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Investor sentiment in the tourism stock market

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A B S T R A C T

This study applies time-series analysis to observe investor sentiment in the tourism stock market. We infer that investor sentiment positively affects the capital flows to illustrate the behavioral finance in the tourism stock market. The vector autoregression and autoregressive-moving-average models of time-series analysis are adopted to analyze individual and overall capital flows of herding behavior. The empirical study collected quarterly data on 45 tourism-related stocks in China from 2018 to 2020. Results reaffirm that investor sentiment causes irrational investment and strong fluctuations of capital flows, including those during the Coronavirus 2019 pandemic. In practice, the overreaction of tourism-related stocks is discovered in the tourism market that requires long-term resilience. Theoretically, the rational capital asset pricing model needs adjustments with the sentiment factor based on behavioral finance theory.

1. Introduction

The tourism market has unique industrial attributes vital to explaining the sentiment influence, such as the significant impacts of the Coronavirus 2019 (COVID-19) pandemic on the tourism market. In behavioral economics, people's behavior is characterized as a subjective initiative resulting from excitement and other psychological factors. As an important psychological factor, investor sentiment is a subjective belief on future investment risk that statistics are not justified (De Long et al., 1990). Given that investor sentiment is highly recognized as a possible explanation of irrational noise trading (Frazzini and Lamont, 2008), the formation of investor sentiment has been extensively investigated. Although numerous studies examine how sentiment influences the stock markets (e.g., Maillet and Michel, 2005; Johnston and Nedelescu, 2006; Nikkinen et al., 2008), differences in public sentiment are observed in the tourism stock market (Chang and Zeng, 2011). Compared with other stock markets, tourism stocks demonstrate better performance after recovering from an initial adverse reaction caused by extraordinary events. Since Sorić (2021)'s recent study suggests the effect of the COVID-19 pandemic influencing the tourism stock market through behavioral and psychological factors, it is thus logical to posit the impact of investor sentiment in the market.

The herding effect is one of the common irrational behaviors in behavior finance theory. Behavioral finance in the tourism stock market is more sensible than in other industries (Wu et al., 2021). Consistent with the investor sentiment behavior, we assume that the practical investment in the tourism market is more sensitive due to the sentiment factor (Baker and Wurgler, 2006). Therefore, examining the sentiment effect in the tourism market can contribute to the capital development of the tourism economy. This study applies a time-series analysis to study behavioral finance by selecting tourism-related stocks to observe the unique financial behavior of the tourism market. The objective is to test whether the tourism stock market needs adjustments for the sentiment index. Based on behavioral finance models, we hypothesize a positive correlation between investor sentiment and capital flows. Since the market overreacts could be observed, the irrational "fluctuation" of capital flows represents a herding behavior that could be identified in tourism investment.

2. Literature review

Fama (1970) proposed the Efficient Markets Hypothesis (EMH), which suggests that stock prices always fully represent the companies' market values (Fama and French, 1988). While such a hypothesis is based on rational investments (Shleifer, 2000); however, the tulip mania and the Internet bubble show that investor behavior may not always be straightforward as the EMH (Lo and Lin, 2005). For example, investor sentiment has been observed to cause market anomalies during the COVID-19 pandemic (Sun et al., 2021).

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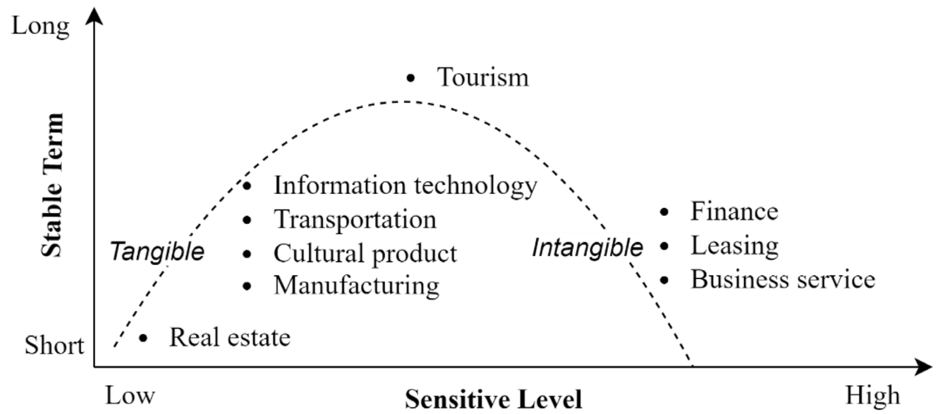

Fig. 1. Behavioral finance cross-sector comparison.

Although these irrational investments are observed and even called "noise traders" (Kyle, 1985; Black, 1986), they are categorized as anomalies with no stakes on the stock market. De Long et al. (1990) suggested that noise traders influence the price formation of stocks as investor sentiment. Specifically, noise traders that are optimistic about the future demand riskier stocks and thus increase the prices. Rationally, investors sell if the price is sufficiently high. At the same time, optimistic noise traders buy more to move prices beyond fundamental values and obstruct arbitrageurs, aiming to gain higher returns in the stock market to contradict EMH. Lee et al. (2002) confirmed the effects of investor sentiment on the stock market using a generalized autoregressive conditional heteroscedasticity in-mean model. We replicate the sentiment study by the vector autoregression and autoregressive-moving-average models of time-series analysis.

2.1. Behavioral finance in general and across industries

2.1.1. Behavior finance in general

Several behavioral finance applications have been conducted in the aggregate stock market and the cross-industry of average returns, indicating different results (Barberis and Thaler, 2003). Even though previous studies proved that irrational behavior has not happened in the whole China stock market, various herding effects in the Shanghai and Shenzhen Stock Exchanges amid the COVID-19 pandemic have been observed (Yuan, 2021; Zheng, 2021). Johnsen and McMahon (2005) argued that cross-industry differences in behavior finances existed after controlling other relevant influence factors on financing choices such as enterprise size, business age, profitability, growth, asset structure, and risk. Related empirical work includes Dreman and Berry's (1995) study found an asymmetry of response to earnings surprise between low and high P/E industrial stocks (Brooks and Byrne, 2008). Hong et al. (2020) investigated symmetric effects of investor herding in the ChinNext board that showed an assertive herding behavior in the market, even after controlling for the impact of COVID-19.

2.1.2. Behavior finance across industries

The stronger asymmetric and herding effects exist in the manufacturing and IT sectors (Hong et al., 2020). The severely intensified herding behavior affects transportation, leasing, business services, and cultural products. The investment decision-making process gets biased during some periods with special events in the financial industry (Copur, 2015), which has concluded significant abnormal features due to behavior finances. In the high-tech industry, anomalous patterns in equity markets have been observed and assumed some form of psychological bias that affects investor behavior. With the benefit of hindsight, it seems clear that the technology sector went through a bubble-like pattern that investor biases may have been even more pronounced (Jaggia and Thosar, 2004). In contrast, the real estate industry did not exist as a herding behavior (Yuan, 2021), suggesting that herding effects varied in different industries with various levels of financial behavior.

2.1.3. Behavior finance in the tourism sector

Investment decision-making has also presented irrational behavior for the tourism industry by examining psychological constructs, such as socioeconomic factors (Mosalev, 2020). Thus, the behavioral finance investigation could significantly benefit the tourism industry to formulate resilient strategies amid the pandemic. Based on the behavioral finance theory, psychological factors for tourism and tourists should be considered when implementing remedy measures or resilience policies (Zheng, 2021). China's tourism market has shown a strong herding effect, indicating that investor sentiment influences the stock market (Wu et al., 2021). Compared to the literature about asymmetric products of investor herding, we found that the tourism industry showed different patterns of herding effects among industries. The herding effect in tourism showed quick overreaction, but reached a stable status in the long term. For example, investor sentiment reflected the COVID-19 pandemic in a short-term reaction; however, the economic recovery was found to be durable over long-term resilience. In line with the study of Yuan (2021), the tourism industry has dispersed stability and prominent volatility at the beginning of a quarter and is prone to noise trading.

Sorić (2021) uncovered evidence of behavioral finance in the tourism market. In addition, Wu et al. (2021) indicated that behavioral finance in the tourism stock market is more sensible than in other industries. We have further indicated the response conditions of behavioral finance between stability and sensitivity, as indicated in Fig. 1. The cross-sector comparison of behavior finance showed that intangible service-orientation industries could be sensitive to an event but relatively stable over short periods. The industries that are high in tangible assets show the opposite behavior. Especially, the tourism industry is sensitive to an event with behavioral effects that need a longer time to stabilize. It is worth investigating the unique herding effect of the tourism industry.

2.2. Investor sentiment

This study investigates investor sentiment affecting the tourism stock market based on behavioral finance theories (Baker and Wurgler, 2007) by observing the cross-period of the pandemic.

In previous studies, individual trading information is the most effective source to measure investor sentiment, even the privacy concern disappoints various scholars and obstructs research from accessing personal information (Chi et al., 2012). Unlike other stock indices that are statistically calculated, investor sentiment measures the overall attitude of investors toward the less measurable stock markets. This non-standardized measurement causes limited consensus on calculating investor sentiment in literature. For example, Lee et al. (2002) computed investor sentiment based on the number of bullish newspapers in New York that encourage investors to buy stocks. Baker and Wurgler (2006) measured investor sentiment using six statistical variables: trading volume, dividend premium, closed-end fund discount, number of initial public offerings, first-day returns on initial public offerings, and equity share in new issues. Their conceptualization of investor sentiment has been widely adopted.

Existing literature on investor sentiment stems from fully mature stock markets, such as those in G7 countries (Scheinkman and Xiong, 2003; Baker and Wurgler, 2007; Ma et al., 2018; Rahman and Shamsuddin, 2019), implying that the measurement may not apply to different regional stock markets. Instead of adopting these measurements, we reviewed several economic studies in Chinese journals to devise four time-series conditioning variables that are suitable for measuring investor sentiment in China's tourism stock market: (1) consumer confidence index; (2) turnover; (3) ratio of stock price to earnings per share (P/E ratio); and opening of several A-share accounts. In evaluating the psychological factors of investors, Xue (2005) found that the consumer confidence index is consistent with the sentiment. The consumer information index must be preferred when selecting control variables. Moreover, the numbers of A-share accounts opened are included because investor sentiment positively correlates with account opening. A high investor sentiment index could be related to the accounts opened (Lu et al., 2015; Wu and Han, 2007).

2.3. Relationship between investor sentiment and capital flow

Investors hold unjustified optimistic expectations toward the stock market during a period of high sentiment and thus are further motivated to invest (Baker and Wurgler, 2007). Investors in an elevated mood increase their asset allocation in actively managed funds, whereas those in a low mood allocate more to passively managed ones (Flynn, 2003). This case is reflected by the mutual fund outflows from the bond to the stock market when the investor sentiment index is high (Edwards and Zhang, 1998). Ben-Rephael et al. (2012) investigated the capital shifts between the bond and stock funds to demonstrate how investor sentiment is more realistic and reliable in interpreting capital flow than the market volatility rate. However, Rahman and Shamsuddin (2019) argued that investor sentiment is statistically insignificant when the short-term interest rate and market volatility increase.

Frazzini and Lamont (2008) observed the effect of investor sentiment on capital flows, but mainly with irrational noise traders. As stated previously, the consumer confidence index is consistent with the sentiment (Xue, 2005); thus the index must be preferred when selecting control variables because a high index raises investor sentiment. Rompotis (2010) often used sentiment to express differences in opinions on the index of the turnover rate in the stock market, suggesting sentiment as one of the indispensable indices for selecting variables in the study of behavioral finance. Ju et al. (2015) found that stock price fluctuations and capital flows with sentiment variables follow a linear trend which constructs the fitting degree of the modified equation for correlation regression analysis. Lu et al. (2018) found the correlation between emotional investment and the Granger causality test of industry capital flows and reverse holds. In examining the effect of capital flows, Yi and Wang (2019) found that margin trading and short-selling system enlarge the channel of stock capital flows and the effect of trading capital flows on stocks. The positive effect reflects the fluctuations of the stock market trading mood in the Chinese market. Lucey and Dowling (2005) believed that emotions affect investors' decisions because uncertainty and risk are important influencing factors. Rahman and Shamsuddin (2019) argued that the investor sentiment index synchronously increases the P/E ratio of stocks, but found that the market sentiment index is statistically insignificant when the short-term interest rate and market volatility increase. Jansena and Nahuis (2003) examined the short-term stock lag period and found that stock returns generally cause consumer confidence in a genuinely short time (two weeks to one month), and the reverse holds. The present study suggests that the sentiment index is susceptible and profoundly affects capital flows.

Rao and Liu (2003) used a new angle to explain why closed-end funds trade at a discount and emphasized the importance of behavioral finance. Chen et al. (2003) studied the abnormal volume in China's security market, reflecting inflation and reducing income change using a linear model. The study concluded that the quantitative model is insufficient because investor behavior generally affects market volatility. Since Shen and Wu (1999) argued that an overreaction occurred in China's stock market, Chinese scholars carried out extensive research on the calendar effect in behavioral finance. For example, Peng (2000) studied the herding effect under asymmetric information. Zhang and Jin (2003) uncovered that Chinese investors collect short-term information which shows herding behavior. Wang and Zhao (2001) analyzed inertia and reversal behaviors in China's stock market, showing an apparent yield reversal in the Shenzhen and Shanghai stock markets but without apparent inertia. Flynn (2003) pioneered the study of the relationship between investor sentiment and capital flow.

Regarding investor judgments on the possibility of active management funds defeating passive ones, Flynn (2003) believed that investors in a high mood increase their asset allocation in actively managed funds. In contrast, those in a low mood allocate more to passively managed ones. Odean (1999) found that if retail investors quickly buy another stock after selling one in the first year, the sold stocks behave better than the new ones. Therefore, overconfidence leads to frequent trading.

Therefore, we propose three research hypotheses to test the behavior finance theory (Blackledge and Lamphiere, 2022) on the sentiment index that might affect China's tourism stock market:

H_1: Investor sentiment is positively correlated with the capital flow.
H_2: The tourism market exhibits behavioral finances by examining overreaction in individual capital flows
H_3: The tourism market exhibits behavioral finances by examining overreaction in overall capital flows.

3. Methodology

The time-series analysis of the vector autoregression and the autoregressive-moving-average models are used to analyze individual and overall capital flows that present investor sentiment. This study took samples from the tourism-related sector and tested the influence of the sentiment index on capital flow. Then, different behavioral finance perspectives (Bigné and Decrop, 2019) contributing to the overreaction fluctuation of capital flows in the tourism market was discussed. The COVID-19 pandemic is a notable event to observe the investor sentiment

Table 1
Indicators for financial development and data sources.

Variable	Definition	Source	Reference
ACC	Number of A-share accounts opened in Shanghai and Shenzhen stock markets	China National Bureau of Statistics	Chen et al. (2001)
CCI	This can also be called consumer sentiment and consists of consumer satisfaction and expectation indexes	China National Bureau of Statistics	Jansena and Nahuis (2003)
RET	Rate of return on investments	Wind Database	Lu et al. (2018)
PE	Ratio of stock price to earnings per share	Wind Database	Lu et al. (2018)
TURN	turnover/total number of shares issued in a certain period ×100%	Wind Database	Wang (2014)
volume	Number of shares brokered within a time unit	RESSET Database	Yan et al. (2014)
price	Reference price in the period	RESSET Database	Ju et al. (2015)
float	Circulation of individual stocks during the period	RESSET Database	Ju et al. (2015)
close	Refers to the final transaction price within the period	RESSET Database	Yan et al. (2014)

Note: A dummy variable COV for COVID-19 is set to test the structure difference.

in China's tourism market, which is severely influenced by the control and prevention measures, such as city and destination lockdowns for a long period of time. This replicable empirical study aims to test the unique behavior finance mentioned in Section 2.1, and at the same time, to observe the herding effect of the pandemic via the time-series analysis methods in the tourism industry.

3.1. Methods, samples, and variables

The time-series analysis methods and the developed models are used to test the hypothesis and examine the herding behavior on China's tourism-related investments. In this study, 45 tourism-related stocks that have been categorized and represented in the Shanghai and Shenzhen stock exchanges are selected as research samples. Since the overreaction effect has been studied in the investment market (Griffith et al., 2020), we investigated it in the tourism market from the perspective of behavioral finance (Tadesse and Abafia, 2019) and collected data from 2018 to 2020 quarterly. The data was analyzed using SPSS Statistics 25 and Eviews10 to observe investor sentiment during the COVID-19 pandemic. The original variable data of capital flows are from the RESSET database, while the other variables are from the Wind database and China's National Bureau of Statistics (see Table 1). The period is relatively short, considering the advantage of the event of the time-series data.

Table 2 shows the descriptive statistical result of each variable. From the mean observation, the return rate decreased slightly to −0.035. By contrast, the rest of the variables are all positive, indicating poor returns on tourism stocks during the period $2018Q_1$–$2020Q_4$ because of the pandemic. The ratio difference between the maximum and minimum capital flows is relatively significant, indicating a large fluctuation. Thus, verifying the actual situation from market sentiment is found.

Factor analysis is carried out on investor sentiment indicators because the compound formula of unobserved variables can be better measured (Zhou, 2018), as shown in Table 3. The Kaiser–Meyer–Olkin (KMO) value is 0.568 and reaches a significant level of 0.05, indicating that the data is suitable for factor analysis (Field, 2018).

The number of components, 1 and 2, with eigenvalues greater than one, is shown in Table 4. Their total variance of interpretation is accumulated at 78.691%, which is extracted from the principal component analysis (PCA). Baker and Wurgler (2006) calculated the investor sentiment composite index adjustment using the PCA. Therefore, this study applies the mathematical equations of PCA in measuring investor sentiment, such as (1), (2):

$$F_1 = C_{11} \cdot TURN + C_{12} \cdot ACC + C_{13} \cdot CCI + C_{14} \cdot PE, \quad (1)$$

$$F_2 = C_{21} \cdot TURN + C_{22} \cdot ACC + C_{23} \cdot CCI + C_{24} \cdot PE. \quad (2)$$

Table 2
Descriptive statistics of variables.

Variable	Minimum	Maximum	Mean	Std. Dev
$ACC_{i,t}$	4.339 M	9.138 M	6.235 M	1.460 M
$CCI_{i,t}$	102.900	123.000	114.855	6.931
$RET_{i,t}$	−0.370	0.440	−0.035	0.130
$PE_{i,t}$	−3696.510	1697.280	29.091	298.159
$TURN_{i,t}$	4.000	68.000	23.270	13.384
$volume_{i,t}$	4.272 M	8566.789 M	658.423 M	1222.162 M
$price_{i,t}$	2.450	23.150	6.093	3.023
$float_{i,t}$	72.944 M	9808.486 M	1234.889 M	2311.015 M
$close_{i,t}$	1.580	667.310	72.230	69.276
$F_{i,t}$	1.395 M	2.939 M	2076 M	0.464 M
$flow_{i,t}$	108.238 M	109,807.224 M	14,730.037 M	21,002.728 M
$tflow_{i,t}$	11.260	4742.460	558.642	534.847

Explanation: ACC: Number of A-share accounts opened; CCI: Consumer confidence index; PE: P/e ratio; RET: Rate of return; TURN: Turnover rate; M: Million.

Table 3
Variable KMO and Bartlett's test.

KMO measure of sampling adequacy		0.568
Bartlett's test of sphericity	Approx. Chi-Square	796.715
	Df	6
	Sig.	0.000**

** and * denote a statistical significance at 1% and 5%, respectively.

The sentiment index compound formula is constructed by obtaining the first and second principal components according to the component score coefficient matrix of the market sentiment index in Table 5, as shown in (3) and (4):

$$F_1 = 0.274 \cdot TURN + 0.447 \cdot ACC - 0.448 \cdot CCI + 0.040 \cdot PE, \quad (3)$$

$$F_2 = -0.380 \cdot TURN + 0.071 \cdot ACC - 0.092 \cdot CCI + 0.891 \cdot PE. \quad (4)$$

Therefore, the compound expression of sentiment index is as follows in (5):

$$F = \frac{52.443}{78.691} \cdot F_1 + \frac{26.248}{78.691} \cdot F_2 \quad (5)$$

We obtain the principal component F of the sentiment index by calculating the variables for regression analysis.

The mathematical expression of individual capital flows is constructed as (6):

$$flow_{i,t} = \frac{close_{i,t} * float_{i,t} * RET_{i,t}}{volume_{i,t}}, \quad (6)$$

where $flow_{i,t}$ is the individual capital flows of the estimated i^{est} stock in t quarter, *close* multiplied by *float* is the transaction *price* minus the reference *price*. This formula is used to measure

Table 4
Principal Component Analysis of explanatory variables.

Ingredients	Initial value feature			Extract square sum load		
	Total	Variance %	Cumulative %	Total	Variance %	Cumulative %
Component 1	2.098	52.443	52.443	2.098	52.443	52.443
Component 2	1.050	26.248	78.691	1.050	26.248	78.691
Component 3	0.732	18.301	96.992			
Component 4	0.120	3.008	100.000			

Extraction Method: PCA.

Table 5
Component score coefficient matrix.

Explanatory variable	Ingredient	
	1	2
TURN	0.274	−0.380
ACC	0.447	0.071
CCI	−0.448	−0.092
PE	0.040	0.891

Extraction method: PCA. Two principal components were extracted.

the individual capital flows of the i^{est} stock in the t quarter, multiplied by the return rate *RET* to eliminate noise trading, and then divided by the total turnover *volume* to measure the average individual capital flows of individual stocks (Pagliari and Hannan, 2017). Yan et al. (2014) employed the AR model as a short-term prediction for bank capital flow intensity, suggesting a correlated and relatively general relation in capital flow construction. In the present study, we refer to the capital flow formula as the overall capital flow construction and subsequently implement improvements and debugging.

The mathematical expression of the overall capital flows is as follows in (7):

$$tflow_{i,t} = \sum_{i=1}^{n} \frac{close_{i,t} - price_{i,t}}{price_{i,t}} * \frac{float_{i,t}}{volume_{i,t}} * TRUN_{i,t}, \tag{7}$$

where $tflow_{i,t}$ is the total capital flows of the i^{est} stock in the t quarter, *close* is the transaction *price* of the i^{est} stock in the t quarter, *price* is the reference price of the i^{est} stock in the t quarter, *float* is the circulation of the i^{est} stock in the t quarter, *volume* is the *TURN* over of the i^{est} stock in the t quarter, and *turn* is the turnover rate of the i^{est} stock in the t quarter.

3.2. Descriptive statistics

The augmented Dickey–Fuller (ADF) test determines the time-serial correlation for stationarity (Harris, 1992). Thus, the following models can apply time-series techniques to test the research hypothesis.

Table 6 lists the optimal Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan Quinn (HQ) Criterion for observation because the cross-section and time data are absolute quantities. Logarithmic processing is used to reduce the fluctuation amplitude. The variables are stable at 5%, except for the *price*, which is stable at 10%. Elimination and differential processing are skipped to prevent losing a large amount of data.

Normality tests were conducted using the EVIEWS Autocorrelation Test Serial correlation, which refers to the study in which the error term in one period is correlated with the error term in any other time period. The Breusch–Godfrey serial correlation LM test was employed to test for serial correlation, as indicated in Table 7. Results indicate that the null hypothesis of no serial correlation is not rejected at a 5% level of significance, as indicated in Table thus, the residuals are not correlated. Residual Serial Correlation LM Test shows that there is no serial correlation at lag length 4.

3.3. Empirical analysis

3.3.1. Individual capital flows

The unit root test of the random model is carried out on the panel data of individual capital flows. We used the summary form and ADF formula containing intercept items without trends, as shown in Table 8. The result is significant without a unit root; thus, the time series is stationary. The LLC and Breiting test formulas initially assume that a unit root exists without exogenous variables. Thus, according to the variables, the expression formula is (8):

$$\Delta flow_{i,t} = \rho_i flow_{i,t-1} + \sum_{j=1}^{k} \gamma i, t - 1 \Delta flow_{i,t-j} + u_{i,t.} \tag{8}$$

According to Table 7, the non-stationary sequence with unit root is originally assumed to be rejected in LLC and Breiting tests; thus, a sequence is stationary when (8) contains an intercept term and non-trend direction.

The individual capital flows are analyzed according to the panel section. The Redundant Fixed Effect Tests of independent variables in the Fixed Effect model rejected the null hypothesis. Instead, we used the Random Effect model and found that the null hypothesis is accepted in the Hausman test, as shown in Table 8. A correlation is observed between the coefficient and the p-value of independent variables. The non-stationary sequence with a unit root rejects the null hypothesis in the LLC, and Breiting tests show a positive coefficient. This finding demonstrates that when compound sentiment index F is high, the explained variable *flow* is positive, implying the occurrence of behavioral finance.

The variable intercept model of the Random Effect is (9):

$$flow_{i,t} = \alpha + \sum_{i=1}^{k} \beta xi, t + u_i + v_{i,t,} \tag{9}$$

where $i = 1, 2 \ldots N$ is expressed as a total of i stocks, and $t = 1, 2 \ldots T$ is the period in the t quarter.

Table 9 shows that the coefficient of F is positive, which means that the explanatory variable *flow* increases by 1. In the same period, the explanatory variable F increases by 1.9, indicating that the influence of the sentiment index on capital flows is positive. Thus, H_1 is sustained. In addition, the case of (8) contains an intercept term and non-trend direction and is a stationary sequence. The random model regression equation is as follows in (10):

$$flow_{i,t} = -4.410 + \beta \cdot 1.97E - 06 \cdot F_{i,t.} \tag{10}$$

We then set up a Panel VAR model based on the panel data to predict and analyzed the individual capital flows, as shown in (11). According to the four periods of quarterly data lag as selection parameters, the mathematical equation of the VAR model is as follows in (11):

$$\begin{gathered} flow_{i,t} = A_1 flow_{i,t-1} + \cdots + A_4 flow_{i,t-4} + \varepsilon_t; \\ flow_{i,t-1} = \begin{bmatrix} flow \\ F \end{bmatrix}. \end{gathered} \tag{11}$$

Table 6
Stationarity test of variables and optimal AIC, SC, HQ without difference.

Variable	(C, T, k)	t-Statistic	AIC	SC	HQ	Prob.**	Result
$ACC_{i,t}$	(0, 0, 1)	−7.942	27.722	27.789	27.749	0.000**	Steady
$CCI_{i,t}$	(C, T, 3)	7.207	4.115	4.182	4.142	0.000**	Steady
$RET_{i,t}$	(C, 0, 1)	−5.961	−1.272	−1.189	−1.239	0.000**	Steady
$PE_{i,t}$	(C, 0, 1)	−6.905	10.189	10.271	10.222	0.000**	Steady
$TURN_{i,t}$	(C, 0, 1)	−4.106	9.684	9.770	9.719	0.001**	Steady
$volume_{i,t}$	(C, 0, 1)	−6.565	43.344	43.397	43.365	0.000**	Steady
$price_{i,t}$	(0, 0, 1)	−1.776	4.802	4.842	4.818	0.072	No
$float_{i,t}$	(C, 0, 1)	−5.705	44.640	44.689	44.659	0.000**	Steady
$close_{i,t}$	(C, T, 0)	−7.767	6.379	6.402	6.388	0.000**	Steady
$lnF_{i,t}$	(0, 0, 3)	−7.624	−3.202	−3.130	−3.173	0.000**	Steady
$flow_{i,t}$	(0, 0, 1)	−4.355	48.232	48.248	48.238	0.000**	Steady
$tflow_{i,t}$	(C, 0, 1)	−12.249	1.845	1.861	1.851	0.000**	Steady

Note: (C, T, k) where C is the intercept term; T is a trend item; k is the lag order; The lag order is based on SIC criterion. **denotes a statistical significance at the 1% level.

Table 7
VAR residual serial correlation LM test.

Lags	LM-Stast	Prob.*
1	49.88797	0.0031
2	43.51474	0.0312
3	27.11310	0.5738
4	13.61785	0.9495

Table 8
Unit root test of individual capital flow.

Method	Statistic	Prob.*	Cross-sections	Obs
Null: Unit root (assumes a common unit root process)				
Levin, Lin, & Chu t*	−6.081	0.000	45	915
Null: Unit root (assumes an individual unit root process)				
ADF—Fisher Chi-square	38.225	0.000**	45	915
PP—Fisher Chi-square	36.841	0.012*	45	963

Note: Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality. ** and * denote a statistical significance at 1% and 5%, respectively.

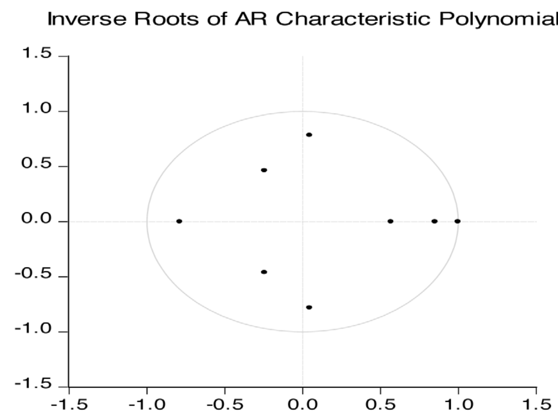

Fig. 2. Individual capital flow and compound sentiment index F and its 8 endogenous variables lags 1 to 4.

The VAR is chosen as the unconstrained model in this study. All variables can be expressed as explained ones, including the lag period of each variable, where *flow* is expressed as the capital flows of i stock in $t, t-1, \ldots, t-4$ lag period, A is the estimated value, and F is the composite sentiment index.

Table 10 shows the modular relative value of the characteristic roots. The VAR model has two endogenous variables and the lag length is 4 based on the sequential modified likelihood ratio (LR) test (Lütkepohl, 2005). Therefore, eight characteristic roots are present. When the modular reciprocals of all characteristic roots are less than 1, the Panel VAR (1, 4) model is stable, as shown in Fig. 2, the modulus reciprocal distribution of AR characteristic roots are all in the unit circle. We judged the relationship between the variables according to the causality test proposed by Granger (1969), which is expressed in the bivariate P-order VAR model, as follows in (12):

$$\begin{pmatrix} flow_{i,t} \\ F_t \end{pmatrix} = \begin{pmatrix} \phi_{10} \\ \phi_{20} \end{pmatrix} + \begin{bmatrix} \phi_{11}^{(1)} & \phi_{12}^{(1)} \\ \phi_{21}^{(1)} & \phi_{22}^{(1)} \end{bmatrix} \begin{pmatrix} flow_{i,t-1} \\ F_{t-1} \end{pmatrix} + \begin{bmatrix} \phi_{11}^{(2)} & \phi_{12}^{(2)} \\ \phi_{21}^{(2)} & \phi_{22}^{(2)} \end{bmatrix} \begin{pmatrix} flow_{i,t-2} \\ F_{t-2} \end{pmatrix} + \begin{bmatrix} \phi_{11}^{(3)} & \phi_{12}^{(3)} \\ \phi_{21}^{(3)} & \phi_{22}^{(3)} \end{bmatrix} \begin{pmatrix} flow_{i,t-3} \\ F_{t-3} \end{pmatrix} + \begin{bmatrix} \phi_{11}^{(4)} & \phi_{12}^{(4)} \\ \phi_{21}^{(4)} & \phi_{22}^{(4)} \end{bmatrix} \begin{pmatrix} flow_{i,t-4} \\ F_{t-4} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} \tag{12}$$

The coefficients $\phi_{12}^{(1)}, \phi_{12}^{(2)}, \phi_{12}^{(3)}, \phi_{12}^{(4)}$ in the matrix (12) are not all 0, and variable F can cause variable *flow* by Granger, complying with the endogenous variables in Fig. 2. Table 11 shows the results that reject the null hypothesis at the significance level of 5%. Compound sentiment index F is the Granger cause of individual capital flows, which is also true. The two variables have mutual prediction ability.

The individual capital flow in this study has two variables, F and *flow*, and thus two regression equations form the VAR model. We select the numerical output of VAR (1, 4) as Table 12 according to the lag period. The model is carried out via a stochastic approach, and the parameters have no uncertainties. Thus, the confidence bands are simply 0 (Blasques et al., 2016). Apparently, the absolute value of T in equation *flow* (absolute value is greater than 1.96 as the benchmark) has one explanatory variable in the lag period and four explanatory variables in the lag period of equation F. These numerical comparisons fully illustrate the dynamic relationship between the two variables.

Substituting the numerical value into Eq. (12), the regression equation for its VAR model estimation is shown in (13):

$$\begin{pmatrix} flow_{i,t} \\ F_t \end{pmatrix} = \begin{pmatrix} \phi_{10} \\ \phi_{20} \end{pmatrix} + \begin{bmatrix} 1.12 & -2,008.23 \\ 1.57 * 10^{-6} & 0.12 \end{bmatrix} \begin{pmatrix} flow_{i,t-1} \\ F_{t-1} \end{pmatrix} + \begin{bmatrix} -0.16 & -7,815.47 \\ -2.56 * 10^{-6} & 0.10 \end{bmatrix} \begin{pmatrix} flow_{i,t-2} \\ F_{t-2} \end{pmatrix} + \begin{bmatrix} 0.18 & 3,956.13 \\ -6.15 * 10^{-7} & 0.01 \end{bmatrix} \begin{pmatrix} flow_{i,t-3} \\ F_{t-3} \end{pmatrix} + \begin{bmatrix} -0.14 & 6,030.85 \\ 1.75 * 10^{-6} & 0.38 \end{bmatrix} \begin{pmatrix} flow_{i,t-4} \\ F_{t-4} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} \tag{13}$$

Table 9
Individual capital flow and panel return of sentiment index.

	Test summary	Chi-Sq. statistic	Chi-Sq. d.f.	Prob.*
	Cross-section random	0.201	1	0.654
Variable	Coefficient	Std. Error	*t*-Statistic	Prob.*
C	−4.410	1.327	−3.322	0.001**
F	$1.97*10^{-6}$	$6.44*10^{-7}$	3.056	0.002*
R-squared		0.225		
Adjusted R-squared		0.143		
F-statistic		2.742		
Prob(F-statistic)		0.000		

Correlated Random Effects—Hausman Test and Cross-section random effect test equation: Dependent Variable: flow; Method: Panel Least Squares. ** and * denote a statistical significance at 1% and 5%, respectively.

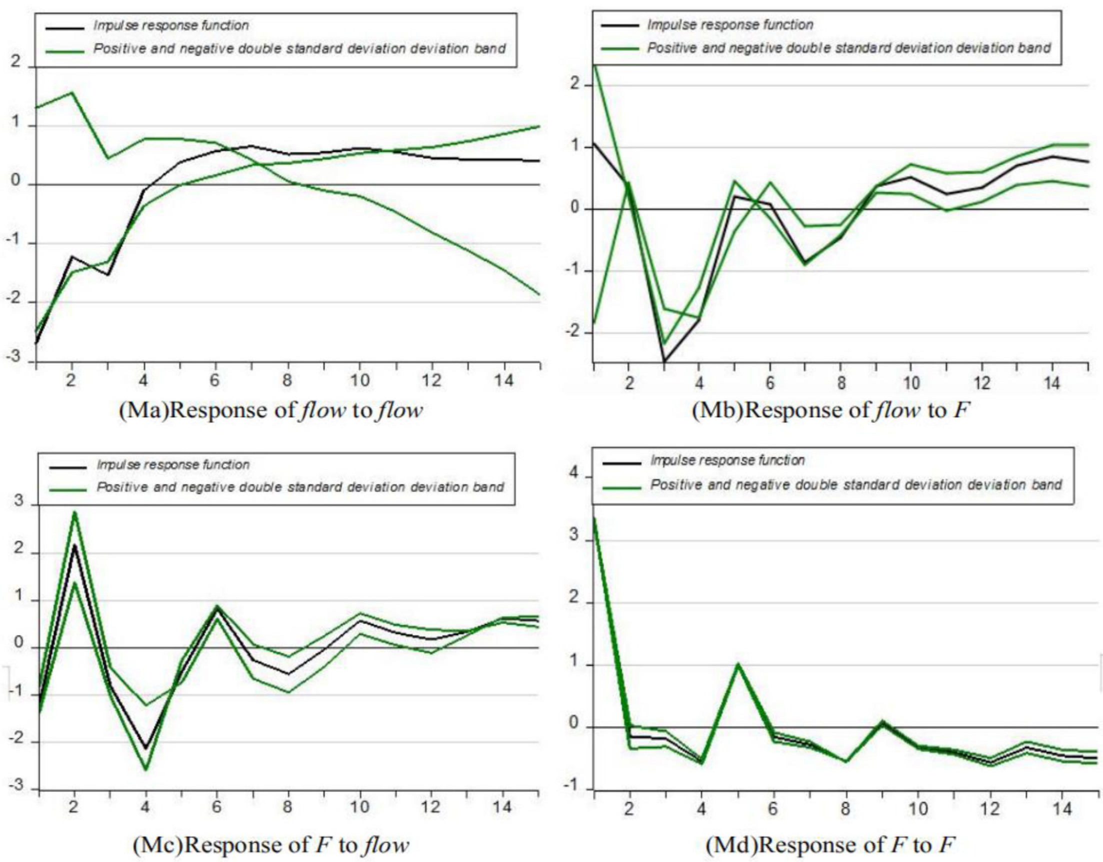

Fig. 3. Individual capital flows and sentiment index that multiple graphs in the VAR model.

Table 10
flow and *F* stability condition check result in the VAR model.

Root	Modulus
0.999	0.999
0.851	0.851
−0.787	0.787
0.047 − 0.782i	0.784
0.047 + 0.782i	0.784
0.569	0.569
−0.244 − 0.463i	0.523
−0.244 + 0.463i	0.523

Lag specification: 4; No root lies outside the unit circle; VAR satisfies the stability condition.

In the VAR model, the goodness of fit of the variable *flow* equation is 0.962, while that of the variable F equation is 0.938, which achieves relatively good results. The better goodness of fit of the former indicates that the VAR model has a high degree of extraction of the equations of the two variables. We pulsed the dynamics, and the response analysis is summarized as follows: Fig. 3 shows the result of the impulse response function in the VAR model. Fig. 3 (Ma) shows that individual capital flows *flow* fluctuates from the current to the fourth period in its positive impact. The flow tends to stabilize from the fourth period and remains positive. Fig. 3 (Mc) mainly shows that individual capital flows fluctuate significantly in the first six periods after being positively affected by investor sentiment index F, reaching the maximum in the second and fourth periods. (The responses are: $\theta_7^{(2)} = 2.2$ value, $\theta_7^{(4)} = -2.1$ value). During the current period, the effect on individual capital flows is positive. Two times of positive information feedback are observed, which is consistent with the test in the random model. Thus, the irrational investment from the sentiment index in individual capital flows in the current period is quite intense and gradually tends to stabilize after the 7th period. However, the effect in the later period

Table 11
Granger relationship test between sentiment index and individual capital flows.

Original hypothesis	Chi-sq	df	Prob.	Test result
Sentiment index is not Granger cause of individual capital flows	13.369	4	0.010**	Reject the original hypothesis
Individual capital flows is not Granger's reason for sentiment index	10.073	4	0.039*	Reject the original hypothesis

VAR Granger Causality/Block Exogeneity Wald Tests. ** and * denote a statistical significance at 1% and 5%, respectively.

Table 12
Individual Capital Flow and VAR Estimation Model results of the sentiment index.

Lag period of variables	Estimated value of flow	Estimated value of F	Standard value of flow	Standard value of F	T value of flow	T value of F
flow (−1)	1.116	$1.57*10^{-6}$	(0.061)	$(6.9*10^{-7})$	[18.362]	[2.269]
flow (−2)	−0.160	$-2.56*10^{-6}$	(0.092)	$(1.0*10^{-6})$	[−1.752]	[−2.459]
flow (−3)	0.182	$-6.15*10^{-7}$	(0.097)	$(1.1*10^{-6})$	[1.868]	[−0.555]
flow (−4)	−0.139	$1.75*10^{-6}$	(0.082)	$(9.4*10^{-7})$	[−1.688]	[1.866]
F (−1)	−2008.226	0.121	(3791.400)	(0.043)	[−0.530]	[2.810]
F (−2)	−7815.467	0.101	(3699.800)	(0.042)	[−2.112]	[2.405]
F (−3)	3956.131	0.006	(2830.930)	(0.032)	[1.397]	[0.175]
F (−4)	6030.853	0.385	(2633.940)	(0.030)	[2.290]	[12.838]
C	$-3.43*10^{9}$	390,196.000	$(2.1*10^{9})$	(23,469.100)	[−1.664]	[16.626]
R-squared		*flow* 0.963		*F* 0.938		
Adj. R-squared		*flow* 0.961		*F* 0.936		
F-statistic		*flow* 887.136		*F* 523.437		

Note: Variables are generally not eliminated in the VAR model due to their lag significance. We keep all the remaining insignificant variables to construct the equation.

is not too large, indicating that investors feedback the rational investment in the current period to the market in one and a half years. H_2 is supported, indicating that the tourism market overreacts to the individual capital flow.

3.3.2. Overall capital flows

After the single variable of the overall capital flows is processed through the stationary sequence, we use the least-squares (LS) method to observe the tailing of the model. The ACF graph shows clear tailing, while the PACF graph shows a slight one. The lag item is also found to fluctuate excessively and becomes messy after processing through the first and second differences. Therefore, the quasi-side of the ARIMA model without a difference is selected and called the ARMA model. This choice is motivated by the following reasons: (i) the model is independent of the mean overall capital flows, and thus we can observe the abnormal financial behavior; (ii) the time-invariant behavior is comparable to the modeling assumption that all time-dependent parameters variations of the investment system are usually neglected in the case of behavioral finance; and (iii) as the behavior finance occurs, wave reflections at discontinuities of the average trend may occur (Hackstein et al., 2020). The ARMA (1, 1) model is established by AIC minimum quasi-lateral selection for analysis and conforms to the (C, 0, 1) analysis of Table 6 $tflow_{i,t}$ according to the optimal lag term selection.

The expression of the ARMA model for the overall capital flows is shown in (14):

$$\begin{aligned} tflow_{i,t} &= c + \alpha_1 F_{t-1} + \alpha_1 tflow_{t-1} + \alpha_2 tflow_{t-2} + \cdots \\ &\quad + \alpha_q tflow_{t-q} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \theta_q \varepsilon_{t-q.}, \end{aligned} \tag{14}$$

and then transformed into (15):

$$tflow_{i,t} = c\cdot(1-ARp)+ARp\cdot tflow_{t-1}+F_{i,t}\cdot c+\hat{\upsilon}_t-MAq\hat{\upsilon}_{t-1}, \tag{15}$$

where $tflow_{i,t}$ represents the total capital flows of the i^{est} stock in t quarter, α is the coefficient, and F_{t-1} and $tflow_{t-1}$ are the correlation sequences of different lag orders corresponding to independent and dependent variables, respectively.

Table 13 is the ARMA model that selects data with different lags. The coefficient reaches a significant level. Preliminary observation ARMA (1, 1) shows the best fit model, and parameters are selected according to AIC, SC, and HQ minimum criteria. Table 12 shows that ARMA (1, 1) has two minimum items. Therefore, we use one model with each lag as an estimation, and its regression equation expression is shown as (16):

$$\begin{aligned} tflow_{i,t} &= -9.08\cdot(1-0.666488)+0.666\cdot tflow_{t-1} \\ &\quad + F_{i,t}\cdot 1.031 + \hat{\upsilon}_t - 0.145\hat{\upsilon}_{t-1}. \end{aligned} \tag{16}$$

The residual Q test is carried out on the main sentiment index F and the total fund flow *tflow* for the White noise test. The p values both accept the independent null hypothesis at the level of 5%. Moreover, the Q value is less than the critical value at the 5% level, which means the data show a white noise sequence. By contrast, the White noise test accepts the null hypothesis and does not need to modify the ARMA (1, 1) model. Thus, it is not necessary to further verify the existence of ARCH effect. As such, the null hypothesis H_3 is not rejected, indicating that the market is not overreacting to the overall capital flow.

In the ARMA model, the adjusted R^2 side explains 40.75% of the sample information, and the same sentiment index influence coefficient in the lag item (1, 1) model is also positively correlated. Table 14 presents the predicted value. A significant prediction gap occurred in Q_1 and Q_2 in 2020, and the latter has a large prediction error. The predicted values for Q_3 and Q_4 are stable. Possibly, the regression results of the lag item at the end of the year have a sound effect, and a rational investment approach exists.

The dummy variable COV, Covid-19, is added to the overall capital flows to isolate the period of 2020Q_1–2020Q_4, given that this period systematically differs from others in the data set. The structural break in the time series shows a more convincing argument for the pandemic effect. The test rejects the null hypothesis of having no structural break, which is detected in the fourth month of 2020 (Table 15).

4. Results and discussions

The independent variable, change of capital flows, is analyzed through factor analysis and principal component dimension reduction to obtain market sentiment indices. The sentiment

Table 13
Regression results of ARMA model.

Type	ARMA (2, 2)	ARMA (2, 1)	ARMA (1, 2)	ARMA (1, 1)
C	P**.0.000	P**.0.000	P**.0.000	P**.0.000
F	P**.0.000	P**.0.000	P**.0.000	P**.0.000
AR (1)	P.0.692	P.0.156	P**.0.000	P**.0.000
AR (2)	P.0.559	P.0.761	–	–
MA (1)	P.0.754	P.0.588	P.0.091	P*.0.043
MA (2)	P.0.174	–	P.0.414	–
Coefficient-C	–	–	−9.034	−9.082
Coefficient-F	–	–	1.028	1.031
Coefficient-AR (1)	–	–	0.712	0.666
Coefficient-MA (1)	–	–	−0.172	−0.145
AIC	1.723	1.509	1.509	1.504
SC	1.766	1.553	1.553	1.548
HQ	1.740	1.526	1.526	1.521
R-squared		–	0.414	0.413
Adjusted R-squared		–	0.408	0.408
F-statistic		–	66.256	82.328
Prob(F-statistic)		–	0.000	0.000
Sum squared resid		–	118.215	118.611

Dependent Variable: tflow. Method: ARMA Maximum Likelihood (OPG - BHHH). Included observations: 530.
** and * denote a statistical significance at 1% and 5%, respectively.

Table 14
Average forecast value after summing 45 stocks.

	$2020Q_1$	$2020Q_2$	$2020Q_3$	$2020Q_4$
True	5.997	5.039	5.175	5.112
Forecast	5.784	5.613	5.574	5.507
Error	3.540%	11.410%	7.720%	7.720%

Table 15
Structural break test.

Test	Statistic	*p*-value
Supremum Wald	14.4180	0.000**_

Note: Observations: 530. ** and * denote a statistical significance at 1% and 5%, respectively.

index is positively correlated with capital flows at the individual level, which is in line with behavioral finance features. However, the sentiment index requires further fluctuations to affect the corresponding capital flows of the tourism stock sector; that is, additional transactions or favorable and unfavorable indices have limited influence on the capital flows. In the VAR model, the individual capital flows in the current period are significantly affected by investor sentiment. After the pandemic period is positively affected, the capital flows continue to rise in the next six months and then reach normal levels. We argue that China's investment quota has a particular, trailing effect on capital flows. The irrational investor behavior is affected in the short term, declines in the next six months, and returns to a stable status. The fluctuation implies an emotional investment behavior that occurs during the six months, likely the internal spillover emerging from the 1st to the 2nd period.

The total capital flows are found relatively stable in the tourism stock market. The effect index is nearly 1:1, with lagging capital flows in applying the rational investment models. The result reveals that institutional holdings in the overall capital flow stabilize the market, which is similar to the result of Yang (2013) that investor sentiment has a weak correlation to overall capital flows. The results explain a high *R*-side, an essential indicator in this time-series analysis. Compared with the findings of Jansena and Nahuis (2003), the one-quarter delay of capital flow index in the ARMA model is affected by the composite sentiment index of the previous quarter. This result also shows no emotional investment behavior in overall cash flows.

Overreactive trading is more likely to exist in the tourism industry than in the overall industry based on the casualty of the sentiment index and individual capital flows. Yan et al. (2014) indicated that the tourism industry has dispersed stability and prominent volatility at the beginning of a quarter due to behavioral finance, and tourism industry is also prone to noise trading. Frazzini and Lamont (2008) believed that stocks with high investor sentiment often occur in the growth stage. Using COVID-19 pandemic as an example, investor sentiment refers to the short-term reaction of the pandemic, whereas the economic resilience contributes to long-term stability in returns. Since investor sentiment in individual stock affects individual capital flows, it is concluded that personal investors in China's tourism market have a "herding effect", indicating that the stock market is easily influenced by individual investor sentiment (Ouyang and Li, 2018).

5. Conclusions

5.1. Conclusion and contribution

Theoretically, this study contributes an economic model of emotional investment, which explains the internal overreaction effect in the tourism market based on the price-to-price feedback theory of behavioral finance through time-series analysis. The results help infer the external volatility spillover in China's tourism market. Risk adjustment of investment in China's tourism market needs to be considered because of the existence of the herding effect; thus, the EMH's risk-and-returns premium might be adjusted by the investor sentiment in the tourism industry. According to the results of emotional investment, China's tourism market is vast and has potentially higher risks and returns. The capital flows in a specific period are relatively active in revealing information caused by investor sentiment. Therefore, investor sentiment must complement the EMH to explain China's tourism market.

The theoretical contribution has been presented on the methodological approach by applying time-series analysis methods to explain the herding behavior of the pandemic event in the tourism stock market. The practical contribution of this study is to find out the different patterns of herding effect and sentiment effect in tourism that are different from other industries. Specifically, unlike other sectors, the herding effect in tourism stock market is observed in the short term and reached a stable status in longer period, This study further pointed out that investor sentiment towards the pandemic is a short-term reaction, whereas economic resilience is needed for long-term returns stability. The findings promote the need of an effective strategy for decision-making guidelines for tourism stocks during distractions such as the COVID-19 pandemic. Coexisting with the virus strategy is an alternative to alleviate investor sentiment for tourism resilience, restoring traveler confidence, and recovering the tourism sector. st

5.2. Implication and limitation

Owing to the influence of COVID-19 pandemic's on the tourism industry, listed companies should develop and launch resilient projects focusing on investors' sentiment during the post-pandemic era. As herding behavior has been found in the tourism market with different behavioral patterns among different industries, there is a need for effective strategies to maintain the value of tourism and foster the trust of tourists to reduce the perceived risk of various events, including the pandemic. Thus, investor sentiment can be softened for the tourism industry resilience.

As limitations, variables in the research may not be completed for other periods or that behavioral finance remains a supplemental principle of EMH. Further, the coefficient value estimated by investor sentiment is much larger than the coefficient value of individual capital flows, which means the range of the two variables is very different from being likely to cause the results of VAR estimation to be different. We keep the data format instead of data transformation to prevent losing the data attributes of the two variables. There are SVAR, SpVAR, SpSVAR, and ISpSVAR with structural or spatial effects that can conduct data analysis, which depends on the research purpose, and assumptions. In addition, investor sentiment is much larger than the coefficient value of individual capital flows in the research model. This is mainly because the range of the two variables is very different, and this factor is likely to cause the results of VAR estimation to be different. Despite the limitations, the study provides a sense of knowledge in the world that has become extremely volatile over an extended period, such as the pandemic period. The reality is that behavioral finance lacks integrated theories and approaches, necessitating the application of general methodology such as the time-series analysis applied in this study. Future research could conduct replicated studies or a comprehensive investigation of cross-industry comparison for general or economic perspectives.

CRediT authorship contribution statement

Kang-Lin Peng: Conceptualization, Methodology, Formal analysis, Model construction, Writing – original draft, Supervision. **Chih-Hung Wu:** Software, Writing – review & editing. **Pearl M.C. Lin:** Resources, Data curation, Writing – review & editing, Validation. **IokTeng Esther Kou:** Writing – review & editing.

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