Predicting Market Crashes Using Systemic Risk and Volatility Spillovers: A Deep Learning Approach

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การทำนายการร่วงลงอย่างรุนแรงของตลาดหุ้น โดยใช้ความเสี่ยงของระบบและการแพร่กระจายของความผันผวน ด้วยวิธีการเรียนรู้เชิงลึก

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วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาศิลปศาสตรมหาบัณฑิต
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งานวิจัยสร้างโมเดลจำลองโดยใช้วิธีการเรียนรู้เชิงลึกสำหรับการตรวจหาข้อมูลที่ผิดปกติบนอนุกรมเวลา (LSTM-VAE) เพื่อศึกษาพฤติกรรมของตลาดก่อนตลาดหุ้นเกิดการปรับตัวลดลงโดยฉับพลันและรุนแรง ข้อมูลที่ป้อนให้กับแบบจำลองนี้ได้แก่ ตัวแปรทั่วไปของตลาดหุ้น และดัชนีชี้วัดความเสี่ยงของระบบและการแพร่กระจายของความผันผวน ซึ่งสามารถบ่งชี้ความผิดปกติที่เกิดขึ้นภายในและภายนอกตลาดหุ้นได้ตามลำดับ ผลการศึกษาพบว่าแบบจำลองมักตรวจพบสัญญาณความผิดปกติหลังจากดัชนีราคาหุ้นตลาดหลักทรัพย์ขึ้นสู่จุดสูงสุดสักครู่หนึ่ง และเป็นระยะเวลานานก่อนที่ดัชนีดังกล่าวจะร่วงลงอย่างรุนแรงถึงจุดต่ำสุด อีกทั้งยังใช้การได้ดีกว่าแบบจำลองอื่น ๆ นอกจากนี้ยังพบว่าหากนำผลการทำนายจากแบบจำลองไปใช้ในการซื้อขายจริง จะทำให้ได้รับกำไรที่สูงกว่ากลยุทธ์การซื้อแล้วถือระยะยาว เพราะผลจากแบบจำลองช่วยให้รอดพ้นจากการร่วงลงอย่างรุนแรงของตลาดหุ้นได้

สาขาวิชา	เศรษฐศาสตร์และการเงินระหว่างประเทศ	ลายมือชื่อนิสิต ....
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We develop a model for predicting market crashes in the Stock Exchange of Thailand using a deep learning-based anomaly detection approach (LSTM-VAE). The model aims to detect market behavior before each market crash. Apart from the common stock market variables, we feed the model with the indices of systemic risk, and of volatility spillovers. With these two indices, the model takes into account the influences from both inside and outside the particular stock market. We find that in large crashes our model gives the crash warning signals shortly after the SET index reaches its peaks and long before the index reaches its troughs. And our model outperforms the existing models in the literature. Besides, when compared with a buy-and-hold strategy, our strategy incorporated signal from the model also leads to a higher return, because it helps us evade from large crashes.

Field of Study:	International Economics and Finance	Student's Signature ....
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Kornprarun Mahutchariyakul

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CHAPTER 1
INTRODUCTION

When people fear that the stock market crash will occur in the next short period, they behave differently from the way they normally would (Vogel, 2018). We, therefore, develop a crash prediction model using market behaviors as features.

Apart from market price movement, volatility, and transaction volume (Vogel, 2018), we can predict crashes using the indices of systemic risk and of volatility spillovers. Kritzman et al. (2010) find that market crashes usually occur during abnormal increases in the measure of systemic risk. Diebold and Yilmaz (2009) measure the interrelatedness among stock markets with the index of volatility spillovers and find that they have become abnormally more interrelated during the crisis periods. When we use these two indices together, the influences from both inside and outside the particular stock market are taken into account.

To develop the crash prediction model, we use a deep learning-based anomaly detection approach. This approach is better than traditional statistical models at grasping the real complexity of the interaction among input variables: the common stock market variables, the indices of systemic risk, and of volatility spillovers. We evaluate its performance on the Stock Exchange of Thailand (SET). We find our model outperforms a linear model and the other crash prediction models; namely, the high P/E model (Lleo & Ziemba, 2017), and the BSEYD model (Ziemba & Schwartz, 1991). Besides, when compared with a buy-and-hold strategy, our strategy incorporated signal from the model also leads to a higher profit, because it helps us evade from large crashes.

The rest of this thesis is organized as follows. Chapter 2 briefly reviews theories of bubbles and crashes. Chapter 3 draws the list of variables used for predicting crashes from the reviewed theories. Chapter 4 explains the deep learning we use in this study. Chapter 5 presents how we develop the model and evaluate it. Chapter 6 shows the results of this study. Chapter 7 provides conclusion and discussion.

CHAPTER 2

THEORIES OF BUBBLES AND CRASHES

There are four interesting theories of bubbles and crashes: rational expectations hypothesis, behavioral finance, chaos, and short-side rationing.

2.1 Rational Expectations Hypothesis Theory

According to a rational expectations hypothesis (REH) theory, the future state of the economy depends partly upon the current expectations of people. The REH fits with the efficient-market hypothesis (EMH) and the capital asset pricing model (CAPM). Stock prices reflect all available information, so it moves when the market participants receive new information. And the market participants respond to the received information following the modern portfolio theory (MPT), in which investors are risk-averse and construct portfolios to maximize expected return based on a given level of market risk. And as they receive new information randomly, the stock returns of each day are independent of one another or what we call "random walk." Therefore, the observed price should be equal to the fundamentals-determined price plus a random error term. And the bubble component is added to the equation when we use it to analyze bubbles and crashes.

2.2 Behavioral Finance Theory

In contrast to the REH, behavioral finance focuses more on the fact that there are limits to arbitrage and psychology in the market. These two factors hinder the market participants to respond quickly to the received information, to construct portfolios following the MPT, and make them become risk obliviousness sometimes. Under this theory, the bubbles are happening while market participants have hope and greed, and the crashes are happening while market participants have fear and anger. This concept also includes the manifestations of collective irrationality in all extreme market events, which we call “herding.” Besides, because the market participants do not behave rationally all of the time, we could find the anomalies in the markets that benefit us. For example, the stock prices likely increase during January, which we call “The January effect.”

2.3 Chaos Theory

Chaos theory bases on the fact that market behavior has both systemic and random components. We begin with measuring the initial condition of the stock market and find its attractors which help us predict how the market price will move. These attractors are determined from market price sensitive dependences on some variables like deposit rate, lending rate (Mian & Wang, 2015), and others. We predict the bubble or crash based on the intuition that the market price moves toward these attractors. Under this theory, we assume that market behavior consists of systemic and random components, and the small errors in the measurement of the initial condition lead to large errors in long-term prediction. Therefore, the market price is predictable to some extent only for short periods and appears to be random in long terms.

2.4 Short-Side Rationing Theory

The key concept of this theory is that the market is incomplete, so there is no Walrasian equilibrium where demand is equal to purchase and supply is equal to sale. The market consists of rationed buyers and rationed sellers. And its price is determined by the quantities of demand and supply. The price increases when the quantity of supply is smaller than that of demand, and the price decreases when otherwise.

In bubbles, the price increases and the equity risk premium (ERP) falls as most market participants are rationed buyers, who cannot purchase as much as they really want to. While in crashes the price decreases and the ERP rises as most market participants are rationed sellers who want to sell as much as possible. In both situations, the transaction volume and the variance rise. Therefore, when we compare the percent changes of variance and the ERP in the form of ERP elasticity of variance, we find that the ERP elasticity of variance rises exponentially in both situations.

Table 1 Summary of Theories of Bubbles and Crashes

	REH	Behavioral finance	Chaos	Short-side rationing
Key concept	Rational investors; Efficient-market hypothesis	Bounded rationality, people herd, anchor, etc.	Prices are attracted onto a new trajectory	Asymmetric information, incomplete markets
Model implementation	Net PV + “bubble” component	Searches for anomalies	Seeks sensitive dependence on initial conditions	Quantity is short-sided, thus expands price variance
Equilibrium	Walrasian	Not applicable	Conditional dynamic stability, depends on parameters and time	Never happens in real world, by this theory, improbable
Pros	Fits with traditional EMH/CAPM	Realistically describes human behavior	Conforms to visual aspects, power laws, fractal nature of price changes	No axioms need be assumed. Conforms to power laws and fractals and consistent with short-

				side rationing. Picks up human behavior aspects. Provides consistent statistical measurements across time and price scales. Relationships to different economic measures and ERP are enabled
Cons	Not a good practical description. Requires assumption of rational man axiom. Empirically indecisive	Difficult to link to economic models	Not consistent with OLG and long-term mean-reversion models	Is new and not yet empirically well developed. Nonlinear curve fitting required. Highly significant

				parameters (1%, 5%) not often estimated

Source: Vogel (2018)

The table above presents the overview of different theories of bubbles and crashes. It begins with the key concepts of each theory, followed by how we use the insights of each theory to predict stock market crashes. Under the REH theory; the investors are rational; the stock price is equal to net present value plus its bubble component, and it moves toward Walrasian equilibrium. Under the behavioral finance theory, people are not fully rational, so the equilibrium cannot exist in such a situation. But we could find some useful anomalies, like the January effects, to predict stock prices. Under the chaos theory, prices are attracted onto a new trajectory. We begin by seeking its attractors. And we predict the stock prices from their movement toward those attractors. Under the short-side rationing theory, the market is incomplete. Most market participants are rationed sellers in crashes, so price variance is expanded. We could predict stock market crashes by observing the high price variance. Besides, the details of the pros and cons of each theory are provided in the table.

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CHAPTER 3

VARIABLES USED FOR PREDICTING CRASHES

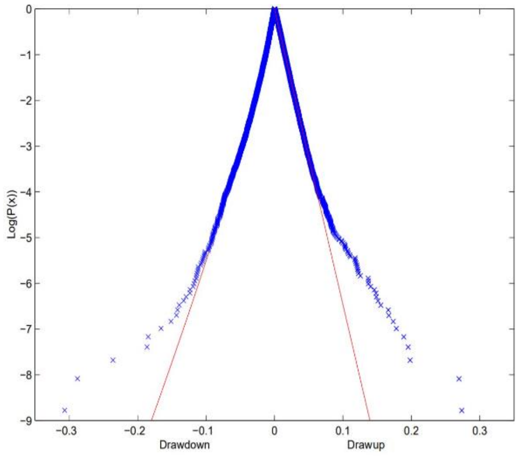
In this chapter, we discuss the variables used for predicting crashes which are related to the theories discussed earlier: the market return, the transaction volume, the daily volatility, the price-to-earnings ratio, the bond-stock earning yield differential, the absorption ratio (systemic risk), and the volatility spillovers index.

3.1 Market Return

When we sample a set of a specific number of consecutive days from non-extreme periods, we shall find it consists of the day with a positive return and the day with a negative return randomly in quantities. But it doesn't appear to be random in extreme periods, that is most of these consecutive days are the day with a positive return in bubbles or the day with a negative return in crashes. This finding is consistent with the bubble component in the REH theory, the herding behavior in the behavioral finance theory, the movement of market price toward some attractors in the chaos theory, and all that is mentioned in the short-side rationing theory.

In addition, Johansen and Sornette (2001) plot the cumulative probabilities of the positive and negative market returns ("drawup" and "drawdown", respectively) in each size, and fit them with the exponential functions. Both the cumulative probabilities and the fit functions are taken the logarithm and represented with blue crosses and red lines, respectively, in Figure 1. The functions can fit well with the small market returns but cannot fit with the large ones that happen in extreme market events like bubbles and crashes. Consequently, they conclude that the distribution which generates the market price in extreme periods is not the same as in more tranquil periods.

Figure 1 Cumulative Probabilities of Market Returns in Each Size and Fit Functions

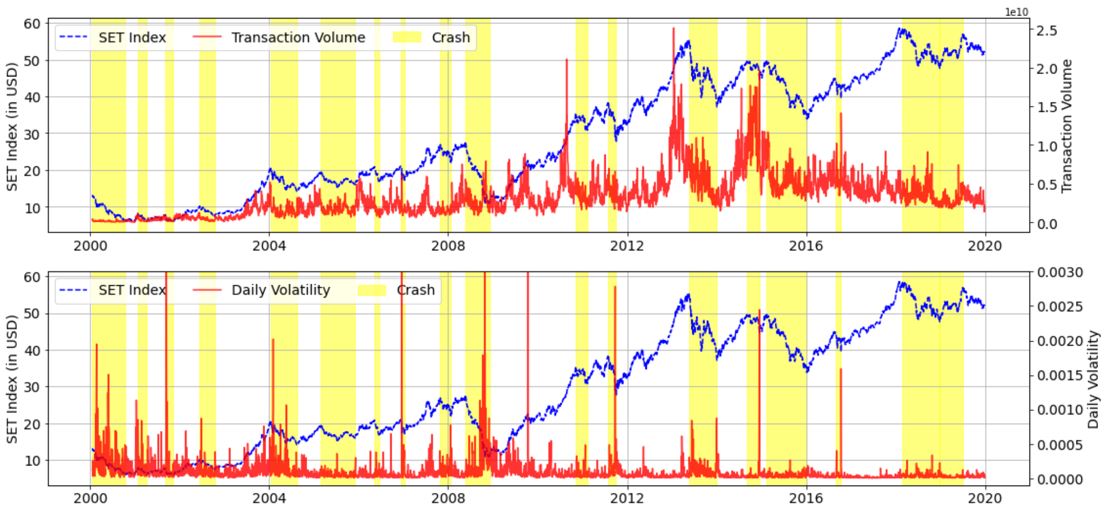


Source: Johansen and Sornette (2001)

3.2 Transaction Volume and Daily Volatility

The reason why we can use transaction volume and daily volatility for predicting stock market crashes could be explained by the short-side rationing theory and the behavioral finance theory. The stock market is full of rationed buyers in bubbles and full of rationed sellers in crashes. In other words, in such situations people do not care about the price anymore, they just want to buy or sell as much as possible. Therefore, there are notable increases in trading volume, and daily volatility due to the herding behavior both in bubbles and crashes (Scheinkman, 2014; Vogel, 2018).

Figure 2 SET Index, Transaction Volume and Daily Volatility



Source: Author

3.3 Price-to-Earnings Ratio

According to the Chaos theory, market price attractors are determined from market price sensitive dependences on some variables. One of the variables is the price-to-earnings ratio (P/E), as we could observe that high return periods usually begin with low price-to-earnings (P/E) ratios and cease with high P/E ratios.

Figure 3 SET Index and Price-to-Earnings Ratio

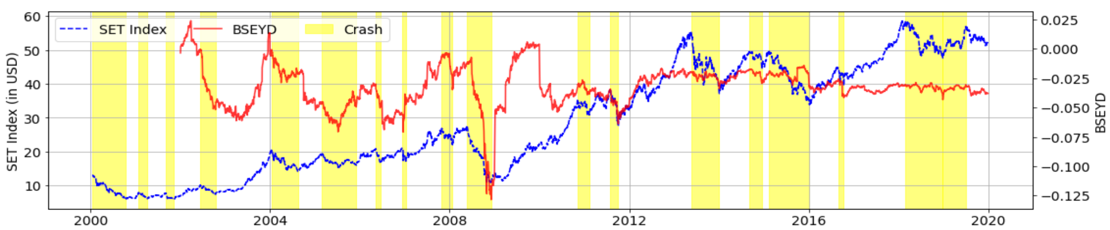
Source: Author

Lleo and Ziemba (2017) successfully predict stock market crashes with high P/E ratios. Their model, called the "High P/E" model, consists of a time-varying threshold which is a standard 95% one-tail confidence interval based on a Normal distribution. A crash warning signal occurs when the value of the P/E ratio exceeds the threshold.

3.4 Bond-Stock Earning Yield Differential

The bond-stock earning yield differential (BSEYD) is another variable related to the market price attractors in the Chaos Theory. As we have the intuition that when the bond yield is abnormally larger than the stock yield, people prefer bonds to stocks. In such a situation, they likely sell stocks to buy more bonds. And this attracts the decrease in the stock market price which can lead to stock market crashes.

Figure 4 SET Index and Bond-Stock Earning Yield Differential



Source: Author

Similarly to the High P/E model discussed previously, Ziemba and Schwartz (1991) successfully predict stock market crashes with BSEYD. Their model, called the "BSEYD" model, consists of a time-varying threshold which is a standard 95% one-tail confidence interval based on a Normal distribution. A crash warning signal occurs when the value of the BSEYD exceeds the threshold.

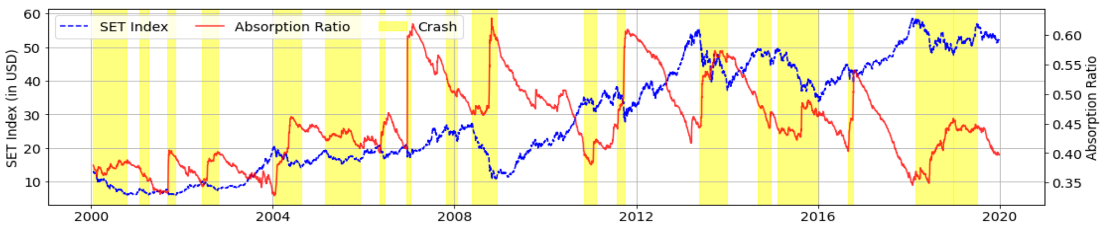
3.5 Absorption Ratio (Systemic Risk)

The systemic risk is the likelihood that the troubles which happen in some small units in the system could spread their impacts to the whole, for example, the failure of systemically important firms led to the financial crisis of 2008.

Kritzman et al. (2010) measure the systemic risk with the absorption ratio (AR), which is the fraction of the total variance of a set of asset returns absorbed by a fixed number of eigenvectors. High Absorption Ratio indicates assets are trading closely together, which usually occurs during crash periods. And this could be explained by the behavioral finance theory and short-side rationing theory.

In crashes, people perceive less difference among assets in the particular stock market. They expect all prices of these assets are going to fall. To evade financial losses, they decide to sell all the assets they have as much as possible no matter what kind of each asset is. Therefore, we find most of the significant drawdowns in stock markets were preceded by the abnormal increases in the AR (Kritzman et al., 2010).

Figure 5 SET Index and Absorption Ratio

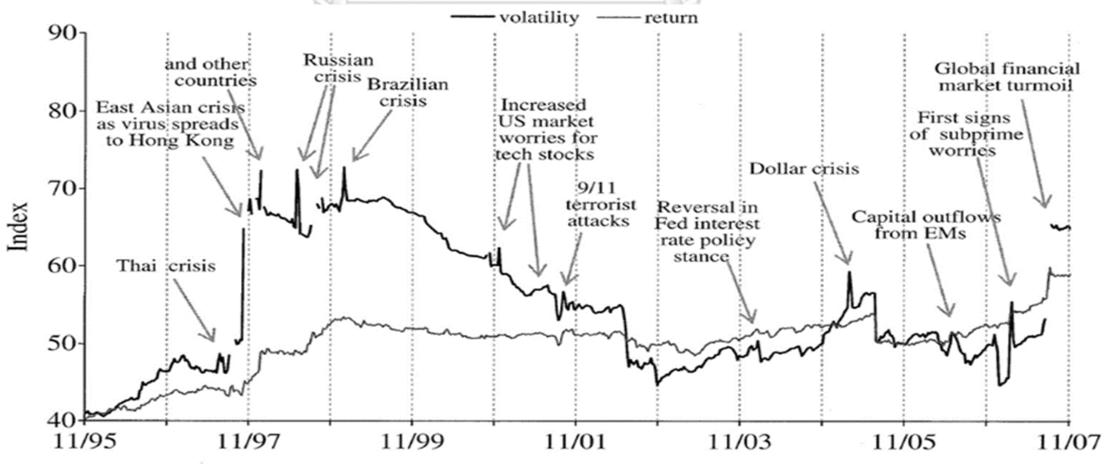


Source: Author

3.6 Volatility Spillovers Index

The reason why we can use the volatility spillovers index for predicting stock market crashes is similar to that of the absorption ratio. Instead of focusing on the assets in a particular market, the volatility spillovers index measures the interrelatedness between stock markets. Several studies find that the stock markets have become abnormally more interrelated during the crisis periods (Vo & Ellis, 2018; Yilmaz, 2010), due to the “herding” behavior of investors (Caporale, Pittis, & Spagnolo, 2006). In such a situation, people perceive less difference among stock markets. They expect all stock markets will fall together. To evade financial losses, they decide to sell all the assets they have as much as possible no matter which stock market their assets belong to. Besides, there are two types of spillovers: the return spillovers and the volatility spillovers. Diebold and Yilmaz (2009) find that “return spillovers display a gently increasing trend, whereas volatility spillovers display no trend but clear bursts” associated with crisis events in global equity markets, as shown in the following figure.

Figure 6 Global Stock Market Return Spillovers Index and Volatility Spillovers Index

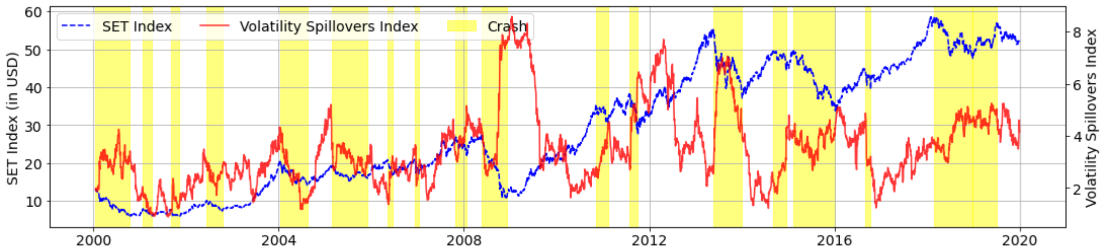


Source: Diebold and Yilmaz (2009)

In this study, we measure directional volatility spillovers received by the SET from major world stock markets (namely S&P 500, Nikkei 225, SSE Composite, Hang Seng, and FTSE100) in a generalized VAR framework of KPPS by following the work of

Diebold and Yilmaz (2012). The result is also in line with the findings by Diebold and Yilmaz (2009), as shown in Figure 7.

Figure 7 SET Index and Volatility Spillovers Index



Source: Author

CHAPTER 4

DEEP LEARNING

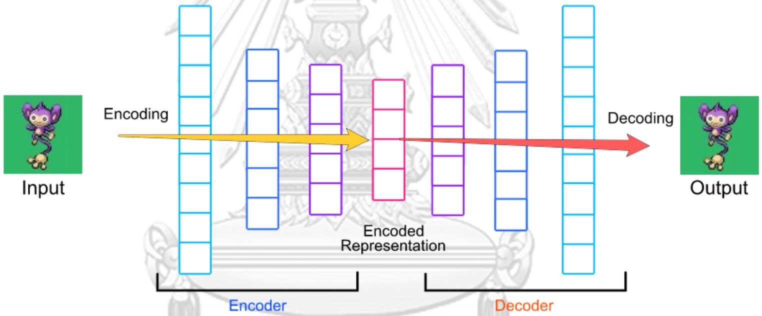
Several studies predict stock market crashes with linear models; for example, the studies of Yan et al. (2011) and Shiryaev et al. (2015). They begin with constructing a probabilistic representation of the market data. The representation contains some parameters like mean and variance. And they develop models to detect the change in these parameters, which occurs during the transition from non-crash to crash periods. However, the stock market data have nonlinear dependencies that are not suitable for linear models. In this study, we use a deep learning approach which is good at dealing with nonlinearities and capturing the complex interaction among variables.

Deep learning is machine learning which becomes popular in these present days. The major difference between conventional machine learning and deep learning approach is about how we extract informative features from data. Conventional machine learning uses the features that are created from raw data by the humans who are specialized in the fields related to the goals of the model they are creating. For example, economists create informative features for the model that we will use it to predict something about the economy. Instead, the deep learning approach uses the informative features that are created with successive layers. In particular, there are multiple layers in the model. The first layer derives simple features directly from raw data. The higher layers draw more informative features from the lower ones. And the last or the highest layer gives us the output that we want. This difference makes deep learning outperform conventional machine learning in various ways, such as image classification, speech recognition, self-driving cars, etc. (Wani, Bhat, Afzal, & Khan, 2020).

4.1 Autoencoder

Autoencoder is a deep learning network, capable of extracting useful features and filtering the unwanted information from each input. In particular, one autoencoder is made of two parts: an encoder and a decoder. The first part, an encoder, converts the inputs to the efficient representations of the inputs which have a lower dimensionality than the dimensionality of the inputs. The second part, a decoder, tries to reconstruct the inputs from the representations which are the product of the first part. In other words, the representations are the informative features of the inputs. And because they have a lower dimensionality, we could conclude that the model must understand the interaction among these key features to be able to reconstruct the input (Wani et al., 2020).

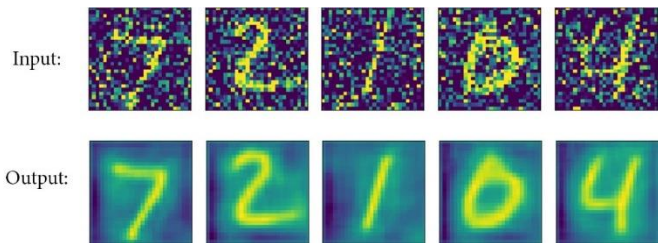
Figure 8 Basic Structure of an Autoencoder



Source: hackernoon.com

There are several practical applications of the autoencoder such as image denoising, anomaly detection, etc.

Figure 9 Inputs and Outputs of an Image Denoising Autoencoder Model

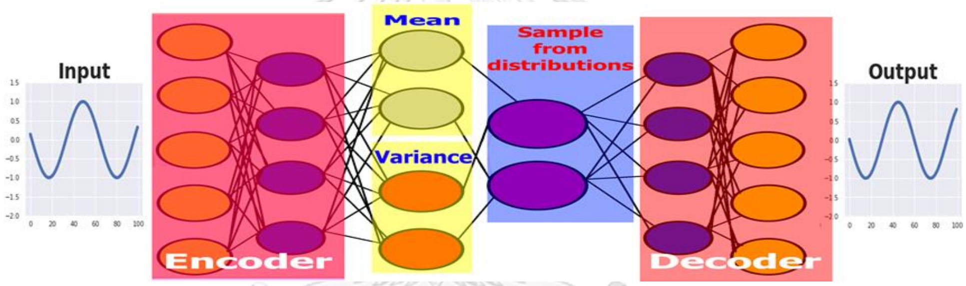


Source: iq.opengenus.org

4.2 Variational Autoencoder

The variational autoencoder (VAE) is the improved version of a common autoencoder. It is also a deep learning network, consisting of two parts: an encoder and a decoder, as shown in Figure 10. An encoder compresses the input into the encoded distributions which are consist of some parameters (when the Gaussian distribution is assumed, these parameters are mean and variance), instead of the fixed representations of inputs as in common autoencoder. And a decoder reconstructs the input from the samples from those distributions. Therefore, the output of the VAE is similar to the input, but not the same.

Figure 10 Basic Structure of a Variational Autoencoder



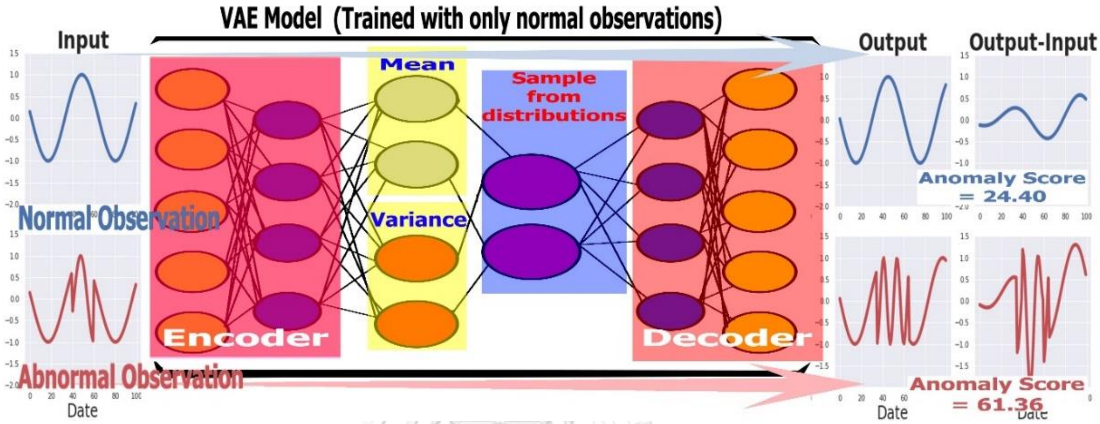
Source: Author

This difference between the common autoencoder and the VAE makes the output of the VAE become less sensitive to noises in the input data. Thus, the VAE is better than the common autoencoder at dealing with the stock market data which contains noises.

4.3 Anomaly Detection Model Based on the Variational Autoencoder

Dunning and Friedman (2014) suggest that “effective anomaly detection is based on the fundamental concept of modeling what is normal to discover what is not.” We train the model, based on the VAE, with only normal observations to be good at capturing the key features and reconstructing the normal inputs. But this same model becomes bad when doing these same things with the anomalies. In other words, the model knows the interaction among variables of normal observations, so it can reconstruct these variables properly. But the model does not know the interaction among variables of anomalies, so it cannot reconstruct the abnormal inputs. Then, we measure the reconstruction error which we call "anomaly score". Consequently, the model gives low anomaly scores with the normal observations, but high with the anomalies. The example is shown in Figure 11.

Figure 11 Time Series Anomaly Detection Model Based on VAE



Source: Author

In this study, the observations that occur in non-crash periods are considered as normal observations, while those that occur in crash periods are anomalies. We develop the model that understands the interaction among variables of the observations occurring in non-crash periods only. So, the model gives high anomaly scores when we feed it with the observations occurring in crash periods but gives low anomaly scores when otherwise. And we could use these high anomaly scores as crash warning signals.

CHAPTER 5

RESEARCH METHODOLOGY

This chapter is all about our crash prediction model. It begins with data processing from which we receive all the needed inputs for the model, followed by defining crash and rebound periods. The chapter proceeds with splitting the dataset for training and testing, and how we develop and evaluate the model.

5.1 Data Processing

We gather the daily data in USD of the market index, transaction volume, subsector indices of the SET, and the market indices of major world stock markets (namely S&P 500, Nikkei 225, SSE Composite, Hang Seng, and FTSE100) from 1998 to 2019 from the Bloomberg Terminal. And we derive the needed inputs as follows.

First, we estimate the daily volatility for each market using daily high and low prices, by following the work of Parkinson (1980): $V_t = 0.361\left[\ln\left(\frac{H_t}{L_t}\right)\right]^2$, where H_t and L_t denote the high and the low prices on day t, respectively.

Second, we estimate the absorption ratio (AR) which is the index of systemic risk, from the returns of the 28 Thailand subsectors, by following the work of Kritzman et al. (2010): $AR = \sum_{i=1}^{n} \sigma_{Ei}^2 / \sum_{j=1}^{N} \sigma_{Aj}^2$; where 'N' is the number of Thailand subsectors; 'n' is the number of eigenvectors, equal to 5; σ_{Ei}^2 is the variance of the i^{th} eigenvector; and σ_{Aj}^2 is the variance of the j^{th} sector.

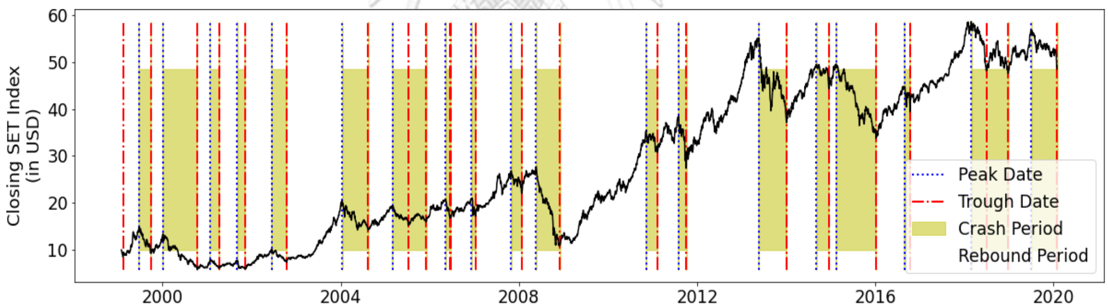
Third, we measure directional volatility spillovers received by the SET from all other markets in a generalized VAR framework of KPPS by following the work of Diebold and Yilmaz (2012) with the values of daily volatilities of each market that we estimate in the first step. Note that we use the rolling windows in the second and the third steps to get the time-varying values.

Finally, we find the percentage changes of all our selected variables: SET index, transaction volume, volatility, the indices of systemic risk, and of volatility spillovers; which are the stationary inputs of our crash prediction model. Besides, we use the rolling windows together with a wavelet method to denoise the percentage changes of the SET index, of transaction volume, and of volatility.

5.2 Defining Crash and Rebound Periods

We must classify the observations into two types to use the anomaly detection model: those occur during crash periods and those occur during rebound periods. The crash (rebound) period begins with a local peak (trough) and ends with a local trough (peak). And the local peak (trough) is the day that the SET index is maximum (minimum) in a window of 90 days before and 90 days after.

Figure 12 Defining Crash and Rebound Periods in the SET



Source: Author

5.3 Model Development

We use the anomaly detection model based on the VAE, discussed in Section 4.3, to develop the crash prediction model in this study. The neural network architecture we use to develop its encoders and decoders is the “Long short-term memory” (LSTM) which is appropriate for time series data.

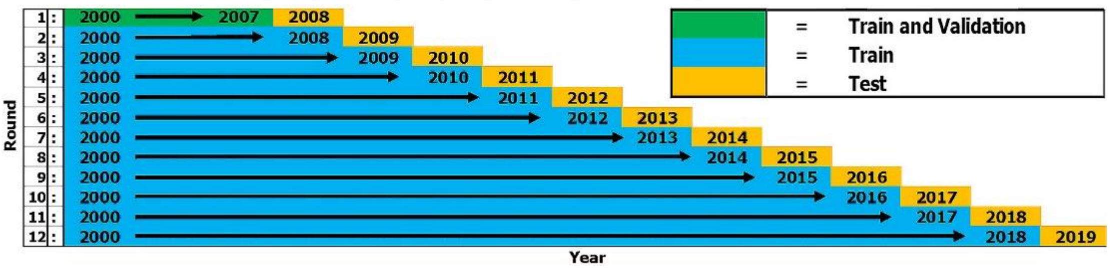
Our crash prediction model consists of two anomaly detection models working together to make the results more stable and accurate. First is the “crash” model that is trained with only the observations that occur during rebound periods, expected that it would give high anomaly scores with the unseen observations that occur during crash periods. Second is the “rebound” model that is trained with only the observations that occur during crash periods, expected that it would give high anomaly scores with the unseen observations that occur during rebound periods. Both models confirm one another, as one model gives a low anomaly score, and another gives a high anomaly score on a particular day. For example; when the crash model gives a high anomaly score while the rebound model gives a low anomaly score, the market crash is likely occurring.

Besides, our anomaly scores of each test set are standardized (with the estimated parameter values of its train set) so that each of them could be considered as ‘high’ when it is greater than zero, and as ‘low’ otherwise.

5.4 Splitting the Dataset for Training and Testing

After we have finished data processing, we get the dataset that begins in the year 2000 and ends in the year 2019. We split it into train and test sets with walk-forward validation, as shown in Figure 13. So, our model would be retrained yearly, and we could evaluate it on the data from 2008 to 2019.

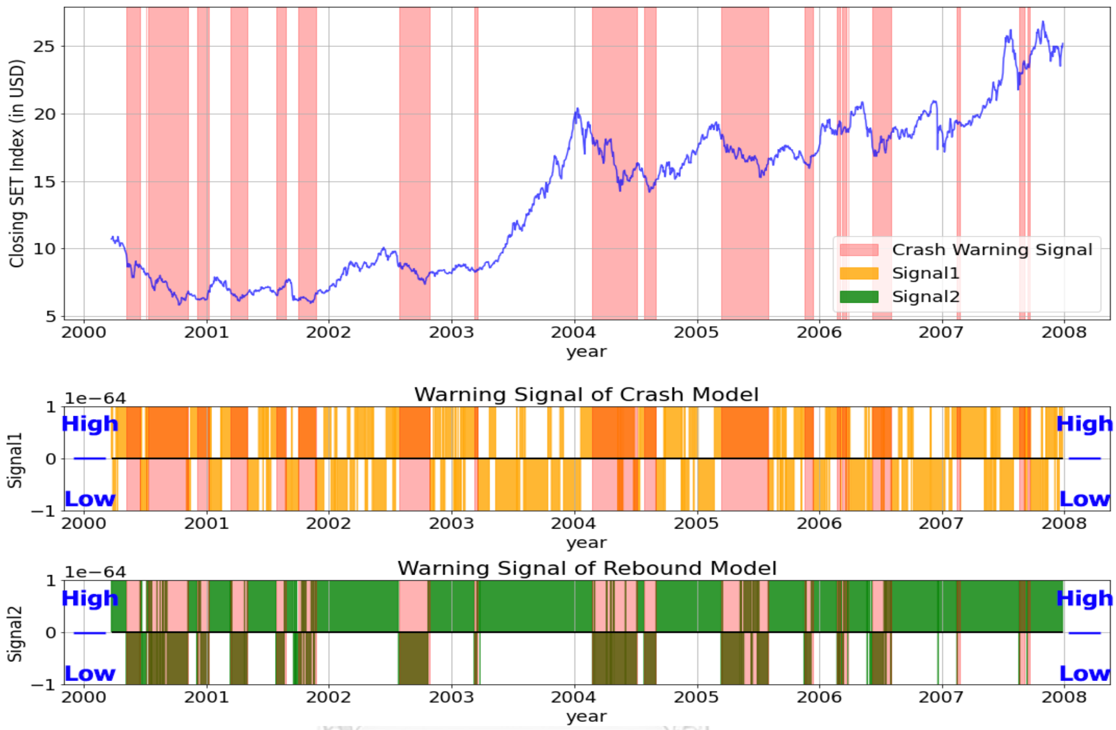
Figure 13 Splitting the Dataset for Training and Testing



Source: Author

Besides, the model has hyperparameters to be tuned: timesteps, learning rate, optimizer, and structure of the VAE. We use the first train set itself for tuning them because we need a long dataset to observe several market crashes to determine whether the model works properly. And we tune them only once because we need several hours to finish it each time. The final results of our model on the validation set are shown in Figure 14, while the results on the test set are shown in the next chapter.

Figure 14 Results of Our Model on the Validation Set (In-Sample)



Source: Author

The criterion we used for tuning hyperparameters is that our model could save us from large crashes but ignore small crashes with the smallest number of mistakes. As can be seen in the figure above; our crash warning signal appears during large crashes in 2000, 2002, 2004, 2005; but it disappears during 2003, because the small crashes occurring during the year are ignored.

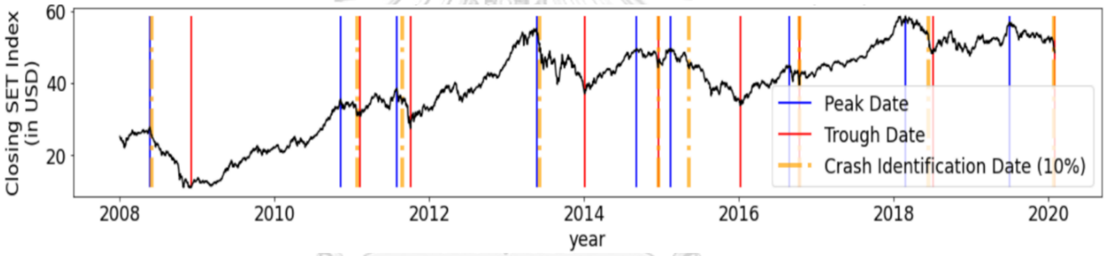
5.5 Model Evaluation

We evaluate our crash prediction model in three aspects: the predictive accuracy, the profitability performance, and the ability to evade large drawdowns.

5.5.1 Predictive Accuracy Evaluation

Following the work of Lleo and Ziemba (2017), we use the test statistics $-2ln\Lambda$ to test whether the rate of predictive accuracy of the crash warning signal from the model is higher than using an uninformed signal. First, we apply the condition that two signals are distinct when a new signal appears after the previous signal has disappeared for at least 30 trading days. Second, we identify the crash as the day on which the SET index is down at least 10% from its most recent peak, as shown in Figure 15. Third, we derive the rate of predictive accuracy of the crash warning signal from the model. The signal is correct when a crash is identified within N days; where N = 20, 61, 122, and 245; which are the numbers of trading days of 1, 3, 6, and 12 months in the SET respectively. Finally, we estimate the test statistics $-2ln\Lambda$ and find their p-values. More details are provided in the work of Lleo and Ziemba (2017).

Figure 15 Crash Identification Dates in the SET



Source: Author

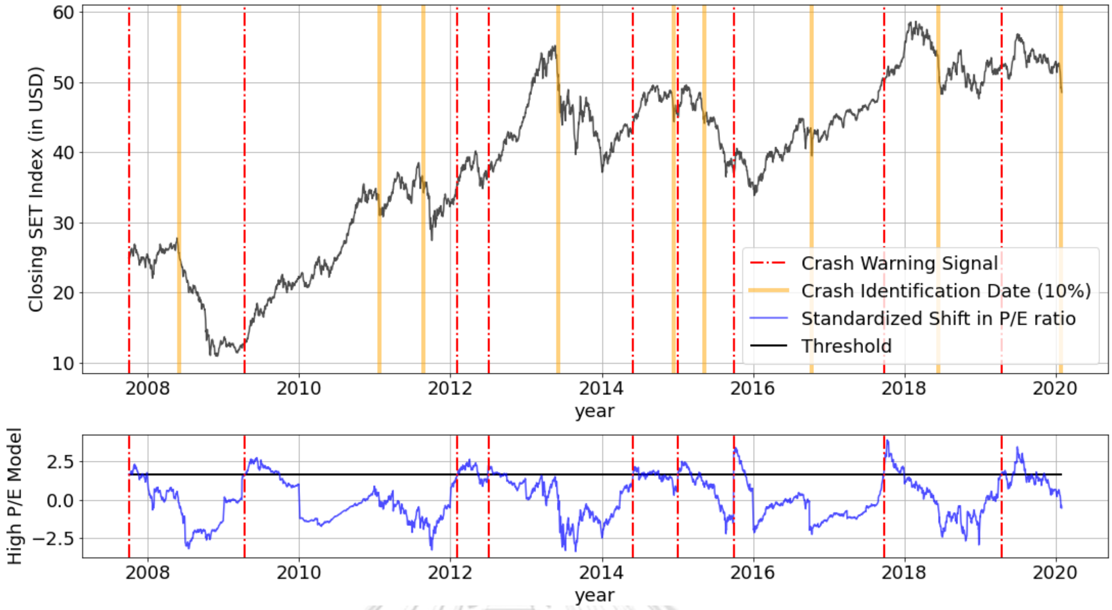
We compare the results with those of the existing models in the literature; namely, the High P/E model (Lleo & Ziemba, 2017) and the BSEYD model (Ziemba & Schwartz, 1991) discussed in Section 3.3 and Section 3.4 respectively. And we also compare the results with those of a linear model, to which we will refer as the "Linear" model, because we want to find the contribution of the deep learning and the variables.

In this study, the High P/E model's variable is the SET price-to-earnings ratio, while the BSEYD model's variable is the Thailand 10-year Bond Yield minus the reciprocal of the SET P/E ratio. We use a rolling window of 1 year to estimate the time-varying threshold which is a standard 95% one-tail confidence interval based on a Normal distribution. A crash warning signal occurs when the value of the variable of each model exceeds its threshold.

The Linear model is the linear regression model fed with the variables which are selected by stepwise regression. Specifically, we begin with performing linear regression whose initial set of independent variables is the same one as we feed our main crash prediction model, and whose dependent variable is a 3-month forward return. After that, we remove the least significant variable. We repeat these steps until the least significant variable has its P-value lower than 0.1. And for this Linear model, we use the same train and test datasets as described in Section 5.4. Its crash warning signal occurs when the value of the predicted 3-month forward return is lower than the threshold, which is the lower limit of a standard 95% one-tail confidence interval based on a Normal distribution.

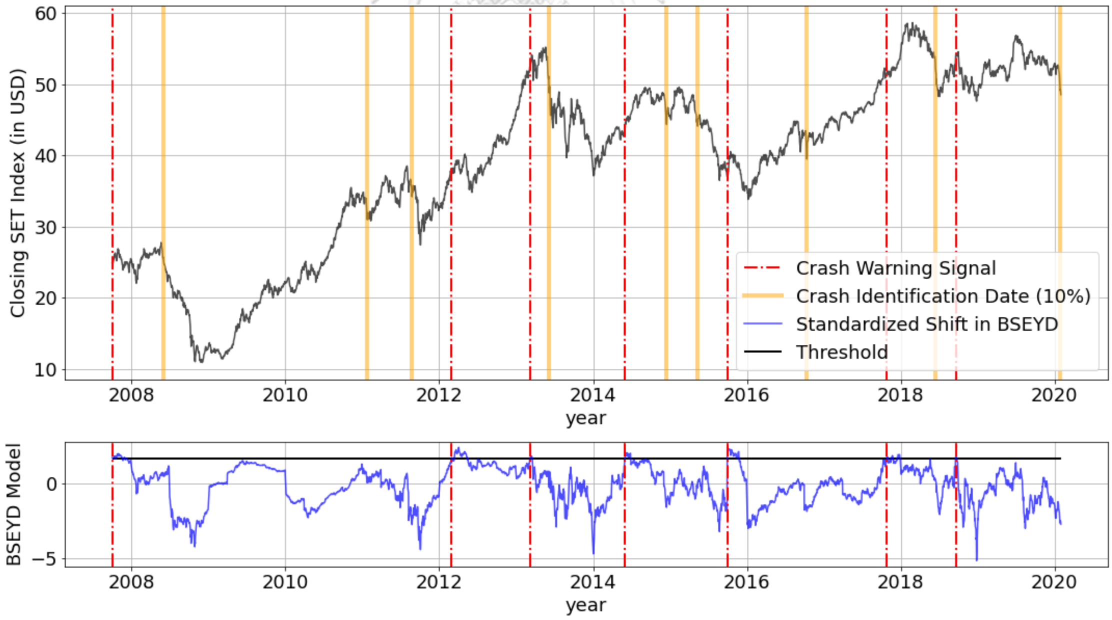
The results of the High P/E, the BSEYD, and the Linear models are shown in Figure 16, Figure 17, and Figure 18, respectively. And the comparison of the results of these models, and our models will be shown in the next chapter. Note that the standardized shift in each variable in this study is the value of the variable on that day decreased by its 1 year moving average and divided by its standard deviation over 1 year. And the threshold is equal to 1.645 for both the High P/E and the BSEYD models, and equal to -1.645 for the Linear model.

Figure 16 SET Index and Crash Warning Signals of High P/E Model



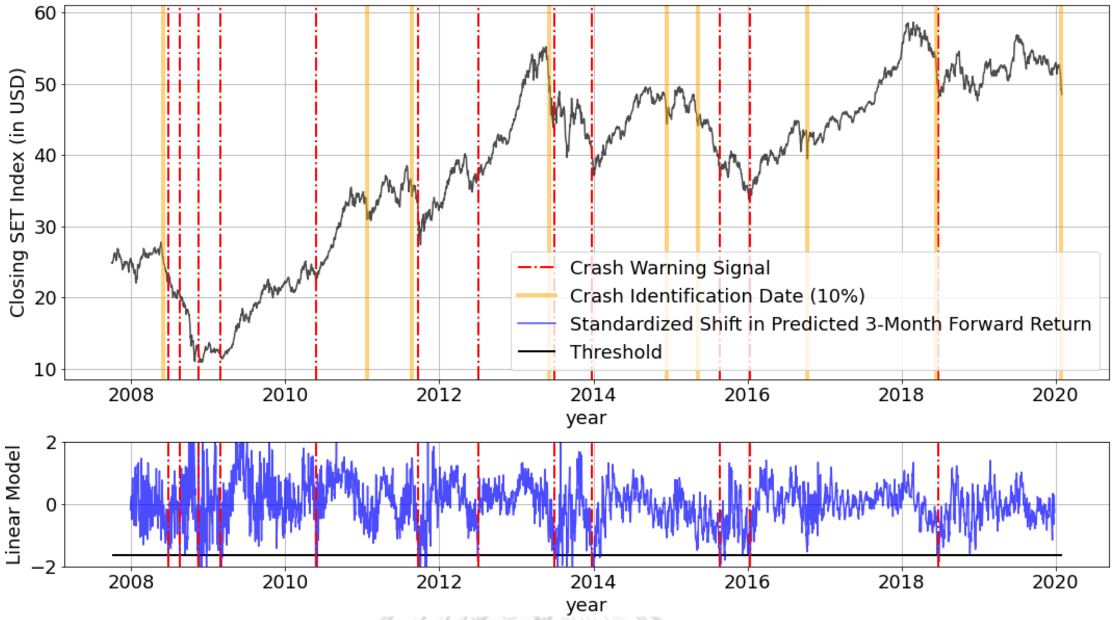
Source: Author

Figure 17 SET Index and Crash Warning Signals of BSEYD Model



Source: Author

Figure 18 SET Index and Crash Warning Signals of Linear Model



Source: Author

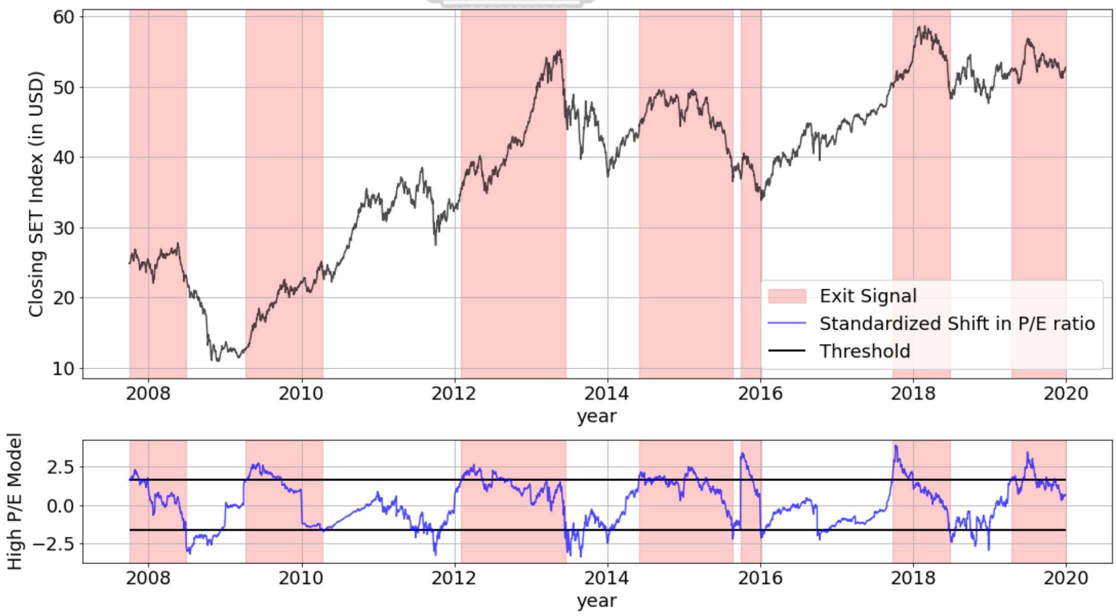
5.5.2 Profitability Performance Evaluation

To test its profitability performance, firstly we assume that we have the cash \$100,000 in hand at the start of 2008. After that, we exit the stock market (0% in equities; 100% in cash) whenever the crash warning signal appears, and enter (100% in equities; 0% in cash) whenever the crash warning signal disappears. We compute the wealth daily with the SET total return index in USD. Note that signal t is calculated and realized after market close on day t, trading action conditional on signal t is executed at the closed price of SET on day t+1.

We compare the results with those of a buy-and-hold strategy, of the strategies incorporated signals from the other models: the High P/E, the BSEYD, and the Linear. For the High P/E and the BSEYD models, we develop exit signals based on the intuition discussed in Chapter 3. The high return periods start with low P/E ratios. And people prefer stocks to bonds when the BSEYD is low, leading to an increase in stock prices. The exit signals of both models, therefore, appear when their crash warning signals appear, and disappear when the value of the variable of each model is lower than its other threshold which is a lower limit of standard 95% one-tail confidence interval based on a Normal distribution. For the Linear model, the exit signals appear when its crash warning signals appear, and disappear when the value of the predicted 3-month forward return exceeds its other threshold which is an upper limit of standard 90% one-tail confidence interval based on a Normal distribution. We use the 90% confidence interval instead; because if we use the 95% confidence interval like in other models, the exit signal will appear continuously from 2014 to 2019.

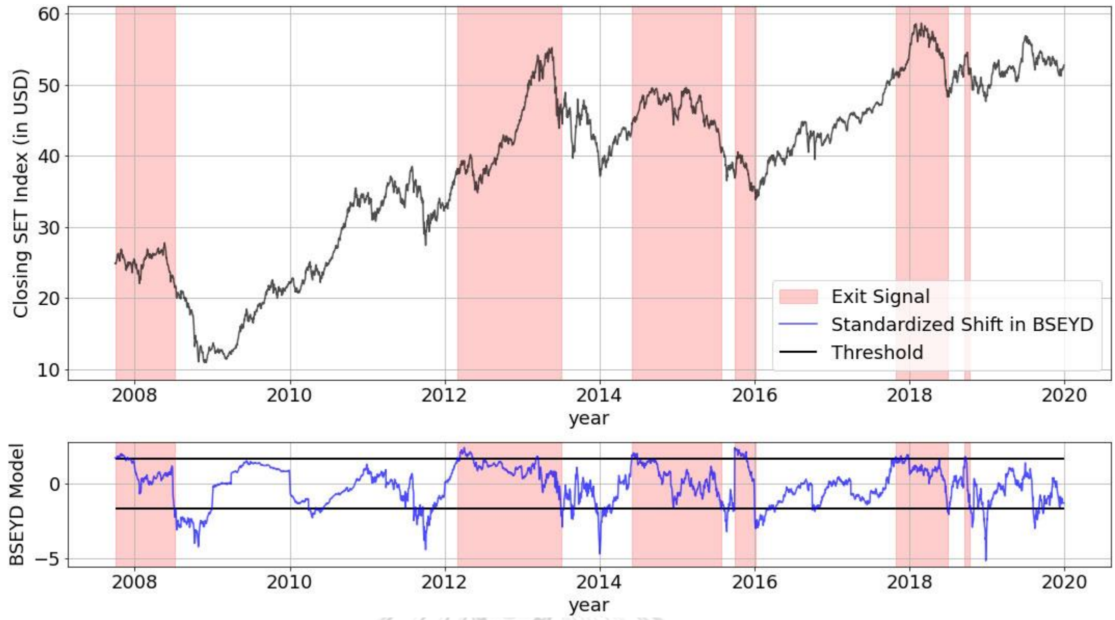
The exit signals of the High P/E, the BSEYD, and the Linear models are shown in Figure 19, Figure 20, and Figure 21, respectively. Note that as we use the standardized shift in each variable, the entry threshold of the High P/E and the BSEYD models is equal to -1.645, while that of the Linear model is equal to 1.282. And the comparison of the wealth of different strategies will be shown in the next chapter.

Figure 19 SET Index, Exit Signals of High P/E Model



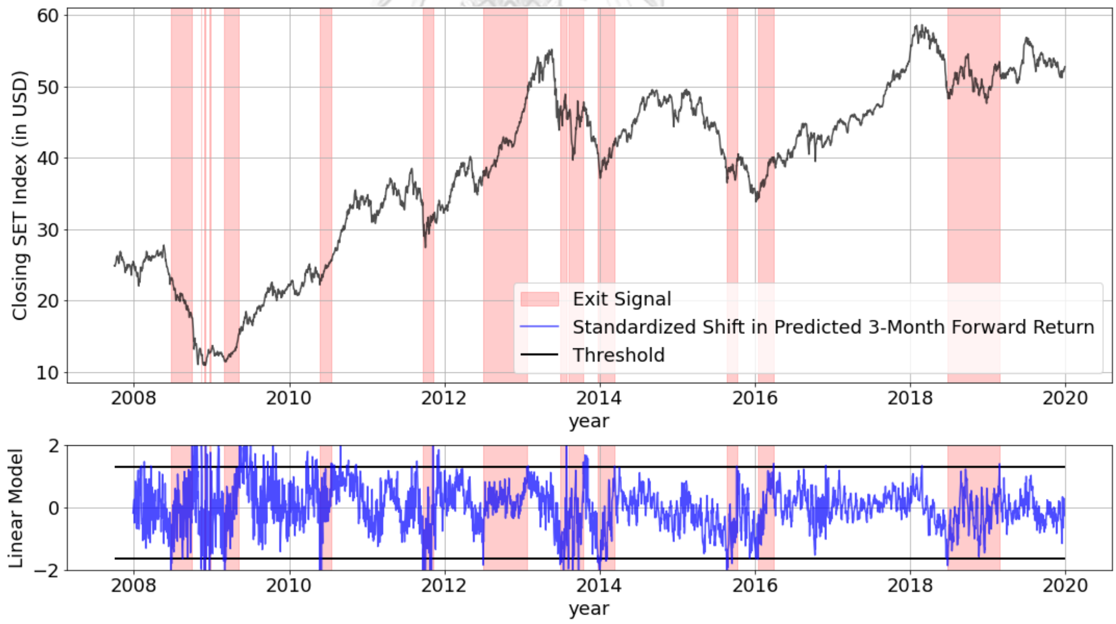
Source: Author

Figure 20 SET Index, Exit Signals of BSEYD Model



Source: Author

Figure 21 SET Index, Exit Signals of Linear Model



Source: Author

5.5.3 Ability to Evade Large Drawdowns

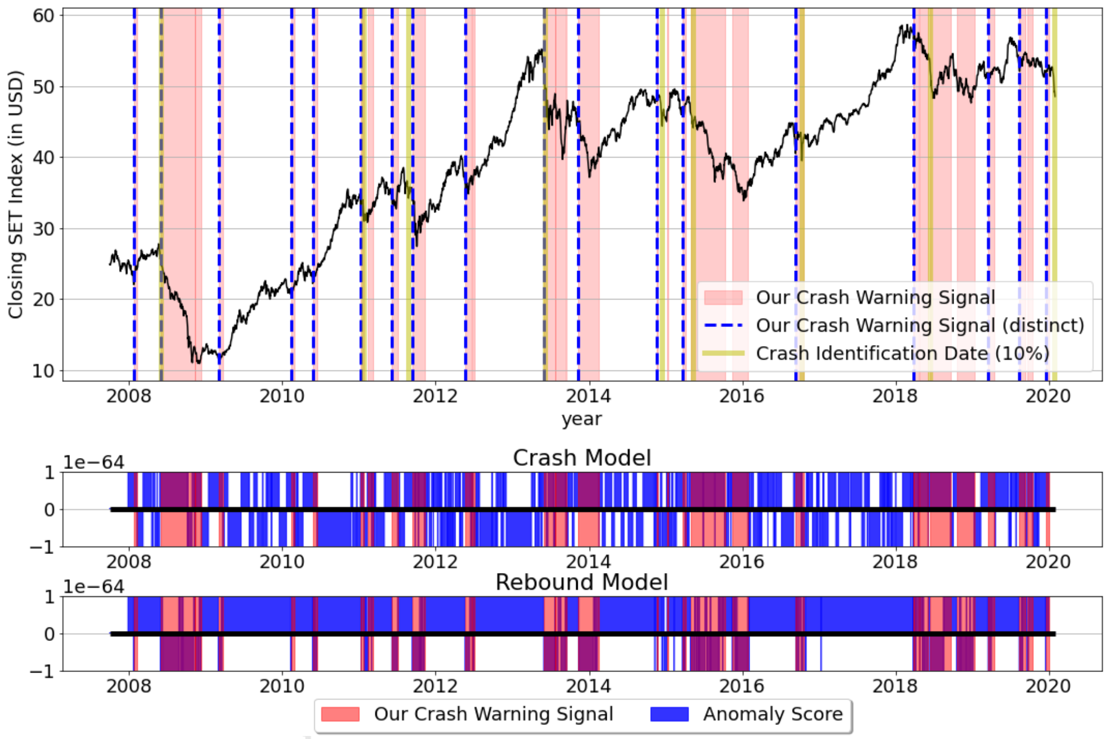
We evaluate the ability to evade large drawdowns by assuming that we have the cash $100 in hand at the start of each month, and we use our strategy incorporated signal from the model discussed previously. We measure the maximum observed loss from \$100 at the start to the minimum point of a portfolio within N months; where N = 1, 3, 6, and 12; measured from each starting point. And we compare the statistic representation of the results with those of the other strategies.

CHAPTER 6

RESULTS

We predict stock market crashes in the SET with our model, and achieve the results as shown in the following figure.

Figure 22 Crash Warning Signals of Our Model (Out of Sample)

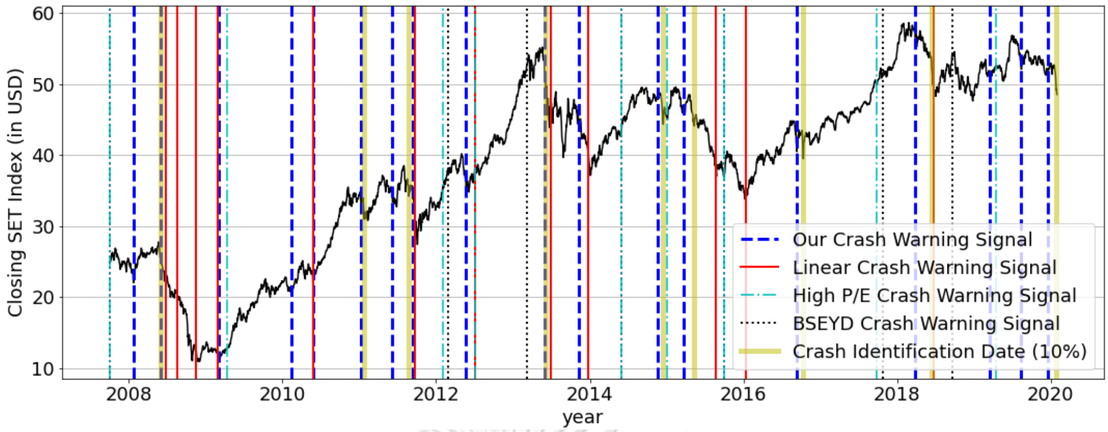


Source: Author

6.1 Predictive Accuracy Evaluation

We compare the prediction results with the dates that their distinct signals appear and test them with the test statistics discussed in Section 5.5.1. Note that even though the signal of our model begins at the start of 2008 and ceases at the end of 2019, we add the most recent signals before the 2008 crash of the other models, and the first crash date after the end of 2019 to make our evaluation complete.

Figure 23 Crash Warning Signals of All Models (Out of Sample)



Source: Author

As shown in Figure 23 and Table 2, we find that in most crashes, including the 2008 crisis, the signal of our model appears shortly after the SET index reaches its peak and long before the index reaches its trough, while the signals of the High P/E and the BSEYD appear for several months before the peak. Besides, we find that most of the Linear model signals appear within a crash period. This indicates that our selected variables can be used for predicting market crashes directly. But we could achieve better results when we combine these selected variables with the deep learning.

As shown in Table 3, with the test statistics, we find that only our model performs significantly better than chance at predicting market crashes in the SET when we set N equal to 1, 3, and 6 months. And the Linear model performs significantly better than chance when N is equal to 1 year.

Table 2 Comparison of Each Model's Predictability With the Dates

Date			Crash Warning Signal			
Crash (10%)	Peak	Trough	High P/E	BSEYD	Linear	Ours
2008-06-02	2008-05-21	2008-12-02	2007-10-01 ■	2007-10-01 ■	2008-06-24 ⊠, 2008-08-18 ⊠, 2008-11-13 ⊠	2008-01-23 ◆■, 2008-05-30 ●★◆■
2011-01-24	2010-11-09	2011-02-10	2009-04-10		2009-02-26, 2010-05-25 ■	2009-03-02, 2010-02-10 ■, 2010-05-26 ■, 2011-01-11 ●★◆■
2011-08-25	2011-08-01	2011-10-04			2011-09-22 ⊠	2011-06-07 ★◆■, 2011-09-12 ⊠
2013-06-06	2013-05-21	2014-01-03	2012-02-03, 2012-07-02 ■	2012-02-29, 2013-03-07 ★◆■	2012-07-02 ■, 2013-06-28 ⊠, 2013-12-24 ■	2012-05-21, 2013-05-31 ●★◆■, 2013-11-12 ⊠
2014-12-16	2014-09-05	2014-12-16	2014-06-02 ■	2014-06-02 ■		2014-11-21 ●★◆■
2015-05-11	2015-02-13	2016-01-07	2015-01-05 ◆■, 2015-09-30 ⊠	2015-09-30 ⊠	2015-08-21 ⊠	2015-03-23 ★◆■
2016-10-12	2016-08-26	2016-10-12			2016-01-15 ■	2016-09-13 ★◆■
2018-06-15	2018-02-26	2018-07-05	2017-09-25 ■	2017-10-27 ■	2018-06-26 ⊠	2018-03-26 ★◆■
2020-01-27	2019-07-03	2020-01-31	2019-04-17 ■	2018-09-19		2019-03-19 ■, 2019-08-14 ◆■, 2019-12-17 ★◆■
●,★,◆,■ The correct signal as the crash (10%) is identified within 1, 3, 6, 12 months, respectively. ⊠ The signal appears within a crash period but after the crash identification date.						

Source: Author

Table 3 Comparison of Each Model's Predictability With the Test Statistics

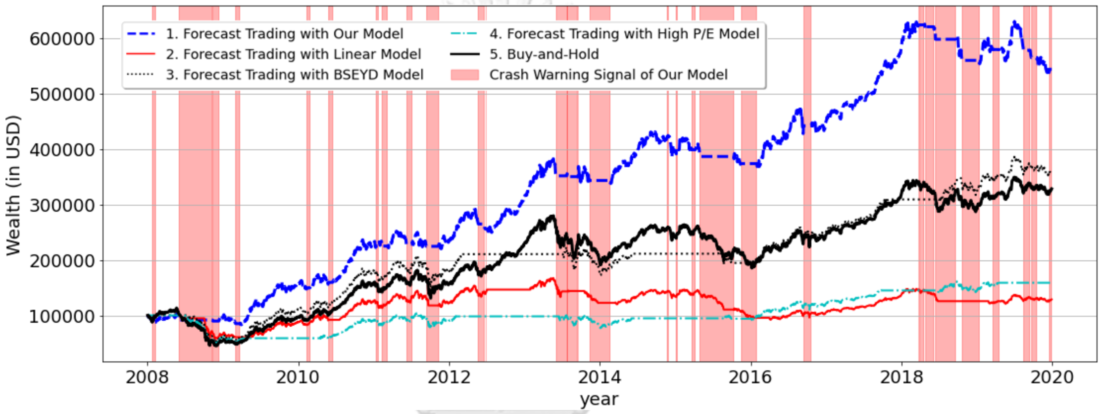
N (Mths)	Proportion of Correct Predictions					P-value of the test statistic $-2\ln\Lambda$			
	Uninformed	High P/E	BSEYD	Linear	Ours	High P/E	BSEYD	Linear	Ours
1	5.98%	0.00%	0.00%		22.22%				2.27%*
3	18.24%	0.00%	14.29%		50.00%		78.00%		0.23% **
6	35.51%	11.11%	14.29%		61.11%	9.36%	20.68%		2.75%*
12	62.03%	66.67%	57.14%	33.33%	77.78%	77.23%	79.16%	4.45%*	15.22%
*Significance at the 5% level. **Significance at the 0.5% level.									

Source: Author

6.2 Profitability Performance Evaluation

After applying the methods discussed in Section 5.5.2, we find that $100,000 at the start of 2008 grew to $328,142 at the end of 2019 with a buy-and-hold strategy, but to $543,723 with our strategy incorporated signal from our model. While this same $100,000 grew to $128,721, to $158,787, and to $362,550 with the strategies incorporated signals from the Linear, the High P/E, and the BSEYD models, respectively.

Figure 24 Comparison of the Wealth of Different Strategies



Source: Author

Besides, the average annual return of a buy-and-hold strategy is 15.73%, while that of our strategy incorporated signal from our model is 16.97%. The average annual returns of the strategies incorporated signals from the Linear, the High P/E, and the BSEYD models are 4.74%, 6.53%, and 15.35%, respectively.

6.3 Ability to Evade Large Drawdowns

We evaluate the ability to evade large drawdowns as we discussed in Section 5.5.3. We find that on average our strategy incorporated signal from our model achieves the best results or the smallest sizes of max drawdowns, followed by the High P/E, the BSEYD, the Linear model. While the buy-and-hold strategy achieves the worst results or the highest sizes of max drawdowns in all our selected durations.

Table 4 Comparison of the Max Drawdown of Different Strategies

	Max Drawdown									
	Over 1 Month					Over 3 Months				
	Ours	Linear	High P/E	BSEYD	Buy-and-Hold	Ours	Linear	High P/E	BSEYD	Buy-and-Hold
Mean	1.80%	2.70%	1.97%	2.20%	3.37%	2.94%	5.36%	3.98%	4.22%	6.39%
SD	2.40%	4.46%	4.39%	4.34%	4.74%	3.18%	6.97%	7.68%	7.45%	8.18%
Med.	0.76%	1.01%	0.00%	0.00%	1.67%	2.08%	3.13%	0.52%	1.43%	3.73%
Max.	12.21%	37.22%	37.49%	37.49%	37.49%	14.60%	38.21%	44.80%	44.80%	44.80%
	Over 6 Months					Over 1 Year				
	Ours	Linear	High P/E	BSEYD	Buy-and-Hold	Ours	Linear	High P/E	BSEYD	Buy-and-Hold
Mean	3.72%	7.92%	6.19%	6.31%	9.15%	4.49%	11.36%	9.25%	9.37%	12.23%
SD	3.55%	9.45%	10.64%	10.13%	11.39%	4.15%	12.27%	13.21%	12.44%	14.19%
Med.	2.84%	3.65%	1.92%	2.54%	5.72%	3.32%	7.14%	3.28%	4.73%	7.22%
Max.	14.60%	44.54%	51.19%	48.20%	57.32%	14.60%	45.41%	51.19%	48.20%	57.69%

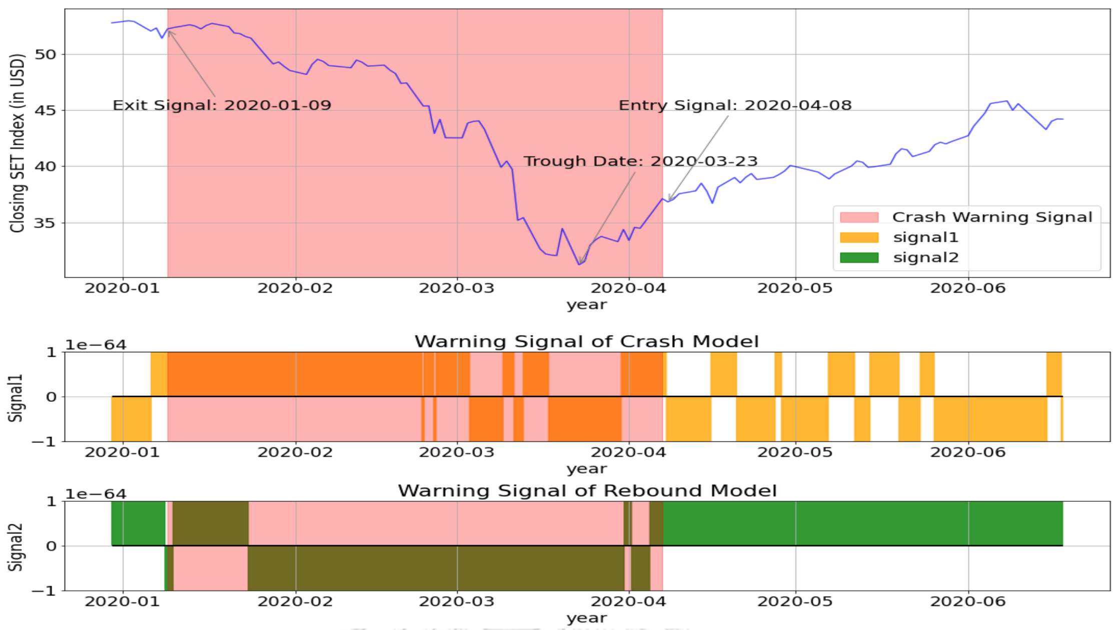
Source: Author

6.4 Live Test During COVID-19 Stock Market Crash

Our model can be used to predict stock market crashes in real situation. For example; we train our model with the data from 2000-2019, and use it predict the 2020 stock market crash due to the COVID-19 pandemic. The result is shown in Figure 22.

We find that our crash warning signal appears on January 9, 2020 or more than two months before the trough date on March 23, 2020. When the authorities are assured with our model that the stock market crash will soon occur, they should be able to manage the negative impacts of stock market crash that will transmit to other markets, like the commodity market, better.

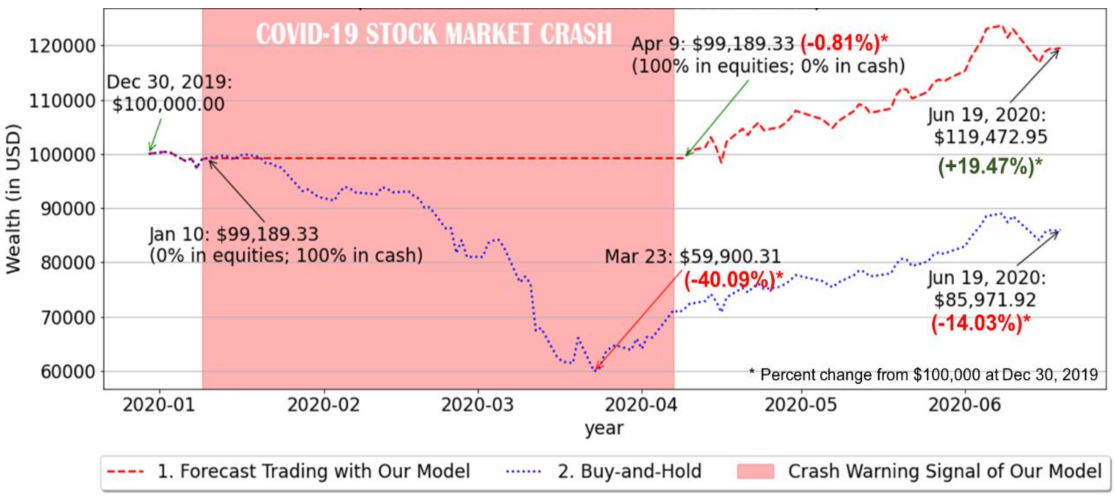
Figure 25 Live Test Results During COVID-19 Stock Market Crash



Source: Author

Besides, when we apply our strategy incorporated signal from the model discussed in Section 5.5.2, we find that $100,000 at the start of 2020 grew to $119,472.95 on June 19, 2020, but shrank to $85,971.92 with a buy-and-hold strategy. In other words, it could save us from financial loss in stock market.

Figure 26 Comparison of the Wealth of Our Strategy and a Buy-And-Hold Strategy (During COVID-19 Stock Market Crash)



Source: Author

CHAPTER 7

CONCLUSION AND DISCUSSION

We develop a model using a deep learning to predict stock market crashes. We feed the model with stock market index, transaction volume, volatility, the indices of systemic risk, and of volatility spillovers. With these indices, the model takes into account the influences from both inside and outside the particular stock market. We use our model to predict the market crashes in the SET, and compare it with the BSEYD model and the High P/E model. We find that our model outperforms the others. Besides, when compared with other strategies, our strategy incorporated signal from our model leads to the highest profit, because it helps us evade from large crashes. This also means the opportunity for short-selling which allows us to make profit when we know that the large crash is occurring.

At the time of this writing, there are some limitations regarding the method to evaluate predictive accuracy, the availability of the data, the availability of computing power, and the currency unit used. First, with the method that we use to evaluate predictive accuracy, the signal that occurs during the crash but after the crash identification date will be count as incorrect. This leads to an underestimate of the rate of predictive accuracy. Second, the existing daily data of the SET is not long enough to train the model well, and it is impossible to use the higher frequency data like the intraday data due to the availability of the data and the availability of computing power. Third, we use only the US dollar in this study because it is the easiest way to handle the influence of exchange rate changes on our factors like volatility spillovers index. Trading with other currencies, like Thai Baht, would achieve different results. Besides, there are other state-of-the-art machine learning models and other interesting variables. Some of them may lead to better results in predicting stock market crashes.

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