A Systematic Risk Factor for Detecting Financial Turbulence in the Thai Stock Market

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งานวิจัยนี้พัฒนาดัชนีชี้วัดระดับความเสี่ยงที่เป็นระบบ (Systematic Risk) และความสามารถในการที่จะคาดการณ์วิกฤตการณ์ทางการเงินในตลาดหลักทรัพย์แห่งประเทศไทย ผลการวิจัยพบว่าในช่วงเวลาที่ระดับเสี่ยงที่เป็นระบบเพิ่มสูงขึ้น ตลาดหลักทรัพย์ไทยจะมีผลตอบแทนที่แย่ลง ช่วงเวลาที่ดัชนีชี้วัดระดับความเสี่ยงที่เป็นระบบมีค่าสูงขึ้นอย่างมีนัยสำคัญมีความเกี่ยวข้องกับเหตุการณ์สำคัญทางการเงิน เช่น การประกาศควบคุมเงินทุนจากธนาคารแห่งประเทศไทย หรือวิกฤตซับไพรม เป็นต้น งานวิจัยนี้ได้ศึกษาผลกระทบของความเสี่ยงที่เป็นระบบ ความผิดปกติของตลาด (market anomaly) ผลการวิจัยพบว่าความเสี่ยงที่เป็นระบบไม่มีความสัมพันธ์กับผลตอบแทนของหุ้นเล็ก (size premium) และหุ้นคุณค่า (value premium) แต่มีผลทำให้ปรากฏการณ์โมเมนตัม และ betting against beta มีความเด่นชัดมากขึ้น สุดท้ายนี้เราได้ทดลองสร้างระบบการลงทุนที่อ้างอิงตามความเสี่ยงที่เป็นระบบ ผลการวิจัยชี้ให้เห็นว่าระบบการลงทุนนี้สามารถทำกำไรและช่วยให้นักลงทุนหลีกเลี่ยงวิกฤตทางการเงินได้ แต่อย่างไรก็ตามเนื่องจากความซับซ้อนในการคำนวณและผลตอบแทนในระยะยาว ระบบการลงทุนนี้ไม่ได้เป็นทางเลือกที่ดีกว่าการลงทุนในกองทุนรวมที่มีอยู่ทั่วไปในตลาด

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Abstract

In this paper, we construct an index that measures the level of systematic risk based on market integration. With the index, we examine the predictive power of systematic risk on the decline of the Thai financial market. We find that the market performs poorly during a period of high systematic risk. An increase in systematic risk is associated with major events in Thai financial market, such as an announcement of capital control or the subprime crisis. We further investigate its effect on market anomalies. While systematic risk has no impact on the size premium and value premium, it is associated to greater magnitudes of momentum and betting against beta, introduced by Frazzini and Pedersen (2014). Finally, we implement a trading strategy based on the systematic risk factor and find that the strategy can help the investor avoid losses during the financial crisis. However, in the long run, it is inferior to many mutual funds that are available in the market.

Introduction

In response to the Subprime financial crisis in 2008, IMF's Global Financial Stability Report (2009) states the need for a tool that can provide a warning signal so that SEC and other related policymakers would be able to handle the situation in time. Without adequate preparations and realistic perceptions, the outcome of financial turmoil could turn into a catastrophe. The IMF's report says that being able to detect the systematic risk in the early stage can help the policymakers to make a necessary preparation to prevent the crisis.

Traditionally, players in financial markets such as institutions, analysts, and retail investors pay attention on individual economic indicators and firms' financial status. Each of these indicators can only provide them a view on a particular aspect of the market while firm information can only tell them of idiosyncratic risk, yet, indicators that have impact to the whole market are rarely seen and used. Literature usually refers to the factor as systematic risk. De Bandt and Hermann (2000) suggest that measuring systematic risk is crucial in preventing or preparing for a financial crisis. This view is greatly strengthened after the financial crisis in 2008. One way to measure the systematic risk is to analyze the correlations between many sectors in the equity market. High correlations between sectors means that the sectors, which normally are loosely dependent, start to closely tie together. This state is called "market integration." It is important to note that the term "market integration" in this context refers the proportion of variations shared by each sector in the market, which its meaning is different from the "market integration" used in international finance context. A high level of market integration is dangerous as all sectors are either united or closely tied together, and one unexpected event can impact the whole market. Pukthuanthong and Roll (2009) and Kritzman, Li, Page, and Rigobon (2011) develop methods to measure market integration. Their methods make it possible to measure the level of systematic risk.

The goal of this research is to develop a measurement for systematic risk in the Thai stock market. Based on Kritzman, Li, Page, and Rigobon's (2011) methodology, we develop a market integration index to capture the level of systematic risk. We then examine the prediction power of systematic risk for market performance. We find that a period of high systematic risk is associated with subsequent low market returns. We further investigate the impact of systematic risk on commonly known market anomalies: the size premium, value premium, momentum, and BAB (betting against beta). Finally, as systematic risk can predict poor performance of the equity market, Kritzman, Li, Page, and Rigobon (2011), we examine the profitability of a trading strategy that bases the trading decisions on level of systematic risk.

Literature Reviews

Systematic Risk and Market Integration

Empirical evidence suggests the rise of correlations between assets is a signal of turbulence in financial market. Billio et al. (2010) use monthly returns of hedge funds, banks, brokers, and insurance companies to perform a principal component analysis. They document that when the four assets are highly interrelated, the level of systematic risk increases and that a financial crisis tends to follow. They find that, during the year 2001 to 2008, the portion of variation that the four assets share raises to 83% which is significantly higher than the level in the period from 1994 to 2000. This eventually was followed by the financial crisis in 2008. The relationship between market integration and turbulence in financial market has been widely studied. Ferreira and Gama (2004) examine the correlation between industries in global markets during the period from 1979 to 2003. They document that the correlations were higher when the market declined than when the market appreciated. Ang, Chen, and Xing (2002) find a similar result in the context of stock returns. Most researchers believe that when market integration is high, many assets in the financial market are tied together. This allows an event that normally impacts one sector to also affect other sectors. Thus the impact can be widespread. The higher market integration is, the wider the impact will be. Kritzman, Li, Page, and Rigobon (2011) study the predictive power of market integration on financial crises. They find that 89% of the worst market declines occurred within a month after spikes in the market integration level. However, they point out that the rise in market integration level does not necessary mean the financial market is entering into a crisis. But, rather, market integration is an important condition that signals a financial crisis.

Measurement of Systematic Risk

Generally, systematic risk can be measured through the level of market integration. Pukthuanthong and Roll (2009) develop a similar ratio to measure global market integration using a regression of country returns on principal components in the previous period. They average the R^2 from their regression to produce a measure for market integration. Kritzman, Li, Page, and Rigobon (2011) measure systematic risk differently. They introduce a measure called “Absorption Ratio” which is calculated from the percentage of total variation that can be explained by a specific number of common eigenvectors from a principal components analysis. They show that their absorption ratio can predict the rise of turbulence in the US market. Moreover, most of the past financial crises can be predicted by major positive spikes in absorption ratio. Both Pukthuanthong and Roll (2009) and Kritzman, Li, Page, and Rigobon (2011) show that their measurements are more reliable than a simple correlations between assets.

Market Anomalies

The simple market model as used in CAPM only considers market risk as a sole factor that explains the return of a company stock. However, the existence of market anomalies has been well documented in the literature and it significantly affects the performance of a portfolio. Banz (1981) finds that small stocks tend to outperform larger stocks. Moreover, DeBondt and Thaler (1985) and Fama and French (1992) document that stocks with high book to market value tend to have higher returns than stocks with low book to market values. By exploiting the size premium and value premium, any investor is able to achieve a better performance than the market. Forming a portfolio with small stocks and value stocks can result in positive and significant alpha. Taking these facts into account, Fama and French (1993) propose a three-factor model that controls for the effect of these anomalies. Jegadeesh and Titman (1993) argue that stocks that performed well in the past year tend to continue to perform well. They call this anomaly “momentum.” Similarly, an investor can achieve a positive alpha just by buying past winner stocks. Carhart (1997) expanded Fama and French’s three factor model by adding momentum. This model can capture the effect of the momentum anomaly. Frazzini and Pedersen (2014), introduce a concept of betting against beta (BAB). BAB is a phenomenon when investors prefer investing in stocks with high beta in order to achieve higher returns with less concern about risk. This is because their access to leverage is limited. Therefore, the demand for high beta stocks is greater than low beta stocks. This results in a lower expected return from high beta stocks. Thus, they become mean variance inefficient and the Capital Allocation line (CAL) will be flatter than it would be expected from theory.

Data and Methodology

Equity Returns

We obtain our dataset from the Stock Exchange of Thailand website (http://www.set.or.th/). The dataset consists of the total return index of SET, SET50, and MAI as well as the index from each SET industry. The industries include Agriculture and Food, Consumer Product, Financials, Industrials, Property and Construction, Resources, Services, and Technology; nine industries in total, including MAI. This dataset covers the total return indices starting form 5 January 2004 to 12 March 2015. Since the index levels are not stationary, we calculate natural logarithm returns from these price indices. We will use these log returns in our analysis. The descriptive statistics are the as shown in Table 1.

The average returns for SET index is 0.041 basis points per day which is equivalent to 10.5% annually. The largest daily gain is 10.6% while the largest loss is 16.1%. An interesting fact is that the largest loss of -16.1% was on 19th December 2006 and the 10.6% gain was on the following day, 20th December 2006. These extreme returns are the result of the announcement of capital control policy and the cancellation right afterward. In terms of volatility, SET faces 1.37% of the standard deviation. The average returns for SET50 index is 0.041 basis points per day which is equivalent to 10.5% annually. The highest average return among the eight industries is for the agricultural industry, which is 0.072 basis points per day which is equivalent to 18.43% annually with a standard deviation of 17.30%. The lowest average return among the eight industries is the industrials, which is 0.017 basis points per day (equivalent to 4.35% annually with the standard deviation of 25.40%).

Constructing Systematic Risk Index

We follow the methodology used by Kritzman, Li, Page, and Rigobon (2011) that they create an index called “Absorption Ratio” in order to measure the systematic risk measure for the US market. They argue that when a financial crisis is about to occur, most of the risk factors are closely integrated, thus, the level of systematic risk rises dramatically. To capture this, they use principle component analysis to estimate eigenvectors and observe the size of the portion of assets’ variance that can be explained by a certain number of eigenvectors. We use this same concept to construct a systematic risk index for the Thai stock market. The value of index is defined as,

$$SR = \frac{\sum_{i=1}^{n} \sigma_{Ei}^2}{\sum_{j=1}^{N} \sigma_{Aj}^2}$$

Where

SR = Systematic Risk index

N = number of industries

n = number of eigenvectors

σ_{Aj}^2 = variance of the j^{th} industry

σ_{Ei}^2 = variance explained by the i^{th} eigenvector

In order to calculate the value of systematic risk index on each particular day, we use observations over the previous 500 days to compute the covariance matrix and eigenvectors. Following Kritzman, Li, Page, and Rigobon's method, we fix the number of eigenvectors to be one fifth of the number of assets; in this case we retain only one eigenvector for the total number of nine industries. Thus, each observation of the systematic risk index is calculated from σ_{Aj}^2 and σ_{Ei}^2, which are estimated from 500 days moving window. Since we have 2,694 observations of each industries total return index from 06 January 2004 to 12 January 2015, we can calculate up to 2,195 observations of the systematic risk index over the period from 17 January 2006 to 12 January 2015.

For the value of market integration index on the 17 January 2006, we use principle components analysis to analyze the factor structure, and the orthogonal rotation method is applied since we expect each factor to be independent from each other. The eigenvalue criterion is used to determine the number of components to be extracted. From the KMP and Bartlett's test, the KMO measure of sampling adequacy is 0.951, which is greater than 0.50, so the indices of the industries are sufficiently correlated to apply factor analysis. In addition, Bartlett's test is significant due to the p-value of 0.000, which is less than 0.01. Furthermore, there is no multicollinearity problem, as the determinant of the correlation matrix is 0.001, which is greater than 0.00001.

Table 2 describes the total variance explained by each component. The table indicates that only one factor or component can explain up to 67.31% of the variation of the variables. Therefore, we select the one factor as the independent variable of the model. The analysis suggests that the nine industries, including Agriculture and Food, Consumer Product, Financials, Industrials, Property and Construction, Resources, Services, and Technology, and MAI, together drive component 1. This factor can be called "Market" because it includes all industries in the stock market to explain the market stock returns. We also run a reliability test, the factor has Cronbach's Alpha of 0.933, which is very good, indicating that all of the industry returns are closely related.

Systematic Risk Level

The process in the previous section is repeated in order to calculate the value of systematic risk index on each day from 17 January 2006 to 12 January 2015. We are able to create an index with 2,195 data points that captures the level of systematic risk in the Stock Exchange of Thailand during the period.

Figure 1 shows the level of systematic risk over our sample period. The lower line is the systematic risk using one eigenvector as stated in the methodology. We also compute the index using two eigenvectors; the result is displayed with a dashed line (upper). The shapes of the two indices are almost identical, with only a difference in level of the indices. Since we are interested in the change in level of systematic risk index, the level itself does not affect the interpretation of the results, and thus, whether we are using one or two eigenvectors will not influence the results.

The shape of the index seems to relate to many events in Thailand. Based on what we can see from Figure 2, there are four spikes in the systematic risk index during our sample period. The first and largest one is around the end of 2006. This is about the time that Bank of Thailand announced a new capital control policy. Another notable one is around the end of 2008 when the subprime crisis occurred. The rest of the spikes are in 2011 and 2013 when there were a major flood and protests in Thailand, respectively. The index level is 67.4% on average and it peaks at 77.25% during the subprime crisis.

Figure 2 shows the graphs of the systematic risk level (solid line) and SET TRI (dashed line). The spikes in systematic risk seem to positively relate to the high volatility of SET daily returns. But the relationship between market integration and SET TRI level is not clear. The relationship will be investigated in the following sections.

Systematic Risk and Equity Market Performance

Based on Kritzman, Li, Page, and Rigobon (2011), when risk factors that impact the financial market are united, or become closely tied together, the market will be on the verge of a crisis. That is, closely tied risk factors or high systematic risk allow one particular event to broadly impact the market and render portfolio diversification less effective. Therefore, high systematic risk level would lead to a possible period of market drawdown. Our hypothesis is that *a change in systematic risk level has a negative impact on market returns*. In the following sections, we will examine this hypothesized relationship in detail.

Short Term Relationship

As stated in the hypothesis, we expect that after a period of high systematic risk, the market would perform poorly. In order to measure the market performance, we compute the average daily return of the market portfolio over a one month period. The one month period is defined as 21 trading days, thus each observation is calculated based on 21 days overlapping windows.

The average daily market return over one month is approximately equivalent to 12.5% per year. The standard deviation of the average return is 0.33% per day or about 5% annually. This low standard deviation is due to the effect of diversification over time and overlapping time period. It is important to note that extreme values are not excluded since that would undermine the purpose of this study that we want to use systematic risk factor to predict financial turbulence.

We conduct a first test of the correlation between systematic risk on a specific day measured by systematic risk index and market performance over a month after that day measured by average daily market returns.

We are able to reject the null hypothesis that there is no correlation between these variables. However, the correlation is 0.064, which means that both variables move together in the same direction. This is a contradiction to what we have expected that market would perform poorly after a period of high systematic risk. However, the magnitude of the correlation is quite low for prediction of market performance. This result is not a surprise since the level of systematic risk on a particular day can hardly indicate an impact of systematic risk factor that tends to build up over time.

Medium Term Relationship

Since systematic risk is built up over time so we focus on the change of systematic risk level over a one month period. Using monthly data in this test benefits us in many ways. First, we expect that the change of the systematic risk level over one month can indicate a more accurate picture of the risk in the market. The process of market integration may take a few months to fully have a significant impact on the market, so using data at a daily frequency can potentially reflect a fluctuation instead of a longer trend. Moreover, using daily data in a time series regression is susceptive to the influence of autocorrelation because investors trading decisions can be affected by the market returns on the day before. Thus, monthly data allows us to avoid or reduce the presence of autocorrelation.

We regress monthly returns of SET TRI (SET Total Return Index) on the change of the level of systematic risk. The change in level of systematic risk in month t is equal to the systematic risk in month t subtracted by the level in month t-1. The model is as follows,

$$\mathrm{SETTRIR}_t = \beta_0 + \beta_1 \Delta SR_t + \varepsilon_t$$

$\mathrm{SETTRIR}_t$ is the return of SET TRI in month t and ΔSR_t is the change in systematic risk level. The OLS assumptions are checked before our regression estimation. Even though we use monthly data, autocorrelation is still present. With Durbin-Watson test, the statistic is 1.5612 with p-value of 0.0278. Therefore, we use robust standard errors to get a more accurate estimation. Beside autocorrelation, there is no other assumption violated. The result of our estimation is shown in Table 4. We find that the coefficient of ΔSR is negative and significant with the p-value of 0.0451, so the null hypothesis is rejected. The ΔSR coefficient with the value of -0.012 indicates that one percentage point increase in the change of systematic risk level is followed by a reduction in market returns by 1.2 basis points per month. This finding is consistent with our hypothesis that there is a negative relationship between the change in systematic risk level and the subsequent market return.

Relationship with Market Anomalies

To further understand more about the role of systematic risk, we investigate how the factors impact various types of market anomalies that are documented in the literature. Fama and French (1993) document the size premium and value premium. The size premium is an anomaly that small stocks tend to outperform bigger stocks. Similarly, the value premium is a phenomenon that value stocks, or low price per book value stocks, perform better than their growth counterparts. These anomalies can be explained by the fact that small and value stocks are perceived as more risky. Since these anomalies are the resulted of additional firm specific unsystematic risk factors, when market integration occurs, we can expected these unsystematic risks to be dissolved into systematic risk. Therefore, as systematic risk increases, the level of unsystematic risk should decrease, and so do these anomalies. From here, we draw two hypotheses. First, *the change in level of systematic risk has a negative impact on the size premium*. And the second hypothesis is *the change in level of systematic risk has a negative impact on value premium*.

Hypothesis on size premium: *the change in level of systematic risk has a negative impact the on size premium*.

Hypothesis on value premium: *the change in level of systematic risk has a negative impact on value premium*.

In addition to these two anomalies, the other well-known anomalies are momentum and Betting against Beta (BAB). Momentum premium does not seem to relate to the riskiness of a particular stock since it purely relies on past performance of the stock. However, when we take a closer look into the source of the anomaly, one of the most common explanations is that investors are slow in reacting to positive information and quickly respond to negative information. Overtime, they begin to realize and correct their reactions. In a period of increasing systematic risk, we may witness a large degree of information circulation, both good and bad. This indirectly widens the gap between investors' reactions to good and bad information, and thus, enhances the effect of momentum. We expect that *the change in level of systematic risk has a positive impact on the momentum premium*. Based on Frazzini and Pedersen (2014), BAB may be driven by investors who are limited in using leverage tend to prefer stocks with high beta. As a consequence, the demand on high beta stocks is relatively higher than for low beta stocks so their yields decrease and high beta stocks become mean variance inefficient. Since beta can be viewed as a sensitivity of a stock to systematic risk, we would expect that an increase in the level of systematic risk makes high beta stocks even more mean variance inefficient. This leads to an increase in the magnitude of BAB factor. Thus, we hypothesize that *the change in level of systematic risk has a positive impact on the Betting against Beta factor*. These two hypotheses can be summarized below,

Hypothesis for the momentum premium: *the change in the level of systematic risk has a positive impact on the momentum premium*.

Hypothesis for the BAB factor: *the change in level of systematic risk has a positive impact on the Betting against Beta factor*.

We test these four hypotheses with regression models similar to the previous section, but with these anomalies as dependent variables. The models are as follows,

$$\mathrm{FACTOR}_t = \beta_0 + \beta_1 \Delta SR_t + \varepsilon_t$$

The variable FACTOR_t denotes the value of these anomalies (SMB, HML, WML, and BAB) at time t. We obtain the data for anomalies from Srithumpong et al. (2013). The authors calculated the values of these anomalies based on the Fama and French (1993) method and limited the universe of stocks to SET100 because of liquidity constraints. Therefore, the results from this study should be interpreted with caution because SET 100 is not a good representative for the market; especially for SMB, as the small stocks in their universe are actually not small since they are in SET100. We also check the OLS assumptions before we go ahead with the regressions. Our tests for linearity show that the assumption of linearity hold. All of our models except SMB encounter autocorrelation problems. We alleviate this problem with heteroskedasticity autocorrelation consistent (HAC) standard errors.

Table 5 shows the results of the regressions. Unlike market returns, size premium and value premium are not affected by the change in systematic risk. The coefficients of ΔSR for both SMB and HML models are not significant. Thus, we do not have enough evidence to reject the null hypotheses. However, the momentum and Betting against Beta factors are affected. The coefficient for momentum is 55.18 with p-value of 0.006. This is consistent with our hypothesis that the effect of momentum becomes greater during periods of increasing systematic risk. This means that the past winners' outperformance will be more eminent during these periods. Similarly, the coefficient of BAB factor is 102.06 and highly significant. We can infer that high beta stocks are affected greatly from a rise in systematic risk level that amplifies the outperformance of the BAB factor.

Trading Strategy based on Systematic Risk

Strategy

Since our findings indicate that the change in level of systematic risk is related to poor future performance of the market, it is interesting to see whether our systematic risk factor can be used as a tool for market timing. In order to test for the feasibility of using systematic risk, we develop a trading rule based on the change in systematic risk. The data is calculated on daily basis because this is for trading purposes. As a result, we define the measure of the change in systematic risk differently from our previous test. Here, we measure the change by a level of systematic risk on a particular day subtracted by its average value over the previous 15 days. Then, we standardize the value by dividing it with its 15 days standard deviation. The formula for change in systematic risk is defined below,

$$\Delta SR_t = \frac{(SR_t \text{ - 15 days average of SR})}{\text{15 days standard deviation (SR)}}$$

We denote SR_t for systematic risk level on day t, the average and standard deviation of SR are is computed based on the level of systematic risk over the past 15 days. The change in systematic risk is considered significant when the absolute value of ΔSR is larger than 2. If ΔSR is greater than +2 then we interpret it as a significant increase, while the value less than -2 indicates a significant decrease.

We use these significant changes in ΔSR as buy/sell signals for our trading strategy. We assume that short selling is not allowed. The trading rule is defined as,

- When we have no position,
  - If ΔSR decreases significantly, we **buy**.
  - Otherwise, we do nothing.
- When are in a long position,
  - If ΔSR increases significantly, we **sell**.
  - Otherwise, we do nothing.

We test our strategy on the SET Total Return Index during the period form 7 July 2006 to 12 January 2015. There are total 2,082 trading days in this sample period. It also includes many interesting events in the Thai market, such as capital a control announcement, the subprime crisis, the 2009-10 bullish market, the U.S. debt ceiling crisis, the Greek crisis, the great flood in Thailand, and the 2014 coup d'état. To make our results more realistic, we impose transaction costs on the trades executed by our strategy. We decompose transaction cost into two parts; commission fee and bid-ask spread. For commission fees, we assume that our trade is executed though an internet trading system with cash account. The commission fee for internet transaction with cash account is 20 basis points with additional 7% VAT. The total cost for commission fee is 21.4 basis points. We assume the bid-ask spread to be 50 basis points based on the bid-ask spreads of highly liquid stocks that are currently traded in SET with high price levels. We apply half the spread for a one way trip transaction, which is equivalent to a full spread for a round trip. Therefore, for each transaction, we subtract the cost of 46.4 (21.4+50/2) basis points from the return. And finally, when the position is liquidated, cash proceeds are assumed to be held ready for the next buy. Therefore, it will not be invested into other securities such as bonds or the money market.

Profitability

The transactions executed by ΔSR strategy are showed in Figure 3. The triangle markers indicate buy transactions while diamond markers indicate sell transactions. There are a total 51 transactions over our sample period. The strategy makes a gross profit of 77.54% and 53.88% after transaction costs. This profit is equivalent to 6.52% annually.

Although our test shows that the trading strategy based on systematic risk is profitable, however, in order to test its performance, we need to have a benchmark. We use a "Buy and Hold" strategy on SET TRI as our benchmark since it requires neither skill nor effort to execute. In addition, we decide to make a comparison to simple technical analysis strategies; 4 and 9 days moving average, denoted as MA(4,9) and Relative Strength Index (RSI) with 14 days formation. We choose these two strategies because they are simple and commonly used by typical technical analysis investors. The details of the transactions executed by these two technical analysis strategies can be found in the appendix.

Table 6 presents the comparison between the performance of the ΔSR strategy, popular technical analysis strategies, the buy and hold strategy, and several mutual funds. Our strategy based on ΔSR performs poorly when compared to other alternative strategies.

An investor can make a profit of 114% over the period, or 13.8% annually, by just simply following a buy and hold strategy. MA(4, 9) is the best performer in this sample period with 136% returns (246% before transaction costs) while RSI (14) performs the worst with -138% returns (122% before transaction costs). This is hardly a surprise since SET was in a trend market during our sample period, so a trend-following strategy like MA(4, 9) gains a direct benefit while an RSI strategy which is suited for a sideway market yields a large amount of loss.

The underperformance of the ΔSR strategy does not mean our use of systematic risk in a trading strategy is completely useless. From our sub-sample period from 7 July 2006 to 30 September 2009, ΔSR based strategy outperforms Buy & Hold by a large margin, 30.4% and 21.5% respectively, even after transaction costs. This is because the ΔSR strategy helps the trader to avoid the market crash during subprime crisis. However, given the complexity of the calculations, ΔSR strategy does not seem to be feasible for individual investors. An investor can just simply buy mutual funds and let the fund managers do their job. In the performance comparison table from Table 6, we select mutual funds that are popular and recommended by Morningstar Thailand. The result shows that Aberdeen Small Cap is the top performer with the best Sharpe Ratio of 1.03, while other funds have the Sharpe ratios around 0.60-0.70, which is higher than 0.48 from the ΔSR strategy.

Conclusion

Our study investigates the role of systematic risk in predicting financial turbulence in the Stock Exchange of Thailand. First we construct an index to capture the level of systematic risk based on the methodology from Kritzman, Li, Page, and Rigobon (2011). The index movement corresponds well with past major events in the Thai financial market such as capital controls and the subprime crisis. The index rose significantly with the shocks in the market. We further examine the relationship between systematic risk and market performance. We find that a rising in level of systematic risk is associated with a lower subsequent return of the Thai stock market. One percentage point increase in systematic risk leads to 1.2 basis points lower return in the market per month, or 14.4 basis points per annum.

We further examine the impact of systematic risk on well-known market anomalies. Contrary to our hypotheses, the impacts on the size premium and the value premium are insignificant. However, we find that during a period of high systematic risk, the effect of momentum and betting against beta are stronger. This suggests that past winners would perform even better because the upward responses are slow in the period.

Finally, we explore the feasibility of using the systematic risk index in a trading strategy. We find that the strategy is profitable, yet, it underperforms a simple buy & hold strategy, both in terms of raw return and Sharpe ratio. Nevertheless, the strategy successfully avoids the drawdown from major crises and substantially outperforms a Buy& Hold strategy during past periods of financial turbulence. For long term investments, buying good mutual funds can be a more feasible choice since the strategy based on systematic risk is too complicated for individual investor and less profitable.

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Tables and Figures

Table 1: *Descriptive Statistics of the Returns of Each Sector*

This table shows the daily total returns of SET index series and sectors during the period from 5 January 2004 to 12 March 2015. These sectors include Agriculture and Food, Consumer Product, Financials, Industrials, Property and Construction, Resources, Services, and Technology.

Index/Sector	Observation	Mean	Std. Deviation	Minimum	Maximum
SET	2694	0.041%	1.37%	-16.10%	10.60%
SET50	2694	0.041%	1.53%	-17.20%	11.40%
MAI	2694	0.048%	1.24%	-11.20%	8.50%
Agriculture	2694	0.072%	1.09%	-9.40%	6.30%
Consumer Product	2694	0.039%	0.71%	-6.60%	6.80%
Financials	2694	0.039%	1.64%	-19.40%	10.70%
Industrials	2694	0.017%	1.60%	-12.80%	8.20%
Property and Cons	2694	0.030%	1.45%	-15.50%	10.00%
Resources	2694	0.034%	1.74%	-17.20%	12.60%
Services	2694	0.061%	1.15%	-11.20%	8.10%
Technology	2694	0.057%	1.62%	-20.80%	12.90%
Average	2694	0.044%	1.38%	-14.309%	9.645%

Table 2: *Principal Component Analysis*

This table shows that amount of variance that can be explained by each component extracted by Principal Component Analysis.

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.058	67.3	67.3	6.058	67.31	67.314
2	0.662	7.4	74.7			
3	0.496	5.5	80.2			
4	0.471	5.2	85.4			
5	0.407	4.5	89.9			
6	0.297	3.3	93.2			
7	0.262	2.9	96.1			
8	0.203	2.3	98.4			
9	0.145	1.6	100.0			

Table 3: *Correlation between Systematic Risk and Market Performance*

This table shows the correlation between systematic risk level and the market performance of the following month. The test statistic is based on Pearson Correlation.

	Pearson Correlation	P-value	Observations
Systematic Risk at Time t and Market Performance at Time t+1	0.06	0.00 ***	2175

Notes: * significant at the 10%; ** 5%; and *** 1% level.

Table 4: *Regression of SET Total Return on Change in the Level of Systematic Risk*

This table shows results of a time series regressions with monthly return of SET TRI as the dependent variable. The independent variable is the monthly change in the systematic risk level.

	SET TRI Return (t)	
Change in systematic risk (t-1)	-0.012	**
(p-value)	*0.045*	
Intercept	0.010	
(p-value)	*0.339*	
R-square	0.140	
Adjusted R-square	0.127	

Notes: * significant at the 10%; ** 5%; and *** 1% level.

Table 5: *The Effect of Systematic Risk on Market Anomalies*

This table shows results of regressions with market anomalies as dependent variables on systematic risk. The market anomalies include size premium, value premium, momentum, and betting against beta.

Funds	SMB	HML		WML		BAB	
Systematic Risk	-0.163	-33.300		55.179	***	102.056	***
(p-value)	*0.367*	*0.155*		*0.006*		*0.000*	
Intercept	0.181	-2.139	***	0.060		0.740	
(p-value)	*0.667*	*0.000*		*0.935*		*0.257*	
R-square	0.01	0.03		0.05		0.22	

Notes: * significant at the 10%; ** 5%; and *** 1% level.

Table 6: Performance Comparison

This table compares the performance of systematic risk based trading strategy, popular technical analysis strategies, buy and hold strategy, and mutual funds during the period form 7 July 2006 to 12 January 2015.

Investment	Returns	Annualized Returns	Annualized Standard Deviation	Sharpe Ratio
Trading Strategies				
SR based Strategy	54%	6.5%	13.7%	0.48
MA (4,9)	136%	16.5%	13.1%	1.26
RSI (14)	-138%	-16.7%	17.8%	-0.94
Buy & Hold	114%	13.8%	22.3%	0.62
Mutual Funds				
UOB LTF	109%	12.4%	22.6%	0.55
Aberdeen LTF	118%	13.4%	17.6%	0.76
Aberdeen Small Cap	126%	14.3%	13.9%	1.03
Bualuang LTF	122%	13.8%	20.0%	0.69
Bualuang Thanakom	126%	14.3%	21.0%	0.68
Bualuang Top Ten	129%	14.6%	21.0%	0.69
SCB Plus LTF	91%	10.3%	20.7%	0.50
SCB MAI LTF	75%	8.6%	21.6%	0.40

Figure 1: Historical Systematic Risk

This is the level of systematic risk in Thai stock market over the sample period from 17 January 2006 to 12 January 2015.

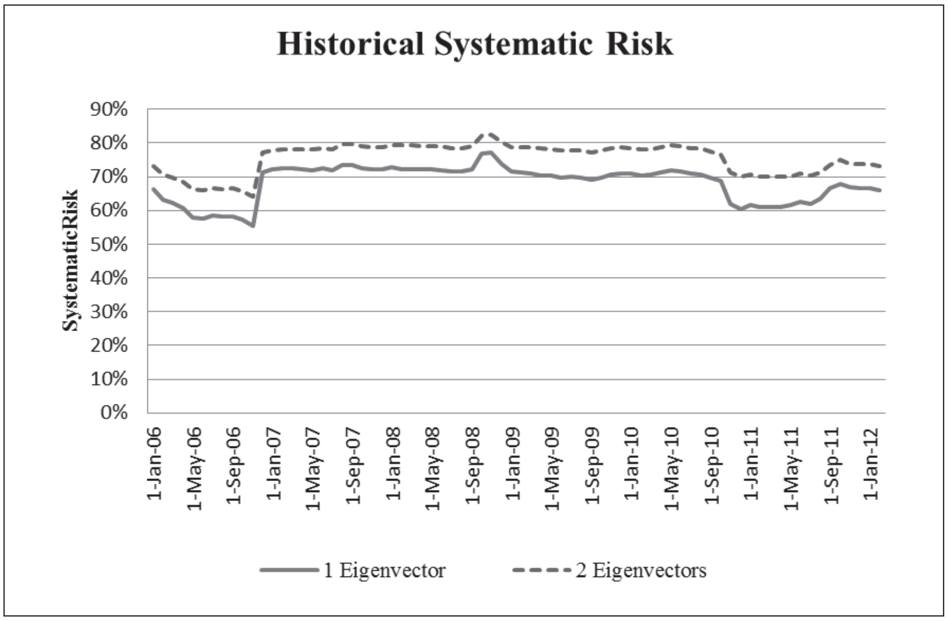

Figure 2: Historical Systematic RIsk and SET Total Return Index

This figure compares SET TRI (on the left) with the level of systematic risk (on the right) over the sample period from 17 January 2006 to 12 January 2015.

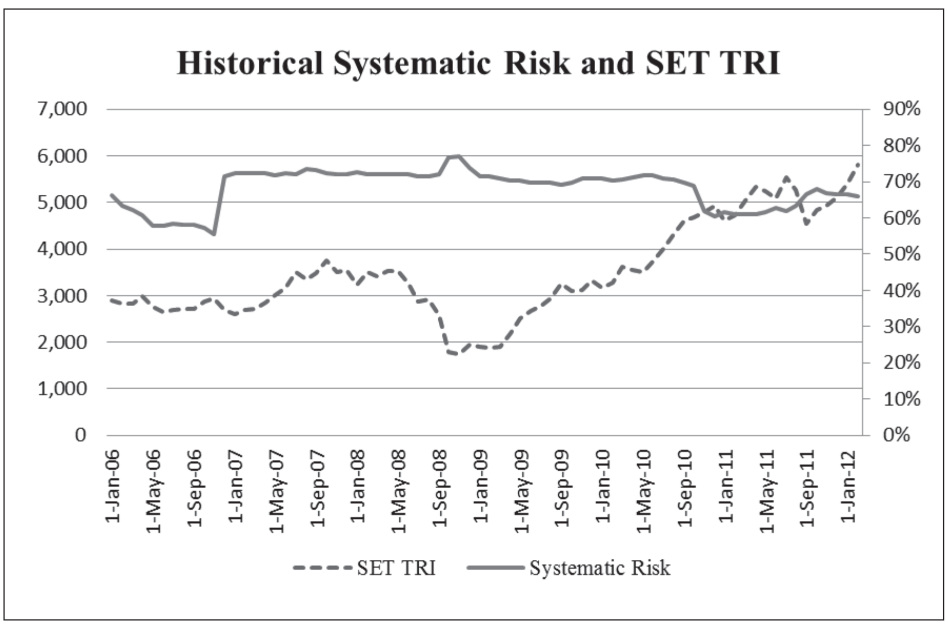

Figure 3: *Executed Transactions*

This chart presents the transactions executed by the systematic risk based trading strategy. Buy transactions are marked with triangle symbol and sell transactions are marked with diamond symbols.