“Investor sentiment measurement based on technical analysis indicators affecting stock returns: Empirical evidence on VN100”

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INVESTOR SENTIMENT MEASUREMENT BASED ON TECHNICAL ANALYSIS INDICATORS AFFECTING STOCK RETURNS: EMPIRICAL EVIDENCE ON VN100

Abstract

The purpose of this study is to examine whether investor sentiment as measured by technical analysis indicators has an impact on stock returns. The research period is from 2015 to mid-2020. 1-year government bond yields, financial data, transaction data of 57 companies in the VN100 basket, and VNIndex are analyzed. The investor sentiment variable is measured by each technical analysis indicator (Relative Strength Index – RSI, Psychological Line Index – PLI), and the general sentiment variable is established based on extracting the principal component from individual indicators. The paper uses two regression methods – Fama-MacBeth and Generalized Least Square (GLS) – for five different research models. The results show that sentiment plays an important role in stock returns in the Vietnamese stock market. Even controlling the factors such as cash flow per share, firm size, market risk premium, and stock price volatility in the studied models, the impact of sentiment is significant in both the model using individual technical indicators and the model using the general sentiment variable. Furthermore, investor sentiment has a stronger power to explain excess stock returns than their trading behavior. The implication from the results shows that the Vietnamese stock market is inefficient, in which psychology is a very important issue and participants need to pay due attention to this factor.

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INTRODUCTION

Daniel Kahneman, an American psychologist, received the 2002 Nobel Prize in economics for the work related to the role psychology plays in people's economic decisions in uncertain situations (The Nobel Prize, 2002). This recognition shows the undeniable role of psychology in economic decisions. At the same time, it also provides a new perspective in explaining stock price changes in the stock market in addition to Fama's efficient market theory and standard asset pricing models.

There are many ways to measure sentiment in financial markets (Baker & Wurgler, 2006). One can use technical analysis indicators to measure investor sentiment in the stock market on a daily basis (Baker & Wurgler, 2006; Ryu et al., 2017; Li, 2021).

In Vietnam, academic studies on the application of technical analysis to the stock market are quite limited. Most of the studies in Vietnam so far have mainly focused on individual indicators such as Moving Average Convergence Divergence – MACD (Hung, 2016), Psychological Line Index – PLI (Phuong, 2020), Relative Strength Index – RSI (Phuong, 2021a), and Money Flow Index – MFI (Phuong,

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2021b). However, a few studies combine separate indicators into a general sentiment indicator. Thus, this study investigates stock markets from this perspective.

This study examines whether investor sentiment as measured by technical analysis indicators has an impact on stock returns in the Vietnamese stock market. To answer this question, the general sentiment indicator is examined for 57 companies under VN100 listed on the Vietnamese stock market in the period from early 2015 to mid-2020.

This article further contributes to academic studies on measuring investor sentiment based on technical analysis indicators on the Vietnamese stock market in various aspects. First, it develops a general investor sentiment indicator on the Vietnamese stock market based on individual technical analysis indicators. Second, it provides empirical evidence demonstrating the impact of the general sentiment on stock excess returns. Third, it proves that investor psychology plays a more important role in explaining excess returns than their trading behavior. Finally, the results from the research models are suggestions for investors, enterprises, and capital market regulators to make future decisions.

1. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

1.1. Background theories

Working (1949, 1961) defined a perfect futures market: the market price is the best estimate taking into account available information and the delivery date of the futures contract. This definition can be seen as a separate case but is similar in nature to the well-known definition of efficient market proposed by Fama (2021). Through theoretical discussion, analysis of empirical results on stock price movements, the efficient market theory was proposed. It has become a standard theory in the financial literature. According to Fama (2021), a market is considered "efficient" when stock prices reflect all available information, and the subset of information reflected in stock prices is classified into three levels: weak, semi-strong, and strong. When prices only reflect historical information, which is indicative of the weak form, the information set is supplemented with other information such as publicly available information, which is indicative of the semi-strong form, and the information set includes both proprietary and inside information, which are manifestations of the strong form. The efficient market theory implies that an investor will not be able to obtain excess returns based solely on the set of information on which the market has been classified.

According to Fama's efficient market theory, price movement is a random walk, historical information has no effect on current prices, and market prices always reflect the fair value or fundamental price of stocks (Fama, 1965). However, Shiller (1983) showed that in many cases stock prices deviate from fair value. Technical analysis using historical data can predict stock prices (Irwin & Brorsen, 1987) showing the shortcomings of efficient markets.

Based on the prospect theory of Kahneman and Tversky (1979), Shiller (1981, 1983) suggested that human irrationality and psychology caused this phenomenon. Therefore, standard asset pricing models, such as the capital asset pricing model (CAPM), should add behavioral and psychological variables to increase efficiency.

1.2. Investor sentiment

Baker and Wurgler (2006) define investor sentiment as the optimism or pessimism of investors towards stocks in general. There are three main ways to measure investor sentiment: a direct measurement based on primary data (surveys), an indirect measurement using secondary data, and a meta measurement using a combination of both direct and indirect ways.

To measure investor sentiment in the financial market, the focus was put on an in-depth study of only one technical analysis indicator (Anderson & Li, 2015; Bhargavi et al., 2017; Phuong, 2020, 2021a,

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2021b). Ryu et al. (2017) and Li (2021) simultaneously applied many different technical analysis indicators in a research model. Thus, the paper review empirical studies using relative strength index (RSI), psychological line index (PLI), and general sentiment indicator of investors in financial markets.

Relative Strength Index (RSI). RSI was introduced by Wilder (1978) and became one of the most famous momentum oscillators (Park & Irwin, 2004). Measuring investor sentiment on a daily basis based on the closing price of Singapore's STI index from January 1, 1974, to December 31, 1994, Wong et al. (2003) showed that RSI can give positive returns considering the establishment of signals from different threshold values. Similar to Wong et al. (2003), Schulmeister (2009) measured intraday sentiment in the spot and futures markets for the S&P500 at a 30-minute frequency from 1983 to 2007. It was shown that a trading strategy using a combination of RSI with a moving average resulted in an average gross profit of 7.2% per year. The evidence from these studies also shows that trading strategies based on signals from RSI provide better performance than a moving average strategy.

Ţăran-Moroşan (2011) investigated the performance of the revised RSI (RSIM) for the US stock market (S&P500 Index) to compare its performance (buy/sell) against the RSI classical period from March 1, 2004, to April 30, 2010. The results show that the RSIM indicator for buy (bullish sentiment) and sell (negative sentiment) for the S&P500 is more effective than the classic RSI.

The choice of analytical parameters is extremely important and can affect the results (Ţăran-Moroşan, 2011), especially using only the buy-sell signal of an indicator. Therefore, to reduce risk, studies need to use many other factors in making investment decisions.

Anderson and Li (2015) used daily data on the US Dollar/Swiss Franc exchange rate from January 5, 1998, to May 22, 2009, with a total of 2,955 observations showing that the use of RSI as a trading signal is still profitable. However, it was noted that the buy-sell threshold of RSI needs to be adjusted slightly from the standard threshold proposed by Wilder (1978) to be more effective.

Bhargavi et al. (2017) researched the Indian stock market and showed that RSI can be used as one of the tools for selecting stocks when setting up a portfolio. It is necessary to select 10 stocks with the highest EPS and 10 stocks with the highest P/E listed on the Stock Exchange of India to form a portfolio. Bhargavi et al. (2017) wanted to investigate whether RSI could be used to construct an optimal portfolio from this portfolio. By calculating RSI on a daily basis from January 2011 to December 2013, it was found that short-term investment performance using RSI-14 is mostly positive when applied in March 2014. Therefore, Bhargavi et al. (2017) argue that the use of RSI in the Indian stock market is valid.

Psychological Line Index (PLI). It was first introduced by Pring (1985). Mizuno et al. (1998) used it in a neural network model to predict buying and selling time for the TOPIX index on the Tokyo stock exchange. Using PLI-25 days to compare with neural network model and buy-hold strategy, it was found that in the buying situation, PLI generates higher returns than the neural network model and the buy-hold strategy, but in the sell situation, the neural network model gives better results than the signal from the PLI. In general, the neural network model applied to the TOPIX index still prevails over the strategy using only signals from PLI.

Hsu (2011) used RSI-13 trading days and some other technical indicators in the process of integrating a self-organizing map and genetic programming to forecast stock prices through the Financial and Insurance Index on the Taiwan Stock Exchange (sub-index of TAIEX). The results show that frequently alternating ups and downs and daily closing price ranges increase the difficulty of prediction, but it was confirmed that the integrated prediction process is an effective and feasible tool for forecasting stock price prediction.

Recently, Phuong (2020) using PLI-12 trading days for various thresholds on the Vietnamese stock market showed a significant impact of this indicator on stock returns. PLI values less than 25 have a negative impact on stock returns; conversely, PLI values greater than 50, PLI greater than 75, and total PLI have a positive impact on stock returns.

General sentiment indicator based on principal component analysis (PCA). Baker and Wurgler (2006) used variables such as the closed-end fund discount, dividend premium, the turnover of shares on the New York Stock Exchange, volume and an average return on the first day of IPO, and newly issued equity to measure investor sentiment. These variables were collected annually from 1962 to 2001 and the study extracted the first component in PCA to form the explanatory variable representing investor sentiment towards stock returns. It was found that stocks with high subjective characteristics and difficulty to arbitrage are characterized by low psychology that brings high profits, and high psychology brings low profits.

Kumar and Lee (2006) studied whether the trading behavior of individual investors (retail investors) has an impact on stock prices in the US stock market. Trading behavior is measured by calculating the difference between the bid and ask volume for each stock on a monthly basis from 1991 to 1996. It was shown that macro information and analysts' earnings forecast adjustments for stocks have no significant impact on stock returns. Stocks with a high percentage of individual investor ownership, such as low capitalization, low institutional ownership, and undervalued stocks, have returns that are explained by the trading behavior of investors in the market. Kumar and Lee (2006) asserted that investor sentiment has a significant impact on stock returns.

Kim and Ha (2010) investigated the influence of investor sentiment on stock prices traded on the Korean stock market. Data were collected on a monthly basis from December 1993 to December 2008 excluding the period of the Korean exchange crisis from 1997 to 1998. The PCA method is used to build a representative variable of investor sentiment. The results demonstrated that investor sentiment has a systematic influence on stock prices of Korean companies, especially companies with small capitalization, low market price, and low market price.

Ryu et al. (2017) investigated investor sentiment and trading behavior that affect stock returns on the Korean stock market from 2000 to 2015. Investor sentiment is the first component when performing PCA on daily data for four technical indicators including RSI, PLI, the logarithm of trading volume, and adjusted turnover rate. Investor behavior is determined based on buying and selling imbalances for 257 companies. It was asserted that investor sentiment plays a more important role than their trading behavior in explaining stock returns.

Complementing Ryu et al. (2017), Seok et al. (2019) showed that investor sentiment has a positive impact on realized profits of companies that are difficult to value on the Korean stock market.

The purpose of this study is to investigate the role of investor sentiment as measured by technical analysis indicators in the excess returns of stocks in the VN100 basket on the Vietnamese stock market. To achieve this purpose, five research hypotheses are raised, including:

H01: Investor sentiment is measured by the relative strength index (RSI), which has no impact on the stock returns of VN100.

H02: Investor sentiment is measured by the psychological line index (PLI), which has no impact on VN100 stock returns.

H03: There is no difference in the explanatory power of the general sentiment and investor trading behavior to VN100stock returns.

H04: The general sentiment of investors is measured based on technical analysis indicators (PLC), which has no impact on VN100 stock returns.

2. METHODOLOGY

2.1. Models

The study refers to the model of Ryu et al. (2017) with amendments when applied to the Vietnamese stock market. The difference of the model in this study compared to Ryu et al. (2017) is to use the market risk premium in the capital asset pricing model in the research models.

Five different research models are used to test the research hypotheses, including:

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- Model (1) shows the influence of investor sentiment, measured by the relative strength index (RSI) on VN100 stock returns.
- Model (2) shows the influence of investor sentiment, measured based on psychological line indicator (PLI) on VN100 stock returns.
- Models (3) and (4) compare the explanatory power of general investor sentiment (model 4) and investor trading behavior (model 3) to the returns of stocks belonging to investors.
- Model (5) shows the influence of general investor sentiment measured based on technical analysis indicators (PLC) on VN100 stock returns.

The variable measuring investor sentiment in this study has an advantage over that of Baker and Wurgler (2006) as it can measure daily sentiment for each stock:

$$Re_{i,t} = \beta_0 + \beta_1\left(R_m - R_f\right) + \beta_2 RSI_{i,t} + \beta_{3N} NBSVd_{i,t} + \beta_4 Size_{i,t-1} + \beta_5 CF_{i,t-1} + \beta_6 Volatility_{i,t} + e_{i,t}, \tag{1}$$

$$Re_{i,t} = \beta_0 + \beta_1\left(R_m - R_f\right) + \beta_2 PLI_{i,t} + \beta_3 NBSVd_{i,t} + \beta_4 Size_{i,t-1} + \beta_5 CF_{i,t-1} + \beta_6 Volatility_{i,t} + e_{i,t}, \tag{2}$$

$$Re_{i,t} = \beta_0 + \beta_1\left(R_m - R_f\right) + \beta_2 NBSVd_{i,t} + \beta_3 Size_{i,t-1} + \beta_4 CF_{i,t-1} + \beta_5 Volatility_{i,t} + e_{i,t}, \tag{3}$$

$$Re_{i,t} = \beta_0 + \beta_1\left(R_m - R_f\right) + \beta_2 PLC_{i,t} + \beta_3 Size_{i,t-1} + \beta_4 CF_{i,t-1} + \beta_5 Volatility_{i,t} + e_{i,t}, \tag{4}$$

$$Re_{i,t} = \beta_0 + \beta_1\left(R_m - R_f\right) + \beta_2 PLC_{i,t} + \beta_3 NBSVd_{i,t} + \beta_4 Size_{i,t-1} + \beta_5 CF_{i,t-1} + \beta_6 Volatility_{i,t} + e_{i,t}, \tag{5}$$

where the dependent variable $Re_{i,t}$ (excess return) is the difference between the raw return of stock *i* and the risk-free rate. The 1-year government bond yield used is the risk-free rate. The right-hand side of the equations is an extension of the CAPM model by adding variables measuring the general sentiment of investors $\left(PLC_{i,t}\right)$ their trading behavior ($NBSV_{i,t}$), control variables on fundamentals $\left(CFPS_{i,t-1}\right)$, size, and trading characteristics $\left(Vol_{i,t}\right)$ of each stock.

Each independent variable including psychometric variables and control variables in the research models is calculated in their ways. Psychometric variables are calculated the following way.

RSI is used to measure the velocity of directional price movement. RSI values range from 0 to 100 and are commonly used to give buy and sell signals in financial markets. A buy signal occurs when the RSI rises above 30 in the upward direction. Conversely, a sell signal occurs when the RSI falls below 70 in the downtrend. The RSI value below 30 is called the oversold, and the area above 70 is called the overbought. The RSI value of 50 is called the average and it divides the RSI into two parts. When the RSI is above 50 it indicates that the average gain for the calculation period is higher than the average loss for that period. In this case, it indicates that the stock price is in an uptrend. Conversely, when the RSI is below 50 it shows that the average loss is larger than the average gain, and a downtrend occurs (Wilder, 1978). Similar to the moving average indicator, RSI can be thought of as smoothed price movements. The advantage of RSI is that it is possible to pre-determine a change in trend based on decreasing momentum before a trend reversal occurs, but it is different for moving averages (Park & Irwin, 2004).

$$RSI_{i,t} = 100 - \frac{100}{1 + RS_{i,t}} = \frac{100 \cdot RS_{i,t}}{1 + RS_{i,t}}, \quad RS_{i,t} = \frac{\sum_{k=0}^{13} \max\left(0, P_{i,t-k} - P_{i,t-1-k}\right)}{\sum_{k=0}^{13} \max\left(0, P_{i,t-1-k} - P_{i,t-k}\right)}. \tag{6}$$

This paper uses the RSI parameter of 14 days (current day and previous 13 days) as suggested by Wilder (1978). This parameter is also used by Țăran-Moroșan (2011) and Bhargavi et al. (2017) when analyzing stock markets. The numerator of RS represents the average total losses over 14 days, the denominator of the RS represents the average total losses over 14 days. $P_{i,t-k}$ is the price of stock i at day (*t*–*k*).

PLI is calculated by dividing the number of bullish days by the total number of days in the selected period, so it is also known as the majority rule. The 12-day parameter consists of the current date and the previous 11 days. The value of PLI runs from 0 to 100. Similar to RSI, PLI also has two thresholds for determining buy and sell signals. When PLI crosses 75, it has moved into the overbought zone, the downside potential increases. On the contrary, when the PLI is lower than 25, it is moving into the oversold zone, the upside possibility prevails.

$$PLI_{i,t} = \\ = 100 \cdot \sum_{k=0}^{11} \left(\frac{\max\left(0, P_{i,t-k} - P_{i,t-1-k}\right)}{P_{i,t-k} - P_{i,t-1-k}} \right) \Big/ 12. \quad (7)$$

PLC. To combine many psychological variables, each of which is measured through an individual technical analysis indicator, the main part analysis method of PCA is often applied to create a general sentiment indicator (Ryu et al., 2017). In this paper, the variable PLC is built by extracting the first principal component in PCA from two indicators RSI and PLI.

Control variables are calculated the following way.

The investor trading behavior variable (NBSV) is built based on the volume imbalance between demand and supply for each stock. The net investment demand (net) of each stock (NBSV) is calculated as the difference between the actual bid volume (representing the demand side) and the actual ask volume (representing the supply side), compared to the total of these two values in each trading day. It represents an imbalance of transactions between buyers and sellers for a particular stock. The higher this value is positive, the greater the imbalance between demand and supply. In other words, the demand side is overwhelming the supply side. Conversely, if this value is negative, the supply side of the stock is overwhelming the demand side.

The NBSV of each stock is calculated by

$$NBSV_{i,t} = \frac{BV_{i,t} - SV_{i,t}}{BV_{i,t} + SV_{i,t}}. \quad (8)$$

where $BV_{i,t}$ and $SV_{i,t}$ are the total bid volume and total sell order volume of investors in the market for stock *i* at day *t*, respectively.

To eliminate the effect of market returns when calculating the investor trading behavior index, the index is obtained from the residuals by

$$BSd_{i,t} = NBSV_{i,t} = \\ = \beta_0 + \beta_1\left(Rm_t - Rf_t\right) + u_{i,t}, \quad (9)$$

where $(Rm_t - Rf_t)$ is the market premium, calculated as the difference between the market return (*Rm*) and the risk-free rate (*Rf*) at time *t*.

Volatility is calculated based on the standard deviation of the daily closing price movement of stock *i* over a certain period.

$$Vol_{i,t} = \sigma_{i,t} = \sqrt{252 \cdot \frac{1}{n+1} \cdot \sum_{k=0}^{n=13} \left(\ln \frac{P_{i,t-k}}{P_{i,t-1-k}} \right)^2}, \quad (10)$$

where $P_{i,t}$ is the closing price of stock *i* at day *t*; 252 is the number of trading days in a year; *n* = (0–13) is the period 13 days before date *t* applied to stock *i*.

Size of the company (Size) is calculated as the logarithm of the volume of shares outstanding multiplied by the daily closing price of each share.

The company cash flow index (CFPS) is calculated as the logarithm of the quarterly value of cash flow from operating activities generated per share.

2.2. Estimation method and principal component analysis (PCA)

The number of components retained in the analytical model is based on the coefficients of Eigenvalues. Only those components with Eigenvalues > 1 are kept.

The KMO test measures the adequacy of sampling, it takes a value from 0 to 1. Kaiser (1974) said that the KMO value must satisfy the condition from 0.5 or more (0.5 ≤ KMO ≤ 1) to be suitable for principal component analysis.

Bartlett test helps to know whether variables in PCA are correlated or not (Bartlett, 1950). If the test re-

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sults show that P-value < 0.05, the tested variables are correlated with each other in the main component. In this case, the use of PCA is appropriate for these variables.

Principal component loadings represent the relationship of each analytic variable to the principal component. The higher the principal component load of a variable, the greater the correlation between this variable and the principal component. According to Hair et al. (2009, p. 116), the condition for a variable to be retained is that the absolute value of the minimum principal component load is 0.3. If this value is 0.5, the retained variable has good statistical significance; if the value is above 0.7, it shows that the retained variable has very good statistical significance.

All five models are estimated by two methods, GLS and Fama-MacBeth, to ensure the robustness of the models. The tests performed include the F-test to remove unnecessary variables, the Wooldridge test for autocorrelation, and the Modified Wald test to check for variance. If the model has variable variance, autocorrelation problems, then corrective measures are used to solve these problems.

2.3. Research data

Based on 100 stocks listed on the Vietnamese stock market in the VN100 basket as of June 30, 2020, the paper selects companies that have enough quarterly financial data from the first quarter of 2015 to the second quarter of 2020 and daily transaction data from January 1, 2015, to July 31, 2020, for analysis. Data collected from FiinPro (n.d.) at the beginning of August 2020 show that 57 companies meet the criteria. In addition, other data from FiinPro (n.d.) by daily frequency during this period are also used in this study, such as 1-year government bond yield representing the risk-free rate and the closing price of VNIndex, to calculate market returns.

3. RESULTS AND DISCUSSION

Descriptive statistics of the variables are presented in Table 1.

Table 2 shows that the correlation coefficient between the pairs of variables is less than 0.5, only for the pair of RSI and PLI a correlation coefficient is 0.63. This result shows that the correlation between RSI and PLI is strong (Pearson, 1896; Pearson & Filon, 1898), so it is not possible to include both of these variables as independent variables in the same regression equation. This is appropriate when RSI and PLI variables are regressed into two different regression models, models (1) and (2).

Table 1. Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
re	75,400	–0.0263	2.3784	–68.831	11.184
$Rm - R_f$	75,400	0.0149	1.0891	–6.486	4.853
NBSV	75,400	5.76e–11	0.2724	–1.0008	1.1093
Size (–1)	75,400	29.5551	1.4570	25.41645	33.6961
CFBS (–1)	75,400	3.3021	7.1163	–10.045	10.649
Vol (–1)	75,400	0.3234	0.1897	0.01	3.07
RSI	75,400	49.6081	13.0984	3.66	95.74
PLI	75,400	41.52	15.0446	0	100

Table 2. Correlation results between pairs of variables

	re	$Rm - R_f$	*NBSV*	*Size (–1)*	*CFBS (–1)*	*Vol (–1)*	*RSI*	*PLI*
re	1.0000							
$Rm - R_f$	0.1478	1.0000						
NBSV	0.0011	0.0403	1.0000					
Size (–1)	0.0057	0.0599	0.4731	1.0000				
CFBS (–1)	0.0015	–0.1176	0.0789	0.0988	1.0000			
Vol (–1)	–0.0640	0.0201	–0.0119	–0.0902	–0.0275	1.0000		
RSI	0.3377	0.0390	0.0011	0.0490	0.0390	–0.0967	1.0000	
PLI	0.1883	0.0544	0.0608	0.1363	0.0196	0.1268	0.6318	1.0000

Table 3. Principal component analysis

	Coef.	Std. Err.	z	*P>z*	[95% Conf. Interval]	
Eigenvalues						
Comp1	1.6318	0.0084	194.16	0.000	1.6153	1.6483
Principal component loadings						
RSI	0.7071	0.0016	447.62	0.000	0.7040	0.7102
PLI	0.7071	0.0016	447.62	0.000	0.7040	0.7102
LR test for independence:	chi2(1) = 38410.23 Prob > chi2 = 0.0000					
LR test for sphericity (Bartlett test)	chi2(2) = 38410.49 Prob > chi2 = 0.0000					
Kaiser-Meyer-Olkin test (KMO test)	0.5000					
Explained variance by components						
Components	**Eigenvalue**	**Proportion**	**SE_Prop**	**Cumulative**	**SE_Cum**	**Bias**
Comp1	1.6318	0.8159	0.0011	0.8159	0.0011	6.3e-06
Comp2	0.3682	0.1841	0.0011	1.0000	0.0000	-6.3e-06

A KMO value of 0.5 indicates that sampling is sufficient (sampling adequacy) to perform PCA (Kaiser, 1974). *P*-value in the Bartlett test is 0.00, less than 0.05, showing that the two variables (RSI and PLI) are highly correlated. The results of this test in Table 3 confirm the results in Table 2 about the high correlation between RSI and the PLI.

The coefficient of Eigenvalues of the first principal component of 1.6318 is greater than 1, indicating that this component should be kept as an explanatory variable in the research model. The first principal component explains 81.59% (1.6318/2) of the total variance, and the part of variance not explained by this principle component is 18.41%.

The first principal component loads for the RSI and PLI variables are both 0.7071. This is the best threshold, according to Hair et al. (2009), to select variables that are kept statistically significant when performing PCA.

The results of testing the hypotheses are shown in Table 4.

Model 1: The regression coefficient of the RSI variable has statistical significance of 1%, rejecting the hypothesis H01. In other words, investor sentiment as measured by the relative strength index (RSI) has an impact on stock returns in the data sample.

Similarly, hypothesis H02 is rejected when the regression coefficient of variable PLI in model 2 is also statistically significant 1%. The results from model 2 show that investor sentiment as measured by the psychological line index (PLI) has an impact on stock returns of VN100.

Table 4. Regression results according to the Fama-MacBeth method

Variable	FMBrsi	FMBpli	FMBnbsv	FMBplc1	FMBplc
	(1)	(2)	(3)	(4)	(5)
$R_m - R_f$	0.317***	0.347***	0.439***	0.286***	0.268***
NBSV	0.915***	1.003***	1.074***		0.935***
Size (–1)	–0.031***	–0.044***	–0.007	–0.041***	–0.051***
CFBS (–1)	0.002*	0.007***	0.009***	–0.000	0.004***
Vol (–1)	–0.551***	–0.898***	–0.396***	–0.899***	–0.918***
RSI	0.059***				
PLI		0.026***			
PLC				0.521***	0.500***
_cons	–1.176***	0.442***	0.322**	1.198***	1.387***
N	75400	75400	75400	75400	75400
r2	0.277	0.209	0.159	0.211	0.252
adjr2	0.206	0.132	0.094	0.150	0.178

Note: *, **, and *** have significance at 1%, 5% and 10%, respectively.

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Model 3 and model 4 differ only by 1 variable in the regression model.

In model 3 using investor trading behavior variable (NBSV), there is no composite investor sentiment variable (PLC) and there is an adjusted R-squared of 9.4%. In model 4, the investor's trading behavior variable (NBSV) is not included but uses the investor's general sentiment variable (PLC) and has an adjusted r-squared j of 15%. Because model 4 has an adjusted R-squared of 15% larger than an adjusted R-squared of 9.4% in model 3, it shows that the explanatory power of the PLI variable is greater than that of the NBSV variable, or there is a difference in the explanatory power of general psychology and investor's trading behavior to stock returns of VN100.

Because the 1% statistical significance level has shown that the general sentiment of investors as measured by technical indicators PLC affects stock returns (Model 5). This result means rejecting hypothesis H04.

Regression results from Table 4 show that the control variables all affect stock returns on the Vietnamese stock market. The regression coefficients of the variables representing investor sentiment are all significantly positive in all four models: (1), (2), (4), and (5); this shows that higher sentiment is associated with higher stock returns. It differs from the results of Baker and Wurgler (2006) on the US stock market. This empirical result also supports the view that the Vietnamese stock market is inefficient.

Factors closely related to day-to-day trading, such as stock price volatility, and the difference in trading volume between buyers and sellers, are all important in explaining the excess returns of a security.

The variable Vol_{t-1} has a significant negative regression coefficient, which shows that stocks with strong daily (t-1) price fluctuations will increase investment risk, so it has a negative impact on excess returns at day *t* of the stock. This finding is in contrast to Ryu et al. (2017), who researched the Korean stock market using the daily estimation model.

Regression coefficients of the trading behavior variable (NBSV) are both positive and significant at 1%, showing that the imbalance between demand and supply in terms of trading volume for a particular stock plays an important role in explaining the stock excess return. The larger this trading imbalance increases, the more likely the stock excess return will be.

In addition to transactional factors, firm characteristics such as firm size and cash flow, are also significant in explaining the stock excess return. The more efficient businesses operate, the more cash flow per share (CFPS(–1)) increases, the more stock excess return is likely to be.

The regression coefficients argued in the CAPM model in all models are statistically significant at 1%, indicating that the market risk premium has a significant contribution to the stock excess return. Values of this coefficient are all less than 1, indicating that the stocks in the sample have less volatility or less risk than the risk of the whole market. This result differs from Li (2021) on the Shanghai-China stock exchange in terms of daily frequency. This is reasonable because the sample studied in this paper are mainly large companies on the Vietnamese stock market, so the risk level of these stocks is lower than the overall risk of the whole market.

The explanatory power from the models also shows some interesting results. Of the five studied models, model (1) has the largest adjusted R^2, which adds another reason why RSI is one of the most commonly used technical analysis indicators to date. The comparison between models (3) and (4) shows that the explanatory power of model (3), excluding the psychological variable PLC, is much lower than that of model (4), excluding the transaction behavior variable NBSV.

Moreover, the importance of the variable NBSV clearly decreases when the psychological variables RSI, PLI, and PLC are used in models (1), (2), and (5), respectively. This result shows that although both trading behavior and investment sentiment are important factors for explaining stock returns, the role of sentiment is more important than the other.

The study further conducts the robustness tests.

Besides the Fama-MacBeth estimation method, to ensure the robustness of the estimation re-

Table 5. Regression results according to GLS

Variable	GLSrsi (1)	GLSpli (2)	GLSnbsv (3)	GLSplc1 (4)	GLSplc (5)
Rm– R_f	0.414***	0.480***	0.518***	0.433***	0.436***
NBSV	1.359***	1.380***	1.466***		1.342***
Size (–1)	–0.029***	–0.049***	–0.011**	–0.040***	–0.052***
CFBS (–1)	0.003**	0.005***	0.006***	–0.001	0.004***
Vol (–1)	–0.403***	–1.027***	–0.715***	–0.790***	–0.832***
RSI	0.053***			0.471***	
PLI		0.026***			
PLC			0.501***	1.401***	0.463***
_cons	–1.680***	0.663***			1.748***
N	75400	75400	75400	75400	75400
r2	0.1718	0.1150	0.0870	0.1318	0.1509
adjr2	0.1717	0.1150	0.0869	0.1317	0.1509
F test	F(56,75337) = 33.73	F(56,75337) = 33.42	F(56,75338) = 33.17	F(56,75338) = 2.49	F(56,75337) = 33.90
	Prob > F = 0.0000	Prob > F = 0.0000	Prob > F = 0.0000	Prob > F = 0.0000	Prob > F = 0.0000
Wooldridge test for autocorrelation	F(1, 56) = 833.251	F(1, 56) = 1215.707	F(1, 56) = 1152.963	F(1, 56) = 1598.188	F(1, 56) = 1328.704
	Prob > F = 0.0000	Prob > F = 0.0000	Prob > F = 0.0000	Prob > F = 0.0000	Prob > F = 0.0000
Modified Wald test for heteroskedasticity	chi2 (57) = 1424.83	chi2 (57) = 1233.49	chi2 (57) = 1295.56	chi2 (57) = 1293.99	chi2 (57) = 1309.40
	Prob>chi2 = 0.0000	Prob>chi2 = 0.0000	Prob>chi2= 0.0000	Prob>chi2= 0.0000	Prob>chi2 = 0.0000

Note: *, **, and *** have significance at 1%, 5%, and 10%, respectively.

sults, this paper uses the GLS regression method for 5 research models. Table 5 presents the test results and the regression results according to the GLS method. After overcoming the problems of autocorrelation and variable variance, the final regression results of the models are shown in Table 5.

Comparing the regression results between Table 4 and Table 5, it is shown that in all 5 models the sign and statistical significance of the variables estimated by the Fama-MacBeth method and GLS method are consistent. This consistency indicates the robustness of the research models, so the estimated results are reliable.

CONCLUSION

This is one of the pioneering studies investigating the Vietnamese stock market on the impact of investor sentiment measured based on synthetic technical analysis indicators on stock returns. This study used quarterly financial data (from Q1/2015 to Q2/2020) and daily transaction data (from January 1, 2015, to July 31, 2020) for 57 companies under VN100 to analyze general sentiment variable measured by first component extraction when applying principal component analysis to individual technical analysis indicators. Research results show that investor sentiment plays an important role in stock returns in the Vietnamese stock market. It exhibits more explanatory power than the trading behavior of investors in the research models even when controlling such factors as firm size, cash flow per share, coefficient of beta in CAPM, and stock price volatility. Investor sentiment is positively related to stock returns. In other words, the higher the sentiment, the more likely it is to increase stock returns.

Compared with previous studies, this study contributes more to academic studies on the use of technical analysis indicators to measure investor sentiment on the Vietnamese stock market in the following aspects:

(i) It developed a general sentiment indicator of investors in the Vietnamese stock market based on individual technical analysis indicators, and this technique can be extended to many other technical analysis indicators that were not applied in this study.

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(ii) It demonstrated the impact of the general sentiment indicator on stock returns even when controlling such factors as trading behavior, company characteristics (size, cash flow), and risks (market, stock price volatility).

(iii) It indicated that psychological impact has greater explanatory power than investor trading behavior.

(iv) Research results are valuable references for parties involved in the Vietnamese stock market. Investors can establish criteria for selecting investment stocks based on the statistical significance of the variables in the research models. Enterprises need to focus on increasing their production and business efficiency so that cash flow from this activity grows sustainably. The greater the price volatility, the stronger the negative effect on the stock market, so capital market managers need to anticipate these things in their management process.

AUTHOR CONTRIBUTIONS

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Writing – review & editing: Lai Cao Mai Phuong.

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