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Household Investment Forecast in The Stock Exchange of Thailand

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Abstract

The investment outlook of households is an important factor for domestic investment, leading to the expansion of domestic economy and possibly resulting in the improvement of household well-being. Therefore, the investment perspective of households can be used as an indicator of consumer confidence in the domestic economic outlook. This study creates a measure that reflects the household investment view through the actual investment in the Stock Exchange of Thailand (SET), forecasted one month ahead. The one month ahead security-by-security net household transaction is forecasted based on the Stock Exchange of Thailand's internal security-by-security factors: stock price, stock trading volume, outstanding value by investors' portfolio, price change effect by investors' portfolio, and unit change effect (net transaction) by investors' portfolio. The data used in this study is from secondary data source, collected monthly from January 2009 to July 2016 total of 91 months from the SET and the authors' calculation. The net household transaction forecast is modelled by two comparison techniques: moving multiple regression (MMR) and moving artificial neural network (MANN). This study finds that MANN forecast produces lesser mean absolute error (MAE), root mean square error (RMSE), and mean absolute percent error (MAPE) statistics than the MMR, but higher directional accuracy (DA test) statistic than the MMR. Both MANN and MMR techniques produces significantly different forecasts with Diebold Mariano (MA test) statistic at 95% confidence level. This finding confirms the MANN forecast is more efficient and more accurate than the MMR forecast. The MANN forecast suggests the household investment is positively affected by stock price and price change effect within household's portfolio. On the other hand, the MANN forecast suggests the household investment is adversely affected by the outstanding portfolio value of the non-financial investors, financial investors, and public investors.

Keywords: Investment outlook; Unit change; Security-by-security; Moving artificial neural network.

JEL Classification: C53; E17; G17

1. Introduction

The perspective of the household sector investor can be used as an indicator of consumer confidence in the economic outlook of the country, encouraging investment, promoting economic growth, and improving the well-being of households in the country.

This study proposes an indicator that reflects the view of household sector investor, forecasted one month ahead, which is a measure of household investor perspective. The measure is calculated using a model based on the data collected from the Stock Exchange of Thailand (SET) and the calculation from the Bank of Thailand (BOT). This indicator is linked to stock price, stock trading volume, outstanding value by investors' portfolio, price change effect by investors' portfolio, and unit change effect (net transaction) by investors' portfolio.

The objectives of this study include:

1. Construct an indicator that reflects the perspective of household sector investor through the net transaction of household investor forecasted one month ahead.
2. Analyze factors that affect the net transaction of household investor forecasted one month ahead.

The hypothesis of this study include:

1. Net transaction of household investor forecasted one month ahead can be effectively predicted by the following factors: security-by-security (stock) price, security-by-security (stock) trading volume, security-by-security outstanding value by investors' portfolio, security-by-security price change effect by investors' portfolio, and security-by-security unit change effect (net transaction) by investors' portfolio.
2. Net transaction of household investor forecasted one month ahead changes in the same direction with stock trading volume, security-by-security unit change effect (net transaction) by investors' portfolio, and price change effect by investors' portfolio.
3. Net transaction of household investor forecasted one month ahead changes in the opposite direction to stock price and outstanding value by investors' portfolio.

The boundaries of this study include:

1. Use monthly information at the end of each month from September 2013 to July 2016 from the Stock Exchange of Thailand (SET), the Bank of Thailand (BOT) and authors' calculation including security-by-security (stock) price, security-by-security (stock) trading volume, security-by-security outstanding value by investors' portfolio, security-by-security price change effect by investors' portfolio, and security-by-security unit change effect (net transaction) by investors' portfolio.
2. Compare the prediction results using moving multiple regression (MMR) and moving artificial neural network (MANN).

The benefits of this study is that analysts can effectively identify factors that affect the investment outlook of household sector investor through the net transaction of the household investor forecasted one month ahead.

2. Literature Review

The economic factor forecasting is based on the relationship between quantitative factors by using a function to convert the causal factors to the factor of interest. Some forecasting methods use explicit functions to indicate the relationship between these factors. (Atikankul, 2012) compares forecasting methods on the Stock Exchange of Thailand (SET) index to find a suitable forecasting model and studies the relationship between the SET index and market indices in other countries in order to find correlations with other indices using four forecasting methods, including simple exponential smoothing, Holt's method, Box-Jenkins' method, and linear regression. Another research by (Khanthavit, 2009) studies the prediction on the size and direction of changes in the securities price in a volatile market, using Bayesian Averaging of Classical Estimates (BACE) as the stock price predictor. This study finds that BACE generates profits to investors at a higher level.

While other SET index forecasting techniques use black-box-liked functions which do not explicitly indicate the relationship between these factors such as artificial neural network (ANN). (Kaewmart & Chancharat, 2013) (Pantuwon, 2014)

(Pantuwon, 2014) studies a mixed model that incorporates an ARIMA (Box-Jenkins method) model and an ANN model, which combines the capabilities of a single model. The mixed model reduces the limitations of a single model, improves the efficiency in describing relationships among data, and improves the forecasting accuracy on the Stock Exchange of Thailand index. This study finds that the mixed model (AR-NN) has the ability to forecast out-of-sample SET50 index with higher forecasting accuracy than single model (ARIMA). (Kaewmart & Chancharat, 2013) studies an ANN model to predict the stock market index of nine countries. The study finds that the ANN model yields an efficient and high accuracy prediction.

Therefore, in this study, the authors choose to use artificial neural network for our prediction method, since it can potentially provide higher forecasting accuracy than linear prediction method (Pantuwon, 2014).

3. Methodology and Data

In this study "household investment forecast in the Stock Exchange of Thailand," the authors conduct the study following the guideline below.

1. Using bottom-up approach, projecting security-by-security household investment and collecting the projected investments into the market-wide household investment (net transaction of household portfolio).
2. Using quantitative approach, analyzing only quantitative data, including security-by-security (stock) price, security-by-security (stock) trading volume, security-by-security outstanding value

by investors' portfolio, security-by-security price change effect by investors' portfolio, and security-by-security unit change effect (net transaction) by investors' portfolio.

3. Using technical approach, utilizing quantitative factors above to describe the movement of the net transaction of household investor forecasted one month ahead.

This study uses secondary data from the Stock Exchange of Thailand, the Bank of Thailand, and author's calculations. These quantitative data are collected at the end of every month between July 2013 and July 2016, total of 37 months. The data collection includes the following items:

1. Security-by-security price from the Stock Exchange of Thailand (stock price; IDX)
2. Security-by-security trading volume (stock turnover) from the Stock Exchange of Thailand (turnover volume; VLM)
3. Security-by-security outstanding value by investors' portfolio[1] from the Bank of Thailand (value; VL)
4. Security-by-security unit change effect (net transaction) by investors' portfolio from the authors' calculation (unit change; UC)
5. Security-by-security price change effect by investors' portfolio from the authors' calculation (price change; PC)

This study screens securities on the Stock Exchange of Thailand to a total of 293 securities in order to reduce the propensity of securities that are rarely traded or not traded at all with the following guideline:

1. Common stocks (excludes preferred stocks, warrants, derivative warrants, ETFs, unit trusts, transferable subscription right, property funds, REITs)
2. The Stock Exchange of Thailand (excludes Market of Alternative Investment)
3. Security is not under rehabilitation.
4. Security has the minimum turnover of 1,000 baht per month (calculated from the accumulative probability of beta distribution, alpha=2, beta=5 at 99% confidence level).
5. Security must meet all of the above requirements in every month during this study period.

This study creates a modeled indicator that reflects the perspective of household sector investor through the net transaction of household investor forecasted one month ahead. The model utilizes the above information from the current month back to 2 previous months, a total of 3 months. The authors believe that the Stock Exchange of Thailand is continuously changing and news affecting the market in short term not exceeding 3 months. The authors define forecasting model for the net transaction of household investor forecasted one month ahead as shown in Equation 1.

[1] Investors are classified into 5 groups: general government (GG), financial corporation (FC), non-financial corporation (NFC), household (HH), and the rest of the world (ROW) by the System of National Accounts 2008.

$$UC_{t+1}^{HH} = f\left(IDX_{t,t-1,t-2}, VLM_{t,t-1,t-2}, VL_{t,t-1,t-2}, UC_{t,t-1,t-2}, PC_{t,t-1,t-2}\right) \quad \textbf{Equation 1}$$

The data or variables used in this study are as follows:

UC_{t+1}^{HH} is the dependent variable measuring the net transaction of household investor forecasted one month ahead (at the end of month $t+1$)

$f(\cdot)$ is the forecasting model predicting the net transaction of household investor forecasted one month ahead. This study will compare predictions of two models: moving multiple regression (MMR) and moving artificial neural network (MANN).

The data or independent variables used in this study are as follows:

$IDX_{t,t-1,t-2}$ is the security-by-security price at the end of months t, $t-1$ and $t-2$ measuring the price of a stock. When the stock price rises, the minimum transaction size for buying or selling a stock for the household investor increases. Household investor needs more capital to buy the same stock. As a result, the net transaction of household investor reduced. Thus, the stock price is correlated in the opposite direction with the net transaction of household investor.

$VLM_{t,t-1,t-2}$ is the security-by-security trading volume at the end of months t, $t-1$ and $t-2$ measuring the turnover of all purchases made in one month for one stock. When the turnover of a stock increases, household investor tends to increase its interest in the stock and thinks the probability that the price of the stock will rise. As a result, the net transaction of household investor increases. Thus, the stock turnover is correlated in the same direction as the net transaction of household investor.

$VL_{t,t-1,t-2}$ is the security-by-security outstanding value by investors' portfolio at the end of months t, $t-1$ and $t-2$ which consists of 5 investor groups: general governments (GG; $VL_{t,t-1,t-2}^{GG}$), financial corporations (FC; $VL_{t,t-1,t-2}^{FC}$), non-financial corporations (NFC; $VL_{t,t-1,t-2}^{NFC}$), households (HH; $VL_{t,t-1,t-2}^{HH}$), and the rest of the world (ROW; $VL_{t,t-1,t-2}^{ROW}$) by the System of National Accounts 2008. It measures the outstanding value of a stock in an investors' portfolio. When the stock accumulation in the household portfolio increases, the household investor tends to invest less in that stock and considers diversifying the risk by investing in another stock instead. As a result, the net transaction on that stock of household investor reduced. Thus, the stock outstanding is correlated in the opposite direction with the net transaction of household investor.

$UC_{t,t-1,t-2}$ is the security-by-security unit change effect (net transaction) by investors' portfolio at the end of months $t-1$ and $t-2$, measuring the net transaction of all buying transactions minus selling transactions made in one month for one stock in the investors' portfolio. When the net transaction of a stock in the household's portfolio increases, household investor tends to increase interest in that stock and thinks the probability that the price of the stock will rise. As a result, the net transaction of household investor increases. Thus, the net transaction of a stock on an investors' portfolio is correlated in the same direction as the net transaction of household investor.

$PC_{t,t-1,t-2}$ is the security-by-security price change effect by investors' portfolio at the end of months $t-1$ and $t-2$, measuring the changes in the value of a stock from price movement that occurs in one month in an investors' portfolio. When the value of a stock in household's portfolio increases from price movement only, household investor tends to increase interest in that stock and thinks the probability that the price of the stock will rise. As a result, the net transaction of household investor increases. Thus, the price change of a stock on an investors' portfolio is correlated in the same direction as the net transaction of household investor.

This study analyzes quantitative information, which tests the relationships between the factors that affect net transaction of household investor forecasted one month ahead, from January 2014 to July 2016. Additionally, this research studies the magnitudes in the relationships by computing the relation coefficient for each independent factor. Then, the authors will summarize and describe the relationships between the independent factors and the net transaction of household investor forecasted one month ahead.

This study evaluates the efficacy of the two forecasting models: moving multiple regression and moving artificial neural network. The authors compare the predictions of the models with actual net transaction of household portfolio in three ways:

1. Model accuracy in forecasting the level of net transaction is measured by the following statistics. The model with smaller statistic has higher level forecasting accuracy.
    a. Mean absolute error (MAE)
    b. Root mean square error (RMSE)
    c. Mean absolute percent error (MAPE)
2. Model accuracy in forecasting the direction of net transaction (directional accuracy; DA test) is measured by comparing the rate of forecasts showing a plus and a minus. The model with greater statistic has higher directional forecasting accuracy.
3. Comparing predictive accuracy (Diebold Mariano; DM test) is measured by the errors of predictions from models with the actual net transaction of household investors and computed the predictive accuracy with a loss function.

4. Forecasting Results

The preliminary statistical analysis of the factors related to net transaction of household investor for all the stocks from April 2009 to June 2016 is analyzed. The preliminary statistical analysis shows that security-by-security price (IDX) has the mean of 24.96 THB per share and the median of 5.80 THB per share, which is vastly different from the mean, the minimum of 0.00 THB per share, the maximum of 538.00 THB per share, and the standard deviation of 56.99 THB per share. This shows that the security-by-security price factor is not normally distributed. The distribution can also be found in the security-by-security trading volume (VLM) and the security-by-security outstanding value by investors' portfolio ($VL^{GG}, VL^{FC}, VL^{NFC}, VL^{HH}, VL^{ROW}$). For the security-by-security unit change effect (net transaction) by investors' portfolio ($UC^{GG}, UC^{FC}, UC^{NFC}, UC^{HH}, UC^{ROW}$) and the security-by-security outstanding value by investors' portfolio ($PC^{GG}, PC^{FC}, PC^{NFC}, PC^{HH}, PC^{ROW}$) have better data distribution than the other factors mentioned above. However, all factors are not normally distributed, as tested in normality tests with Shapiro-Wilk, D'Agostino-Pearson and Jarque-Bera tests.

The test of correlations among the factors (Multicollinearity) uses the correlation matrix to compute the correlations among the factor pairs. The correlation matrix shows that there are two factor pairs that have a correlation of 0.8 and higher: the security-by-security unit change effect (net transaction) of household investors' portfolio (UC^{HH}) and the security-by-security outstanding value of household investors' portfolio (PC^{HH}) pair with the correlation of -0.93 and the security-by-security unit change effect (net transaction) of non-financial corporation investors' portfolio (PC^{NFC}) and the security-by-security outstanding value of non-financial corporation investors' portfolio (PC^{NFC}) pair with the correlation of -0.80. These pairs introduce the problem of multicollinearity. Therefore, the authors choose to use only the security-by-security unit change effect (net transaction) of household investors' portfolio and nonfinancial corporations' portfolio, since these factors reflects the investment perspective of household and non-financial corporation investors. This applies only to the moving multiple regression (MMR), since the moving artificial neural network (MANN) can mitigate the multicollinearity problem.

From the preliminary statistical analysis of the factors related to net transaction of household investor above, the authors propose a moving multiple regression showing the relationships of the 15 factors, tested multicollinearity, with the net transaction of household investor forecasted one month ahead, as shown in Equation 2.

$$\begin{aligned} UC_{t+1}^{HH} = {} & a_0 + a_1 IDX_t + a_2 IDX_{t-1} + a_3 IDX_{t-2} \\ & + a_4 VLM_t + a_5 VLM_{t-1} + a_6 VLM_{t-2} \\ & + a_{7,8,9,10,11} VL_t + a_{12,13,14,15,16} VL_{t-1} + a_{17,18,19,20,21} VL_{t-2} \\ & + a_{22,23,24,25,26} UC_t + a_{27,28,29,30,31} UC_{t-1} + a_{32,33,34,35,36} UC_{t-2} \\ & + a_{37,38,39} PC_t + a_{40,1,42} PC_{t-1} + a_{43,44,45} PC_{t-2} \end{aligned}$$

Equation 2

The relationship coefficient of all factors is calculated by moving multiple regression, moving in the previous three-month period, with the pooled regression technique covering all securities. The moving multiple regression is tested for model reliability with F-statistic test, R^2, and Adjusted R^2.

From the model reliability test, we can conclude that using the F-statistic test to check the model reliability the calculated F value is in the range from 6.6787 to 18.5303, which is statistically significant at 0 percent to 5 percent. As a result, we cannot reject the null hypothesis (H_0) that no factor has influence the dynamics of net transaction of household investors forecasted one month ahead at the significance level of 95%. Additionally, we accept the alternative hypothesis (H_0) that there exists at least a factor affecting the change in net transaction of household investor forecasted one month ahead at the significance level of 95%.

The moving multiple regression forecasts the net transaction of household investors from Equation 2 is shown in Figure 1. The actual net transaction of household investor (blue line) between January 2014 to July 2016 compares with the net transaction of household investor forecasted one month ahead (red line).

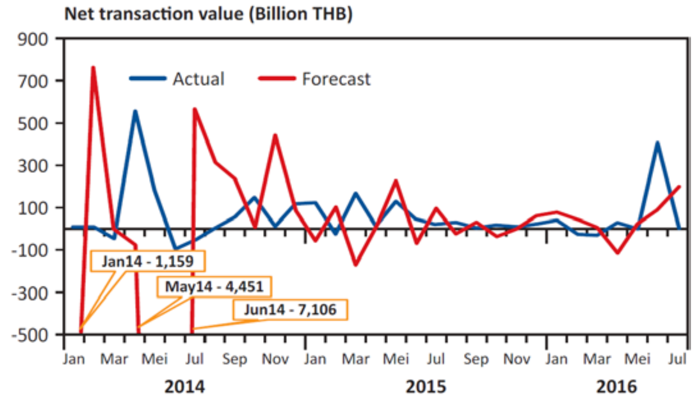

Figure 1. The forecast of net transaction of household investor using moving multiple regression in Equation 1

Moving artificial neural network shows the relationship of the 17 factors with the net transaction of household investor forecasted one month ahead, as shown in Equation 3.

$$UC_{t+1}^{HH} = ANN(IDX_t, IDX_{t-1}, IDX_{t-2}, VLM_t, VLM_{t-1}, VLM_{t-2}, VL_t, VL_{t-1}, VL_{t-2}, UC_t, UC_{t-1}, UC_{t-2}, PC_t, PC_{t-1}, PC_{t-2}) \quad \textbf{Equation 3}$$

The moving artificial neural network forecasts the net transaction of household investors from Equation 3 is shown in Figure 2. The actual net transaction of household investor (blue line) between January 2014 to July 2016 compares with the net transaction of household investor forecasted one month ahead (red line).

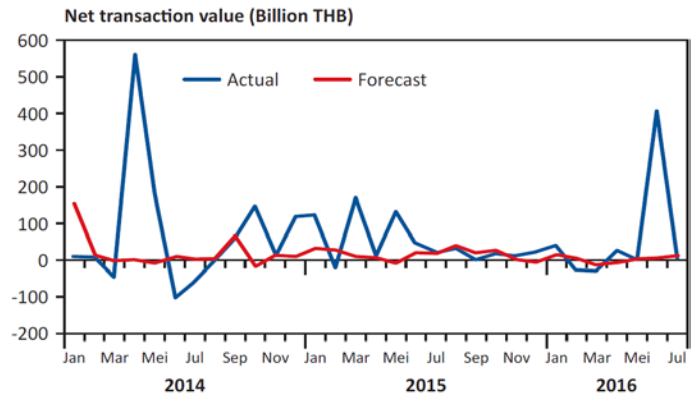

Figure 2. The forecast of net transaction of household investor using the moving artificial neural network in Equation 1

The performance evaluation of the forecasting models of moving multiple regression (Figure 1) and the forecasting model of the moving artificial neural network (Figure 2) are shown in Table 1.

Performance Statistics	Moving multiple regression	Moving artificial neural network	DM Test (Probability) Significance Level
MAE	535	80	-4.738 (0.0%) ***
RMSE	1,405	144	-4.738 (0.0%) ***
MAPE	12,153%	583%	-4.738 (0.0%) ***
DA	30%	63%	

Table 1. The performance evaluation of the forecast from the moving multiple regression (Figure 1) and the forecast from The moving artificial neural network (Figure 2)
[* is 90% confidence level; ** is 95% confidence level; * is 99% confidence level]**

5. Conclusions

This study of the household sector investment behavior in the equities market reflects the net transaction of household investor forecasted one month ahead with the following factors, including security-by-security (stock) price (IDX), security-by-security (stock) trading volume (VLM), security-by-security outstanding value by investors' portfolio (VL), security-by-security unit change effect (net transaction) by investors' portfolio (UC), and security-by-security price change effect by investors' portfolio (PC). This research studies how these factors affect the net transaction of household investor forecasted one month ahead, by modeling with moving multiple regression and moving artificial neural network. This study covers monthly data from July 2013 to July 2016, a total of 37 months.

The moving multiple regression cues that the net transaction of household investor for July 2016 is correlated in the same direction as the stock price, the stock outstanding value of financial corporation, non-financial corporation, and the rest of the world investors' portfolio, the net transaction of general government and household investors' portfolio, and the stock price change effect of general government investors' portfolio. On another hand, the net transaction of household investor is correlated in the opposite direction with the stock trading volume, the stock outstanding value of general government and household investors' portfolio, the net transaction of financial corporation, non-financial corporation, and the rest of the world investors' portfolio, and the stock price change effect of financial corporation and the rest of the world investors' portfolio. However, the influential factors show no significant changes in the net transaction of household investor forecasted one month ahead.

The moving artificial neural network cues that the net transaction of household investor for July 2016 is correlated in the same direction as the stock price, the stock trading volume, the stock outstanding value of non-financial corporation and household investors' portfolio, and the stock price change effect of nonfinancial corporation, household, and the rest of the world investors' portfolio. On another hand, the net transaction of household investor is correlated in the opposite direction with the stock outstanding value of each investors' portfolio, the net transaction of general government, financial corporation, and the rest of the world investors' portfolio, and the stock price change effect of general government and financial corporation investors' portfolio. The stock outstanding value of non-financial corporation investors' portfolio is the most influential factor to the net transaction of household investment forecasted one month ahead. However, the stock trading volume factor shows no significant changes in the net transaction of household investor forecasted one month ahead.

The performance evaluation in predicting the net transaction of household investors' portfolio one month ahead using the forecasting models: the moving multiple regression and the moving artificial neural network is shown in Table 1. Table 1 shows that the moving artificial neural network has lower MAE, RMSE, MAPE statistics. We conclude that the moving artificial neural network has higher level forecasting accuracy. Table 1 also shows that the moving artificial neural network has higher DA statistic. We conclude that the moving artificial neural network has higher directional forecasting accuracy. Lastly, the moving multiple regression and the moving artificial neural network have the DM statistic for MAE, RMSE, MAPE at -4.738 at the 99% confidence level. We can conclude that the prediction by the moving multiple regression is statistically significantly different from the prediction by the moving artificial neural network. Finally, we can conclude that the moving artificial neural network is a more powerful forecasting model than the moving multiple regression.

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