The Performance of Analysts' Stock Recommendations: Evidence from Thailand

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Abstract

This research assesses the performance of stock investments recommended by analysts of brokerage companies in the Stock Exchange of Thailand (SET). Price data and analyst reports are used to simulate a portfolio, and performance measurements follow Jensen (Jensen, 1968), Sharpe (Sharpe, 1966) and Treynor (Treynor, 1965) models.. Results show that the portfolio underperforms the market in daily returns under all three performance measures. Recommended stocks show a small increase in price and return one day after the recommendation, and investors can earn positive returns if they buy the recommended stock and sell the next day. Instead, positive returns lead to a buy recommendation. The inability of analysts to routinely pick stocks to beat the market is supporting evidence of an efficient market. Retail investors without sophisticated technical tools are advised to focus on longer-term investments rather than short-term speculation.

Keywords: Analysts' Recommendations, Emerging Stock Markets, Event Studies, Information, Market Efficiency

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1. Introduction

Investors in the Stock Exchange of Thailand (SET) are a diverse group representing various levels of sophistication. Institutional investors, foreign investors, and securities companies possess technical tools and manpower to monitor stock movements and study fundamentals. Retail investors using their own money to invest are typically less sophisticated. Retail investors often rely on analysts' recommendations for investment decisions (Baker & Dumont, 2014), among other sources of information. These are provided by brokerage firms, extending the broker's role beyond carrying out buy/sell orders. Given that important role, we see the need to assess the reliability of these recommendations.

This paper studies the efficacy of the analyst recommendation from brokerage companies that act as intermediary in the SET. We do so by creating a hypothetical portfolio that would result from following all "buy" recommendations from brokerage companies during a period of one month, and analyzing that portfolio's performance. We then assess its performance as if all the investments take place on the same day. This research adds to the discussion on the usefulness of analyst recommendations, and is the first to take on this topic for the Thai stock exchange. The ability of stock analysts to forecast prices have been in debate for some time (Cowles, 1933), but analytical and technical tools have become much more sophisticated since then.

The efficacy of analyst recommendations in other contexts (Womack, 1996; Baker & Dumont, 2014; Barber et al., 2001, 2003; Chatterjee et al., 2020)., but none has done so for an emerging market in Southeast Asia. This fills this gap and assesses the returns on stocks recommended by broker agencies in the Stock Exchange of Thailand (SET). We create an experimental portfolio consisting of stocks with "buy" recommendations and evaluate its performance. Above-market returns would suggest that brokers' recommendations are useful for retail investors. Several studies have measured the effectiveness of mutual fund investments (Carhart, 1997; Fama & French, 1993; Pendaraki et al., 2005) and portfolio investment strategies of mutual funds (Chan & Lakonishok, 2004). These help to form a framework for analyzing the performance of our hypothetical portfolio.

There is also a possibility that analyst recommendations affect returns on assets. If announcements of “buy” or “sell” come from trusted sources, these recommendations themselves constitute information to which the market reacts. In this case, the performance of involved assets will be magnified and straightforward correlation would capture both the “predictive” as well as the “causative” effects of analyst recommendations. The performance results are supplemented by the Granger-Causality Test to address this possibility.

Our results show that securities recommended by analysts perform no better than the market, and often underperform the market. Investors following buy recommendations can earn consistent profits only by buying stocks on the day of the recommendation and selling them the next. Transaction costs are likely to cut further into the profit. We do not find conclusive evidence that recommendations cause price changes in the market. On the contrary, analyst recommendations consistently follow high returns in a few days earlier, indicating instead that analysts recommend stocks that have been gaining rather than identifying those likely to rise. These findings inform investors wishing to incorporate analyst recommendations into their investment strategy.

The paper is organized as follows. The next section provides background and related literature, followed by the description of the method and data used. Section 4 provides the study results. Section 5 discusses the findings and concludes the paper, suggesting directions for future work.

2. Background and Related Literature

Our objective is to assess the returns on a hypothetical portfolio consisting of stocks recommended by analysts. We use standard measures of portfolio performance for this objective, and supplement the performance results with direct assessments of the relationship between stock recommendations and stock price and returns. Above-market performance of the hypothetical portfolio would suggest that investors can earn above-normal returns by following the analysts' recommendations. A positive relationship between stock outcomes and stock recommendations would imply similarly.

Several measures of securities or portfolio performance have been proposed. The best measure often depends on the objective of the researcher. In this paper, we are interested in positive returns from holding stocks recommended by analysts, which is above the market return where retail investors might alternatively invest in a stock index. We use three alternative performance measures. These are 1) the Jensen's alpha,2) the Treynor ratio, and 3) the Sharpe ratio (Jensen, 1968; Treynor, 1965, 2015; Sharpe, 1966, 1994).. The Jensen's alpha estimates the average returns on an asset in excess of CAPM predictions, while the Sharpe ratio and Treynor ratio compare the asset's excess returns to its risk level.

These performance measures have been used in several previous work to study the performances of various funds. McDonald (1974) use all three measures to assess the performances of American mutual funds in the 60s, while Malkiel (1995) assesses American equity funds between 1971-1991 using Jensen's Alpha. Both studies find that mutual funds do not outperform the market. Exchange-traded funds (ETFS) also seem to perform no better than Index Funds (Sharifzadeh & Hojat, 2012). The above performance measures have also been applied in Asia (Abdullah et al., 2007; Shamsher et al., 2000), Europe (Pendaraki et al., 2005), as well as in Thailand (Wuthivigaigan S., 2006; Ratanasimanon, 2011), which find similarly that managed funds do not outperform their respective markets.

Yet in other contexts, researchers have found that certain funds can outperform the market. An open-ended fund in India outperformed the benchmark during the period of study (Dhanda et al., 2012). The Islamic Stock Exchange is found to generate better returns than the overall market in Malaysia (Karim et al, 2014) as well as in the UK (Alam, 2013), suggesting that the ability to pick assets for investment is still relevant. Mutual fund characteristics are associated with fund performance in Sweden (Dahlquist et al., 2000), further confirming the role of fund managers. A study asks if some managers are better than others in picking stocks, and find that these are positively related to past academic achievements, namely the SAT (U.S. Scholastic Aptitude Test) scores (Chevalier & Ellison, 1999).

The ability to predict stock returns may depend on the working of the market itself. If the market adjusts very quickly to a piece of new information, the market is said to be efficient (Fama, 1970). In such a market it is impossible to predict prices since these prices already reflect all available information. The ability of analysts to pick stocks to generate above-market returns is thus an indicator of market efficiency.

Most efficient markets are typically located in developed countries such as Japan NIKKEI and dominated by Western European markets while the least efficient are in Latin America, Asia, and Oceania (Kristoufek & Vosvrda, 2013). The least efficient markets tend to have a strong short-term trend, and a high correlation with the global perspective (Kristoufek & Vosvrda, 2013). The finding on short-term trend has also been confirmed elsewhere (Wright, 2001; Podobnik, et al., 2006), with developed markets usually exhibiting only very short or no memory compared to less developed markets. In the Asia-Pacific markets, there is empirical evidence that monthly prices do not follow random walks, and investors can earn profits with the right trading technique (Hamid et al., 2010).

Several studies have directly studied the impact of information on stock markets to directly assess market efficiency. These studies tend to find a definite link but lasting for only short periods. U.S. evidence suggests that information on trading activity can affect stock returns in the short horizon (Conrad et al., 1994), while overreaction to firm-specific information allows for short term profits in Australian markets (Lee et al., 2003). Evidence from Thailand (Udompongluckana T., 2012) shows that the market responds to news for only a few days. Recent negative returns lead to higher volatility mostly in the short-term in the U.S. market, suggesting the short-lived nature of the effect of information (Pan and Liu, 2018). At any rate, recent multi-country evidence of a positive relationship between external financing and earnings management at least indicates the importance of firm-specific information on investor behavior (Zhang et al., 2020).

Since an important source of information is the financial analyst report, researchers have become interested in the quality of their information and the extent that investors use them. In the U.S., a higher number of analysts does not lead to more information-based trade (Easley et al., 1998), which suggests a limited use of analyst recommendations. Barth and Hutton (2004) find that analyst earnings forecast revisions can help investors generate abnormal returns but investors do not use this information to the full extent. The limited use of analyst reports may owe partly to the fact that price forecasts among analysts are only partially accurate (Kerl, 2011; Bilinski et al., 2012; Chatterjee et al., 2020). Yet some research find that brokerage services including research and analysis affects stock liquidity and volume (Liu et al., 2017), while others show the importance of the information network between brokers and institutional investors on trading pattern and profits (Maggio et al., 2019).

The reliability of analyst recommendations have been a topic of discussion for some time (Cowles, 1933). Previous studies have assessed the efficacy of analyst recommendations in other contexts. The well-known study by Womack (1996) finds modest positive price increases after a buy recommendation that is short-lived, but large price decreases that continue for months after a sell recommendation. Attesting to the market's uncertainty, Barber et al. (2003) find that U.S. stocks recommended by analysts on the buy-side outperform the market during the late 90's but fail to do so during 2000-2001 period. To realize these returns, however, investors have to follow disciplined strategies and trade in high volumes and transaction costs drown out most of the profit (Barber et al., 2001). In this article we evaluate analysts' recommendations in the Thai context. The findings inform investors in the Thai market of how best to use these recommendations, and add to the larger debate over the efficacy of analyst recommendations.

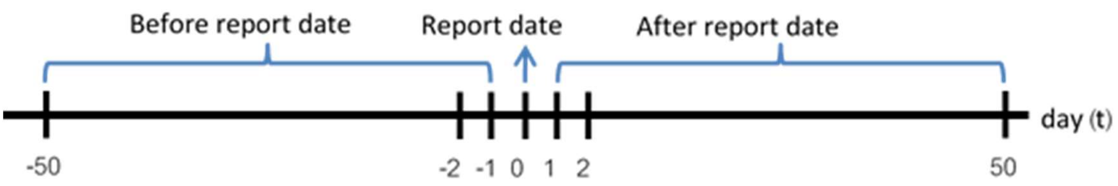
3. Methodology and Data

We simulate the return of a portfolio of stocks created by following analyst "buy" recommendations, ignoring both short-selling where investors borrow stocks to sell at a later date when the stock price falls, as well as long positions where investors buy and hold the stocks expecting its price to rise in the long run. We also ignore transaction costs associated with executing trade orders, which can be substantial. Analyst recommendations come from research articles of 12 brokerage firms (available on their websites) for a period of 6 months from August 2017 to January 2018. The period was the most recent that we can use as of the start of the research project, and no other reason drove this decision. Research articles were collected using a computer program with Thai interface (eFin StockPickUp). We have a total of 1,384 research articles during these months.

We then gathered daily price data for each of the recommended securities 50 days backward and 50 days forward, resulting in 100 total days of price movements for each security. The price and transaction (buy) data was compiled from Thomson Reutors Eikon data stream, consisting of closing price of shares in the Stock Exchange of Thailand, from January 2017 to June 2018. Some stocks are recommended by the same analyst more than once, or are recommended by more than one analysts at different dates. We use only the first incident as the recommendation event. From the 1,384 reports, we have a total of 233 securities recommended by analysts during this period.

Price data from recommended securities were then combined with recommendations to make a hypothetical portfolio consisting of all securities recommended during this period. The dates in the price data are all converted to a value relative to the purchase date, such that the prices correspond to the day number relative to the report date. We use stock prices 50 days before and after the report, such that the converted dates range from -50 to 50, with day 0 as the report date as illustrated in figure 1.

Figure 1 *date conversion for stock price data*



We convert stock prices to price indices, using as reference the price at the start of the analysis. To use consistent notation, this refers to the price at t = -50. The price index is thus given by $\pi_t = \frac{p_t}{p_{-50}}$, where p_t is the price index at day t, p_t is the stock price at day t, and p_{-50} is the stock price at day -50, the first day of each stock's price data. Daily returns are computed based on these price indices, and each is given by $r_t = \frac{p_t - p_{t-1}}{p_{t-1}} \times 100$. We also consider cumulative returns, given by $cr_t = \sum_{i=1}^{t} r_i$. We use the average of the price indices and daily returns across securities to assess the performance of this simulated portfolio.

We use well-known measures for assessing the portfolio performance. These include the Sharpe Ratio (Sharpe, 1994), the Treynor Ratio (Treynor, 2015), and Jensen's Alpha (Jensen, 1968). Jensen's alpha indicates the degree to which a particular asset or portfolio outperforms the market, whereas the Sharpe Ratio and the Treynor ratio compares the asset returns to risk-free returns and account for the riskiness of the asset captured in either beta (β) or the standard deviation of returns.

The Jensen's alpha is based on the CAPM (Fama & French, 2004) model of asset pricing, where the returns of an asset is determined by both its correlation with the overall market. It follows from estimating the equation

$$r_{it} = \alpha_i + \beta_i r_{mt} + e_{it}. \quad (1)$$

The left-hand-side variable r_{it} is $R_{it} - R_{ft}$, our hypothetical portfolio's daily returns R_{it} in excess of the risk-free returns R_{ft}. On the right hand side, r_{mt} is the market's daily excess returns $R_{mt} - R_{ft}$. The β_i coefficient shows the response of the portfolio's excess returns to market excess returns. Jensen's alpha, α_i, shows the amount by which the portfolio excess returns differ from the return predicted by CAPM ($\beta_i r_{mt}$)..

The Sharpe Ratio and the Treynor Ratio compare the asset's excess returns with its own risk level. Whereas the Sharpe Ratio uses the standard deviation as a risk measure, the Treynor Ratio compares excess return with the asset's beta.. The Sharpe Ratio is given by

$$S_i = \frac{r_i - r_f}{\sigma_i}. \quad (2)$$

The numerator on the right-hand side is the difference between the average daily return of asset i (*r_i)* and the daily return of the risk-free asset *(r_f)* during a specified period.

The denominator σ_i is the standard deviation of the daily returns for the asset during the same period. Thus the Sharpe Ratio is a returns-to-risk ratio where the risk is measured as the standard deviation. The Treynor Ratio is computed in a similar manner as

$$T_i = \frac{r_i - r_f}{\beta_i}. \tag{3}$$

Whereas the Sharpe ratio uses standard deviation as the measure of risk, the Treynor ratio uses the asset's response to market fluctuations β_i as the risk measure.

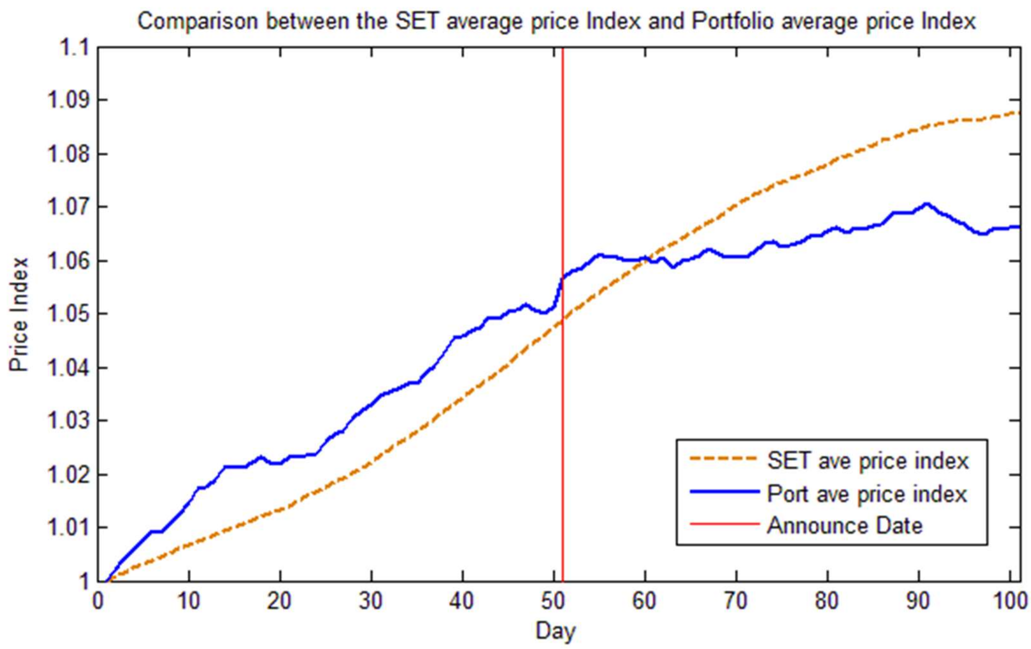
The Sharpe ratio and Treynor ratio are then compared to the market benchmark. As previously discussed, all the dates are converted to be relative to the report date. The market benchmark, namely the SET index, follows the same conversion. As each recommendation occurs on different date, the corresponding SET index for each stock would also be different. Thus, the benchmark SET index for each day (from -50 to 50) is the average of the corresponding index across recommended stocks.

The relationship between the recommendation and the stock price movement further clarifies the issue. If recommended stocks see consistent upward price trends after recommendations, then we would conclude that these recommendations are reliable and therefore useful. To evaluate the relationship between recommendations and stock price, we estimate an autoregressive distributed lag (ARDL) model for stock price or returns as the dependent variable and the incidence of a recommendation as independent variable. The latter is operationalized as an indicator variable, taking a value of 1 for the day the recommendation is made, and 0 for all other days. We are thus able to test the statistical significance of the effect of stock recommendation on stock price or returns, as well as to estimate the dynamic relationship between stock recommendation and performance.

4. Results and Discussion

This section carries out the evaluation of the performance of the hypothetical portfolio constructed from buying all stocks recommended by various brokerages between August 2017 and January 2018. To get a first glance at the performance of recommended securities, figure 2 below shows a time-series plot of the average stock price for 101 days, going 50 days back and 50 days forward starting from the day of the recommendation (blue line). We also show the time series of the SET price index for comparison (brown line), the construction of which is described in the previous section.

Figure 2 Average price index for the portfolio

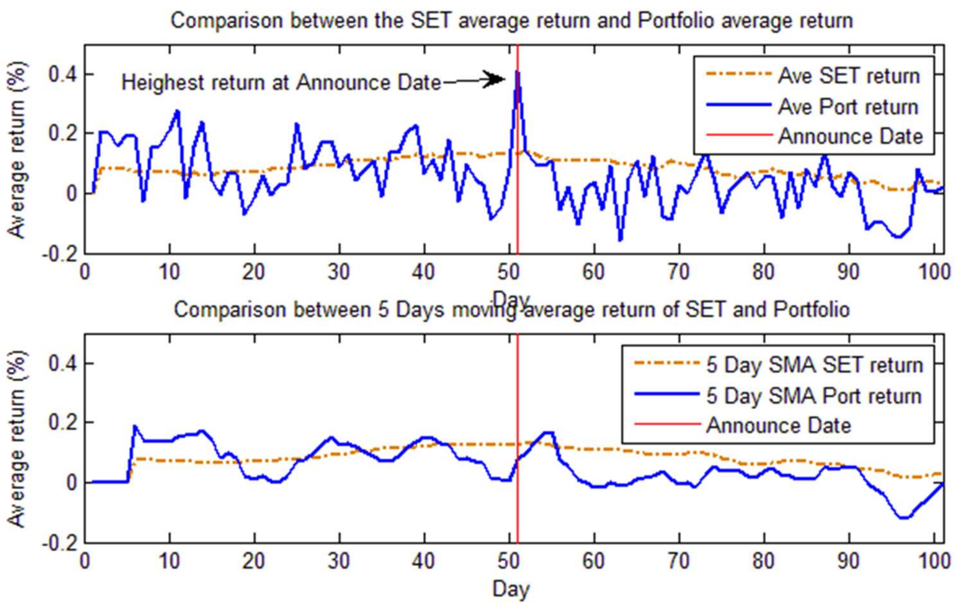


Both series show an upward trend for the 101-day period. However, while the SET index has a consistent upward trend, the recommended securities exhibit steep upward trend before the recommendation date, and a mostly flat trend after the recommendation. Notably, there is a spike in the stock price on the day of the recommendation, followed by a modest upward trend that is less steep than before the recommendation.

Also notable is the actual values of the price indices before and after the recommendation date. The price index for recommended securities are higher than the SET index before the recommendation, and continues to be higher for a little more than 10 more days. After that, the SET index surpasses the recommended securities and the gap continues to widen. If investors buy the SET index every time brokerage firms recommend a stock, they would generate far superior returns than purchasing the recommended stocks.

We also consider daily returns to assess the results from purchasing stocks based on brokerage firms' recommendations. Figure 3 below shows the time series for daily returns of the hypothetical portfolio (blue line) along with returns for the SET index (brown line). There is visibly more volatility in the returns of recommended securities compared to the SET index. This might owe to the fact that the SET contains more than 800 securities while our portfolio contains a little more than 200 securities.

Figure 3 Daily returns for hypothetical portfolio and SET



Considering the returns, the SET index returns are not much different from our portfolio before the recommendation, but clearly generates higher returns after the day of the recommendation. Interestingly, our portfolio exhibits sharp increasing trend for daily returns about 4 – 5 days before the day of the recommendation. There is a spike in returns the day before the recommendation, reflecting the price spike on the day of the recommendation. It appears that brokers recommend stocks whose price has been increasing during the last few days. These stocks underperform the SET index consistently after the recommendation.

Portfolio Performance

The first performance index is the Jensen's alpha. As the portfolio may perform differently across different lengths of security holdings, we calculate the statistic for various number of days after the recommendation. These are 2, 4, 10, 20, 30, 40, and 50 days. Number of days of 2 and 4 represent very short term and highly speculative investments. Results are shown in Table 1 below. We find that the Jensen's alphas are negative for all portfolio holding lengths considered, with the exception of the 2-day holding period, and are significantly negative for holding periods of 10 days and 20 days. This provides evidence that the portfolio consisting of all recommended securities perform significantly worse than the market for short holding periods of 10 – 20 days, and perform no better than the market for longer holding periods of more than 20 days.

Table 1 Jensen's Alpha for portfolio

Days after report	α	Std.Error	t-Statistic	β
2	1.1537	2.3342	0.4942	-11.3340
4	-0.1353	0.5255	-0.2575	3.2695
10	-0.5731	0.2219	-2.5829	8.3650
20	-0.1038	0.0350	-2.9643	3.3257
30	-0.0568	0.0405	-1.4016	0.9757
40	-0.0942	0.0577	-1.6313	0.5447
50	-0.0324	0.0614	-0.5278	1.1480

Next we proceed to the Sharpe Ratio for the portfolio, comparing with the SET index. The results are given in table 2 for various number of days after the recommendation. For periods of 20 days or less, the portfolio underperforms the SET index using both measures.

For a very short holding period of 2 days, the Sharpe ratios are 21.48 and 1.23 for SET and the hypothetical portfolio, respectively. For a 20-day holding period, the Sharpe ratios are 1.00 and -0.47 for SET and the hypothetical portfolio, respectively. For periods less than 20 days after recommendation, the portfolio underperforms the SET index. The pattern is reversed after 20 days from the report, with both indices underperforming risk-free assets while SET index has lower standard deviations.

Table 2 Sharpe Ratio for portfolio and SET Index

Days after report	S.D. (Portfolio)	S.D. (SET Index)	Sharpe Ratio (Portfolio)	Sharpe Ratio (SET Index)
2	0.1683	0.0057	1.2338	21.4806
4	0.1348	0.0114	1.1291	9.4170
10	0.1381	0.0110	0.1318	6.4054
20	0.1194	0.0144	-0.4671	1.0006
30	0.1016	0.0224	-0.9836	-1.9675
40	0.0934	0.0265	-1.5949	-3.7834
50	0.0981	0.0339	-2.1843	-4.6696

We further compute the Treynor Ratio where risk adjusted returns use the portfolio's β as the adjustment factor. By definition, the β for SET is 1 for any length of holding. The results from Treynor ratio are shown in Table 3 below also confirm that the hypothetical portfolio underperforms the SET index for holding periods of 50 days or shorter. Only for 4 days after report do we see a higher Treynor ratio for our hypothetical portfolio. At the same time, while we find that the portfolio underperforms the SET index for all but one holding period considered, the ratio is mostly negative for both indices.

Table 3 Treynor ratio for portfolio and SET

Days after report	β_{port}	Treynor ratio (Portfolio)	Treynor ratio (Set Index)
2	-11.3340	-0.0183	-0.0109
4	3.2695	0.0465	0.0328
10	8.3650	0.0021	0.0084
20	3.3257	-0.0167	0.0043
30	0.9757	-0.1024	-0.0453
40	0.5447	-0.2734	-0.1843
50	1.1479	-0.1868	-0.1381

We find that the hypothetical portfolio tends to underperform the SET index for any number of days after the analyst recommendation. The results from Jensen's alpha show that the portfolio performs no better than the market for any number of days after the recommendation, and perform worse at 10 and 20 days after. Using risk-adjusted returns measures like the Sharpe ratio or the Treynor ratio confirms the finding. The portfolio tends to underperform the market. One exception is in the Sharpe ratio where the SET index has a more negative risk-adjusted return at holding periods of more than 20 days, but this results from both indices having negative returns but the portfolio has about 4 times higher variability (s.d.).

Stock price, stock returns, and recommendations to buy

In this section we estimate the statistical relationship between incidences of "buy" recommendations and subsequent stock price and returns. This is to determine if it is profitable to follow analyst's advice. As stock prices routinely rise and fall, we consider the relationship between recommendations and stock outcomes for various lengths of time. We estimate the ARDL (autoregressive distributed lag) model as follows.

$$y_t = \delta_0 + \sum_{i=0}^{p} \delta_i report_{t-i} + \sum_{j=1}^{q} \gamma_j y_{t-j} + e_t. \tag{4}$$

The dependent variable y_t is either the daily close price or daily return, and δ_i's are coefficients of interest. The indices p and q are the optimal lags for $report$ and y_t, respectively. The parameters δ_i's, our coefficients of interest, give the response of price or daily return following a recommendation for various time lags, namely the distributed lag effects. A positive δ_i would indicate that stock price or returns respond positively in the i^{th} period since the initial recommendation, such that buying stocks as recommended generates positive returns in that period. The γ_j are autoregressive coefficients to complete the model. The Augmented Dickey Fuller Test (ADF) was used to determine stationarity. All series are stationary at the 1% significance level under the Augmented Dickey Fuller Test (ADF).

Table 4 Tests of Stationarity

Variables	ADF t-statistic	MacKinnon Critical Value 1%	5%	10%	N
price	-4.501	-3.510	-2.890	-2.580	100
return	-6.776	-3.511	-2.891	-2.580	99
report	-10.000	-3.510	-2.890	-2.580	100

Using both the AIC and BIC criteria, the optimal lag for both variables is 1 in the price outcome. For returns, the optimal lag is 3 under AIC and 2 under BIC. Table 4 displays the results. The incidence of "buy" recommendation in the previous day is associated with higher current day price and return. Therefore, investors who follow buy recommendations can make a profit on average if stocks are sold the next day. However, the small magnitude of the association means that practical significance is realized only at high volumes.

Table 5 ARDL estimation results for recommendation incidence and stock outcomes

	Outcomes (y_t)		
Variables	Price (AIC, BIC)	Returns (AIC)	Returns (BIC)
$report_t$	0.001	0.086	0.091
	(0.001)	(0.086)	(0.087)
$report_{t-1}$	0.005***	0.401***	0.380***
	(0.001)	(0.087)	(0.087)
y_{t-1}	0.978***	0.219**	0.254***
	(0.005)	(0.094)	(0.093)
y_{t-2}	-	0.180*	0.229**
		(0.096)	(0.094)

y_{t-3}	-	0.175* (0.093)	-
R-squared	0.998	0.322	0.296
n	97	96	96

P-values of 0.1, 0.05, and 0.01 levels are denoted by *, **, and ***, respectively. Observations are lost when estimating using AIC and BIC criteria.

Two-way relationship between stock outcomes and recommendations

Whereas recommendations by analysts to buy stocks have little bearing on future stock outcomes, it is possible that a buy recommendation follows good recent performance. In this regard, recommendations serve only to formalize positive gains rather than predict future outcomes. To test this possibility, we apply the Granger Causality Test (Hamilton, 1994) to investigate the two-way relationship between stock recommendations and stock outcomes. The procedure starts with specifying a Vector Autoregressive (VAR) model for stock recommendations and stock outcomes, then test the significance of lagged coefficients of one variable in the time series equation of the other. The VAR model is given by

$$y_t = \delta_0 + \sum_{i=0}^{p} \delta_i report_{t-i} + \sum_{j=1}^{q} \gamma_j y_{t-j} + e_{y,t} \tag{5}$$

$$report_t = \tau_0 + \sum_{i=0}^{p} \tau_i y_{t-i} + \sum_{j=1}^{q} \theta_j report_{t-j} + e_{report,t}. \tag{6}$$

Given the number of lags of no more than 2 in ARDL in the previous section, we specify the Granger causality test using VAR with 2 lags. Table 5 shows the results for both the price and returns outcomes. The null hypothesis that *report* does not Granger-cause the outcome, *y*, is not rejected for both the stock price and stock returns since the p-values for both tests are above the critical value, indicating that the report does not statistically precede these outcomes. However, we reject the null hypothesis that the price and return outcomes do not Granger-cause the report, as the p-values for both tests are less than the 0.05 significance level. In this market, analyst reports are mostly useful in identifying stocks with good recent performance, while investors should supplement the report with other tools when making investment decisions.

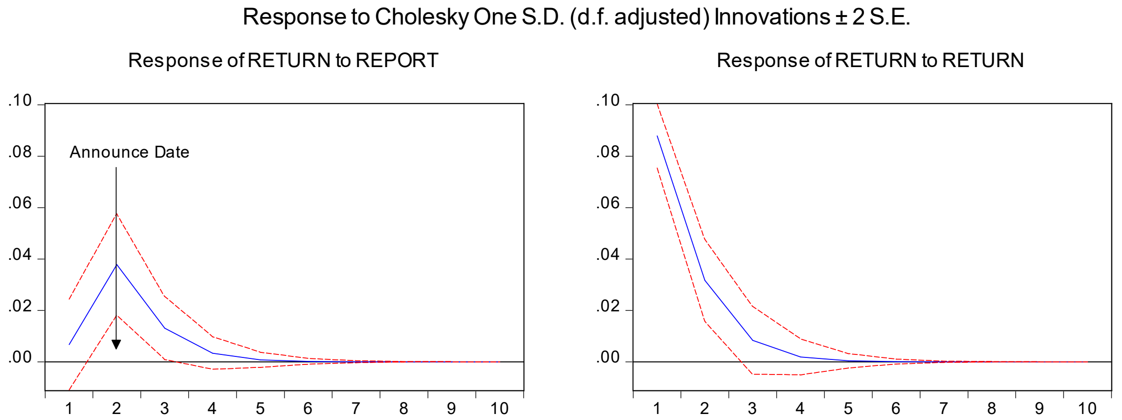
Table 6 Granger causality tests for report and stock outcomes

Test Hypothesis	Outcomes	
	Price	**Daily Returns**
H_o: report does not Granger-cause y	χ^2= 1.270 p-value = 0.530	χ^2= 2.461 p-value = 0.292
H_o: y does not Granger-cause report	χ^2= 127.434*** p-value = 0.000	χ^2= 20.494*** p-value = 0.000

P-values of 0.1, 0.05, and 0.01 levels are denoted by *, **, and ***, respectively.

We additionally conduct an impulse response function (IRF) analysis to estimate the dynamic effect of a shock in one variable on another variable. The left graph of figure 4 shows the IRF of an innovation in REPORT to the response of rate of return of the portfolio (RETURN). The highest unit impacts to RETURN caused by the shock of REPORT (Report Announcement). A one-unit shock increases the RETURN by 0.35 impact units, then vanishes after roughly 6-7 days. Thus, the report does not seem to have a lasting effect on stock returns. The graph on the right presents IRF of RETURN to itself, showing that a positive shock in returns leads to positive future returns for a few days and dies out after about 7 days. The return itself is not persistent, with current returns affecting future returns for no more than a week.

Figure 4 Impulse response function of Return and Report for the portfolio



5. Conclusion and Recommendations

This paper assesses the efficacy of analyst recommendations in the stock market of Thailand. We do so by simulating a stock portfolio consisting of all stocks with buy recommendations during a period of 6 months between 2017-2018. The main finding is that a buy recommendation is associated with a higher price and return on the day of the report, but both price and return flatten out soon after. One profitable investment strategy is to execute the buy on the day the report comes out and sell the next. There is stronger evidence of recommendations reacting to recent performance of stocks. The price trends of recommended stocks show a steep increase the day before the recommendation, flattening out afterwards. The inability to consistently predict stock price movements might be evidence of an efficient market, where investors can only beat the market by taking bolder bets and picking specific stocks. For the most part our recommended stocks tend to bear out the down side of these risks. Meanwhile, the jump in stock price prior to recommendation is indicative of analysts recommending mostly stocks that are on the rise.

Well-known performance measures like Jensen's alpha, Sharpe ratio, and Treynor ratio all indicate worse-than-market performance of the hypothetical portfolio. Econometric estimates of the relationship between stock outcomes and recommendation mostly confirm the findings. Nonetheless, the results show a consistent increase in recommended stock prices the day after the recommendation. Investors looking to use analyst reports for their investment decisions should buy recommended stocks on the day the report comes out and sell the stocks the next day. Investors following analysts' recommendations must be ready to make a trade throughout the day. This is not a viable option for many retail investors. To generate above-market returns, an investor might conduct further research of their own, or to consider how these stocks combine with others to create a broad investment strategy.

Appraising the two-way relationship with Granger causality test shows that stock outcomes precede a “buy” recommendation while a recommendation does not precede these outcomes. Analyst reports for the most part serve to identify stocks whose recent performances are positive, which help investors screen out non-performing stocks. As past performance does not indicate future performance, the recommendations should not be interpreted as investment advice. In fact, all analyst reports include disclaimers to the effect that the reports are intended only to inform investment decisions and do not offer guidance in a particular direction.

The practical implications of our findings depend on the way retail investors actually use information from analyst reports. For example, our results show that it is not advisable to follow “buy” recommendations from analysts, but retail investors may nonetheless rely on them to make investment decisions (Baker & Dumont, 2014). This seems to be more of a concern for less sophisticated investors, who are more likely to look for guidance from a variety of sources. Investors relying solely on analyst recommendations would only make normal profits while expending time and effort following market reports, as they could realize the same profit simply by investing in the market index. Understanding how investors use analyst reports, among other sources of information, would assist in the design of policy and regulations that are appropriate for respective markets.

The efficacy of analyst recommendations likely differs across various dimensions. The analysis used in this paper can be extended to other segments of the recommendation landscape. Larger brokerage firms may have more resources and experience allowing them to make better predictions. Alternatively, smaller firms may be more specialized and use more current techniques. Firms specializing in industries may be better at analyzing stocks in those industries. Geographic proximity to industry centers (Huang et al., 2018) has been found associated with more accurate forecasts, suggesting that some brokerage firm may be in a better position than others to make stock recommendations. All of these are interesting topics to pursue in future work.

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