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INFLUENCE OF INVESTOR SENTIMENT ON THE RETURN RATE OF TRANSNATIONAL INVESTMENT BEHAVIOUR

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Abstract

Despite its rapid growth, the transnational investment market in China is not as mature as the capital markets in developed countries. The anomalies in China's transnational investment market are difficult to be explained by traditional financial theories like market efficiency theory. Drawing on the behavioural finance theory, this paper empirically studies how investor sentiment affects the return rate of transnational investment behavior. Several proxy variables were selected and fitted to the composite index of investor sentiment using principal component analysis. The empirical data were collected from China's transnational investment market from January 2010 to January 2019. Through the data analysis, it is concluded that investor sentiment has a significant positive impact on future market returns; an optimistic investor sentiment improves the return rate of the market, and a pessimistic investor sentiment suppresses the return rate of the market. The research findings promote the healthy and rapid development of the transnational investment market.

Key words: *Investor Sentiment, Transnational Investment, Return Rate, Behavioural Finance.*

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INTRODUCTION

In the past three or four decades, behavioural finance theory has gradually emerged, and scholars at home and abroad have increasingly inclined to apply financial theory into analysing and explaining the anomalies in capital markets (Chen, 2012; Oliveira, Cortez, & Areal, 2017). The transnational investment market has the characteristics of abnormal price fluctuations and unreasonable investor behaviour, making it unable to satisfy the basic assumptions of traditional finance theory (Chen, Chong, & She, 2014). Therefore, in the behavioural finance theory, scholars have introduced relevant factors such as investor behaviour, which can make up for the deficiency of traditional finance theory to a certain extent (Schmeling, 2009; Stambaugh, Yu, & Yuan, 2012).

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A number of studies have shown that investor sentiment, as a branch of behavioural finance theory (Bozionelos, 2006), can make the investment decision-making be influenced by their own internal subjective factor, which ultimately leads to systematic bias in investment decisions (Lux, 2011). Theorists define this subjective factor as investor sentiment (Pan, Shiu, & Wu, 2015). Therefore, the amplification mechanism of investors' positive feedback and negative feedback on future market changes will have a significant impact on the investment market (Cetin, 2014; Smimou, 2014). With the rise of empirical studies on investor sentiment, more and more scholars believe that investor sentiment may affect the volatility of transnational investment returns to a certain extent (Møller, Nørholm, & Rangvid, 2014).

Western scholars have conducted a large number of empirical studies under the framework of behavioural finance theory (Kaustia & KNüPFER, 2008). These studies are mainly concentrated in the mature capital markets of developed countries, but there are few empirical studies on the psychological sentiment of investors in China's multinational investment market (Han, 2008), because of limited introduction of investor sentiment theory in China within such short period of time (Schmeling, 2007) and insufficient public data in China's capital market (Joseph, Wintoki, & Zhang, 2011). As an emerging market, China's transnational investment market is relatively ineffective, but there is still much room for improvement in terms of systems, products, and structures. Thus, the anomalies of China's multinational investment market may need to be explained from the perspective of investor sentiment.

In summary, this paper attempts to study the impact of investor sentiment and investment return on the transnational investment market using the data of China's transnational investment market, and comprehensively reveal the relationship between investor sentiment and market return of China's multinational investment. The research findings can better help the supervision departments to grasp the characteristics of the transnational investment market and generate new policy thoughts.

RESEARCH OBJECTS AND METHODS

Selection of proxy variables

This paper attempts to fit the selected proxy variables to the composite index of investor sentiment using principal component analysis.

The definition of the proxy variable is shown in Table 1.

$$CFED_t = \frac{\sum_{i=1}^{n}[(P_{it}-NAV_{it}{*}N_t)]}{\sum_{i=1}^{n}(NAV_{it}{*}N_t)}{*}100\% \quad (1)$$

$$TURN_t = V_t \div O_t{*}100\% \quad (2)$$

$$RIPO_t = \frac{\sum_{i=1}^{n}(P_i-P_i'){*}LN_i}{\sum_{i=1}^{n}P_i'{*}LN_i}{*}100\% \quad (3)$$

The empirical data used in this paper was taken from the monthly data of the sample companies from January 2010 to January 2019. Based on the data collected, Table 2 lists the statistical characteristics of the proxy variables.

The correlation coefficients of the proxy variables are shown in Table 3.

The results listed in Table 3 shows that there is not much correlation between different proxy variables. Among them, the correlation coefficient between the variable CEFD and the variable TURN was the largest, reaching 0.908; the correlation coefficient between the variable TURN and the variable RIPO reached 0.794; the correlation coefficient between the variable CEFD and CCI correlation was 0.694; the correlation coefficient between the variable BAIDU and CCI was the lowest, only 0.124.

Table 1. **Definition of proxy variables**

Variable name	Variable Symbols	Variable Symbols	Expected relationship with investor sentiment
Discount of Closed-end Fund	CEFD	Formula (1)	positive correlation
Average turnover rate of A shares	TURN	Formula (2)	positive correlation
First-day return on IPO	RIPO	Formula (3)	positive correlation
Consumer Confidence Index	CCI	Consumer Confidence Index for the Month	positive correlation
Number of new investors opening accounts	NIA	Difference between the number of new accounts and the number of accounts sold	positive correlation
Baidu index	BAIDU	Six keywords Baidu index sum index	positive correlation

Table 2. **Descriptive statistics of proxy variables**

variable	Company	Number	Mean value	Standard deviation	Maximum value	minimum value
CEFD	%	111	-12.7491	11.47796	3.5743	-52.82
TURN	%	111	41.11149	25.30019	126.8667	14.67533
RIPO	%	88	8.1845	8.7866	48.2334	-4.8855
CCI	——	111	98.0545	4.9966	106.6534	81.4845
NIA	Ten thousand	111	37.7345	31.1066	506.2934	-589.226
BAIDU	——	111	11.5145	8.3466	14.3534	6.4745

Table 3. **Correlation coefficients of proxy variables**

variable	CEFD (%)	TURN	RIPO	CCI	NIA	BAIDU
CEFD (%)	1					
TURN	0.908	1				
RIPO	0.244	0.794	1			
CCI	0.694	0.394	0.507	1		
NIA	0.124	0.303	0.475	0.403	1	
BAIDU	0.310	0.334	0.484	0.204	0.635	1

Principal component analysis

Table 4 lists the initial eigenvalue matrix, in which the cumulative variance contribution rate of the first three principal components reached 95.328%, satisfying the statistical standard of not less than 85%. Therefore, the weighted average of the first three components was used in this study to construct the composite index of investor sentiment.

Table 4. **Initial eigenvalue matrix**

Component	Total	Variance%	Cumulative%
1	3.464	71.519	71.519
2	1.406	13.415	84.265
3	1.135	10.842	95.328
4	0.806	4.721	99.382
5	0.214	0.362	100.00

After principal component analysis, the initial factor load matrix was obtained in Table 5.

Table 5. ***Initial factor load matrix***

Component	Component		
	1	2	3
CEFD (%)	0.295	0.803	0.694
TURN	-0.37	0.293	0.407
RIPO	0.16	-0.191	0.516
CCI	-0.277	0.954	0.204
NIA	0.515	0.92	-0.89

Table 5 shows the degree of correlation between each variable and the first three main components.

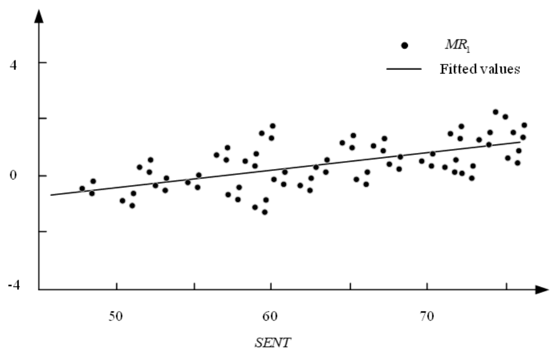
Therefore, the composite index $SENT$ of the investor's psychological sentiment is expressed as:

$$SENT = 0.39CEFD + 0.15TURN + 0.099RIPO + 0.129CCI + 0.19NIA + 0.36BAIDU \quad (4)$$

EMPIRICAL RESEARCH RESULTS AND ANALYSIS

The fitting straight lines of MR1 and SEAT are shown in Figure 1.

Figure 1. **Scatter plot and fit curve of MR1 and SENT**



It can be seen that the slope of the straight line fitted by MR1 and SENT was positive, indicating that there may be a positive correlation between the two.

Unit root test

First, we performed a unit root test on MR1 and SENT using the DF test. Table 6 shows the DF test results for the variable SENT.

Table 6. **DF test results of SENT**

	T-statistics	1% Critical value	5% Critical value	10% Critical value
$z(t)$	-3.589	-3.497	-3.002	-2.603
	p-value for z(t)=0.0045			

Using the same procedure, the variable MR1 was also tested, finding that for MR1, it can also be verified at the 1% level that there is no "unit root" hypothesis. Therefore, the variables used in this study have no unit roots.

VAR estimation

First, the order of this VAR system was estimated.

Table 7. **The lag order of the VAR model**

Lagging	AIC	HQIC	SBIC
0	4.5675	4.5879	4.6180
1	3.6158	3.6772	3.7674
2	3.6103	3.7127	3.8633
3	3.6368	3.7802	3.9907
4	3.6284	3.8136	4.0842

Table 8. **Regression results of VAR model**

		MR1 (-1)	MR2 (-2)	SENT (-1)	SENT (-2)	_cons
	Coefficient	0.134	0.2921	0.1304	0.1216	-0.2057
MR1	Standard deviation	0.2184	0.2172	0.1252	0.1254	0.2195
	P value	0.131	0.196	0.124	0.668	0.124
	Coefficient	-8.5243	2.5134	0.7896	0.3221	8.102
SENT	Standard deviation	4.1979	4.1443	0.2174	0.2245	4.2425
	P value	0.157	0.676	0.123	0.1721	0.176

Further, regression was performed on this second-order VAR model. The regression results are shown in Table 8.

As shown in Table 8, in the model with the explanatory variable MR_1, the coefficients of the first-order lag variables of $SENT$ and MR_1 were significantly positive at the 1% level, and the coefficient of the second-order lag variable for MR_1 was significantly Positive at the level of 10%; in the model with the explanatory variable $SENT$, the first-order lag variable of MR_1 was significant.

Therefore, based on the regression results, this binary VAR model is given as:

$$MR_{1t} = -0.2057 + 0.134MR_{1t-1} + 0.2921MR_{1t-2} + 0.1304SENT_{t-1} + \varepsilon_{1t} \quad (5)$$

$$SENT_t = -0.87 + 0.7896SENT_{t-1} + 0.3221SENT_{t-2} + \varepsilon_{2t} \quad (6)$$

According to formula (5), it's found that there is a significant positive correlation between the first-order lag variable of investor sentiment index and the multinational investment return, indicating that investor sentiment has a significant impact on the return of multinational investment market. Specifically, optimistic investor sentiment will lead to an increase in market returns, while pessimistic investor sentiment will result in a decline in market returns, thereby reducing the overall rate of return on the multinational investment. Based on the above analysis, investor sentiment is one of the important factors affecting the overall return of China's transnational investment market.

According to formula (6), it's found that there is a significant negative correlation between market returns and current investor sentiment index (significant at 5%). This indicates that when the market return rises, the current investor's psychological mood tends to decline. In addition, it can be seen from the model (6) that the current investor's psychological sentiment has a certain impact on the future investor's psychological sentiment.

VAR system stability

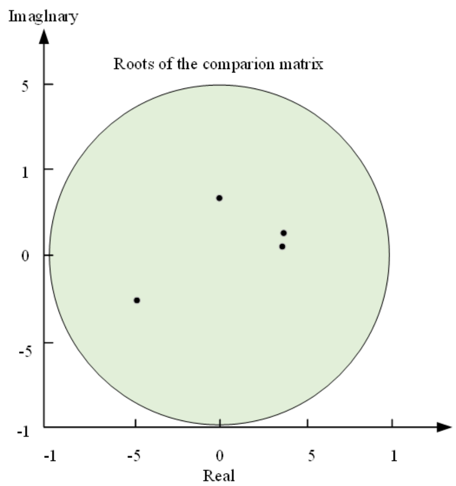
The stability of the VAR model was then estimated. The results are shown in Table 9 and Figure 2.

Table 9 and Figure 2 show that all of the eigenvalues are contained within the unit circle, indicating the stability of this binary VAR system. In order to fully explore the relationship between the two variables MR_1 and $SENT$, the Granger causality test was carried out under the framework of the binary VAR model. The test results are shown in Table 10.

Table 9. **Test results of VAR system stability**

Eigenvalue	Modulus
0.86	0.87
0.41	0.42
-0.29+0.12i	0.33
-0.30+0.15i	0.33

Figure 2. **Determination of the VAR system stability**



It can be seen from Table 10 that when MR_1 was the explanatory variable, its p value was much smaller than 0.05; when $SENT$ was explanatory variable, its p value was greater than 0.05. Thus, it's concluded that at the 5% significance level, $SENT$ is the Granger reason of MR_1, while MR_1 is not the Granger reason of $SENT$.

Table 10. **Granger test results**

Equation	Excluded	Chi2	Prob>chi2
MR1	SENT	18.57	0.000
MR1	ALL	18.57	0.000
SENT	MR1	4.9032	0.091
SENT	ALL	4.9032	0.091

CONCLUSIONS

This paper aims to conduct an empirical study on the psychological effects of investors in China's transnational investment market using the data of China's multinational investment market from 2010 to 2019. The following conclusions have been drawn:

(1) From the fitted line of investor sentiment index and market return, the slope of the straight line was positive, indicating that the existence of investor sentiment does affect the entire transnational investment market;

(2) There is a significant positive correlation between the returns of the multinational investment market and the first-order lag variables of the investor's psychological sentiment index. When the investor sentiment tends to be optimistic, the future transnational investment market return will increase; on the contrary, when the investor's psychological sentiment tends to be pessimistic, it will decrease;

(3) Granger causality test results also prove that the investor sentiment is the Granger reason for the return of the multinational investment market.

REFERENCES

Cetin, C. (2014). The time varying relation between consumer confidence and equities. *Journal of Behavioral Finance, 15(4)*, 312-317.

Chen, H., Chong, T. T. L., & She, Y. (2014). A principal component approach to measuring investor sentiment in china. *Quantitative Finance, 14(4)*, 573-579.

Chen, S. S. (2012). Consumer confidence and stock returns over market fluctuations. *Quantitative Finance, 12(10)*, 1585-1597.

Han, B. (2008). Investor sentiment and option prices. *Review of Financial Studies, 21(1)*, 387-414.

Joseph, K., Wintoki, M. B., & Zhang, Z. (2011). Forecasting abnormal stock returns and trading volume using investor sentiment: evidence from online search. *International Journal of Forecasting, 27(4)*, 1116-1127.

Kaustia, M., & KNüPFER, S. (2008). Do investors overweight personal experience. evidence from ipo subscriptions. *The Journal of Finance, 63(6)*, 2679-2702.

Lux, T. (2011). Sentiment dynamics and stock returns: the case of the german stock market. *Empirical Economics, 41(3)*, 663-679.

Møllera, S. V., Nørholm, H., Rangvid, J. (2014). Consumer confidence or the business cycle: what matters more for european expected returns. *Journal of Empirical Finance, 28*, 230-248.

Nikos, B. (2006). Mentoring and expressive network resources: their relationship with career success and emotional exhaustion among hellenes employees involved in emotion work. *The International Journal of Human Resource Management, 17(2)*, 362-378.

Oliveira, N., Cortez, P., & Areal, N. (2017). The impact of microblogging data for stock market prediction: using twitter to predict returns, volatility, trading volume and survey sentiment indices. *Expert Systems with Applications*, *73(Complete)*, 125-144.

Pan, G. G., Shiu, Y. M., & Wu, T. C. (2015). Investor beliefs and the demand pressure on index options in taiwan. *Journal of Futures Markets, 35(12)*, 1117-1132.

Schmeling, M. (2007). Institutional and individual sentiment: smart money and noise trader risk. *International Journal of Forecasting, 23(1)*, 127-145.

Schmeling, M. (2009). Investor sentiment and stock returns: some international evidence. *Journal of Empirical Finance, 16(3)*, 394-408.

Smimou, K. (2014). Consumer attitudes, stock market liquidity, and the macro economy: a canadian perspective. *International Review of Financial Analysis, 33*, 186-209.

Stambaugh, R. F., Yu, J., & Yuan, Y. (2012). The short of it: investor sentiment and anomalies. *Journal of Financial Economics, 104(2)*, 288-302.