An Empirical Study on the Effectiveness of Bi-LSTM-Based Industry Rotation Strategies in Thai Equity Portfolios

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Abstract. Portfolio optimization poses a significant challenge due to asset price volatility caused by various economic factors. Portfolio optimization typically aims to achieve a high risk-adjusted return through asset allocation. However, high-volatility assets such as equities can lead to significant losses in the event of crises, such as trade wars. An industry rotation strategy can reduce portfolio risk by investing in industry indexes. This research aims to develop industry rotation strategies for Thailand by analyzing previous consecutive months of economic variables with the goal of maximizing the portfolio's Sharpe ratio in the following period. Two strategies are proposed in this paper, one with cash and the other without, both of which include eight Thai industry indexes in their portfolios. Both strategies are developed using Bidirectional Long Short-term Memory (Bi-LSTM) models, which generate the allocation ratio based on historical economic variable data. The models then optimize the allocation ratio by using a modified loss function to maximize the Sharpe ratio. In addition to the Sharpe ratio, the return on investment and the Calmar ratio are used to assess the performance of the strategies. The results showed that our strategies outperformed the baseline buy-and-hold SET50 and equal-weight strategies.

Keywords: Asset Allocation · Bidirectional Long Short-time Memory · Deep Learning · Investment Strategies · Portfolio Optimization · Sector Rotation

1 Introduction

Portfolio optimization is a method of determining the asset distribution or asset ratio that gives the best performance based on certain objectives, such as the portfolio's return on investment. Given numerous economic factors such as interest rates, market sentiment, or political events, a constant fluctuation in asset prices could be expected, thus making portfolio optimization a challenging problem.

In 1996, Stovall presented an investment strategy according to economic timing in his book. His strategy, so-called "sector rotation" or "industry rotation", suggested investing in stocks based on industry sector behavior and economic cycle phases. Sector rotation

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usually divides the equity market into phases, then constructs portfolios according to the historical performance of market sectors in those phases, which are usually identified directly from macroeconomic indicators. For example, Fidelity Investments, one of the largest financial corporations, divided the equity market into four phases and utilized the historical performance calculation to suggest an investment strategy accordingly [2].

Many research studies, however, did not consider business cycle phases when performing sector rotation. For instance, Conover et al. conducted sector rotation experiments under monetary conditions [4], to which they classified industries as cyclical or noncyclical and rearranged the portfolio in response to changes in Federal Reserve policy. Tangjitprom [5], on the other hand, used a momentum strategy in sector rotation. He implemented the strategy by utilizing Thailand's industry sectors via The Stock Exchange of Thailand (SET) industry indexes. The strategy focused on the momentum of those indexes by capturing each index's return over months. The return indexes for those months were then calculated, and the highest return index was invested by holding for a period.

Machine learning has been extensively applied due to its proven success in a wide strand of research. To perform sector rotation in particular, many efforts have been made using machine learning, as evidenced in several studies. For example, Raffinot and Benoit applied Random Forest and Boosting algorithms to predict economic turning points in the United States and the Eurozone [6]. In comparison with the buy-and-hold benchmark strategy, they used a dynamic asset allocation strategy during different phases. The result showed that the proposed strategy outperformed the buy-and-hold strategy, particularly in terms of risk-adjusted return. Deep learning models, among other techniques, have also been used to optimize portfolios in sector rotation strategies. Karatas and Hirsa used deep learning models to predict asset prices in eight major U.S. industry sectors [7]. They decided to invest in the top four industries with the highest return. In addition, the study was tested in multiple lookback windows and was evaluated using investment return, Sharpe ratio, and Calmar ratio. The results indicated that all tested models outperformed the equal-weight portfolio benchmark. Zhang et al. also presented portfolio optimization using deep learning models to determine the optimal portfolio with the best Sharpe ratio among four U.S. indexes [8]. They used LSTM with 51 days of four indexes as the model's input to optimize the allocation ratio of those four assets. According to the results, LSTM was demonstrated to outperform all other strategies.

Previous research on sector rotation that uses machine learning can be divided into two categories: those using business cycle prediction and those focusing on portfolio optimization. The studies that used business cycle prediction sought to optimize the static proportion of assets at various stages of the business cycle. However, it has been observed that no sector behaves consistently in the same way during specific phases [3]. Furthermore, these phases are frequently identified by National Bureau of Economic Research (NBER) committees, which can be subject to delays and human biases. On the other hand, some study has adopted an alternative strategy by predicting asset prices and choosing the top performers for investments from the prediction [5, 7]; some paper has employed optimized ratios throughout all business cycles [8]. This study implements an industry rotation strategy for Thailand's economy by proposing a dynamic sector rotation strategy that adjusts asset allocation to the various market conditions in Thailand. A deep

learning model is used to implement the sector rotation strategy because it can capture the nonlinearity effect of many economic factors and learn the complex relationships between them [1]. In contrast to the United States, where many exchange-traded funds (ETFs) track sector indexes and allow investors to buy and sell them to implement sector rotation strategies, Thailand has no ETFs that track industry indexes. This study assumes that investors can trade stocks that closely track those indexes, and the cost of trading is not factored in.

2 Methodology

2.1 Data Aggregation

This study relies solely on economic variables derived from publicly available data. The goal of this study is not to improve model performance through the selection of economic variables. The dataset used consists of macroeconomic data and industry indexes.

Macroeconomic Data. Six of Thailand's macroeconomic time-series variables are collected from the Office of the National Economics and Social Development Council (NESDC) [13], the Bank of Thailand (BOT) [14], the Office of Industrial Economics (OIE) [15] and National Statistical Office of Thailand (NSO) [16]. The time-series variables in this dataset present monthly and quarterly data from October 2006 to November 2021. Table 1 provides information about this dataset.

Table 1. Macroeconomic variables used in this paper.

Macroeconomic variables	Frequency	Symbol abbreviation	Source
Industrial Production Index	Monthly	INDPRO	OIE
Unemployment Rate	Monthly	UNEMPLOY	NSO
Retail Sales Index	Monthly	RETAIL	BOT
Private Final Consumption Expenditure	Quarterly	PFCE	NESDC
Real Gross Domestic Product	Quarterly	Real GDP	NESDC
Gross Domestic Product	Quarterly	GDP	NESDC

Industry Indexes. An industry index is a capitalization-weighted index calculated from the prices of the common stocks in Thailand with the same fundamentals [12]. The Stock Exchange of Thailand (SET) categorizes listed companies into eight industry groups as shown in Table 2. All eight SET industry group indexes will then be used in this study. The dataset compiles the closed value of those indexes in each month from October 2006 to November 2021.

Table 2. SET Industry Group Index

Industry group	Symbol abbreviation
Agro & Food Industry	AGRO
Consumer Products	CONSUMP
Financials	FINCIAL
Industrials	INDUS
Property & Construction	PROPCON
Resources	RESOURC
Services	SERVICE
Technology	TECH

2.2 Data Preprocessing

Firstly, three quarterly macroeconomic variables in the dataset are interpolated to monthly data using Cubic spline interpolation, which has been shown in [10, 11] to be efficient when used with economic data. Secondly, missing data is handled because many macroeconomic data are not available in real-time. For example, to make a prediction for February, Thailand's GDP data from October to January of the previous year is required; however, since NESDC normally releases the GDP of the fourth quarter in February of the following year, such timing constraint thereby brings about a scenario where portions of data are unavailable. After testing different methods for data preparation, it was discovered that our model performs best when the monthly interpolated macroeconomic data is forward shifted based on the missing time since the most recent data is then used to make predictions. In this study, the data from NESDC, PFCE, GDP, and Real GDP are shifted by four months, the data from INDPRO and UNEMPLOY are shifted by one month, and the data from RETAIL are shifted by two months. Figure 1 depicts an example of shifted macroeconomic data used in the February 2017 prediction.

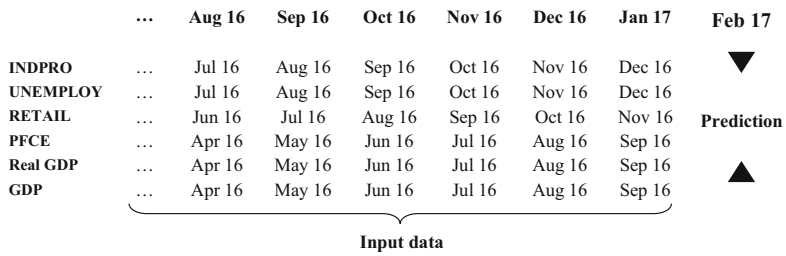

Fig. 1. An example of shifted macroeconomic data used in the February 2017 prediction.

Thirdly, the first difference or percent change of all variables in the dataset is then computed and used as a feature to capture the growth rate and make the data stationary.

Finally, the prepared data is transformed for use in Bi-LSTM models. To train the models, monthly growth rate data from the six macroeconomic variables and eight industry indexes for m consecutive months are used as inputs (X). The next k months growth rates of the eight industry indexes are used as holding period data (Y) to compute the portfolio's Sharpe ratio from the portfolio allocation (Z) returned by the Bi-LSTM models. Figure 2 depicts the overall model framework with a 12-month holding period ($k = 12$). The inputs to the Bi-LSTM models are denoted as $x_1, x_2, \ldots, x_n$, where n is the number of input data points, which is calculated by multiplying 14 input attributes by m consecutive months ($n = 14 \times m$). The output vector of the Bi-LSTM's last layer is represented as $z_1, z_2, \ldots, z_a$ where a is the number of assets in the portfolio. $y_{h,k}$ represents the investment return on asset h during the next k-th month of the holding period. The goal of the models is to maximize the Sharpe ratio of the portfolio by optimizing portfolio allocation. Two portfolio allocation strategies are investigated in this study: (1) with-cash and (2) no-cash, provided that both include eight industry indexes in their portfolios. The holding period data (Y) for the cash strategies contain a cash growth rate of zero over the next k months.

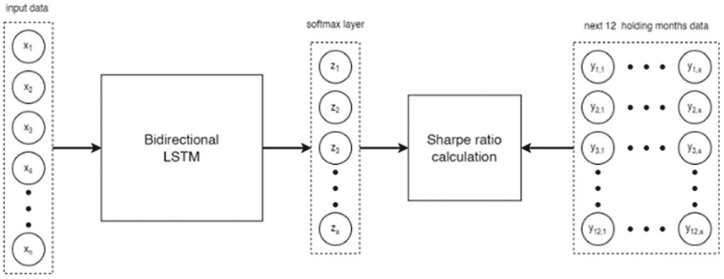

Fig. 2. Overall model framework with a 12-month holding period.

2.3 Model

According to the results of a previous study [9], LSTM performed the best in portfolio optimization. The current study investigates Bi-LSTM models, an improved LSTM variant. Bi-LSTMs use two sets of LSTMs to process data in both forward and reverse directions. It enables the model to predict using both past and future context, making it well-suited to the task of using time series data as input. Figure 3 depicts the overall architecture of Bi-LSTM.

As shown in Fig. 2, the Bi-LSTM model's output will be the asset ratio in the portfolio, which is the ratio of the eight assets in the no-cash portfolio and the nine assets in the with-cash portfolio. Our Bi-LSTM models are built in the following layers.

1. Input layer to receive input data.
2. Bi-LSTM layer with *n_BiLSTM* nodes and a dropout rate of 0.50.
3. Flatten layer that transforms the output to a one-dimensional vector.
4. The first dense layer with *n_Dense* nodes, ReLU as the activation function, He uniform as the weight initializer.

5. Dropout layer with 0.50 dropout rate.
6. The second dense layer with eight or nine nodes for the no-cash and the with-cash models, respectively; *softmax* calculated by Eq. (1) is used as the activation function and He uniform is used as the weight initializer.

$$Softmax(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}} \tag{1}$$

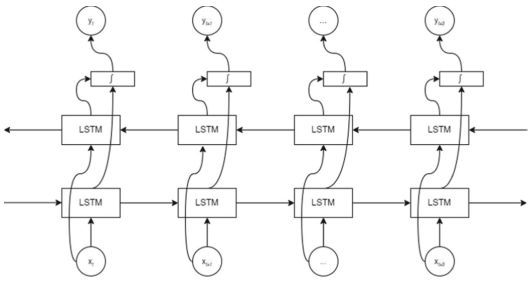

Fig. 3. An architecture of Bi-LSTM.

The goal of this research is to use the Bi-LSTM models to optimize the portfolio's Sharpe ratio. The Adam algorithm is used as the model's optimizer. As in [9], the Sharpe ratio is calculated directly in the loss function of the model using the portfolio output from the softmax layer. The model will then be able to predict the assets ratio for the subsequent k-month holding period that maximizes the Sharpe ratio, using information from the previous m months. However, since this study aims to maximize the Sharpe ratio while Bi-LSTM minimizes the loss function, the loss function is modified to minimize the exponential of the negative of the Sharpe ratio, as shown in Eq. (2).

$$Loss = e^{(-sharperatio)} \tag{2}$$

2.4 Evaluation Metrics

In addition to the Sharpe ratio, which is used in the loss function, the performance of the baselines and our predicted strategies is also evaluated using the rate of return and the Calmar ratio.

Return on Investment. Return on investment is the profit or loss on an investment over time. In this study, the return on investment each year is calculated as the value increased from the portfolio's initial value divided by the portfolio's initial value (Eq. (3)).

$$Return\ on\ investment = \frac{portfolio's\ value\ at\ the\ end - portfolio's\ value\ at\ initial}{portfolio's\ value\ at\ initial} \tag{3}$$

Sharpe Ratio. The Sharpe ratio measures the portfolio's return in relation to its risk. It is calculated by dividing the difference between the expected return and the risk-free rate by the volatility, as shown in Eq. (4).

$$Sharpe\ ratio = \frac{R_p - R_f}{\sigma\left(R_p\right)} \tag{4}$$

where R_p is the expected return of the portfolio, R_f is the risk-free return, and $\sigma\left(R_p\right)$ is the standard deviation of R_p. The risk-free return (R_f) is the return on an investment that is guaranteed to return to the investor with no possibility of loss, such as a government bond. In this study, R_f is set to zero because no risk-free investment is made. Monthly returns can be calculated by multiplying the growth rate of the assets over the next k months by their weights based on the portfolio allocation from the model's output. The return of the portfolio (R_k) at the k-th month is calculated by Eq. (5).

$$R_k = \sum_{i=1}^{a} w_i \cdot r_{i,k} \tag{5}$$

where a is the number of assets in the portfolio, w_i is the proportion of asset i from the model's output, and $r_{i,k}$ is the growth rate of asset i at month k-th. R_p is the average of R_k over k months. The Sharpe ratio of the portfolio can then be rewritten as shown in Eq. (6).

$$Sharpe\ ratio = \frac{R_p}{\sqrt{\frac{1}{N}\sum_n \left(R_k - R_p\right)^2}} \tag{6}$$

During the model testing phase, however, the Sharpe ratio will be calculated annually using Eq. (4).

Calmar Ratio. Calmar ratio is a risk-adjusted return metric similar to the Sharpe ratio, except that it uses maximum drawdown as the denominator rather than the standard deviation. The maximum drawdown metric computes the loss in portfolio value between the highest peak and lowest trough prior to the new peak. It evaluates the downside risk and shows investors the maximum possible portfolio drawdown. Eq. (7) illustrates the Calmar ratio calculation.

$$Calmar\ ratio = \frac{average\ yearly\ return}{Maximum\ drawdown} \tag{7}$$

2.5 Experimental Setup

The pre-processed dataset is divided into training and testing data with January 2016 as the dividing date. The training data ranges from October 2006 to December 2015, while the testing data ranges from January 2016 to November 2021. Our experiments begin with the training phase, in which the data is divided into the training set and the validating set by 67% and 33%, respectively. Using the values shown in Table 3, hyperparameters are tested to find the set of values that produced the best results.

Table 3. Set of parameters used in creating Bi-LSTM models.

Parameter	Value
Input time horizontal (m)	6, 12, 18, 24, 30, 36
Holding period after getting the allocation ratio (n)	3, 6, 12
Number of nodes in Bi-LSTM layer (n_BiLSTM)	256, 512, 1024
Number of nodes in the first Dense layer (n_Dense)	128, 256, 512

In each experiment, the Bi-LSTM model with each hyperparameter combination is built and run for thirty rounds. The average value of the Sharpe ratio in the loss function is used to assess the model's performance in each experiment. The combination with the highest Sharpe ratio using the validation set is chosen. Then, the model is tested in the testing phase by using the previous $\boldsymbol{m}$ consecutive months as input, and holding assets based on the model's output ratio for the next $\boldsymbol{k}$ months. During the testing phase, backtesting is conducted using the model for twelve different time intervals to make sure that our models do not accidentally perform well at any particular time as shown in Fig. 4. Each interval contains data for a period of five years. The first interval runs from January 2016 to December 2020. For the remaining intervals, each will be advanced by one month. For example, the second interval runs from February 2016 to January 2021, and the twelfth interval runs from December 2016 to November 2021.

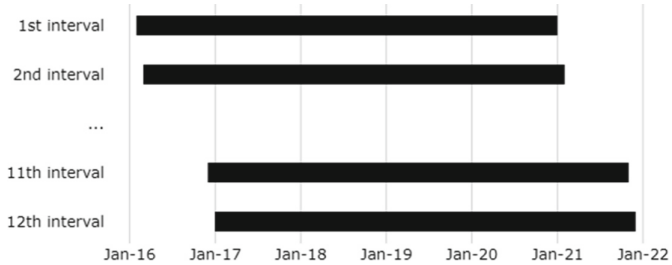

Fig. 4. Twelve intervals used in testing phase.

Since this study focuses on Thailand's industry rotation, the SET50 index, which is a stock price index used to show the price movement of the 50 largest common stocks in terms of market capitalization, and the equal weight allocation are used as baselines in this study.

3 Results and Discussion

Results from the training phase show that the best hyperparameter combination for the with-cash strategy is $m = 24$, $k = 3$, $n_{BiLSTM} = 1024$, and $n_{Dense} = 512$, with an average Sharpe ratio of 1.9647. The best combination for the no-cash strategy is $m = 24$,

$k = 3$, $n_{BiLSTM} = 512$, and $n_{Dense} = 256$, with an average Sharpe ratio of 1.886. The testing phase then uses twelve intervals to test each model. As shown in Table 4, the three evaluation metrics are calculated and compared to baselines. The results show that, apart from the with-cash model's average annual return for the period starting in November 2016, both proposed strategies outperformed the baselines across all three metrics and all time periods. Furthermore, our proposed strategies outperformed the baselines for all average metrics values derived from twelve intervals.

In terms of average yearly return, the no-cash strategy outperformed the with-cash strategy for all interval average values. These findings suggest that the no-cash strategy can provide us with a higher return on investment year after year. In terms of the Sharpe ratio, however, the with-cash strategy outperformed the no-cash strategy which demonstrates that the with-cash strategy can reduce portfolio volatility. Therefore, while the no-cash strategy outperforms in terms of return, the with-cash strategy outperforms in terms of risk. Regarding the Calmar ratio, it can be observed that the with-cash strategy performed better than the no-cash strategy. The results demonstrated that the with-cash strategy significantly reduced the maximum drawdown, which occurred during the market crash at the beginning of 2020 due to fear of COVID-19, with the average values of all intervals being 17.74% compared to 34.15%, 38.09%, and 37.47% of the no-cash, equal weight, and SET50 strategies, respectively.

To investigate the movement of the portfolios' return for each strategy, Fig. 5 presents the cumulative return from our proposed strategies during the testing phase along with the baselines for four out of twelve intervals beginning in January, April, July, and October 2016. The figure demonstrates a similar pattern in the movement of our proposed strategies from the four intervals. Around the middle of 2017, the no-cash strategy begins to outperform the baselines with a higher upside. Then, it behaves similarly to the SET50, including during the COVID-19 crisis in the early 2020s, when values dropped by more than 30%. However, as illustrated in the figure, the no-cash strategy outperformed the baselines significantly during the post-crisis recovery period.

The with-cash strategy, on the other hand, performs quite differently than the no-cash strategy. Up until the beginning of 2018, when the market fell as a result of the US-China trade war [12], it performed worse than other strategies. By overweighting cash by roughly 67% during that year, the with-cash strategy was able to lower the downside and outperform the equal weight strategy while still trailing the other two. During the COVID-19 market crash, however, the with-cash strategy significantly outperformed other strategies by allocating the portfolio to an average cash level of about 70%. Figure 6 displays the cumulative return from November 2016 to October 2021, which is the only period where, as we mentioned earlier, the with-cash strategy underperformed the baselines in terms of average yearly return. The findings reveal that the with-cash strategy underperformed in terms of upside return in the first half of 2019 and following the COVID-19 crash compared to the intervals in Fig. 5, as it chose to overweight in cash instead of other indexes. The results in Table 4 also indicate the inconsistency of the deep learning model in the with-cash strategy, where it has a higher standard deviation of Sharp ratio in twelve testing intervals at 0.3632 in comparison to the no-cash, equal weight, and SET50, which are 0.0836, 0.0515, and 0.0722, respectively.

Table 4. Results from the testing phase compared with the baselines.

Metric	Strategy	Date of beginning testing												Avg
		Jan 2016	Feb 2016	Mar 2016	Apr 2016	May 2016	Jun 2016	Jul 2016	Aug 2016	Sep 2016	Oct 2016	Nov 2016	Dec 2016	
Average return (yearly)	With-cash	0.067	0.044	0.056	0.073	0.047	0.068	0.068	0.023	0.045	0.061	0.020	0.051	0.052
	No-cash	0.072	0.076	0.082	0.104	0.095	0.093	0.082	0.047	0.053	0.074	0.058	0.045	**0.074**
	Equal weight	0.032	0.030	0.029	0.037	0.025	0.018	0.018	0.003	0.012	0.022	0.030	0.003	0.021
	SET50	0.023	0.026	0.029	0.046	0.036	0.030	0.029	0.008	0.018	0.023	0.023	0.006	0.025
Sharpe Ratio (yearly)	With-cash	1.151	0.494	0.818	0.606	0.713	0.984	1.566	0.336	0.450	0.940	0.212	0.914	**0.765**
	No-cash	0.625	0.617	0.469	0.372	0.495	0.562	0.530	0.391	0.383	0.482	0.405	0.470	0.483
	Equal weight	0.236	0.217	0.193	0.178	0.173	0.156	0.145	0.024	0.087	0.120	0.147	0.031	0.138
	SET50	0.219	0.218	0.203	0.194	0.215	0.219	0.200	0.071	0.126	0.149	0.142	0.084	0.170
Calmar Ratio	With-cash	0.450	0.230	0.290	0.491	0.244	0.350	0.459	0.120	0.231	0.415	0.106	0.262	**0.304**
	No-cash	0.211	0.220	0.243	0.306	0.275	0.275	0.242	0.137	0.157	0.217	0.167	0.133	0.215
	Equal weight	0.083	0.079	0.077	0.097	0.065	0.046	0.048	0.008	0.032	0.057	0.079	0.008	0.055
	SET50	0.061	0.069	0.078	0.122	0.096	0.080	0.076	0.021	0.047	0.063	0.061	0.017	0.066

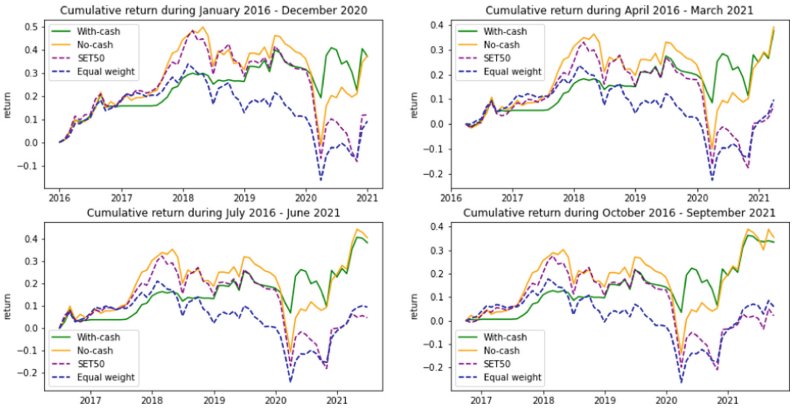

Fig. 5. Cumulative returns of all strategies in four intervals which are intervals beginning in January 2016 (top-left), April 2016 (top-right), July 2016 (bottom-left), and September (bottom-right).

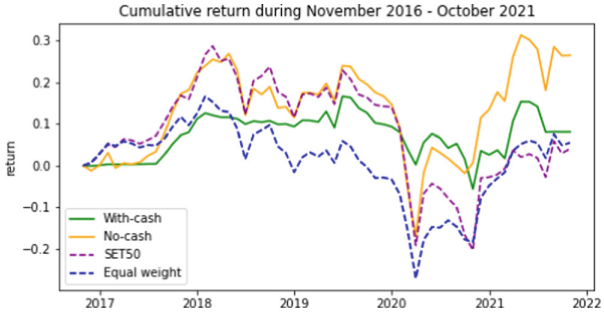

Fig. 6. Cumulative returns of all strategies in the interval beginning in November 2016

4 Conclusion

In this paper, we have proposed two strategies for Thailand's industry rotation: with-cash and no-cash. Both strategies' portfolios include eight of Thailand's industry indexes, but the with-cash strategy includes cash. We constructed the Bi-LSTM model for each strategy, which take historical data of economic variables for consecutive m months as input and give the allocation ratio as the model's output. The ratio will be used to hold the assets for the next n months. The models optimize the allocation ratio directly with a modified loss function that maximizes the Sharpe ratio. The models were trained and tested in twelve different intervals. The results showed that our proposed strategies outperformed the baselines, which are SET50 and the equal weight strategies. The with-cash strategy showed it could reduce the drawdown when the market dropped by overweighting cash during that period. However, the deep learning model in the with-cash strategy shows inconsistency when testing with different intervals. One direction of future works could be using the other assets instead of indexes that we can actually trade and including the trading cost in the calculation.

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