. If Halloween effect exists in Thailand equity mutual funds, we should see the positive coefficient of Halloween Dummy. Furthermore, we run exponential GARCH (EGARCH) model to allow for asymmetric shock to volatility.

Regression result from Table 16 shows that loser portfolio's Halloween dummy coefficient is positive at 0.0159 with 10% significant using OLS and EGARCH model. This implies that Halloween effect exist in loser portfolio. Our result is consistent with Bhootra (2019)'s findings which show that loser momentum portfolios perform well in winter period of November to April than summer period of May to October. However, our result shows that for winner portfolio, the coefficient of $Hal_t$ is positive which means that return during winter months is higher than summer months, but it is not statistically significant. Moreover, the variance equation of EGARCH model shows that both portfolio seems to have an asymmetric behavior or leverage effect.

**Table 16** Regression result of Halloween effect for Winner portfolio and Loser portfolio

This table presents the result of coefficient of Halloween effect by running ordinary least square (OLS) model

$$r_t = \mu + \alpha_1 Hal_t + \alpha_2 Covid_t + \varepsilon_t$$

and exponential GARCH (EGARCH) model. The regression model are as follow:

$$r_t = \mu + \alpha_1 Hal_t + \alpha_2 Covid_t + \varepsilon_t$$

$$logh_t = \omega + \beta \left|\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right| + \alpha \frac{\epsilon_{t-1}}{\sigma_{t-1}} + \gamma \log(\sigma_{t-1}^2) + \delta Covid_t$$

This model, we use data from all funds and construct into portfolio of winner funds and portfolio of loser funds. We defined the dependent variable by returns of winner and loser portfolio and dummy variable represent the Halloween effect. $r_t$ is average monthly return of each type of portfolio. $Hal_t$ is equal to 1 during winter period of November to April and equal to 0 during summer period of May to October. In addition, we added $Covid_t$ as control variables during high return fluctuation during crisis during January until March 2020. For OLS model's error term, we utilise Newey and West (1987) autocorrelation and heteroscedasticity consistent standard errors. For EGARCH variables, $\beta_i$ is size effect which shows relationship between past variance and current variance in absolute term. $\alpha_k$is sign effect or leverage effect which shows relationship of past return volatility to future return volatility. $\gamma_i$ is garch term. Value in parenthesis indicates t-value of coefficient. Significant level at 1%, 5% and 10% are denoted as ***,** and * respectively.

| Variable | Winner | | Loser | |
|---|---|---|---|---|
| | OLS | EGARCH | OLS | EGARCH |
| $\mu$ | 0.0038 | -0.0063 | 0.0016 | 0.0022 |
| | (0.6805) | (1.3756) | (0.3359) | (0.4664) |
| $Hal_t$ | 0.013 | 0.0011 | 0.0159* | 0.013* |
| | (1.3780) | (0.1550) | (1.9768) | (1.9284) |
| $Covid_t$ | -0.1158*** | -0.0726 | -0.1225** | -0.1032 |
| | (-5.1901) | (-1.3783) | (-6.5002) | (-1.6159) |
| $\omega$ | | -0.6925* | | -2.6459 |
| | | (-1.9489) | | (-1.2435) |
| $\beta$ | | 0.2476 | | 0.0084 |
| | | (1.5065) | | (0.0338) |
| $\alpha$ | | -0.0185 | | -0.2162* |
| | | (-0.2298) | | (-1.8589) |
| $\gamma$ | | 0.9283*** | | 0.6006* |
| | | (18.1031) | | (1.9309) |
| $Covid_t$ | | 0.8669* | | 0.7571 |
| | | (1.6760) | | (0.8247) |
| Observations | 120 | 120 | 120 | 120 |
| R-squared | 0.1838 | 0.1762 | 0.1838 | 0.1762 |

We then create modified momentum strategy. This strategy is created based on the result of the presence of Halloween effect of both winner and loser portfolio. According to Table 2, loser portfolio has a higher return during winter of 0.03% and lower during summer of 0.22% than winner portfolio. Therefore, we formulate the modified momentum strategy as to long loser in winter and in summer, we long winner and short loser portfolio to create zero investment strategy.

The cumulative return over the past 10 years of momentum strategies are presented in Figure 5. The modified momentum strategy's cumulative return gives a better performance than the benchmark, Conventional long-short momentum strategy. It also outperform the market portfolio of passive funds over the investment period. At the end of investment period in December 2021, modified momentum strategy generate cumulative returns of 2.08% compared to its benchmark of conventional momentum strategy which generate cumulative returns of 1.09%. Table 17 presents the performance of momentum strategies. Result shows that modified momentum strategy outperform its benchmark of conventional momentum strategy. Average monthly return of modified and conventional strategy is 0.5356% (or 6.4268% per annum) and 0.0837% (or 1.0039% per annum). The risk-adjusted return from sharpe ratio shows that modified momentum strategy is better than conventional momentum strategy. While annualized sharpe ratio for modified strategy is 0.3605, annualized sharpe ratio for conventional strategy is -0.2048.

**Figure 5** Cumulative return of modified momentum strategy compared to its benchmark and its market portfolio

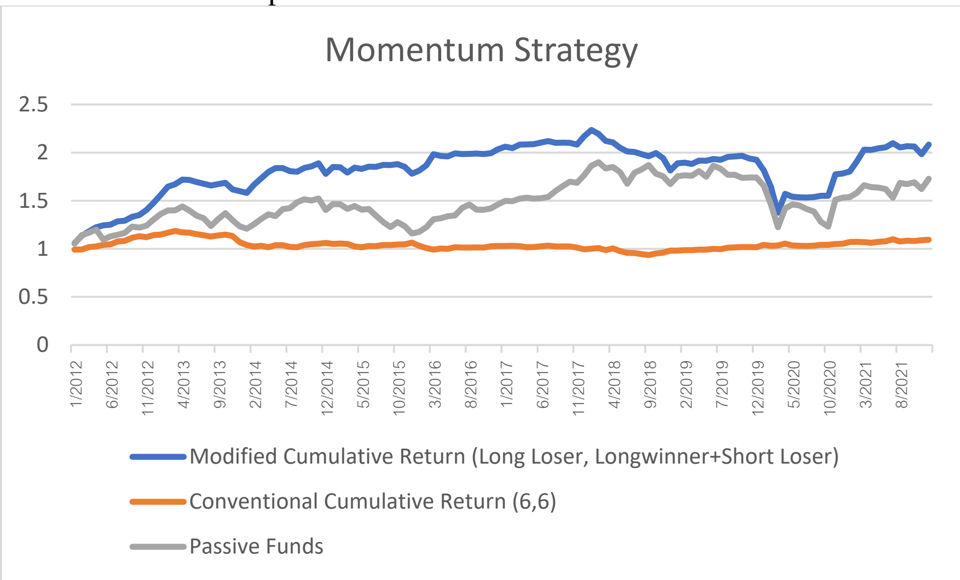



**Table 17** Momentum Strategies Performance

This table presents the average monthly return, standard deviation and sharpe ratio of modified momentum strategy and conventional momentum strategy. The modified strategy is to take long position in loser portfolio of loser funds in winter period of November to April and in summer period of May to October, we take long position in winner and short loser portfolio. The momentum strategy is based on 6-month formation/6-month holding period. The portfolios are equally-weighted and returns are computed using the approach of Jegadeesh and Titman (1993). The return to the modified momentum strategy is obtained by averaging the excess return to loser portfolio in winter months, and the return to winner-loser portfolio in summer months. The return to the conventional momentum strategy is obtained by winner-loser portfolio.

| Momentum Strategy | Average (%) | SD (%) | Sharpe Ratio |
|---|---|---|---|
| Modified Strategy | 0.5356 | 3.5705 | 0.1041 |
| (Per annum) | 6.4268 | 12.3686 | 0.3605 |
| Conventional Strategy | 0.0837 | 1.3583 | -0.0591 |
| (Per annum) | 1.0039 | 4.7054 | -0.2048 |

Next, we test the excess return of both momentum strategies by CAPM, Fama and French 3 factor model and Carhart 4 factor model. Regression result of CAPM from Table 18 shows that none of excess return of both strategies are statistically significant. This implies that none of the strategy generates abnormal return compared to the market portfolio. However, even though excess return from other strategies is not statistically significant, these strategies generate a positive abnormal return. Regression result of Fama and French 3 factor model from Table 19 also shows that none of the strategy generates abnormal return compared to the market portfolio even after control for value and size effect. Moreover, regression result of Carhart 4 factor model from Table 20 shows that none of the strategy generates abnormal return compared to the market portfolio. From all regression result, momentum strategy does not generate abnormal return.

**Table 18** Regression result of Momentum Strategies by CAPM
This table presents the result of rotation strategies by running the ordinary least square regression model. Abnormal returns are estimated using CAPM.

$$r_t^p - r_t^f = \mu + \beta\left(r_t^m - r_t^f\right) + \varepsilon_t$$

$r_t^p$ is the strategy return. $r_t^m$ is the market portfolio which represent by passive funds. Value in parenthesis indicates t-value of coefficient. Significant level at 1%, 5% and 10% are denoted as ***,** and * respectively.

| Variable | CAPM | |
|---|---|---|
| | **Modified Momentum Strategy** | **Conventional Momentum Strategy** |
| Constant | 0.0022 | 0.0006 |
| | (1.0402) | (0.5174) |
| Market Premium | 0.6186*** | 0.0377 |
| | (13.1228) | (1.3497) |
| Observations | 120 | 120 |
| R-squared | 0.5934 | 0.0152 |

**Table 19** Regression result of Momentum Strategies by Fama and French 3 Factor Model

This table presents the result of rotation strategies by running the ordinary least square regression model. Abnormal returns are estimated using Fama and French 3 factor model.

$$r_t^p - r_t^f = \mu + \beta\left(r_t^m - r_t^f\right) + sSMB_t + hHML_t + \varepsilon_t^p$$

$r_t^p$ is the strategy return. $r_t^m$ is the market portfolio which represent by passive funds. Value in parenthesis indicates t-value of coefficient. Significant level at 1%, 5% and 10% are denoted as ***,** and * respectively.

| Variable | Fama and French 3 Factor Model | |
|---|---|---|
| | **Modified Momentum Strategy** | **Conventional Momentum Strategy** |
| Constant | 0.0013 | $9.37 \times 10^{-5}$ |
| | (0.5915) | (0.0792) |
| Market Premium | 0.6596*** | 0.0382 |
| | (13.3588) | (1.4319) |
| SMB | 0.1657 | 0.1048* |
| | (1.4818) | (1.7345) |
| HML | -0.1646* | -0.1967*** |
| | (-1.6742) | (-3.7018) |
| Observations | 120 | 120 |
| R-squared | 0.6105 | 0.14 |

**Table 20** Regression result of Momentum Strategies by Carhart 4 Factor Model

This table presents the result of rotation strategies by running the ordinary least square regression model. Abnormal returns are estimated using Carhart 4 factor model.

$$r_t^p - r_t^f = \mu + \beta\left(r_t^m - r_t^f\right) + sSMB_t + hHML_t + uUMD_t + \varepsilon_t^p$$

$r_t^p$ is the strategy return. $r_t^m$ is the market portfolio which represent by passive funds. Value in parenthesis indicates t-value of coefficient. Significant level at 1%, 5% and 10% are denoted as ***,** and * respectively.

| Variable | Carhart 4 Factor Model | |
|---|---|---|
| | **Modified Momentum Strategy** | **Conventional Momentum Strategy** |
| Constant | 0.0035 | -0.0006 |
| | (0.9785) | (-0.3185) |
| Market Premium | 0.6571*** | 0.0390 |
| | (13.2587) | (1.4539) |
| SMB | 0.1845 | 0.0988 |
| | (1.6102) | (1.5923) |
| HML | -0.1905* | -0.1883*** |
| | (-1.8331) | (-3.3467) |
| UMD | -0.0369 | 0.0119 |
| | (-0.7803) | (0.4649) |
| Observations | 120 | 120 |
| R-squared | 0.6125 | 0.1416 |

# CHAPTER 6

## Conclusion

We investigate the existence of Halloween effect in Thailand equity mutual funds. Our monthly data during 2012-2021 suggests that winter period's return of November to April is higher than summer period's return. We found that Halloween effect exist in equity fund which is consistent with Kenourgios and Samios (2021). As documented by Jacobsen and Visaltanachoti (2009) and Arendas et al. (2018) which suggest the strength of Halloween effect varies across different types, we examine in micro perspective of mutual funds by investigate into different characteristics of mutual funds, including investment style of passive and active, value, capitalization of large and midsmall. For OLS model, regression result exhibit Halloween effect in every characteristic except for growth funds. After controlled for heteroskedasticity and autocorrelation and allow for asymmetric shock to volatility by using EGARCH model, this anomaly is significant in active, passive, large, value and tax saving funds. We also found the different magnitude of Halloween effect in different types. Passive funds have a stronger Halloween effect than Active funds. Kenourgios and Samios (2021) suggests that European fund manager pay no attention to Halloween effect. Fund manager actually expose to higher equity exposure during May to October. Therefore, those who invest in active funds are not as worry about Halloween effect than those who invest in Passive funds which is invested according to the index. Large-cap have a stronger Halloween effect than Midsmall-cap funds. Value has a stronger Halloween effect than Growth funds. One of the possible reasons is dividend payment. Investors hold mutual fund unit in value funds may decrease their holdings during the ex-dividend month, where as growth stocks rarely payout their dividend. Out of three sector funds, energy funds have the highest magnitude of Halloween effect. Our result are in line with evidence from Jacobsen and Visaltanachoti (2009) in US 17 sector and 49 industries stock indices reveal that different sector funds might have different strength of Halloween effect.

We also generate the rotation strategy which we long a type of characteristic with strongest Halloween effect in winter period and long a type of characteristic with no or less Halloween effect. Our results show that only rotation strategy of active/passive and large-value/midsmall-value generate abnormal return by using CAPM, Fama and French 3 factor model and Carhart 4 factor model. In addition, we create winner portfolio and loser portfolio from all equity funds by ranking past 6 months cumulative return. We observe that both portfolios have a positive effect, but only loser portfolio has a significant Halloween effect. Using this result to formulate the modified momentum strategy by long loser portfolio in winter, and long winner and short loser portfolio in summer, our evidence shows that modified momentum portfolio generate a better return than conventional long-short momentum strategy. However, it does not give abnormal return after using CAPM, Fama and French 3 factor model and Carhart 4 factor model.

Implication of our findings could be of use to investors. If Halloween effect is present, then the result from this study will provide useful information of what months or periods are the best time to buy and sell mutual funds units for investors. Therefore, investors can create trading strategies that exploit the Halloween effect based on different characteristics as well.



**6.1 Limitations**

There may be some potential limitations in the current research that should be considered as caveats. Since the study uses mutual funds data obtained from Morningstar, the sample size is small for some type of funds. Unlike developed markets, fund characteristics are limited in Thailand mutual fund market. Open-end Thailand equity mutual funds are concentrated in certain types of styles, such as large-cap funds, active funds and value funds. Therefore, there is limited number of funds in each characteristic.

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