An analysis of momentum strategy's failure in Stock Exchange of Thailand

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การวิเคราะห์ความล้มเหลวของกลยุทธ์โมเมนตัมในตลาดหลักทรัพย์แห่งประเทศไทย

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วิทยานิพนธ์ฉบับนี้ได้ศึกษาถึงความล้มเหลวของกลยุทธ์โมเมนตัม ระหว่างปี พ.ศ. 2544 - 2561 โดยการศึกษาครั้งนี้มุ่งเน้นตอบคำถามว่า ในตลาดหลักทรัพย์แห่งประเทศไทยมีช่วงเวลาที่กลยุทธ์โมเมนตัมให้ผลตอบแทนที่ติดลบอย่างรุนแรง หรือเรียกอีกชื่อว่า โมเมนตัมแคลช หรือไม่ ซึ่งผลการศึกษาพบว่ามีช่วงเวลาที่กลยุทธ์โมเมนตัมจะให้ผลตอบแทนติดลบอย่างรุนแรง ซึ่งเกิดขึ้นเมื่อตลาดกลับตัวขึ้นจากตลาดขาลงและเป็นช่วงที่ตลาดมีความผันผวนที่สูง ผลตอบแทนที่ติดลบอย่างรุนแรงนี้เป็นผลมาจากลักษณะพฤติกรรมเลียนแบบออปชั่นของกลยุทธ์โมเมนตัมที่คล้ายกับการขายคอลออปชั่น ซึ่งในตลาดขาลงกลยุทธ์โมเมนตัมจะให้ผลตอบแทนเป็นบวกเพียงเล็กน้อยเมื่อผลตอบแทนของตลาดเป็นลบ แต่จะให้ผลตอบแทนติดลบอย่างรุนแรงเมื่อผลตอบแทนของตลาดเป็นบวก ลักษณะพฤติกรรมเลียนแบบออปชั่นนี้เกิดขึ้นจากหุ้นกลุ่มที่ผลตอบในอดีตต่ำในกลยุทธ์โมเมนตัมและเกิดขึ้นแค่ในตลาดขาลงเท่านั้น การศึกษาครั้งนี้ยังได้เพิ่มแบบจำลอง Fama-French เพื่อสำรวจลักษณะของเบต้าที่เปลี่ยนตามเวลาและผลกระทบต่อกลยุทธ์โมเมนตัม ซึ่งผลการศึกษาพบว่าเบต้าในแบบจำลอง Fama-French ไม่เปลี่ยนแปลงตามเวลาและไม่มีผลอย่างมีนัยสำคัญทางสถิติต่อกลยุทธ์โมเมนตัม.

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This study examines the negative return characteristic of momentum strategy, also known as momentum crashes, in Stock Exchange of Thailand from January 2001 to December 2018. This study aims to answer one main question. Do momentum crashes exist in Stock Exchange of Thailand? The result show that momentum crashes do exist in Stock Exchange of Thailand, where momentum portfolio perform poorly during panic state, defined by period that market rebound from its decline with high volatility. This poor performance is mainly driven by the option-like payoff characteristic of momentum portfolio, where the portfolio behave itself as a short call option, the portfolio gains a little when the market decline but loses a lot when the market increase. This option-like characteristic exist only in bear market and mainly driven by loser portfolio. In addition, the Fama-French factor is included into the model in order to see the time-varying characteristic of the factor toward momentum portfolio. The result show that the Fama French factor do not have a time-varying characteristic toward momentum portfolio.

Field of Study:	Finance	Student's Signature ....
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CHAPTER 1 Introduction

After Jegadeesh and Titman (1993) paper was published, the finding of their paper that buying stocks with high historical returns and sell the stocks with low historical returns can generate an abnormal return from the market. This is also known as momentum anomaly. This finding is a counter-argument for the efficient market hypothesis (EMH) by Fama (1970) that dominated the field at that time. The hypothesis states that investors are not able to generate excess returns more than the market consistently with their given strategies such as using historical data or fundamental data of the company.

Unsurprisingly, momentum anomaly has gain popularity among finance scholars for over two-decade. There has been a study about this anomaly in many asset class such as performance of momentum strategy among asset classes by Rouwenhorst (1998) for international markets, Asness et al. (1997) for market indices, Bhojraj and Swaminathan (2006) for currencies, Gorton et al. (2012) for commodities and Faber (2017) for tactical asset allocation.

Despite the countless number of research on the topic, it is still inconclusive about the actual source of this anomaly. Some potential answers could be from Subrahmanyam (2018) which summarizes the current finding about the source of momentum anomaly. The potential explanation is that momentum arises because investors underreact to information arriving in small bits similar to the frog in the boiling pan that underreact as the water is slowly warmer as in Da et al. (2014), or the other explanation could be the disposition effect causes momentum. Specifically, an investor holds on to the losers but quickly sell winners (the disposition effect) cause the price to underreact to true fundamental news for losing stocks from Grinblatt and Han (2005).

On the other hand, some critique about this anomaly could argue that momentum is just a result of data mining since there is no conclusive explanation toward the anomaly. Moreover, it's not an actual thing to be considered as a counter-argument toward the efficient market hypothesis mentioned in Asness et al. (2014) where the authors discuss the current myth and fact about momentum anomaly. However, it is still an ongoing quest to understand this anomaly, while most studies about momentum tend to explain the sources of the momentum premium based on their underlying assumptions, such as verifying the bias by an investor, under-reaction of an investor. In other words, they are answering what drives momentum return. In contrast to most momentum studies, Daniel and Moskowitz (2016) focus on a return characteristic that exists in momentum anomaly which the authors called momentum crashes. It is a period where the momentum portfolio generates a large and significant negative return. In addition, it usually occurs during the period with negative past two-year market return with high market volatility and contemporaneous with market rebounds.

Therefore, knowing that this characteristic exists on every asset class will be a piece of supporting evidence toward momentum anomaly. In this research, I will study whether there is a characteristic of momentum anomaly such as momentum crashes in Thai's equities market or not? Since Thai's equities market is relatively young with only 30 years of data compared to the major market such as NYSE with 200 years of data, due to the different degrees of economic development. This makes Thai's equities relatively unpopular and receives little attention in finance literature.

However, there are two interesting issues about Thai's equities. First, it has faced many market crashes since the Asian financial crisis in 1996. Some market crashes are related to the global financial market and some are not related, such as in 2011 flood and 2016 market panic. Moreover, most of the crashes are match with the conditions for momentum crashes mentioned in Daniel and Moskowitz (2016), which is a period that market rebound from its decline with high volatility.

Second, the majority of the investor in Thai's equities market is the retail investor instead of institutional, based on trading data from SET website the cumulative trading value of retail investor from 1 January 2019 to 6 August 2019 account for 34.1% of the total trading value while the local institutional account for only 11.0% of the total trading value.

With retail investors as the majority participant in the market, it can be expected that retail investors tend to trade differently from institutional investors, from Barber and Odean (2013), resulting a Thai's equities market to be less efficient than the developed market. This could yield a different result from the existing literature that had studied in the developed markets. In addition, Thai's market has different sectors weighting from other countries such as the US. In the US's market, the top three largest sectors, which are technology, healthcare and financials sector, account for 50% of the S&P500 index weight. In Thai's market, the top three largest sectors, which are financials, energy, and consumer staples sector, accounting for 39.7% of the SET index weight. This could also imply a different factor exposure toward investors as well. Note that, the sector weight data are from the Bloomberg terminal, which classifies stocks into sector based on GICS standard.

The objective of this study is to provide supporting evidence toward momentum anomaly by answering the main question of this paper which is "Whether there is a momentum crashes in Thai's equities market or not?" Knowing that whether there is a momentum crashes or not can be a bold evidence that helps reject the fact that momentum anomaly is just a result of data mining since momentum crashes is one of the anomaly's characteristic. On the other hand, if there momentum anomaly and without momentum crashes, It will be evidence to support the idea that momentum is just a result of data mining. Also by answering this question, it will clarify whether a large proportion of retail investor plays a role in explaining momentum return or not. Since, I use Thai's equities market data, which is known to be less efficient than the developed market, due to large proportion of retail investors.

This study uses total return index data of all the stock listed in SET from January 2001 to December 2018, which also included dead and delisted stock as well. The data can be obtained from Datastream. The reason to use data for almost 20 years period is to capture the period of financial crises and the market decline as much as possible. Daniel and Moskowitz (2016) mentioned that the crashes usually occur during a period that market rebounds from its decline with high volatility. For the market return, the monthly total return index of SET index is used for calculation, which is obtainable from Datastream. For the risk-free rate, the monthly data for yield of one-month T-bill is used as risk-free rate for the calculation, which is obtainable from Bank of Thailand website in a statistical section. For the Fama-French factors, the monthly data of both market capitalization and price to book value ratio are used for the calculation, which are obtainable from Datastream.

To examine momentum crashes in Thai's equities market, by following Daniel and Moskowitz (2016) methodologies, I will separate the methodology into three parts. The first part will be the construction of the momentum portfolio, which will discuss in detail about the portfolio construction, starting from data classification to constructing a momentum portfolio. The second part will be the examination of momentum crashes, which will explore the relationship of momentum portfolio with each factors that are mentioned in Daniel and Moskowitz (2016), such as beta of winner and loser portfolio, the time-varying beta of the momentum portfolio, the option-like characteristic of momentum portfolio, asymmetry in optionality, and the conditional variable. The third part will be a discussion about the exposure of momentum portfolio toward Fama-French 3 factors, starting from data classification to Fama-French factors construction. Then perform a regression with the variables and the Fama-French factors.

The rest of the paper is organized as follows. Chapter 2 discuss the literature review and relevant theories. Chapter 3 discuss the research question and hypothesis in this study. Chapter 4 explain the data used in this study. Chapter 5 discuss the methodology. Chapter 6 discuss the empirical result. Chapter 7 conclude the paper.

CHAPTER 2 Literature Review

The efficient market hypothesis (EMH) developed by Fama (1970), has gain popularity among finance scholars for many decades. The hypothesis state that market participants are rational and have equal access to the information, which results in an immediate reaction toward new information. Prices will adjust accordingly based on the arrival of new information. The degree of market efficiency has been divided into three levels based on the information available, which are Weak form, Semi-strong form, and Strong form.

Weak form efficient implies that the past-price and historical information are already reflected in the current price. Therefore, an investor using this past information will not able to generate an abnormal return over the market.

Semi-strong form efficient implies that all public information are already reflected in the current price. All public information included financial statements, company news, and past information as well. Therefore, an investor using this public information will not able to generate an abnormal return over the market.

Strong form efficient implies that all type information including inside information are already reflected in the current price. This means every investor in the market will not able to generate an abnormal return over the market. Even with the inside information.

In summary, the efficient market hypothesis implies that investors are not able to generate excess returns more than the market consistently with their given strategies such as technical and fundamental analysis.

Momentum strategy

The idea of momentum strategy first appeared in US stock markets by Jegadeesh and Titman (1993) which is a counter-argument for the efficient market hypothesis. By sorting a firm into ten portfolios based on their past J months return, where J is 3, 6,9,12 months. From this ranking ten portfolios are formed with equal weight, then buy the portfolio with highest past return and sell the portfolio with lowest past return and holding this position for K month, where K is 3,6,9,12 months. Also known in the literature as J-month/K-month strategy. From this strategy, they have found that it generates a positive and abnormal return over a 3 to 12 month holding period, produces an average abnormal return of 1% per month, which is statistically significant abnormal profit.

Before looking deeper into momentum anomaly, it is worth mentioning the well-known capital asset pricing model (CAPM), from Sharpe (1964). The model is known as a benchmark to determine a theoretically appropriate required rate of return of an asset. The model shows a relationship between systematic risk and expected return for an asset, particularly a stock. The stock with higher systematic risk, beta, is supposed to have high expected return. Therefore, the abnormal return is the difference between actual return and expected return from the CAPM model. The abnormal return used as evidence against the efficient market hypothesis, if the market is efficient no information or participant should be able to generate the abnormal return, which Jegadeesh and Titman (1993) raised an issue.

After Jegadeesh and Titman (1993) work, momentum strategy has gain popularity among finance scholar, there has been a study on momentum strategy in many aspects such as a performance of momentum strategy among asset class by Rouwenhorst (1998) for an international market, Asness et al. (1997) for market indices, Bhojraj and Swaminathan (2006) for currencies, Gorton et al. (2012) for commodities and Faber (2017) for tactical asset allocation. Moreover, from Geczy and Samonov (2016) work, where they backtest the momentum strategy on US's equities from 1801 to 2012 to verify its robustness. They also mentioned that momentum strategy is dynamically exposed to market risk and it depends on the sign and duration of the previous market state which is consistent with Cooper et al. (2004). Where, at the beginning of each market state, momentum's portfolio beta is opposite from the new market direction, generating a negative contribution to momentum profits around market turning points.

Despite known for its robustness for a long period, different country has different exposure toward momentum factor. Based on Asness (2011) and Asness et al. (2014) where the authors mentioned that momentum strategies fail to deliver a good return in Japan. This raised a concern toward the anomaly and could be evidence against momentum. By referring to the existing studies of Asness et al. (2013), Fama and French (2010) and Rouwenhorst (1998) which pointed out the issue of poor momentum performance in Japan. Despite saying that momentum strategy did not perform well in Japan, it is still a supportive argument for momentum anomaly and it is not just a result of data mining, because it is still a debate about the actual source of momentum. Since the studies that have mentioned the idea of momentum perform poorly in Japan, consider only at the return aspect of an anomaly. What Asness (2011) argues toward the issue is that the studies on momentum should consider the value factor in it as well due to its negative correlation characteristic of momentum and value factor. In the case of Japan, where the negative correlation still hold, momentum perform quite poorly due to very high performance of value factor, which imply that the characteristic of these two anomaly are still hold. Due to different factor exposure that each country has, the return from each factor can be vary across countries. This argument is an example that looking at return driver alone without considering the return characteristics may lead to a false conclusion.

Although its popularity in the literature, it is still inconclusive about the source of momentum. From Subrahmanyam (2018), there a potential explanation for momentum such as Da et al. (2014) argue that momentum arises because investors underreact to information arriving in small bits similar to the frog in the boiling pan that underreact as the water is slowly warmer. They show that stocks with the past returns accumulated gradually exhibit more momentum than stocks in which returns are accumulated in a lumpy fashion.

Grinblatt and Han (2005) argue that the disposition effect causes momentum. Specifically, investors hold on to the losers but quickly sell winners (disposition effect) cause the price to underreact to true fundamental news for losing stocks. They show that momentum is related to unrealized capital gains in their setting, as their model predicts.

Antoniou et al. (2013) argue that momentum arises because of cognitive dissonance. Investors react properly to news that confirms their beliefs but underreacts to news that disconfirms their beliefs. On average, they underreact, which gives rise to momentum. They show that momentum arises in optimistic periods because investors underreact to bad news.

Grinblatt and Moskowitz (2004) demonstrate that return consistency is important for momentum profits. Returns accumulated gradually exhibit much more momentum than returns accumulated in a lumpy fashion. They attribute this finding to the disposition effect in that as stocks rise slowly. This is similar to the "frog-in-the pan" theory of Da et al. (2014). However, Da et al. (2014) argue that the effect of return consistency on momentum does not arise from the disposition effect but from slow reaction to consistent, modest news.

Sagi and Seasholes (2007) identify observable firm-specific characteristics that create price momentum. They found that momentum strategy that using these characteristics, such as revenue growth, low costs, or valuable growth options to form a momentum portfolio will outperform traditional momentum strategy by approximately 5% per year.

Overall, the possible explanation about momentum so far is either risk-based or a behavioral-based. For risk-based explanation, it can be viewed that momentum premium is compensation for risk, which could be economic risks that affect firm investment and firm growth rates that can impact the long-term cash flows and dividends of the firm that generate momentum pattern. The idea is that high momentum stocks face greater cash flow risk because of their growth prospects. Such as Sagi and Seasholes (2007). For behavioral-based explanation, it is due to under reaction of an investor, which, could be caused by a disposition effect or the idea that information slowly transfers into prices. Such as Grinblatt and Han (2005), Da et al. (2014).

While in emerging market such as Thailand, there also a studies on momentum anomaly in Thai's equities market such as in Laksanaboonsong (2009), where the authors compare volume-based momentum with volume-based 52-week momentum and found that the momentum anomaly do exist and the volume-based 52-week momentum significantly outperform the volume-based momentum. Also, Thachasongtham (2015), where the author proves that stocks that recently achieved the 52-week high price have a superior return than stocks that achieved the 52-week high price in the distant past. The bias on the 52-week high price will increases when stocks have been traded at this price level shortly. Investors are uncomfortable to bid a higher price. But if the stock price breaks out a 52-week high price, there will be enough momentum to continue the price move in a favorable direction. More recently, Hussaini et al. (2016) have study a momentum effect in Thai's market which ranges from 2010 to 2014 which they found that momentum strategy realizes a significantly positive return in large size stocks category but not in small size stocks during this period. Overall, these papers have given a piece of evidence that momentum anomaly do exist in Thai's equities markets.

Momentum crashes

Apart from its reputation for their robustness among each and every asset class, there are some critiques about momentum anomaly such as Bhattacharya et al. (2012) , which point out that its profitability is becoming insignificant since 1990. And it's wonderful performance also comes with a severe drawdown as in Barroso and Santa-Clara (2015) where they point out that the strategy has high kurtosis and negative skewness which implies a fat tail risk and could cause a large crash that wipes away good performance in the past.

The concept of momentum crashes is a period where momentum portfolio generates an infrequent and persistent string of negative return, introduced by Daniel and Moskowitz (2016). They found that the momentum crashes usually occur in a bear market where the past market return is negative with high market volatility and contemporaneous with market rebounds. By using a conditional variable that depends on the ex-ante market volatility and past market return to capture the negative return. In addition, most of the extreme losses are clustered which means the crash period occurs closely together.

What Daniel and Moskowitz (2016) argue to be the main source of the crash are from the loser portfolio, portfolio with lowest past return, where the down-market beta of the past loser portfolio is low, but the up-market beta is high, which result in a large loss when the loser portfolio rebound since we short the loser portfolio for momentum portfolio. In a layman's term, the crash occurs because there is a very high beta in the loser portfolio when the market goes up but very low beta in the loser portfolio when the market goes down. Since we short the loser portfolio in our momentum portfolio, an increase in the market will result in a large loss

What Daniel and Moskowitz (2016) found to be the main drivers that contribute to momentum crashes are past market return, market volatility, and it's time-varying characteristics of beta. By referring to Stivers and Sun (2010) and, Cooper et al. (2004) for past market return and market volatility, which has an effect on momentum premium, the intercept term in the CAPM model.

On the other side, the time-varying exposure to its market beta is mentioned in Kothari and Shanken (1992), Grundy and Martin (2001), Geczy and Samonov (2016) respectively, where past-return sorted portfolios like momentum portfolio will have significant time-varying exposure to its market beta. This idea has been tested by Geczy and Samonov (2016) in a two-century sample and found that at the beginning of each market state, momentum's equity beta is opposite from the new market direction, generating a negative contribution to momentum profits around market turning points. which simply means past market return not only affect the premium of momentum portfolio, the intercept term, but also its beta, which is the systematic component, as well.

This beta asymmetry and time-varying beta lead to a conclusion for Daniel and Moskowitz (2016) that in the bear market, momentum portfolio behaves itself as a short call option which means that when the market go down it gains a little but when it goes up it loses a lot. In addition, this asymmetric payoff occurs only in a bear market. They refer to the option idea from Merton (1990) that a share of common stock is a call option on the underlying firm value. From this theory, the underlying firm values in the past loser portfolio have generally suffered severe losses, therefore much closer to a level where the option convexity would be strong. The past winners, in contrast, would not have suffered the same losses, and would still be “in-the-money.” where the convexity is lower. Daniel and Moskowitz (2016) have mentioned in their paper that this explanation applies only to equities. Nevertheless, they also found that momentum do crash on other asset class as well such as futures and currencies. Therefore, this is not a conclusive explanation for every asset class. However, their paper gives a lot of insight toward momentum anomaly.

CHAPTER 3 Research question and Hypothesis Development

The objective of this study is to provide supporting evidence toward momentum anomaly by answering the main question of this paper which is "Whether the equity market with a large proportion of retail investors can experience this negative return phenomenon or not?" By verifying the characteristic of momentum crashes in Thai's market**.**

As a contribution toward existing literature, the Fama-French factors will be included in this study as well in order to see whether the exposure of other factors such as Fama French factors exhibit the time-varying characteristic as well and whether these time-varying characteristics of these factors are contribute to momentum crashes?

Knowing whether there is a momentum crashes or not can be beneficial for three reasons. First, it can be a bold evidence that helps reject the fact that momentum anomaly is just a result of data mining since momentum crashes is one of the anomaly's characteristic. On the other hand, if there momentum anomaly but without momentum crashes, It will be evidence to support the idea that momentum is just a result of data mining. Second, it will clarify whether a large proportion of retail investor plays a role in explaining momentum return or not. Since, I use Thai's equities market data, which is known to be less efficient than the developed market, due to large proportion of retail investors. Third, it will be a supporting evidence for the risk-based explanation of the momentum anomaly since one of our variable is the past market return which is the proxy for macroeconomics condition as in Cooper et al. (2004).

Hypothesis development

As mentioned in the literature review, such as in Geczy and Samonov (2016) where they backtest the momentum strategy on US's equities from 1801 to 2012 to verify its robustness. The ongoing question toward understand the anomaly is to answer what drives momentum return?

Some studies such as Stivers and Sun (2010), Geczy and Samonov (2016) and Cooper et al. (2004), found that past market return and market volatility has a significant effect on momentum portfolio return. Followed by Daniel and Moskowitz (2016), they examine these factors with a conditional measure toward the momentum portfolio with the market return. Moreover, the result is consistent with past literature. As a result, they found a characteristic of momentum portfolio, momentum crash, which is a period where momentum portfolio generates an infrequent and persistent string of large negative returns. These negative returns can potentially wipe out all the good performance in the past due to large kurtosis as mentioned in Barroso and Santa-Clara (2015). Moreover, Daniel and Moskowitz (2016) give us an insight of ex-ante market characteristics that the momentum crashes likely to occur, which are the periods when a market rebound from its decline during a high volatility period.

Since they have been a studies on momentum anomaly in Thai's market. Based on Laksanaboonsong (2009), Thachasongtham (2015) and Hussaini et al. (2016) where they found that anomaly exist. Also since Thai's market has a period that matches what was described in Daniel and Moskowitz (2016) to be a characteristic of momentum crashes. Therefore, I hypothesize the first hypothesis that they exist a periods that momentum portfolio will generate an infrequent and persistent string of negative return, also known as momentum crashes, in Thai's equity market, which occur during market rebound from its decline with high ex-ante market volatility.

Apart from past market return and market volatility that are driving momentum return there also other important characteristics of momentum portfolio which are time-varying characteristics of its market beta. It was mentioned in Kothari and Shanken (1992), Grundy and Martin (2001) and Daniel and Moskowitz (2016), that by their nature, past-return sorted portfolios like momentum portfolio will have significant time-varying exposure to its market beta and this time-varying beta characteristic is a one causes of momentum crashes. In other words, the beta of momentum portfolio changes over time due to the portfolio component change every period. Those changes in beta cause the momentum portfolio to perform poorly. From studies about momentum anomaly in Thai's stock market, such as Hussaini et al. (2016), which conclude that there is momentum anomaly in Thai's market. Therefore, I hypothesize a second hypothesis that there also a significant difference between momentum portfolio beta during bear and non-bear market in Thai's market as well.

From Daniel and Moskowitz (2016) finding, not only they've found that beta changes over time and depend on past market return but also a significant difference between up-beta and down-beta in momentum portfolio. Up-beta is defined as upside risk of an investment. It is defined to be the amount which an asset tends to move compared to a benchmark, calculated only on days when the benchmark's return, which is the market, is positive. Down-beta is defined as downside risk of an investment, which it is defined to be the amount that an asset tends to move, compared to a benchmark, calculated only on days when the benchmark's return, which is the market, is negative. Beta asymmetry can be beneficial sometimes if the up-beta is very large and down-beta is very low, resulting in an asymmetric payoff, For example, if the market increase 1% the portfolio increases 3% on the other hand if market decline 1% the portfolio decline 0.5%. But in our case, what Daniel and Moskowitz (2016) found is that the up-beta of momentum portfolio is significantly lower than the down-beta only in a bear market, which makes the strategy less preferable in bear market. In a layman term, during bear market when, a market increase 1% the portfolio gains only 0.2% while the market declined 1% the portfolio loses 1.5%. This up-down beta asymmetry does not exist in a non-bear market. Moreover, its loser portfolio mainly drives this beta asymmetry, which is the portfolio with the lowest past return that we short in the momentum portfolio. By looking at up beta and down beta, instead of one beta, it can separate the upside-risk and downside-risk of investment that normal CAPM model assumes to be identical and helps investors to make better-informed decisions. Therefore, I hypothesize the third hypothesis that there is a statistically significant difference between beta of momentum portfolio during positive and negative current month market return that only in bear market and it's mainly driven by the loser portfolio.

Moreover, it is mentioned in Daniel and Moskowitz (2016) that momentum portfolio tends to perform poorly during a period of high market volatility. Theses relationship is supportive evidence toward the idea that momentum portfolio behaving as a short-call option in a bear market which implies the negative relationship of momentum portfolio return and market volatility. Therefore, I hypothesize the fourth hypothesis that market variance has a negative impact on momentum portfolio return only in bear market.

Since there is changes in the beta of momentum portfolio overtime. It raised a question that whether momentum portfolio also has time-vary exposure to other factors such as size premium (SMB) and value premium (HML) as well. Since momentum portfolio is past return sorted by nature. Which implies time-vary exposure to its systematic factor. With a negative correlation of momentum factor with size and value factor, because momentum strategy buy past winner and sell past loser. While value strategy tends to buy past loser and sell past winner such as in De Bondt and Thaler (1987), it is reasonable to assume that during bear market, when momentum portfolio performs poorly, the HML, SML return will be higher. But it is unclear for the beta of these two factors. Therefore, I hypothesize the fifth hypothesis to explore the issue that they are time-varying exposure to other factors such as size premium (SMB) and value premium (HML). In addition, this time-varying exposure is one part of momentum negative return.

In conclusion, this paper aims to investigate the momentum crashes in Thai's market and look into the main ex-ante characteristic that mentioned in Daniel and Moskowitz (2016) such as past market return, market volatility, optionality in a bear market and time-varying beta of momentum portfolio. Moreover, compared the result with the existing literature.

CHAPTER 4 Data

1. Period of study

This study uses data from January 2001- December 2018, which include the total return index of all firms listed in SET, total return index of SET index, one-month T-bill, market capitalization and price to book ratio. Due to data unavailability of T-bill, which the earliest data is from January 2001, it limits our study to start from January 2001 instead of January 1990, which is the period that most data are available. The reason to use almost 20 years of data is to capture most financial crises and shock events that occur in the market as much as possible, which past literature claims to be the period where momentum crashes occur. The data used in this study are listed below

1. Monthly data of total return index of all firms listed in SET, which also includes the death stock, the stock that has been delisted and merged. In order to avoid the survivorship bias problem.

2. Monthly and daily data of the total return index of a SET index for calculating a market return and variance.

3. Monthly data for the yield of a one-month T-bill for calculating a market excess return, which matched with the monthly rebalancing policy of momentum portfolio.

4. Market capitalization of all firm listed in SET for SMB factor and momentum portfolio construction.

5. Price to Book value ratio of all firms listed in SET for HML factor construction.

2. Data explanation

2.1 Total return index of all firms listed in SET

Since most of our data are concern with equities, the total return index is used as a proxy for stock return because it captures both capital gain return and other issues such as dividends, interest, rights offerings and other distributions realized over a given period. While looking at the price of securities alone will neglect these issues. Total return index of a stock can be calculated as follow:

$$Daily\ Total\ Index_{i,t} = Daily\ Total\ Return\ Index\ _{i,t-1} \times (1 + \ Daily\ Total\ Return_{i,t})$$

$$Daily\ Total\ Return\ _{i.t} = \frac{(P_{i,t} \times \ Shares\ Outstanding_{i,t}) + (DPS_{i,t} \times \ Shares\ Outstanding_{i,t})}{\left(P_{i,t-1} \times \ Shares\ Outstanding_{i,t-1}\right) \pm (Adjusted\ Price_i \times Adjusted\ shares_i)}$$

Where,
$P_{i,t}$ = closing price of stock i at time t
$Shares\ Outstanding_{i,t}$ = Number of share of stock i at time t
$DPS_{i,t}$= Dividend per share at time t for stock i
$Adjusted\ Price_i$ = Price of stock i after adjustment when a corporate action occurs
$Adjusted\ shares_i$ = Shares of stock i after adjustment when a corporate action occurs

For the firm listed in SET, I used both active and delisted firms, which also include the firms that have been merged together as well. These monthly data can be obtained from Datastream. By including the dead and delisted stock into the sample, making the data become more realistic for the real market condition. In contrast, focusing only on the high turnover stock or large-cap stock such as SET100 / SET50 could cause a survivorship bias. Since the stock that has been listed in SET100/SET50 is likely to be the winner and perform well in their business in the first place. Also not including the delisted stock into the sample will cause a bias toward overall stock returns since the losing stocks are not included in the calculation.

The figure below represents the number stock in the market from 2001 to 2018. The dark blue area represent the number of active stock while the light blue represent the number of delisted stocks that are traded at a specific year. It is obvious that delisted stock plays an important role in the market especially from 2001 to 2010. By excluding, the delisted stock in the studies is a road to the biased calculation of momentum portfolio. Despite the stock data are available from 1990 to 2018 as mentioned earlier, the one-month T-bill data is only available from 2001 to 2018, which limit our period of study to start from 2001 instead of 1990.

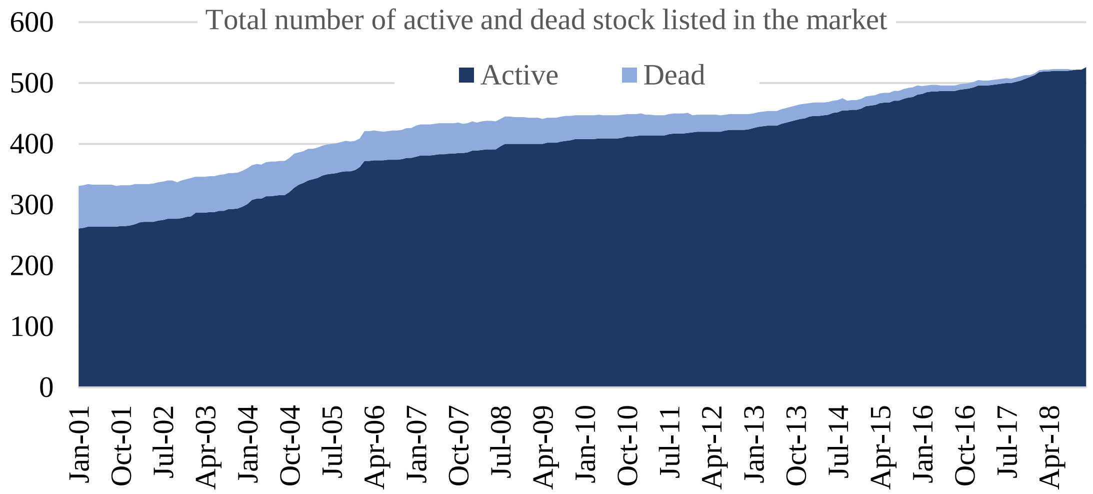

Figure 1. Total number of stock in the market at the end of each year.

For the stock to be included in the study, especially for the delisted stocks, it is required to have current total return index, previous year data of book value or current book-to-market ratio and current market capitalization data. This process will remove the stock listed in NVDR board and the stock that not have both market cap and price to book value ratio as well. (Note that the same stock that listed in the foreign board is removed as well since it will cause a double-counting problem and affect the factor construction in the later part).

2.2 Total return index of SET index

The set index used as a proxy for market return. SET index is a value-weighted index, which means components are weighted according to the total market value of their shares outstanding. Therefore, the impact that individual stock's price change has on the index is depended on the company's overall market value. If the value of small-cap company changes it may not affect the SET index as much as the changes in the value of large-cap companies.

In this study, I obtained the monthly and daily data for total return index of SET index from Datastream. The data used in this study is from 2001 to 2018, which the majority of our study will be focus on monthly timeframe.

2.3 Yield of one-month T-bill

In this study, a one-month treasury bill used as a proxy for a risk-free rate, which is matched with our portfolio rebalancing condition that rebalanced monthly. The data can be obtained from Bank of Thailand's website in the statistics section. Due to data unavailability, the earliest data that gathered on the one-month risk-free rate is from year 2001 which limits our study to start from 2001 instead of 1990 as the data availability of stocks.

In this study, I will use the monthly rate of one-month risk-free rate, which quoted annually, to calculate the monthly excess return of a portfolio. For monthly risk-free rate, we divided the quoted a one-month risk-free rate with 12 to get a monthly interest rate for that period. For daily risk-free rate, we divided the quoted a one-month risk-free rate with 365 to get a daily interest rate for that period.

$$R_{fm,t} = R_{f,t} \div 12$$
$$R_{fd,t} = R_{f,t} \div 365$$

Where,

$R_{f,t}$ = one-month risk-free rate at month t (quoted annually)

$R_{fm,t}$ = monthly one-month risk-free rate at month t

$R_{fd,t}$= daily one-month risk-free rate at day t

2.4 Market Capitalization

Market Capitalization, used as a proxy to construct Fama-French's SMB factor, which calculated by multiplication of share price at a certain period with the total number of shares outstanding. It represents the total dollar market value of a company's outstanding shares. The monthly data can be obtained from Datastream with a unit of million baht. The monthly data used in this study is from 2001 to 2018.

$$MKTCAP_{i,t} = P_{i,t} \times Total\ Number\ of\ Outstanding\ Shares_{i,t}$$

Where,
$MKTCAP_{i,t}$ = market capitalization of stock i at time t
$P_{i,t}$ = current market price of stock i at time t (per share)
$Total\ Number\ of\ Outstanding\ Shares_{i,t}$= total number of outstanding shares of stock i at time t

2.5 Book-to-market ratio

Book-to-market ratio, used as a proxy to construct Fama-French's HML factor, which calculated by dividing book value per share with market price per share or an inverse of price to book ratio. The book-to-market ratio is an indication of the cheapness of a stock relative to its book value. The higher the book-to-market ratio the cheaper it is. The underlying reason to use book to market ratio not the earning to market ratio, the inverse of price-earnings ratio, is that earning of a firm can be negative and negative earning doesn't mean it is cheap. Despite book value of a firm can be negative, it rarely occurs. The monthly data can be obtained from Datastream. The monthly data are used in this study ranged from 2001 to 2018.

$$Book - to - market\ ratio_{i,t} = BV_{i,t}/P_{i,t}$$

Where,
$BV_{i,t}$= book value per share of stock i at month t (equivalent of Total asset minus total liabilities)
$P_{i,t}$= current market price per share of stock i at month t

CHAPTER 5 Methodology

The methodology consists of three parts, which are 1.Momentum portfolio construction 2.Momentum crashes in Thai's market 3.Exposure to other risk factors.

1. Momentum portfolio construction

1.1 Monthly return calculation

1.1.1 Current month return calculation

The monthly return is calculated by using the total return index of stock at the beginning of month t+1 divided by total return index of stock at the beginning of month t and minus one. The formula can be written as below.

$$R_{i,t} = (\frac{TRI_{i,t+1}}{TRI_{i,t}}) - 1$$

Where,
$R_{i,t}$ = monthly return of stock i at month t
$TRI_{i,t+1}$ = total return index of stock i at the beginning of month t+1
$TRI_{i,t}$ = total return index of stock i at the beginning of month t

1.1.2 Past 12 month return calculation

Following Daniel and Moskowitz (2016) methodologies, by using the past 12-month return with a one-month gap between the ranking period and the portfolio formation period. As shown in the formula and figure below. This one-month gap process help to avoid short term reversal which consistent with Jegadeesh (1990) and Lehmann (1990). (E.g. Forming a portfolio at beginning of January 2003 and the past 1-month return will be equal to the one month return in November 2002, which is equivalent of dividing TRI of stock i at beginning of December 2002 with TRI of stock i at beginning of November 2002).

$$R_{PAST12M,i,t} = (\frac{TRI_{i,t-1}}{TRI_{i,t-13}}) - 1$$

Where,
$R_{PAST12M,i,t}$ = past 12 month return of stock i at month t
(Past 12 month return of stock i at the beginning of January 2003)
$TRI_{i,t-1}$ = total return index of stock i the beginning of month t-1
(TRI at beginning of December 2002 from our example)
$TRI_{i,t-13}$ = total return index of stock i the beginning of month t-13
(TRI at beginning of December 2001 from our example)

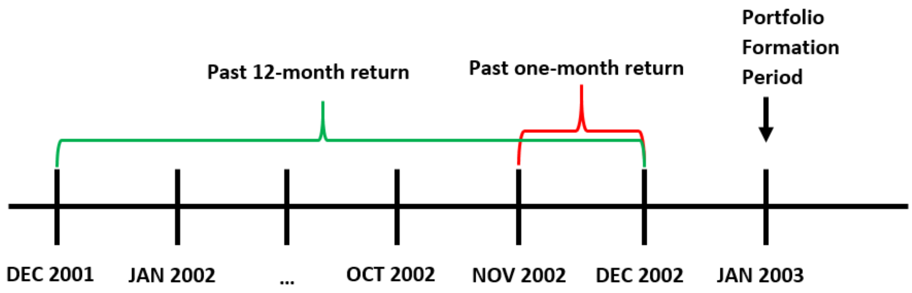

Figure 2. Example of computing the past 12 month return with one-month gap.

1.2 Momentum portfolio

Starting from raw data, the stock that has total return index, market capitalization and price to book value ratio are included in the portfolio calculation. The remaining are excluded from the calculation. This process applied to both active and dead stock. By doing this, it will solve the data unavailability problem, especially dead stock, which could lead to an error in calculation.

After excluding stock with data unavailability, the ten valued-weighted portfolios are constructed by sorting the stock based on their past 12-month return, from 10th decile to 1st decile. Where 10th decile represents the group with highest 10% past return and 1st decile represents the group with lowest 10% past return. In these ten portfolios, stocks are weighted based on their market capitalization in order to match with its benchmark, which is SET index.

Then, after stocks are grouped into ten portfolios based on their past return, to create a momentum portfolio, which is equivalent of long the portfolio with highest past return (10th decile) and short the portfolio with lowest past return (1st decile) which is equivalent of the difference between return of two portfolios. (Note that, 10th decile portfolio will be called winner portfolio and 1st decile will be called loser portfolio.) This monthly momentum portfolio return can be written as

$$R_{WML,t} = R_{P10,t} - R_{P1,t}$$

Where,

$R_{WML,t}$ = monthly return of momentum portfolio at month t

$R_{P10,t}$ = monthly return of winner portfolio (10th decile) at month t

$R_{P1,t}$ = monthly return of loser portfolio (1st decile) at month t

After one month passed, the portfolio will be rebalanced, which means all of the stock will be rank based on their past 12 months return again with a rolling window and then sorted all the stock into a ten value-weighted portfolio. After that, the momentum portfolio return will be obtained by long the portfolio with the highest past return (10th decile) and short the portfolio with the lowest past return (1st decile). In short, the process from section 1.1 to 1.2 will be repeated with a set of new data. This method of portfolio construction is adopted from Daniel and Moskowitz (2016). The reason to rebalance the portfolio on a monthly basis is to emphasize the time-varying characteristic of momentum portfolio, which is the main cause for momentum crashes.

2. Momentum crashes in Thai's market

According to literature, momentum crashes tend to occur when there is a market rebound from its consecutive market downturn with high ex-ante volatility. Listed below are the period of interest, where I suspect that there is a momentum crashes. The first two periods are linked with the financial crisis that occurs in the market.

1. January 2008 to January 2010 during the global financial crisis and the market rebound
2. July 2011 to February 2012 during the flood in Thailand
3. May 2013 to March 2014 during a 19% market decline from a 2012 bull run

As mentioned earlier, the three main factors that create momentum crashes are past market return, time-varying beta of momentum portfolio, and market volatility. As a result, these three factors create optionality for momentum portfolio, which causes momentum portfolio to crash. In the following section, I will explore the relationship between these three factors respectively.

2.1 Time-varying beta of the momentum portfolio

To verify that beta varies over time and depends on past market returns, which is one of the causes for momentum crashes. The full-sample regression on monthly momentum portfolio returns with the monthly market excess returns is constructed, which is equation (1). In addition, a dummy variable (D_{BEAR}) is added for both intercept and market risk premium where it equal to 1 if 2-year past market return is negative, which is equation (2). The underlying reason for adding the market state variable (D_{BEAR}) is to differentiate the performance and beta of momentum portfolio during both bear and non-bear market, which is determined by past two years market return. Moreover, a dummy variable ($D_{U,t}$) is added in equation (3), which distinguish the effect of beta when the contemporaneous market return is positive ($D_{U,t}$ = 1) and not positive ($D_{U,t}$ = 0). In other word, it show the difference between up-beta and down-beta during bear market. These models are adopted from Daniel and Moskowitz (2016).

$$R_{WML,t} = \alpha_0 + \beta_0(R_{me,t}) + \epsilon_t \qquad (1).$$

$$R_{WML,t} = \alpha_0 + \alpha_{BEAR}(D_{BEAR}) + \beta_0(R_{me,t}) + \beta_{BEAR}(D_{BEAR} \times R_{me,t}) + \epsilon_t \qquad (2).$$

$$R_{WML,t} = \alpha_0 + \alpha_{BEAR}(D_{BEAR}) + \beta_0(R_{me,t}) + \beta_{BEAR}(D_{BEAR} \times R_{me,t}) + \beta_{U,t}(D_{U,t} \times D_{BEAR} \times R_{me,t}) + \epsilon_t \qquad (3).$$

Where,
$R_{WML,t}$ = monthly momentum portfolio return at month t
$R_{me,t}$ = $R_{m,t}$ - $R_{fm,t}$ monthly market excess return at month t
D_{BEAR} = dummy variable where it equal to 1 if 2-year past market return is negative. (Bear market indicator)
$D_{U,t}$ = dummy variable where it equal to 1 if the current month market return is more than zero ($R_{m,t}$ > 0).

For all three equation, the variable of interest are β_0 , β_{BEAR} and $\beta_{U,t}$, these three variables will be a key indication whether the beta of momentum portfolio changes over time? Whether there is an up-down beta asymmetry in the momentum portfolio? The up-down beta asymmetry imply the option-like payoff characteristic for the momentum portfolio.

According to past literature, the coefficient β_0 , α_{BEAR}, β_{BEAR} and $\beta_{U,t}$ are expected to be significantly negative, which is the same as Daniel and Moskowitz (2016). From equation (1), the negative coefficient β_0 imply a negative exposure toward market factor, which means momentum portfolio will perform poorly when the market increase in general. From equation (2), the negative coefficient α_{BEAR} can be interpreted that the premium of momentum portfolio return is lower than a non-bear market by the amount of α_{BEAR} during bear market. The negative coefficient β_{BEAR} can be interpreted that the beta of momentum portfolio during the bear market is lower than the non-bear market by β_{BEAR}. For equation (3) the negative coefficient $\beta_{U,t}$ mean that in a bear market, the up beta, represented by coefficient $\beta_0 + \beta_{BEAR} + \beta_{U,t}$, is lower than the down beta of momentum portfolio, represented by coefficient $\beta_0 + \beta_{BEAR}$, by the amount of $\beta_{U,t}$.

From equation (3), the coefficient $\beta_{U,t}$ will be an indication for an option-like payoff in the momentum portfolio. According to Daniel and Moskowitz (2016), the coefficient $\beta_{U,t}$ is significantly negative which implies an up-down beta asymmetry, where the up-beta is lower than down beta. This up-down beta asymmetry in momentum portfolio implies that momentum portfolio behaves itself as a short-call option on the market, when the market fall they gain a little but when the market rises they lose a lot. For simplicity, the following diagram show the payoff for short-call option during each maturity.

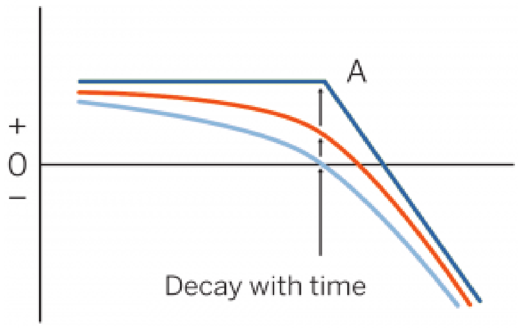

Figure 3. The payoff for short-call option that vary over time

Where,
The horizontal axis = underlying price of an asset
The vertical axis = profit and loss from an option at a specific price level of the underlying asset.
A = Strike price of an option
The straight payoff line = option value at maturity date
The curve payoff line = option value at longer maturity date

From the figure, show a payoff chart of a short call option, if the market decline the profit of the option will increase until it reaches its limit, which is equal to the premium of that option. On the other hand, if the market increases the profit of the option will decline in proportion to the changes in price and it can go infinitely since the price can increase infinitely.

The option payoff line will vary over time, the longer the maturity date the more linear payoff line it is which is similar to shorting an asset. On the other hand, the closer to its maturity date the more option-like payoff it becomes. In short, the option-like payoff is a payoff, which one side of the payoff is limited and the other side of the payoff is not limited such as in this case the short call option has limited upside but unlimited downside.

Looking only a return aspect, in our momentum portfolio cases, the up beta is expected to be lower than the down beta, which implies a payoff structure that is similar to the short call option that is far from the maturity date. At this point, we can expect that up beta and down beta is not the same but it is still unclear whether the momentum portfolio exhibits a convexity, a curved line payoff, as the option or not? Since the model only used to distinguish up beta and down beta only which only shows the linear relationship.

2.2 Asymmetry in optionality

After seeing that beta of momentum portfolio varies overtime, which depends on past market return and performs poorly when the market reverses its direction as in section 2.1 equation (3). It raised another question, whether momentum crashes and the optionality exist in non-bear market as well as bear market? Moreover in non-bear market, is there also a period that similar but opposite to what is mentioned in Daniel and Moskowitz (2016) to be the condition for momentum crashes? In other words, the main question in this section is whether the crashes occur when the market moves in the opposite direction of its past trend with high volatility regardless of its past market state?

To answer this question the regression is run on a full sample from January 2001 to December 2018, by following the same model from section 2.2 equation (3) with a slight twist. By adding the term $(D_{U,t} \times R_{me,t})$ instead of construct a non-bear market variable which is what Daniel and Moskowitz (2016) did, it will help distinguish the difference between up and down beta during each market state in one equation and still answer the same question. The equation can be written as follow.

$$R_{WML,t} = \alpha_0 + \alpha_{BEAR}(D_{BEAR}) + \beta_0(R_{me,t}) + \beta_{BEAR}(D_{BEAR} \times R_{me,t}) + \beta_{up\_bear,t}(D_{U,t} \times D_{BEAR} \times R_{me,t}) + \beta_{up,t}(D_{U,t} \times R_{me,t}) + \epsilon_t \quad (4).$$

Where,
$R_{WML,t}$ = monthly momentum portfolio return at month t
$R_{me,t}$ = $R_{m,t}$ - $R_{fm,t}$ monthly market excess return at month t
D_{BEAR} = dummy variable where it equal to 1 if 2-year past market return is negative. (Bear market indicator)
$D_{U,t}$ = dummy variable where it equal to 1 if the current month market return is more than zero ($R_{m,t}$ > 0).

From equation (4), during bear market the up beta equal to $\beta_0 + \beta_{BEAR} + \beta_{up\_bear,t} + \beta_{up,t}$ and the down beta equal to $\beta_0 + \beta_{BEAR}$. During non-bear market, opposite of bear market, the up beta equal to $\beta_0 + \beta_{up,t}$ and the down beta equal to β_0. The four beta during each market state in this equation can be summarized as the table below.

	Bear market	Non-bear market
Up-beta	$\beta_0 + \beta_{BEAR} + \beta_{up\_bear,t} + \beta_{up,t}$	$\beta_0 + \beta_{up,t}$
Down-beta	$\beta_0 + \beta_{BEAR}$	β_0

Table 1. Up-down beta calculation of momentum portfolio during each market state

The indication asymmetry of optionality during each market state can be identified by the coefficient $\beta_{up\_bear,t} + \beta_{up,t}$, and $\beta_{up,t}$ which represents the difference between up-beta and down-beta of the momentum portfolio during bear and non-bear market respectively. From the regressions, I expect to see that the coefficient $\beta_{up\_bear,t}$ will statistically significant but the coefficient $\beta_{up,t}$ will not be statistically significant, which implies that there is up-down beta asymmetry only in a bear market, which is consistent with Daniel and Moskowitz (2016). (Note that optionality mean that when certain asset behave like an option but it is not an actual option).

Additionally, to identify the source of this optionality, a regression on 10th decile and 1st decile portfolio will be conduct for equation (5), (6) with the same independent variable as in equation (4), but replacing the dependent variable which is the whole momentum portfolio monthly return with the 10th decile and 1st decile portfolio monthly return, winner ($R_{W,t}$) and loser ($R_{L,t}$) portfolio respectively.

$$R_{W,t} = \alpha_0 + \alpha_{BEAR}(D_{BEAR}) + \beta_0(R_{me,t}) + \beta_{BEAR}(D_{BEAR} \times R_{me,t}) + \beta_{up\_bear,t}(D_{U,t} \times D_{BEAR} \times R_{me,t}) + \beta_{up,t}(D_{U,t} \times R_{me,t}) + \epsilon_t \quad (5).$$

$$R_{L,t} = \alpha_0 + \alpha_{BEAR}(D_{BEAR}) + \beta_0(R_{me,t}) + \beta_{BEAR}(D_{BEAR} \times R_{me,t}) + \beta_{up\_bear,t}(D_{U,t} \times D_{BEAR} \times R_{me,t}) + \beta_{up,t}(D_{U,t} \times R_{me,t}) + \epsilon_t \quad (6).$$

Where,
$R_{W,t}$ = winner portfolio return at month t (10th decile)
$R_{L,t}$ = loser portfolio return at month t (1st decile)
$R_{me,t}$ = $R_{m,t}$ - $R_{fm,t}$ monthly market excess return at month t
D_{BEAR} = dummy variable where it equal to 1 if 2-year past market return is negative. (Bear market indicator)
$D_{U,t}$ = dummy variable where it equal to 1 if the market return of current month is more than zero ($R_{m,t}$ > 0).

The up and down beta for both portfolio during each market state can be interpreted as $\beta_0 + \beta_{BEAR} + \beta_{up\_bear,t} + \beta_{up,t}$ for the up beta during bear market and $\beta_0 + \beta_{BEAR}$ for the down beta during bear market. For non-bear market, the up beta equal to $\beta_0 + \beta_{up,t}$ and the down beta equal to β_0. The interpretation four beta during each market state is the same as the table on the previous page.

The coefficient $\beta_{up\_bear,t}$ in equation (6) for the loser portfolio (1st decile) will be the main variable of interest and it is expected to be significant, which implies the option-like payoff exist only in a bear market. Since it is mentioned in Daniel and Moskowitz (2016) that the loser portfolio is the cause for the whole momentum portfolio option-like payoff.

2.3 Momentum return and ex-ante market variance

From up-down beta asymmetry in sections 2.2 and 2.3 imply that momentum portfolio behaves itself as a short-call option only in a bear market. It raised a question of whether the momentum portfolio also has a negative relationship with market variance as well since it is a short call option. To answer the question, a full sample regression on monthly momentum portfolio returns with an ex-ante market variance is constructed. The ex-ante market variance is estimated from the past 126 daily market return from that month. For example, the estimated market variance at the January 2000 is using the past 126 daily data of market return starting from the beginning of July 1999. In addition to the regression, a bear market indicator (D_{BEAR}), which is a dummy variable, is included for both intercept and market variance, where it equal to 1 if 2-year past market return is negative. The reason to include bear market indicator (D_{BEAR}) is to distinguish the effect of market variance toward the momentum portfolio during non-bear and bear market. Which the equation is (7).

$$R_{WML,t} = \alpha_0 + \alpha_{BEAR}(D_{BEAR}) + \gamma_0(\sigma^2_{m,t-1}) + \gamma_{BEAR}(D_{BEAR} \times \sigma^2_{m,t-1}) + \epsilon_t \qquad (7).$$

Where,
$R_{WML,t}$ = monthly momentum portfolio return at month t
D_{BEAR} = dummy variable where it equal to 1 if 2-year past market return is negative. (Bear market indicator)
$\sigma^2_{m,t-1}$ = ex-ante monthly market variance which estimated from past 126 daily market return.

(For example, the market variance in month t is calculated by using the daily return of past 126 days market return as a sample for variance calculation. The reported variance are not annualized so the unit will still be daily return squared)

The variable of interest in this section is the coefficient γ_{BEAR}, which explain the relationship between market variance and momentum portfolio return during bear market. According to Daniel and Moskowitz (2016), the coefficient γ_{BEAR} in equation (7), is expected to be negatively significant while the coefficient γ_0 alone will not be significant, which mean the relationship exist only in bear market and it imply that the optionality of momentum portfolio exists only in a bear market. (Note that optionality mean that when certain asset behaves like an option but it is not an actual option)

The reported t-statistic in this section will be calculated by using Newey-West standard error with six lags as a reported standard error. By data structure, market variance data are subject to the serial correlation problem, the calculated market variance are correlated with lagged version of itself. For example, the market variance at beginning of January 2002 is calculated from daily market return at from past 126 days which is roughly from the beginning of July 2001 to the beginning of January 2002. In addition, market variance at beginning of February 2002 are calculated from daily market return from the beginning of August 2001 to the beginning of February 2002. In this case, the same component of daily return for computing variance in January 2002 is also included in variance at February 2002. It means we use the same data point twice and this could potentially cause a serial correlation problem.

2.4 Conditional variable

In previous sections, the relationship of momentum portfolio return with past market return and ex-ante market variance are separately shown. From past literature, it can be expected that during bear market or high volatility the momentum portfolio will perform poorly.

Nevertheless, the interaction among the past market return and market variance together in one equation are still unclear. Exploring this relationship help clarify whether the market variance has an effect on the beta of momentum portfolio during bear market or not? In other words, how beta of momentum portfolio will change when it is scaled based upon market variance. Moreover, whether the market variance has an effect on the beta of momentum portfolio only in bear market? Therefore, I construct a conditional variable, which adopted from Daniel and Moskowitz (2016) that aims to capture time variation in factor loading on the market. Note that in Daniel and Moskowitz (2016) did normalize the term by dividing the market variance with the full-sample average of market variance for all month that D_{BEAR} equal to one for easier interpretation. However, in our case, the variable are not normailized and it does not affect the statistical significance of the result. The conditional variable can be written as follow.

$$I_{B\sigma^2} = D_{BEAR} \times \sigma^2_{m,t-1}$$

Where,
D_{BEAR} = dummy variable where it equal to 1 if 2-year past market return is negative. (Bear market indicator)
$\sigma^2_{m,t-1}$= ex-ante monthly market variance which estimated from past 126 daily market return

In a layman's term, it can be viewed as a panic state indicator (volatile bear market) that scale the coefficient based on ex-ante market volatility. The higher the value of the conditional variable ($I_{B\sigma^2}$) the higher the volatility during that bear market period.

To see the relationship of this conditional variable toward the momentum portfolio return and other factors, I adopted a regression from section 2.1 equation (2) but with a slight change from using D_{BEAR} to using a conditional variable $I_{B\sigma^2}$ instead. Moreover, the term $\left(\sigma^2_{m,t-1} \times R_{me,t}\right)$ is included in order to distinguish the effect of market variance toward the portfolio beta during each marking state. The regression is constructed on a full sample from January 2001 to December 2018. The equations can be written as follow.

$$R_{WML,t} = \alpha_0 + \alpha_{cond}(I_{B\sigma^2}) + \beta_0(R_{me,t}) + \gamma_{cond}(I_{B\sigma^2} \times R_{me,t}) + \epsilon_t \quad (8).$$

$$R_{WML,t} = \alpha_0 + \alpha_{cond}(I_{B\sigma^2}) + \beta_0\left(R_{me,t}\right) + \gamma_{var\_bear}\left(I_{B\sigma^2} \times R_{me,t}\right) + \gamma_{var}\left(\sigma^2_{m,t-1} \times R_{me,t}\right) + \epsilon_t \quad (9).$$

Where,
$R_{WML,t}$ = monthly momentum portfolio returns at month t
$R_{me,t}$ = $R_{m,t}$ - $R_{fm,t}$ monthly market excess return at month t
$I_{B\sigma^2}$ = conditional variable which equivalent of $D_{BEAR} \times \sigma^2_{m,t-1}$
α_0 = premium during non-panic state
α_{cond} = difference in premium during panic and non-panic state
$\gamma_{cond} \times \sigma^2_{m,t-1}$= difference between beta during panic and non-panic state

For the equation (8), the conditional variable alone, $\alpha_{cond}(I_{B\sigma^2})$, can be viewed as the effect of D_{BEAR} on $R_{WML,t}$ which is equal to $\alpha_{cond} \times \sigma^2_{m,t-1}$. (Note that $I_{B\sigma^2} = D_{BEAR} \times \sigma^2_{m,t-1}$). In other word, it shows the difference between momentum premium during panic state, bear market with high volatility, and non-panic state while the premium is scaled based on the market variance.

The conditional variable with market excess return,($I_{B\sigma^2} \times R_{me,t}$), show the effect of market excess return during bear market, ($D_{BEAR} \times R_{me,t}$), on $R_{WML,t}$ which is equal to $\gamma_{cond} \times \sigma^2_{m,t-1}$, given that ($I_{B\sigma^2} = D_{BEAR} \times \sigma^2_{m,t-1}$). The multiplication of $\gamma_{cond} \times \sigma^2_{m,t-1}$ is simply the beta during bear market on a normal CAPM with bear market dummy variable but in this equation, beta is not constant. It is scaled based upon the market variance at that month, ($\sigma^2_{m,t-1}$). By doing so, we can see how beta of the portfolio affected by level of market variance during that time. The effect of market variance on beta is simply the coefficient γ_{cond}. Since the multiplication of $\gamma_{cond} \times \sigma^2_{m,t-1}$ is simply the beta during bear market.

From equation (8), the variable of interest are the coefficient α_{cond} and γ_{cond} which expected to be significantly negative as in sections 2.1, 2.3 and in Daniel and Moskowitz (2016). The negative coefficient implies that the momentum portfolio performs poorly during bear market with high volatility (panic-state). This result emphasizes the idea of the option-like characteristic of momentum portfolio is causes for momentum crashes. Note that the reported t-statistic in this section will be calculated by using Newey-West standard error with six lags as a reported standard error which the same as previous section.

For equation (9), by adding the variable $(\sigma^2_{m,t-1} \times R_{me,t})$, the effect of market variance toward the momentum portfolio beta is separated into two periods, which are bear and non-bear market. The effect of the market excess return toward portfolio return during bear market equal to $\beta_0 + (\gamma_{var\_bear} \times \sigma^2_{m,t-1}) + (\gamma_{var} \times \sigma^2_{m,t-1})$. On the other hand, the effect of the market excess return toward portfolio return during non-bear market equal to $\beta_0 + (\gamma_{var} \times \sigma^2_{m,t-1})$. The variable interest in this equation is simply the coefficient, γ_{var}, since it represent the effect of market variance toward portfolio beta outside of the bear market period. If the coefficient, γ_{var}, is statistically significant it mean that variance has an effect toward portfolio beta outside bear market.

3. Exposure to other risk factors

Since Daniel and Moskowitz (2016) have shown that there is a time-varying in exposure in its market beta for momentum portfolio. Combine with the different datasets in the emerging market country, Thailand, which have different factor exposure from the developed market. It raised the question whether the exposure of other factors such as Fama French factors exhibit the time-varying characteristic as well? Whether these time-varying characteristics are contributing to momentum crashes? Therefore, in this section, I investigate this effect with Fama-French 3 factors model. Adopted from Fama and French (1993), where they use the small minus big factor and high minus low factor.

3.1. Factor construction

3.1.1 Six value-weighted portfolios.

By following Fama and French (1993) methodology on factor construction with a slight twist, I construct a six value-weighted portfolios (S/L, S/M, S/H, L/L, L/M, L/H), constructed at the each month, which are the result from sorting firms into two group based on their market capitalization at that month by using the median as an indicator to distinguish between small(S) and large (L) companies.

Then these two size-sorted groups will be sorted into three groups, by using book-to-market ratio (B/M) at that month as an indicator, which is the bottom 30% (low book-to-market), medium 40% (medium book-to-market) and high 30% (high book-to-market). For example, S/H is portfolio with small firm (firm with market cap less than the median) that have high book-to-market ratio (firm with highest top 30% book-to-market ratio). L/M is portfolio with large firm (firm with market cap higher than the median) that also have medium book to market ratio (firm with book-to-market ratio that are in the middle 40th percentile).

	High B/M (above 70% percentile)	Medium B/M	Low B/M (below 30% percentile)
Small size (below median)	small size high B/M (SH)	small size medium B/M (SM)	small size low B/M (SL)
Large size (above median)	large size high B/M (LH)	large size medium B/M (LM)	large size low B/M (LL)

Table 2. Portfolio classification for Fama-French factors construction

The portfolio will be constructed and rebalanced on monthly basis, which mean the six portfolios will be sorted based on their market capitalization and book-to-market ratio as the process mentioned earlier again every month. The underlying reason for monthly rebalanced is to emphasize on the time-varying exposure of the two factors and it is matched with the momentum portfolio rebalancing policy. (Note that in Fama and French (1993), authors rebalance the portfolio on a yearly basis)

Additionally, the reason that Fama and French (1993) sorted firm into two groups based on size and three groups based on book-to-market is that the evidence in Fama and French (1992) show that book-to-market equity has a stronger role in average stock returns than size.

3.1.2 Monthly return calculation of six value-weighted portfolios.

The monthly return of each portfolios are calculated by the sum product of weight on each stock (weight by market capitalization) and the monthly return of stock as formula below.

$r_{Port,t} = \Sigma_{i=1}^{n}(\omega_{i,t-1} \times r_{i,t})$; Port = S/L, S/M, S/H, L/L, L/M, L/H
$\omega_{i,t-1} = MKTCAP_{i,t-1} \div TOTAL_{Port,t-1}$

Where,
$r_{Port,t}$ = monthly return of the portfolio for the six portfolios (S/L, S/M, S/H, L/L, L/M, L/H) at month t
n = number of stocks in that portfolio
$r_{i,t}$ = monthly return of stock i that are included in the portfolio at month t
$MKTCAP_{i,t-1}$ = market capitalization of stock i at month t - 1
$TOTAL_{Port,t-1}$ = total market capitalization of stock listed in that specific portfolio at month t-1. (For example, if there are two stocks listed in S/L Portfolio the $TOTAL_{Port,t-1}$will be equal to the sum of the market capitalization of those two stocks.)
$\omega_{i,t-1}$ = weight of stock i at month t-1

3.1.3 SMB, HML factor construction

To obtain the small minus big factor (SMB) is equivalent to the average monthly return of stock in small size minus the average return of monthly return of stock in large size. By doing so it will eliminate the effect of value factor out of the size factor. Since the value factor are already included in both small and large stock portfolios, which will cancel each other out at the end.

$$SMB_t = \frac{(r_{SH,t} + r_{SM,t} + r_{SL,t}) - (r_{LH,t} + r_{LM,t} + r_{LL,t})}{3}$$

Where,
SMB_t = small minus big factor at month t
$r_{SH,t}$ = monthly return of stock listed in small size with high B/M
$r_{SM,t}$ = monthly return of stock listed in small size with medium B/M
$r_{SL,t}$ = monthly return of stock listed in small size with low B/M
$r_{LH,t}$ = monthly return of stock listed in large size with high B/M
$r_{LM,t}$ = monthly return of stock listed in large size with medium B/M
$r_{LL,t}$ = monthly return of stock listed in large size with low B/M

To obtain the high minus low factor (HML) is equivalent to the average of monthly return of stock with high book-to-market ratio minus the average of monthly return of stock with low book-to-market ratio. By doing so will remove the effect of size factor in the HML factor since both high book-to-market ($r_{SH,t}$,$r_{LH,t}$) and low book-to-market ($r_{SL,t}$,$r_{LH,t}$) have already included stock with small and large size in it.

$$HML_t = \frac{(r_{SH,t} + r_{LH,t}) - (r_{SL,t} + r_{LL,t})}{2}$$

Where,
HML_t = high minus low factor at month t
$r_{SL,t}$ = monthly return of stock listed in small size with low B/M at month t
$r_{LL,t}$ = monthly return of stock listed in large size with low B/M at month t
$r_{SH,t}$ = monthly return of stock listed in small size with high B/M at month t
$r_{LH,t}$ = monthly return of stock listed in large size with high B/M at month t

3.2 Time-varying characteristics of other factors in momentum portfolio

After examining the effect of time-varying beta in momentum portfolio toward momentum crashes. It raised another question whether the exposure of other factors such as Fama French factors exhibit the time-varying characteristic toward momentum portfolio as well? Whether these time-varying characteristics of these factors are contributing to momentum crashes? To answer the question, Fama-French 3 factors model is used to capture time-varying characteristics of the factors. Equation (10) represents a normal Fama-French 3 factors model on monthly data.

Equation (11) represent a Fama-French 3 factors model with a dummy variable for bear market on each factors (D_{BEAR}), which equal to one if past two year market return is negative, by adding the dummy variable we can see the changes in its factors exposure during each market state. Equation (12) include the dummy variable ($D_{U,t}$) which represents a contemporaneous market return, when the contemporaneous market return is positive ($D_{U,t}$= 1). By adding $D_{U,t}$ will help distinguish the difference between up-beta and down-beta of each factor. All three regressions are conducted on a full sample from January 2001 to December 2018. The formula can be written as follows.

$$R_{WML,t} = \alpha_0 + \beta_0(R_{me,t}) + \beta_1(SMB_t) + \beta_2(HML_t) + \epsilon_t \qquad (10)$$

.

$$R_{WML,t} = \alpha_0 + \alpha_{BEAR}(D_{BEAR}) + \beta_0(R_{me,t}) + \beta_{0,BEAR}(D_{BEAR} \times R_{me,t}) + \beta_1(SMB_t) + \beta_{1,BEAR}(D_{BEAR} \times SMB_t) + \beta_2(HML_t) + \beta_{2,BEAR}(D_{BEAR} \times HML_t) + \epsilon_t \qquad (11).$$

$$R_{WML,t} = \alpha_0 + \alpha_{BEAR}(D_{BEAR}) + \beta_0(R_{me,t}) + \beta_{0,BEAR}(D_{BEAR} \times R_{me,t}) + \beta_{0,U,t}(D_{BEAR} \times D_{U,t} \times R_{me,t}) + \beta_1(SMB_t) + \beta_{1,BEAR}(D_{BEAR} \times SMB_t) + \beta_{1,U,t}(D_{BEAR} \times D_{U,t} \times SMB_t) + \beta_2(HML_t) + \beta_{2,BEAR}(D_{BEAR} \times HML_t) + \beta_{2,U,t}(D_{BEAR} \times D_{U,t} \times HML_t) + \epsilon_t \qquad (12).$$

Where,
$R_{WML,t}$ = monthly momentum portfolio return at month t
$R_{me,t}$ = $R_{m,t}$ - $R_{fm,t}$ monthly market excess return at month t
SMB_t = small minus big factor at month t

HML_t = high minus low factor at month t
D_{BEAR} = dummy variable where it equal to 1 if 2-year past return of the market is negative. (Bear market indicator)
$D_{U,t}$ = dummy variable where it equal to 1 if the market return of current month is more than zero ($R_{m,t}$ > 0).

The variable of interest in this section is the coefficient $\beta_{1,BEAR}$, $\beta_{2,BEAR}$ which indicates the difference of factor exposure of momentum portfolio during bear and non-bear market. Based on Asness et al. (2013), Fama and French (2010), it is clear that there is a negative correlation of momentum factor with SMB and HML factor. But it is unclear whether the sensitivity of these two factors toward portfolio return changes or not during each market state.

Additional note for equation (12), which the $D_{U,t}$ dummy variable is added to both factors. The reason to include this variable is to see whether these additional factors are contributing to momentum negative return or not? Since momentum crashes occur during the period when the market rebounds from its decline with high volatility. By adding variable $D_{U,t}$ with the new factors into the equation, will help clarify the exposure of these factors during crashes period toward momentum portfolio return.

CHAPTER 6 Empirical Result

In this chapter, the contents are separated into three parts, which are overall momentum performance, descriptive statistics, and regression result from the methodology section.

5.1 Overall Momentum performance

5.1.1 Performance

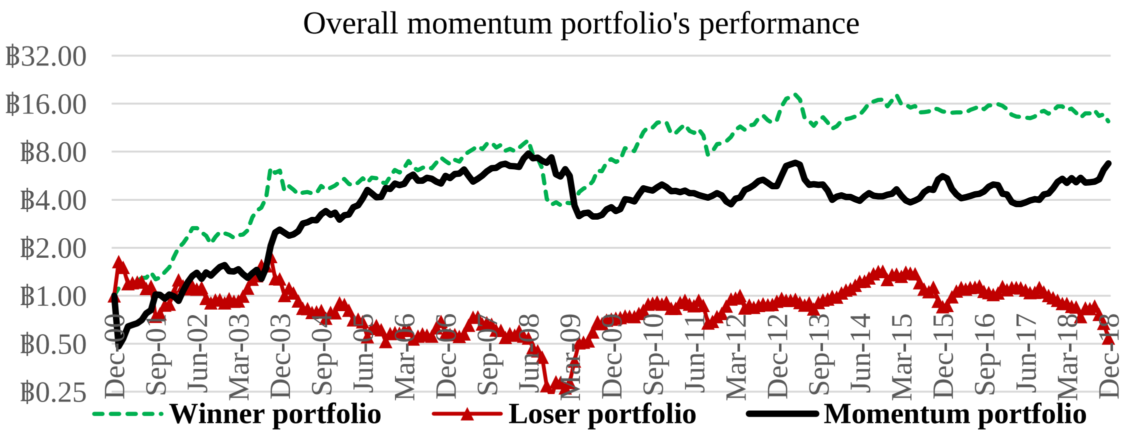

Figure 4. Examining the overall momentum portfolio performance.
The figure above represent the cumulative return of 1 baht investment for three portfolios plotted on a logarithmic scale, which are momentum, winner, and loser portfolio, from the beginning of January 2001 to December 2018. The dotted green line is the top decile "winner" portfolio. The red solid line with a triangle represent the bottom decile "loser" portfolio. Lastly, the black solid line represent the momentum portfolio, winner minus loser portfolio

5.1.2 Momentum, Bear market, and Variance

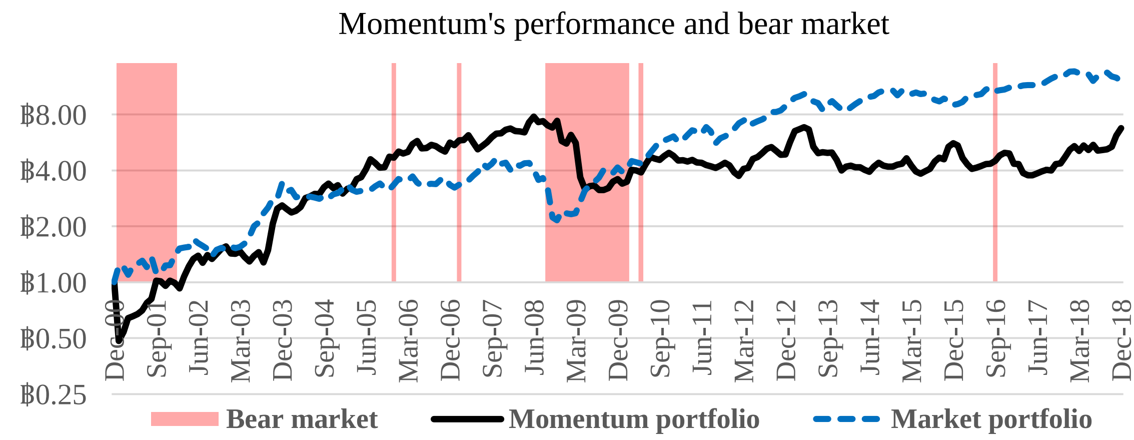

Figure 5. Examining the momentum portfolio performance with the market and bear market.
The figure above represent the cumulative return of 1 baht investment for two portfolios plotted on a logarithmic scale, which are momentum and market portfolio, from the beginning of January 2001 to December 2018. With an addition of market state dummy variable, D_{BEAR} to distinguish the momentum

portfolio performance during bear and non-bear market, defined by past 24 months market return. The red highlighted area represent the time when there is a bear market. The black solid line represent the momentum portfolio, winner minus loser portfolio. The blue dashed line represent the market portfolio.

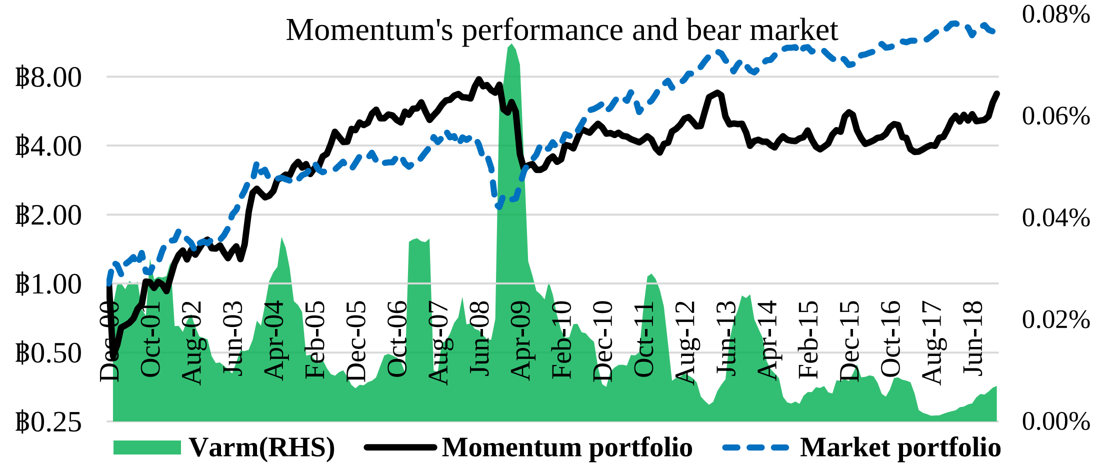

Figure 6. Examining the momentum portfolio performance with the market and market variance.
The figure above represent the cumulative return of 1 baht investment for two portfolios plotted on a logarithmic scale, which are momentum and market portfolio, from the beginning of January 2001 to December 2018. With addition of ex-ante market variance, calculated from past 126 days past market return, plotted in green area at the background, which the value is show on the right hand side axis. The black solid line represent the momentum portfolio, winner minus loser portfolio. The blue dashed line represent the market portfolio.

From figure 5 and 6, there are three points to be mention. The first point, momentum strategy underperforms the market because the beginning of January 2001 strategy suffers from a severe loss of -51.8%. If that month excluded the strategy will outperform the market. As a result, it is hard to identify whether the momentum strategy beat the market or not since the timing of the strategy also plays a role in explaining overall performance.

The second point, momentum portfolio performs poorly during high market variance period, plotted as an area chart and its axis is on the right hand side. The obvious case is the global financial crisis in 2008-2009, which the market variance reaches it record high and the momentum portfolio declines rapidly.

The third point, momentum crashes occur during the market rebound from its decline which consistent with Daniel and Moskowitz (2016). The obvious case is the global financial crisis in 2008-2009, which the market decline sharply and rebound. During the market decline, momentum portfolio did not suffer much but once the market start to rebound the momentum portfolio suffer a large loss.

5.1.3 Momentum's top 10 worst and best monthly performance

	$R_{W,t}$	$R_{L,t}$	$R_{WML,t}$	$R_{me,t}$	D_{BEAR}	$D_{U,t}$
Jan-01	11.9%	63.6%	-51.8%	23.5%	1	1
Apr-09	1.6%	36.3%	-34.7%	15.6%	1	1
Dec-08	4.1%	25.9%	-21.9%	11.9%	1	1
Jun-13	-22.6%	-3.4%	-19.2%	-7.3%	0	0
Feb-16	-0.7%	13.5%	-14.2%	2.6%	0	1
May-09	15.9%	30.0%	-14.1%	14.3%	1	1
Dec-13	-8.6%	3.7%	-12.3%	-5.4%	0	0
Aug-03	3.9%	15.9%	-12.0%	11.7%	0	1
Jan-17	-2.2%	9.6%	-11.7%	2.1%	0	1
Mar-17	-7.3%	3.2%	-10.5%	1.5%	0	1

Table 3. Momentum portfolio top 10 worst performance.

The table above represent the worst ten months return of momentum portfolio ($R_{WML,t}$) along with the winner ($R_{W,t}$) and loser ($R_{L,t}$) portfolio monthly return, monthly market excess return ($R_{me,t}$), a bear market state dummy variable (D_{BEAR}) and contemporaneous market state dummy variable ($D_{U,t}$). The bear market state dummy variable equal to one if past 24 months market return is less than zero. The contemporaneous market state dummy variable equal to one if the current month market return is positive.

	$R_{W,t}$	$R_{L,t}$	$R_{WML,t}$	$R_{me,t}$	D_{BEAR}	$D_{U,t}$
Oct-03	53.7%	14.5%	39.2%	10.4%	0	1
Sep-01	-9.6%	-35.0%	25.4%	-17.4%	1	0
Nov-03	-6.8%	-27.2%	20.5%	1.2%	0	1
Mar-01	-1.8%	-20.8%	19.0%	-9.6%	1	0
Nov-15	-1.5%	-18.1%	16.7%	-2.6%	0	0
Jan-13	20.7%	4.4%	16.3%	5.7%	0	1
Sep-03	15.4%	-0.8%	16.2%	7.7%	0	1
Mar-02	7.3%	-8.4%	15.7%	1.1%	0	1
Mar-10	18.0%	2.5%	15.6%	10.0%	0	1
Feb-13	11.9%	-3.1%	15.0%	4.6%	0	1

Table 4. Momentum portfolio top 10 best performance.

The table above represent the best ten months return of momentum portfolio ($R_{WML,t}$) along with the winner ($R_{W,t}$) and loser ($R_{L,t}$) portfolio monthly return, monthly market excess return ($R_{me,t}$), a bear market state dummy variable (D_{BEAR}) and contemporaneous market state dummy variable ($D_{U,t}$). The bear market state dummy variable equal to one if past 24 months market return is less than zero. The contemporaneous market state dummy variable equal to one if the current month market return is positive.

From table 3, four out of the top five worst performing month happen during a period which the current month market return is positive as suggested by a contemporaneous market state dummy variable, $D_{U,t}$, equal to one. It implies that momentum portfolio performs poorly during market increase or rebound. Moreover, out of the four month with positive market returns the top three of them are happen during bear market as suggested by bear market state dummy variable, D_{BEAR} which further suggests that momentum crashes in Thai's equities market are similar to what Daniel and Moskowitz (2016) found. However, in table 4 there is no such relationship in the top 10 best performing months. The similarity between both extreme return is that most returns are coming from the loser portfolio. This could imply the price inefficiency of the stocks toward short selling since it is not available to all types of investors in the market especially retail investors in Thailand.

5.1.4 Implication of momentum strategy with market state dummy variable

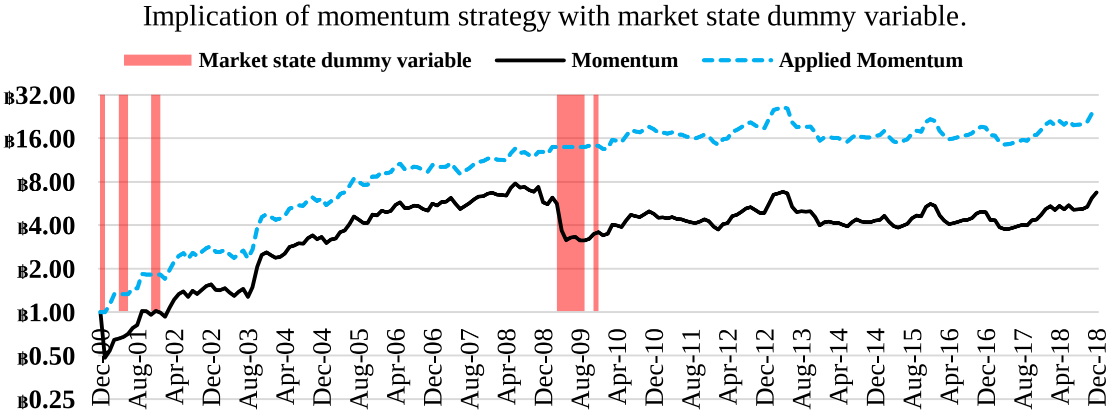

Figure 7. Examining the momentum strategy performance with the applied momentum strategy.
The figure above show the comparison between the normal momentum strategy and the applied momentum strategy from January 2001 to December 2018. The applied momentum strategy is simply the momentum strategy with a market timing, by closing all the position during the time of market rebound from it decline, which measured by the multiplication of dummy variables D_{BEAR} and $D_{U,t}$. For example, if the multiplication of dummy variables equal to one at that month, the applied momentum strategy is simply not invest in the market at all, which result a portfolio return for that month to be zero. The dummy variables consist of two variables. First, bear market state dummy variable D_{BEAR} which equal to 1 if past 24 months market return is less than zero. Second, the contemporaneous market state dummy variable, $D_{U,t}$, which equal to one if the current month market return is positive. The black line represent normal momentum strategy and the dashed line represent the applied momentum strategy. The highlighted area represent the period that market rebound from it decline.

Figure 7 shows the implication of momentum crashes. By forming the applied momentum strategy, the strategy is simply a normal momentum strategy with a market timing, by not investing in the market during a period when market rebound from its decline, which measured by the multiplication of dummy variables D_{BEAR} and $D_{U,t}$. For example, if the multiplication of dummy variables equal to one at that month then the strategy will not invest in the market, which mean the portfolio return for that month will be zero regardless of the actual momentum return that month. On the other hand, if the multiplication equal to zero the applied momentum is simply the same as the normal momentum strategy from the methodology section 1.2.

The applied momentum strategy outperforms the normal momentum strategy. It is obvious that the market state dummy variable both variables, D_{BEAR} and $D_{U,t}$, have the predictive power toward momentum portfolio negative return. The obvious case is during the 2008-2009 financial crisis where the applied momentum strategy correctly time the momentum crashes by not invest using a momentum strategy. However, the applied momentum strategy is not an ex-ante strategy since it required the value of the current month market return for the variable $D_{U,t}$.

5.2 Descriptive statistics

Three tables below represent the data used for the regression in the next section. Table 5 represent the variable used in the monthly regression, which is the focus of this study. Table 6 report the dummy variable used in the regression which are bear market state dummy variable, D_{BEAR} and contemporaneous market state dummy variable, $D_{U,t}$.

	Count	Mean	Max	Min	Median
$\boldsymbol{R_{WML,t}}$	216	1.3%	39.2%	-51.8%	1.5%
$R_{W,t}$	216	1.5%	53.7%	-36.0%	2.4%
$R_{L,t}$	216	0.2%	63.6%	-35.0%	0.6%
$\boldsymbol{SMB_t}$	216	0.4%	13.6%	-19.1%	0.0%
$R_{Small,t}$	216	1.7%	19.3%	-22.4%	2.1%
$R_{Big,t}$	216	1.3%	23.0%	-23.4%	1.3%
$\boldsymbol{HML_t}$	216	0.9%	15.4%	-9.9%	0.9%
$R_{High,t}$	216	2.0%	34.0%	-27.2%	1.9%
$R_{Low,t}$	216	1.0%	21.3%	-21.2%	1.1%
$\boldsymbol{R_{me,t}}$	216	1.2%	23.5%	-30.4%	1.5%
$\boldsymbol{R_{f,t}}$	216	0.2%	0.4%	0.1%	0.2%
$\boldsymbol{\sigma^2_{m,t-1}}$	216	0.016%	0.074%	0.001%	0.013%

Table 5. Descriptive statistics used in the monthly regression

The table above represent the descriptive statistics of monthly data used in regression. The reported statistics are count, mean, max, min and median respectively. The variables included in the table are: (1) Momentum portfolio monthly return ($R_{WML,t}$); (2) Winner portfolio monthly return ($R_{W,t}$); (3) Loser portfolio monthly return ($R_{L,t}$); (4) Small minus big factor monthly return (SMB_t); (5) Small size portfolio monthly return ($R_{Small,t}$); (6) Big size portfolio monthly return ($R_{Big,t}$); (7) High minus low factor monthly return (HML_t); (8) High book to market portfolio monthly return ($R_{High,t}$); (9) Low book to market portfolio monthly return ($R_{Low,t}$); (10) market excess return ($R_{me,t}$); (11) monthly return of one month risk-free rate($R_{f,t}$) and (12) ex-ante market variance ($\sigma^2_{m,t-1}$);

		$\boldsymbol{D_{BEAR}}$		
		Equal to 1	Equal to 0	Total ($\boldsymbol{D_{U,t}}$)
$\boldsymbol{D_{U,t}}$	Equal to 1	21	122	143
	Equal to 0	14	59	73
	Total($\boldsymbol{D_{BEAR}}$)	35	181	216

Table 6. Dummy variable used in monthly regression.

The table above represent the classification of dummy variable, used in the monthly regression, into group based on its value. The dummy variable included in the table are bear market state dummy variable, D_{BEAR} and contemporaneous market state dummy variable, $D_{U,t}$. The bear market state dummy variable equal to one if past 24 months market return is less than zero. The contemporaneous market state dummy variable equal to one if the current month market return is positive.

5.3 Regression result

In this section, the content is formatted in the same order as the methodology section, from Momentum crashes in Thai's equities market to Exposure to other risk factors.

5.3.1 Time-varying beta of momentum portfolio.

Variable	Eq. (1)	Eq. (2)	Eq. (3)
D_{BEAR}		-0.0969	**0.0613**
		(0.52)	**(0.01)**
$R_{me,t}$	**-0.2623**	0.1457	0.1457
	(0.00)	(0.23)	(0.20)
$D_{BEAR} \times R_{me,t}$		**-0.9196**	0.0362
		(0.00)	(0.88)
$D_{U,t} \times D_{BEAR} \times R_{me,t}$			**-1.8270**
			(0.00)
Constant	0.0160	0.0154	0.0154
	(0.01)	(0.01)	(0.01)

Table 7. Examining the Time-varying characteristic of momentum portfolio.
The table above represent the result of full sample OLS regression from January 2001 to December 2018. The dependent variable is the momentum portfolio monthly return, which the portfolio rebalance on a monthly basis. The controlled variable are bear market indicator (D_{BEAR}), market excess return ($R_{me,t}$), a multiplication of bear market indicator and market excess return ($D_{BEAR} \times R_{me,t}$) and multiplication of market excess return with bear market indicator and up market indicator ($D_{U,t} \times D_{BEAR} \times R_{me,t}$). The results are segmented into three equations based on its controlled variable. Reported here are the coefficient and p-value in the parenthesis.

$$R_{WML,t} = \alpha_0 + \beta_0(R_{me,t}) + \epsilon_t \qquad (1).$$

$$R_{WML,t} = \alpha_0 + \alpha_{BEAR}(D_{BEAR}) + \beta_0(R_{me,t}) + \beta_{BEAR}(D_{BEAR} \times R_{me,t}) + \epsilon_t \qquad (2).$$

$$R_{WML,t} = \alpha_0 + \alpha_{BEAR}(D_{BEAR}) + \beta_0\left(R_{me,t}\right) + \beta_{BEAR}\left(D_{BEAR} \times R_{me,t}\right) + \beta_{U,t}\left(D_{U,t} \times D_{BEAR} \times R_{me,t}\right) + \epsilon_t \qquad (3).$$

Table 7. Report the regression result from the equation in methodology section 2.1 and 2.2. The equations designed to answer whether the beta of momentum portfolio

changes overtime and whether momentum portfolio has an option-like characteristic in terms of a return aspect or not? Equation (1) represent a normal CAPM model with monthly momentum portfolio return as a dependent variable.

Equation (2) is similar to equation (1) but with an addition of past market state dummy variable D_{BEAR} on both intercept term and market excess return variable. (D_{BEAR} equal to one if the past 24 month of market return is negative) By adding D_{BEAR} into the regression, we can see that whether beta changes over time or not by looking at the reported p-value of the coefficient.

Equation (3) is an addition of equation (2). By including the current market state dummy variable, $D_{U,t}$, which equal to one if current month market return is positive, to the market excess return variable in order to distinguish the difference between up-beta and down-beta of the portfolio during the bear market. The difference will tell whether momentum portfolio behaves its self as a short-call option or not?

From all three equations, it show that momentum portfolio beta do vary over time as the coefficient of variable $D_{BEAR} \times R_{me,t}$ suggested in equation (2) and the coefficient of variable $D_{U,t} \times D_{BEAR} \times R_{me,t}$ in equation (3). The negative coefficient for $D_{BEAR} \times R_{me,t}$ in equation (2) imply that during bear market, where past 24 month market return is negative, the beta of momentum portfolio is lower than the normal period by 0.9196, from 0.1457 to -0.7739 with a p-value of 0.00. These changes in beta imply that momentum strategy is simply a trend following strategy. The result is consistent with existing literature as in Geczy and Samonov (2016), Daniel, and Moskowitz (2016).

The negative coefficient of $D_{U,t} \times D_{BEAR} \times R_{me,t}$ in equation (3) imply that during bear market the up beta of the momentum portfolio is significantly lower than the down beta by -1.8270 with the p-value of 0.00, which result an up beta of -1.6451 (0.1457+ 0.0362 -1.8270) and down beta of 0.1819 (0.1457+0.0362) during bear market. In other word, during bear market, when market increase by 1% the momentum portfolio will decrease by 1.83% and when the market decline by 1% the momentum portfolio will decline by 0.18%. The result is consistent with Daniel and Moskowitz (2016) that momentum portfolio behave itself as a short-call option in term of the return aspect during bear market, when the market fall it gain a little but when the market increase it loses a lot.

On the other hand, the positive coefficient intercept term D_{BEAR} in equation (3) show that during bear market the premium of momentum portfolio is higher than non-bear market by 0.0613 with p-value of 0.01. This evidence is contradict with the existing literature for the momentum premium and the market state that momentum premium supposed to be lower in the bear market. However, in Daniel and Moskowitz (2016), for the result of equation (3), they did not find any significant toward the D_{BEAR} variable as well.

The positive coefficient of intercept term D_{BEAR} could arise due to the two facts. First, overall market is relatively undervalued during bear market compared with the other period, therefore stock are more likely to yield positive return than negative. Second, The reversal nature of momentum portfolio which the portfolio return tend to reverse as the time progress, evidence from Jegadeesh and Titman (1993) and De Bondt and Thaler (1987), which in this case the momentum strategy in Thailand likely to reverse faster than the existing literature. Resulting a significantly positive intercept term.

In summary, momentum portfolio do behave as a short call option as suggested in equation (3) with an up beta that significantly lower than down beta during the bear market. Nevertheless, the premium of the momentum portfolio during bear market is significantly higher than non-bear market, which contradicts to existing literature.

5.3.2 Asymmetry in Optionality

		Eq. (4)	Eq. (5)	Eq. (6)
Variable	D_{BEAR}	0.0589	0.0330	-0.0258
		(0.01)	(0.04)	(0.15)
	$R_{me,t}$	0.2132	1.4175	1.2042
		(0.36)	(0.00)	(0.00)
	$D_{BEAR} \times R_{me,t}$	-0.1037	-0.2227	-0.1190
		(0.75)	(0.34)	(0.65)
	$D_{U,t} \times D_{BEAR} \times R_{me,t}$	**-1.7049**	-0.4625	**1.2424**
		(0.00)	(0.23)	**(0.00)**
	$D_{U,t} \times R_{me,t}$	-0.1221	**-0.3613**	**-0.2392**
		(0.741)	**(0.17)**	**(0.42)**
	Constant	0.0178	0.0080	-0.0098
		(0.05)	(0.22)	(0.19)

Table 8. Examining the option-like characteristic and it sources outside the bear market.

The table above represent the result of full sample OLS regression from January 2001 to December 2018. The dependent variable are the momentum portfolio monthly return, winner portfolio monthly return and loser portfolio monthly return respectively. The controlled variable are bear market indicator (D_{BEAR}), market excess return ($R_{me,t}$), a multiplication of bear market indicator and market excess return ($D_{BEAR} \times R_{me,t}$), a multiplication of market excess return with bear market indicator and up market indicator ($D_{U,t} \times D_{BEAR} \times R_{me,t}$) and multiplication of market excess return and up market indicator ($D_{U,t} \times R_{me,t}$). The result are segmented into three equations based on its dependent variable. Reported here are the coefficient and p-value in the parenthesis.

Table 8. Report the regression result from the methodology section 2.2 equation that aim to answer two questions. First, whether the up down beta asymmetry exist only in

bear market? Second, what causes the beta asymmetry? By adding the variable, $D_{U,t} \times R_{me,t}$, which represent the difference between up and down beta during the non-bear market, in order to distinguish both the beta difference between two market states and difference between up down beta in one equation. The up beta represent how the positive movement of market affects the momentum portfolio return. On the other hand, down beta represent how the negative movement of market affects the momentum portfolio return. For simplicity, the table and equation below show the calculation of beta on each market state for momentum portfolio in equation (4).

$$R_{WML,t} = \alpha_0 + \alpha_{BEAR}(D_{BEAR}) + \beta_0(R_{me,t}) + \beta_{BEAR}(D_{BEAR} \times R_{me,t}) + \beta_{up\_bear,t}(D_{U,t} \times D_{BEAR} \times R_{me,t}) + \beta_{up,t}(D_{U,t} \times R_{me,t}) + \epsilon_t \quad (4)$$

	Bear market	Non-bear market
Up-beta	$\beta_0 + \beta_{BEAR} + \beta_{up\_bear,t} + \beta_{up,t}$	$\beta_0 + \beta_{up,t}$
Down-beta	$\beta_0 + \beta_{BEAR}$	β_0

Table 9. Up-down beta calculation of momentum portfolio during each market state

For equation (4), the up beta during non-bear market is equal to the sum of β_0, $\beta_{up,t}$ which is the coefficient of market excess return ($R_{me,t}$) and multiplication of market excess return and up market indicator ($D_{U,t} \times R_{me,t}$) respectively. The down beta during non-bear market is equal to β_0.

The up beta during bear market equal to the up beta during non-bear market, $\beta_0 + \beta_{up,t}$, plus the difference in bear market which are β_{BEAR}, $\beta_{up\_bear,t}$ from ($D_{BEAR} \times R_{me,t}$) and ($D_{U,t} \times D_{BEAR} \times R_{me,t}$) respectively. The down beta during bear market is equal to the down beta in non-bear market, β_0, plus the difference, which is β_{BEAR} from ($D_{BEAR} \times R_{me,t}$).

The three equations in the table above are segmented by the dependent variable which equation (4) use monthly momentum portfolio return as a dependent variable while equation (5) and (6) use winner and loser portfolio monthly return as a dependent variable respectively.

For the first question, whether momentum portfolio has an up-down beta asymmetry outside of bear market, it is clear that there is no statistical significant for the coefficient, $\beta_{up,t}$, in the equation (4) for the variable ($D_{U,t} \times R_{me,t}$) with p-value of 0.74. Looking deeper into momentum portfolio component, which is the winner and loser portfolio on equation (5), (6) respectively. The result is consistent with what is mentioned earlier that there is no up down beta asymmetry outside of the bear market for the coefficient $\beta_{up,t}$ for the variable ($D_{U,t} \times R_{me,t}$) with the p-value of 0.17 and 0.42 for winner and loser portfolio respectively.

From equation (4), momentum portfolio up beta is significantly lower than the down beta by -1.7049 with p-value of 0.00 during bear market, which determined by the variable ($D_{U,t} \times D_{BEAR} \times R_{me,t}$). In addition, the source of this beta symmetry is the loser portfolio being the main driver for the up down beta asymmetry with the value of 1.2424 and p-value of 0.00, which determined by the variable ($D_{U,t} \times D_{BEAR} \times R_{me,t}$) from equation (6). This scenario is consistent with what Daniel and Moskowitz (2016) theorize in their paper that when the market decline the loser portfolio suffered severe loss. Therefore, it embodies a very high premium compared to the winner portfolio. As a result, when market start to rebound the loser portfolio experience a strong increase, which results a negative return for momentum portfolio, since we short the loser portfolio.

On the other hand, some of the result in bear market is contradicting to what Daniel and Moskowitz (2016) found. The bear market indicator D_{BEAR} for equation (4) and (5) are significantly positive which is different from what Daniel and Moskowitz (2016) found which are not statistically significant. The difference in term of positive bear market indicator could arise from the small number of sample used in regression, 18 years, compared to approximately 90 years in Daniel and Moskowitz (2016).

In summary, the up-down beta asymmetry of momentum portfolio exist only in bear market and caused by the loser portfolio which is consistent with the existing literature. The obvious difference is the positive significant of market state variable D_{BEAR} which implies that momentum portfolio premium increase during bear market while there is no statistical significant in the existing literature.

5.3.3 Momentum return and ex-ante market variance

		Eq. (7)
Variable	D_{BEAR}	0.0261 (0.50)
	$\sigma^2_{m,t-1}$	-46.5168 (0.45)
	$D_{BEAR} \times \sigma^2_{m,t-1}$	-128.2995 (0.26)
	Constant	0.0231 (0.02)

Table 10. Examining relationship between momentum portfolio and market variance.
The table above represent the result of full sample OLS regression from January 2001 to December 2018. The dependent variable are the monthly return of momentum portfolio. The controlled variable is the 126 days ex-ante market variance ($\sigma^2_{m,t-1}$), bear market indicator (D_{BEAR}), and the multiplication of market variance and bear market indicator ($D_{BEAR} \times \sigma^2_{m,t-1}$). Reported here are the coefficient and p-value in the parenthesis which calculated by the Newey-West standard error with six lags in order to avoid the serial correlation problem.

$$R_{WML,t} = \alpha_0 + \alpha_{BEAR}(D_{BEAR}) + \gamma_0\left(\sigma^2_{m,t-1}\right) + \gamma_{BEAR}\left(D_{BEAR} \times \sigma^2_{m,t-1}\right) + \epsilon_t \qquad (7).$$

Table 10 report the regression of the equations above. The regressions aim to answer the question that whether momentum portfolio during bear market behave itself as a short call option in variance aspect as well as the return aspect? In other word, during bear market do momentum portfolio have a negative relationship with the market variance or not? By regressing the momentum portfolio monthly return with the market variance and bear market indicator. Note that in this regression the reported p-value are calculated by using Newey-West standard error with six lags in order to avoid serial correlation problem.

Based on Daniel and Moskowitz (2016), it expected that the coefficient (γ_{BEAR}) alone will be negative and statistically significant while the coefficient (γ_0) will not, which mean during bear market the variance has an effect toward momentum return while during non-bear market there is no such relationship. Since they hypothesize that momentum portfolio behave itself as a short call option, in term of variance aspect, during the bear market.

From table 10, the result in equation (7) is differ from what Daniel and Moskowitz (2016) found. There is no statistical significant for effect of market variance (γ_0) and market variance during bear market (γ_{BEAR}) toward the momentum portfolio return with the p-value of 0.45, 0.26 respectively. Which mean the market variance has no effect toward portfolio return level at that time regardless of market state. This result reject the idea that momentum portfolio behave itself as a short call option during the bear market in term of variance aspect. The difference could arise from the small number of sample used in regression, 18 years, compared to approximately 90 years in Daniel and Moskowitz (2016).

In summary, the result is not consistent with Daniel and Moskowitz (2016) that there are no statistical significant effect of market variance toward momentum portfolio return regardless of the market state. Which the potential causes could arise from the small number of sample used in the calculation. However, it is still unclear about how market variance affect the beta of momentum portfolio, which will be discuss in the next section.

5.3.4 Conditional variable

		Eq. (8)	Eq. (9)
Variable	$I_{B\sigma^2}$	3.2284	
		(0.95)	
	$R_{me,t}$	0.1438	0.2155
		(0.32)	(0.53)
	$I_{B\sigma^2} \times R_{me,t}$	-3225.814	-2819.762
		(0.00)	(0.09)
	$\sigma^2_{m,t-1} \times R_{me,t}$		-584.345
			(0.75)
	Constant	0.0159	0.0163
		(0.00)	(0.00)

Table 11. Examining relationship between momentum portfolio and market variance with conditional variable.

The table above represent the result of full sample OLS regression from January 2001 to December 2018. The dependent variable are the monthly return of momentum portfolio. The controlled variable are the market excess return ($R_{me,t}$), conditional variable ($I_{B\sigma^2}$), the multiplication of market excess return and conditional variable, and the multiplication of market excess return and market variance ($\sigma^2_{m,t-1} \times R_{me,t}$). Reported here are the coefficient and p-value in the parenthesis which calculated by the Newey-West standard error with six lags in order to avoid the serial correlation problem.

$$I_{B\sigma^2} = D_{BEAR} \times \sigma^2_{m,t-1}$$

$$R_{WML,t} = \alpha_0 + \alpha_{cond}(I_{B\sigma^2}) + \beta_0(R_{me,t}) + \gamma_{cond}(I_{B\sigma^2} \times R_{me,t}) + \epsilon_t \quad (8).$$

$$R_{WML,t} = \alpha_0 + \beta_0(R_{me,t}) + \gamma_{var\_bear}(I_{B\sigma^2} \times R_{me,t}) + \gamma_{var}(\sigma^2_{m,t-1} \times R_{me,t}) + \epsilon_t \quad (9).$$

Table 11 report the regression result of the equation (8) and (9), which the dependent variable is the monthly momentum portfolio return and the controlled variable is the market excess return and the conditional variable. The regression aim to answer how market variance affect the beta of momentum portfolio during bear market and how the premium of the momentum portfolio changes during panic state. By replacing, a bear market indicator D_{BEAR} with the conditional variable, which is the multiplication of bear market indicator and market variance, $I_{B\sigma^2}$. The conditional variable can be view as a panic state variable, high volatility during bear market. The higher the value the higher the volatility at that bear market period.

From equation (8), the coefficient γ_{cond} for the variable $I_{B\sigma^2} \times R_{me,t}$ is negatively significant with the value of -3225.814 and p-value of 0.00, which mean during panic state the beta of momentum portfolio, calculated by ($\gamma_{cond} \times \sigma^2_{m,t-1}$), have a negative relationship with the market variance. The higher the market variance the lower the beta of momentum portfolio. The lower the beta the larger loss for momentum portfolio when the market rebound. The result is consistent with what Daniel and Moskowitz

(2016) found. Note that the conditional variables in this equation are calculated without normalized by the term full-sample average market variance.

However, the coefficient α_{cond} for the variable $D_{BEAR} \times \sigma^2_{m,t-1}$, $I_{B\sigma^2}$, is contradict with what Daniel and Moskowitz (2016) found. Instead of being negatively significant, the p-value of the coefficient turn out to be not statistically significant with the p-value of 0.94, which mean market variance alone did not affect momentum portfolio return. The result is consistent with last section, where the market variance and bear market are regressed with momentum portfolio return. The difference could arise from the small number of sample used in the regression, 18 years of data, which result captured only one period that variance changes a lot in 2008-2009 financial crisis.

From equation (9), the coefficient γ_{var} for the variable $\sigma^2_{m,t-1} \times R_{me,t}$ which represent the effect of market excess return toward momentum portfolio return that is scaled based upon market variance during non-bear market state, $\gamma_{var} \times \sigma^2_{m,t-1}$. The result show that there is no statiscaly siginificant for the coefficient with the p-value of 0.75, which mean the market variance has no effect toward portfolio beta outside of the bear market.

The coefficient γ_{var_bear} for the variable $I_{B\sigma^2} \times R_{me,t}$, which represent the effect of market excess return toward momentum portfolio return that is scaled based upon market variance during bear market state. The result show that there tend to be a negative relationship between market variance and momentum portfolio beta during bear market state with the value of -2819.762 and p-value of 0.09

In summary, the market variance has an effect on momentum portfolio beta but not for the portfolio premium, which support the idea of momentum portfolio behaves as a short call option. However, for the portfolio premium, there is no relationship of market variance toward momentum portfolio return during bear market, which is major difference from what Daniel and Moskowitz (2016) found. Moreover, the result from equation (9) show that the market variance tend to have an effect on the portfolio beta only in bear market.

5.3.5 Exposure to other risk factor

Variable	Eq. (10)	Eq. (11.1)	Eq. (12.1)
$R_{me,t}$	-0.0249	0.1556	0.1522
	(0.79)	(0.18)	(0.18)
SMB_t	**0.6734**	**0.3712**	**0.3397**
	(0.00)	**(0.04)**	**(0.05)**
HML_t	***-1.002***	***-0.7865***	***-0.8000***
	(0.00)	***(0.00)***	***(0.00)***
$D_{BEAR} \times R_{me,t}$		**-0.4128**	-0.045
		(0.04)	(0.87)
$D_{BEAR} \times SMB_t$		**0.5723**	-0.3677
		(0.06)	(0.50)
$D_{BEAR} \times HML_t$		-0.0107	0.0488
		(0.47)	(0.20)
$D_{BEAR} \times D_{U,t} \times R_{me,t}$			***-1.4250***
			(0.01)
$D_{BEAR} \times D_{U,t} \times SMB_t$			**0.6047**
			(0.34)
$D_{BEAR} \times D_{U,t} \times HML_t$			**0.0243**
			(0.62)
Constant	0. 0200	0.0192	0.0190
	(0.00)	(0.00)	(0.00)

Table 12. Examining time-varying characteristic of momentum portfolio with Fama-French factors. The table above represent the result of full sample OLS regression from January 2001 to December 2018. The dependent variable are the monthly return of momentum portfolio. The controlled variable are market excess return ($R_{me,t}$), size factor (SMB_t), value factor (HML_t) and the combination of bear market indicator (D_{BEAR}) with the contemporaneous market indicator ($D_{U,t}$) and the Fama-French factors. The calculation of $D_{U,t}$, D_{BEAR} are the same as previous table. The result are segment into three equations based on the variable included in the regression. Reported here are the coefficient and p-value in the parenthesis.

$$R_{WML,t} = \alpha_0 + \beta_0(R_{me,t}) + \beta_1(SMB_t) + \beta_2(HML_t) + \epsilon_t \qquad (10).$$

$$R_{WML,t} = \alpha_0 + \beta_0(R_{me,t}) + \beta_{0,BEAR}(D_{BEAR} \times R_{me,t}) + \beta_1(SMB_t) + \beta_{1,BEAR}(D_{BEAR} \times SMB_t) + \beta_2(HML_t) + \beta_{2,BEAR}(D_{BEAR} \times HML_t) + \epsilon_t \qquad (11.1).$$

$$R_{WML,t} = \alpha_0 + \beta_0(R_{me,t}) + \beta_{0,BEAR}(D_{BEAR} \times R_{me,t})$$
$$+ \beta_{0,U,t}(D_{BEAR} \times D_{U,t} \times R_{me,t}) + \beta_1(SMB_t) + \beta_{1,BEAR}(D_{BEAR} \times SMB_t)$$
$$+ \beta_{1,U,t}(D_{BEAR} \times D_{U,t} \times SMB_t) + \beta_2(HML_t) + \beta_{2,BEAR}(D_{BEAR} \times HML_t)$$
$$+ \beta_{2,U,t}(D_{BEAR} \times D_{U,t} \times HML_t) + \epsilon_t \qquad (12.1).$$

From Table 12, the main question is whether the momentum portfolio has time-varying exposure to other factors or not? Moreover, whether these factors contribute to momentum crashes or not? Note that Fama-French factors used in these regressions are constructed and rebalanced on a monthly basis in order to match with momentum portfolio.

Equation (10) represents a normal Fama-French 3 factors model on monthly data. Equation (11.1) represent a Fama-French 3 factors model with a dummy variable for bear market on each factors (D_{BEAR}), which equal to one if past two year market return is negative, by adding the dummy variable we can see the changes in its factors exposure of momentum portfolio during each market state. Equation (12.1) include the dummy variable ($D_{U,t}$) which represents a contemporaneous market return, equal to one when the contemporaneous market return is positive ($D_{U,t}$= 1). Since momentum crashes likely to occur when market rebounds from its decline. By adding $D_{U,t}$ will help distinguish the difference between up beta and down beta of each factors and answer the question whether these factors contribute to momentum crashes or not? (Note that equation (11.1), (12.1) are similar to equation (11), (12) in the methodology section but without D_{BEAR} for the intercept term variable due to multicollinearity problem)

Based on Daniel and Moskowitz (2016), there is a negative relationship of momentum factor with SMB and HML factor. However, it is unclear whether the sensitivity, beta, of these two factors changes during each market state or not? From the result of equation (10), both Fama-French factors are statistically significant. However, the coefficient of size factor β_1 is positively significant, with a value of 0.6734 and p-value of 0.00, which contradicts with the existing literature that the size factor and momentum factor are negatively correlated. The error may come from the nature of portfolio construction, which rebalanced the portfolio monthly and the nature of sorting stocks into two groups instead of ten in order to form a portfolio.

When adding bear market indicator to both factor in equation (11.1), there are statistical significant for the beta of market excess return during bear market ($\beta_{0,BEAR}$) with p-value of 0.04 but not beta of value factor during bear market ($\beta_{2,BEAR}$), with p-value of 0.47. Nevertheless, the size factor, SMB, beta also changes over time as well with its beta higher than non-bear market by 0.5723, p-value of 0.06, from 0.3712 to 0.9435. In other word, during bear market the size factor have stronger effect toward momentum portfolio.

To answer the second question, the contemporaneous market indicator ($D_{U,t}$) is added for all three return factors in equation (12.1). The result shows that all Fama-French factors does not have an option-like payoff characteristic during bear market, determined by the difference between up beta and down beta that indicated by p-value of the coefficient $\beta_{1,U,t}$, $\beta_{2,U,t}$ for SMB and HML which are 0.34 and 0.62 respectively. In other word, all Fama-French factors beta are the same for both upward and downward movement of the market. On the other hand, only the market excess return show a significant option-like characteristic with a value of -1.4250 and p-value of 0.00, which mean the up beta of the market factor is lower than the down beta of the market factor by -1.4250. The up beta equal to -1.3178 and the down beta equal to 0.1072. For example, when market increase by 1% the portfolio loses 1.3178% and when the market decline by 1% the portfolio loses 0.1072%.

In summary, By including Fama-French factors and the dummy variables ($D_{U,t}$,D_{BEAR}) into the equation to distinguish the difference between up beta and down beta of each factor, the result shows that momentum portfolio behave as a short call option for the market which is consistent with what Daniel And Moskowitz (2016) found. In addition, Fama-French's SMB factor beta do changes overtime but all the Fama-French's factor did not exhibit an option-like characteristic as the market excess return. The major differences is the coefficient value of size factor that are positively related with momentum portfolio return instead of negatively related.

CHAPTER 7 Conclusions

The main question in this paper is whether the equity market with a large proportion of retail investors can experience this negative return phenomenon or not? By exploring the momentum crashes characteristics in Thai's market. As a contribution toward existing literature, this paper also investigates the time-varying exposure of Fama-French factors toward momentum portfolio and the effect of market variance toward portfolio beta outside of bear market.

Based on the result, momentum strategy do experience a momentum crashes in Thai's market as well. The momentum crashes are mainly driven by the option-like characteristic of the loser portfolio that exist only in bear market, which results in a significantly negative up-beta for the momentum portfolio. These characteristic result a large loss for the portfolio when the market increase in that month. This large loss occurred only in bear market. Moreover, the result show that market variance have an effect on portfolio beta only in bear market. However, there are two points that differ from the existing literature. First, they are no direct relationship between the market variance toward momentum portfolio during bear market. Second, the premium of momentum portfolio is significantly higher during bear market. This imply that during bear market the momentum portfolio likely to generate a higher return than non-bear market. The differences could arise due to the three facts. First, the overall market is relatively undervalued during bear market compared with the other period. Therefore, stocks are more likely to yield positive return than negative. Second, The reversal nature of momentum portfolio. Third, the small number of sample used in this study.

For the contribution toward existing literature in Thai's market, the result show that market variance have no effect toward momentum portfolio beta outside bear market. Moreover, the Fama-French SMB factor is the only factor that exhibits the time-varying exposure toward momentum portfolio with the beta coefficient higher than the non-bear market. However, none of the Fama-French factors exhibited the option-like characteristic toward the momentum portfolio during the bear market.

There are some key insights that can made from this study, First, momentum do experience a crash in Thailand as well even with some minor differences. Second, the time-varying characteristics of the momentum portfolio, negative up beta during bear market, is the most robust characteristics in this study. Therefore, one should also include this characteristic in their study on momentum as well. These insights open a new area to be a future research in Thai's market such as the profitability improvement of the strategy, the convexity relationship with the past market return, market state definition apart from using past two years market return , and the effect of market return toward Fama-French factors and the momentum portfolio return.

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