Overconfidence Bias in Equity Market: A Comparative Analysis of Market Uncertainty and Tranquil Periods in Asian Economies

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Abstract. The current study aims to examine the phenomenon of overconfidence bias in Asian stock markets, encompassing both market stress and tranquil periods. Utilizing daily data spanning from January 1, 2013, to April 30, 2023, the study employed bivariate vector autoregression (VAR) models and impulse response functions. The findings of the VAR model yield several significant conclusions. First, within our sample period, a notable and substantial correlation between market return and volume seems more prominent in advanced and rapidly expanding emerging markets such as China. Further, investors are more confident in the advanced market during the turbulence caused by the Covid-19 lockdown. The findings indicate that throughout the Russia-Ukraine crisis, Chinese and Thai investors exhibited assertive, overconfident behaviour. The implications of overconfidence bias, which ranges from investor protection to economic stability, demonstrate the significance of understanding and addressing behavioural biases in financial decision-making. This study is one of the early attempts to examine the empirical evidence of overconfidence bias at a cross-country level in the aftermath of the recent global crisis.

Keywords: Overconfidence Bias, Behavioral Finance, Vector Autoregression, Asian Equity Markets..

1 Introduction

Standard finance theories such as the capital asset pricing model (Sharpe 1964; Linter, 1965; Mossin, 1966), efficient market hypothesis (Fama, 1963, 1965), arbitrage opportunities (Modigliani & Miller, 1958) and others are developed to provide mathematical explanations for the problems raised in the financial markets. A specific set of assumptions that excessively oversimplify the actual situation serves as the foundation for conventional financial theories. For instance, all standard finance theories assume that all investors should behave rationally in the market and have equal access to information. It implies that there will always be ideal market circumstances, and investors make logical economic decisions. In the late 1980s, authors relaxed these assumptions and highlighted the importance of psychological, sociological, and

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highlighted the importance of psychological, sociological, and emotional factors in investment decision-making (Shiller, 1984). Within this framework, behavioural finance developed as a separate discipline to supplement the advancement of contemporary finance theory (Pompian, 2006; Shleifer, 2000; Shiller, 2003). It attempts to understand the psychological phenomena of an investor and how human psychological phenomena drive the financial markets.

The literature on behavioural finance makes the case that investors may not always consider the cost-benefit ratio and may choose to stray from the best course of action (Tversky and Kahneman, 1979; Simon, 1955). This causes stock returns to deviate from intrinsic value and raises the possibility that a financial bubble will form (Shiller, 2000; Shleifer & Vishny, 1997; Statman et al., 2006). Overconfidence bias is one such phenomenon that behavioural scientists and psychologists have been interested in over the past few decades. Overconfidence bias involves excessive trading that has contributed to the financial crises. Overconfidence bias occurs when investors overestimate their knowledge's reliability and capacity to make wise, analytical financial decisions (Bruno et al., 2005; Huang et al., 2022). When investors are overconfident, they think they have better information than others or have an advantage over others in terms of experience, knowledge, and other aspects of investing from which they hope to make money. These investors are more likely to trade, which raises market volume (Statman et al., 2006; Glaser & Weber, 2009).

The empirical literature on overconfidence bias in financial markets can be broadly categorized into two groups: the first group includes approaches that study overconfidence bias using market data (Statman et al., 2006; Chuang et al., 2014; Chuang & Susmel, 2011; Prosad et al., 2017; Shrotriya & Kalra, 2021; Huang et al., 2022; Ganesh et al., 2020). In contrast, the second group focuses on approaches that study overconfidence among investors using surveys, experiments and transaction history-based data (Chen et al., 2007; Kim & Nofsinger, 2007; Senol & Onay, 2023; Filiz et al., 2021; Zhang et al., 2019). This study deals with the first strand, which has macroeconomic implications for Asian economies. Notably, research on overconfidence bias is primarily restricted to established markets, with relatively little effort dedicated to this facet of overconfidence in developing economies. This study extends the literature by analyzing a broader range of Asian markets using a more extensive dataset, providing a comprehensive understanding of overconfidence behaviours in the region.

Moreover, the earlier studies focus on different market conditions, such as market volatility and risk (Chuang et al., 2014; Chuang & Susmel, 2011). Kim and Nofsinger (2007) study the impact of the developed market gain on overconfident trading behaviour in Asian markets. This study further extends the discussion and argues that the market prices can deviate dramatically from their underlying values over a protracted period, as demonstrated by the current Russia-Ukraine conflict, the Covid-19 outbreak and the global financial crisis. These instabilities decrease the level of investors' trust and confidence in the market, which hampers the market liquidity. Therefore, it is vital to study and quantify the overconfidence phenomenon in stock markets so that regulators can take the necessary actions to maintain investors' trust. Studies focused on examining investors' confidence during such downturns are nascent.

Current work aims to fill these gaps and contributes to the overconfidence bias literature in multiple ways. First, we provide evidence on investor confidence using a comprehensive dataset from January 2013 to April 2023, as this period covers economic concerns and disasters, including the Russia-Ukraine war, the Covid-19 outbreak, and the high inflation period. Further, throughout the sample period, we offer a comparative examination of investor overconfidence in advanced, rapidly growing emerging and emerging markets of the Asian region. Lastly, we provide an overview of investor overconfidence in the crisis period of the Covid-19 pandemic and the Russia-Ukraine war. Using a market-wide Vector Autoregressive (VAR) model based on the lead-lag relationship between historical market return and trading volume, We find significant evidence of overconfidence bias in Advanced and fast-growing emerging economies. However, a lack of investors' confidence in the stock market was reported during the market uncertainty, which suggests the intervention of regulators and policymakers to boost the investors' confidence in the market. The remaining part of this paper is as follows: Section 2 summarises the body of research on overconfidence bias and hypothesis development. Section 3 discusses the empirical design, followed by the data description in Section 4. Our empirical results are presented in Section 5. The policy implications, conclusion and further research areas are covered in Sections 6 and 7, respectively.

2 Literature Review and Hypothesis Development

Numerous psychologists and academicians have demonstrated that people typically overestimate their correctness regarding knowledge, which leads to overconfidence in their behaviour (Fischoff et al., 1977; Taylor & Brown, 1988). Daniel et al. (1998) and Odean (1998) consider investors' propensity to overvalue their personal information and create general equilibrium models of the capital markets that can better account for market anomalies. In an online survey of 3,000 participants, Glaser and Weber (2007) showed that traders who thought they had above-average investing skills traded more frequently. The degree of overconfidence bias and investment horizon is directly correlated (Kinari, 2016). Overconfidence bias in financial markets arises when investors overestimate expected gains while undervaluing potential risks (Tecke & Yilmaz, 2015; Shrotryia & Kalra, 2021).

Chordia et al. (2000) examined the degree to which information is priced and the cross-autocorrelation between trading volume and returns based on daily stock-market data. Using monthly data from August 1962 to December 2002, the authors investigated the relationship between market return and increased market trading volume (Statman et al., 2006). They conclude that successful investing (increase in market returns) raises the overconfidence levels of investors and subsequently increases trade volume. Ekholm and Pasternack (2008) examined the association between investor overconfidence and market trading volume using a vector autoregressive (VAR) model on the monthly data of the US stock market. They opposed that high returns cause investors to become overconfident, which increases trading volume. Zaiane (2013) found that the trading volume on the Chinese stock market and lagging market returns have a positive association, with the first lag being considerable and confirming the overconfidence theory. Prosad et al. (2017) and Azam et al. (2022) exhibit an overconfidence bias in Indian markets towards the Nifty 50 stocks at both the market and security levels. Similar results were reported by Zia et al. (2017) on the Karachi stock exchange.

The current globalization process has increased market correlations and economic interdependence, which has increased correlation returns in equity markets (Gebka & Serwa, 2015; Ferreruela et al., 2022). This association may include the actions of investors. It is probable that this overconfidence bias will spread to other marketplaces when fresh information enters the market, making it impossible to benefit from diversification. Moreover, international investments and regional economic alliances in Asian markets, such as the Asia-Pacific Economic Cooperation and Association of South East Asian Countries, enhance the interaction among stock markets. Understanding the investor's behaviour across the region will help the investors by increasing the diversification benefits. Therefore, the current study aims to investigate the presence of overconfidence-driven trading in Asian markets in light of the severity of market shocks and their impact on the volume of stocks traded in Asian markets. Therefore, the study proposes the first alternative hypothesis:

H1. There is a notable overconfidence bias in the Asian equity markets.

The highly developed market is generally treated as more regulated, safe, and IT-driven than developing and frontier markets. Many emerging and frontier markets are still lagging in terms of financial awareness (the number of investors in comparison to the overall adult population is very low, high investment in traditional assets, etc.), inclusion (number of adults having bank accounts, number of bank branches, ATMs, etc.) and regulatory frameworks (more number of economic downturns, corporate governance failure, etc.) (Bommer et al., 2023). Moreover, historical experiences show that people's behaviour in emerging and frontier markets is significantly different (Verma, 2023). Therefore, brief shreds of evidence can be drawn about the difference in overconfidence bias concerning the two economic development levels. We use the IMF 2023 economic outlook classification for comparative analysis. To observe this difference in terms of investor overconfidence, we posed our second hypothesis:

H2. There is a notable difference in investors' overconfidence levels between developed and emerging markets.

Notable volatility was observed in financial markets during the recent economic downturn induced by the Covid-19 pandemic and the Russia-Ukraine war. Haroon and Rizwi (2020) show that there is an inverse relationship between the volume of Covid-19 instances and trading or liquidity in the stock market. Therefore, maintaining market liquidity and investors' confidence in the stock market during such uncertainty is important. Kuranchie-Pong and Forson (2021) and Shrotryia and Kalra (2021) explain the investor overconfidence during the Covid-19 pandemic and reported mixed evidence. The literature explaining the role of behavioural factors such as overconfidence bias in the market downturn is still at a nascent stage. Limited context-specific and mixed evidence in the literature motivates us to study this difference. In line with this, we proposed our third hypothesis:

H3. There is a notable overconfidence bias in the Asian equity markets during the market uncertainty.

3 Empirical Design

3.1 Vector Autoregressive Model (VAR)

An investor's confidence in his investments grows with each incremental increase in the observed market return. Consequently, investors will likely invest more aggressively in that security (Statman et al., 2006). As a result, the market's aggregate trading volume will experience an upward trend. This increase in trading activity results in a positive coefficient between market return lag and trading volume. The overconfidence hypothesis is supported by this observation, which exemplifies the theory of the lead-lag relationship, in which the lead variable (market volume) is cross-connected with the lag variable (market return) at various periods (Statman et al., 2006). The disposition effect also explains the positive lead-lag relationship. Therefore, the two biases are examined independently, the overconfidence bias being examined at the market level and the disposition effect being examined at the level of individual stocks (Ganesh et al., 2020; Statman et al., 2006). In this study, we examined historical market data in Asian economies. Hence, the positive lead-lag relationship between market return and volume supports the overconfidence hypothesis.

Apart from the disposition effect and overconfidence bias, the positive lead-lag relationship between returns and volume may come with other interpretations, such as portfolio rebalancing and heterogeneous interpretation of informational events. Statman et al. (2006) incorporate both concurrent and lagged return volatility and dispersion observations to control these possible explanations on the monthly dataset of four decades. Further, Ganesh et al. (2020), Zia et al. (2016), Qamar Azam et al. (2022), and Shrotryia and Kalra (2021) adapt the Statman et al. (2006) model and isolate overconfidence bias more effectively by using daily data. These studies use daily data to mitigate the effects of heterogeneous interpretation and portfolio rebalancing, providing a more thorough understanding of the positive lead-lag relationship between returns and volume. Furthermore, studies recognize that there is a strong positive correlation between turnover and return volatility, as demonstrated by Shalen (1993), Karpoff (1987), and Gryphon et al. (2007), and incorporate return volatility as a controlling variable.

To investigate the cross-sectional time-series association between markets' lagged returns and trade volume market-wide, bivariate Vector autoregressive models and Impulse response functions are utilized. This model solves the endogeneity issue by allowing the two dynamic endogenous variables to interact. The endogeneity problem arises when there is a relationship between the error term and one or more independent variables. After adjusting for the exogenous variable (volatility), the current VAR model shows how one endogenous variable is a function of past values of itself, other endogenous variables, and the residual term. Finally, bivariate VAR shown in equation (1) is used:

$$X_t = \alpha + \sum_{k=1}^{K} \beta_k X_{t-k} + \beta_t Y_t + \epsilon_t \qquad (1)$$

Where, X_t is the *2× 1* column vector of market return and volume (endogenous variables) on day *t*. Y_t is the column vector of market volatility (exogenous variables) on day *t*. β_k is the coefficient of endogenous variables to assess how endogenous variables and their lag values relate to one another. β_t is the coefficient of exogenous variables to assess how the endogenous and exogenous variables relate to one another. ϵ_t is the error, and α is constant. Daily log normal market return is calculated using the equation (2),

$$R_{m,t} = LN(CP_t/CP_{t-1}) \tag{2}$$

Where $R_{m,t}$ is the market return on day *t*. CP_t is the closing value of market index on day *t*. CP_{t-1} is the closing value of market return on previous day.

Our empirical model includes three variables: market volatility, volume, and returns. Dickey and Fuller (1979) Augmented dicky fuller (ADF) test is used to examine the stationarity of all variables. No trend was reported in these variables, and tests support the idea that all three variables exhibit stationarity at level. This demonstrates that these variables do not co-integrate. Further, the optimal lag length *k* is calculated using the Akaike information criteria (AIC), which depend on the data category.

3.2 Impulse Response Function (IRF)

Utilizing the IRFs, the relationship between endogenous variables over time is displayed. The behaviour of an endogenous variable in response to a shock from another endogenous variable is represented graphically by the IRF. The IRF of a stable VAR model should converge to zero, but the cumulative response should converge to a constant that is not zero. Therefore, the random perturbation term's present and future dynamic impacts on the VAR model system can be achieved by administering a shock of standard deviation magnitude to it. IRF graphs have been used to forecast volume and return trends in the future. Equation (1) enlarged into:

$$\begin{bmatrix} vol_{m,t} \\ R_{m,t} \end{bmatrix} = \begin{bmatrix} \alpha\ vol_{m,t} \\ \alpha\ \ R_{m,t} \end{bmatrix} + \sum_{k=1}^{k} \beta_k \begin{bmatrix} vol_{m,t-k} \\ R_{m,t-k} \end{bmatrix} + \{\sigma\} + \begin{Bmatrix} \epsilon\ vol_{m,t} \\ \epsilon\ \ R_{m,t} \end{Bmatrix} \ldots. \tag{3}$$

Where, $vol_{m,t}$ is the market volume on day *t*. $R_{m,t}$ is the market return on day *t*. $\begin{bmatrix} vol_{m,t} \\ R_{m,t} \end{bmatrix}$ represents the vector of endogenous variables at time *t*. $\begin{bmatrix} \alpha\ vol_{m,t} \\ \alpha\ \ R_{m,t} \end{bmatrix}$ is the coefficient matrix related to the variables' concurrent effects on themselves. $\sum_{k=1}^{k} \beta_k \begin{bmatrix} vol_{m,t-k} \\ R_{m,t-k} \end{bmatrix}$ presents the lagged effect of variables. k denotes the number of lagged periods.

Here, equation (3) demonstrates how the shift in residuals $\epsilon R_{m,t}$ effects market returns ($R_{m,t}$), volume's ($vol_{m,t}$) present and future value. In order to determine if overconfidence bias is present in the Asian equity market, we use the predicted coefficients from the dynamic structure of VAR. We shock the market return residual $\epsilon R_{m,t}$ by one sample standard deviation and see how the trading volume reacts to the $\epsilon R_{m,t}$ shock over time *t*. The impulse response function gives an overview of the relationship between the endogenous variables across time.

4. Data Description

Ten major Asian economies are included in our sample, including China, Japan, and India. The Asian region is important because of its substantial crude oil trade. Several smaller emerging economies in this region also saw a significant influx of Foreign Institutional Investments (FII) into their stock markets. This economic bloc alsp comprises of high and low per capita GDP countries such as Singapore, Hong Kong and India. Moreover, our sample comprises many advanced and emerging economies (Table 1). The only factor used in choosing markets and their corresponding indices is the accessibility of pertinent data. Further, behavioural biases are defined as short-lived phenomena and can be better explained using high-frequency data (Tan et al., 2008). Therefore, we use the indices' daily closing value and trading volume on the respective days. All the required data is sourced from S&P Global CapitalIQ.

The study period is from January 2013 to April 2023. The Covid-19 outbreak and the Russia-Ukraine war are the big crises and economic concerns that occurred during the study period, which caused a great deal of market volatility. The heightened levels of uncertainty and market instability stemming from the Covid-19 pandemic have given rise to a notable surge in irrational exuberance among market participants. Consequently, this has led to increased speculative activities and a corresponding escalation in market volatility. This period's notable fluctuations in the stock market trading volume provide an intriguing examination of behavioural factors, particularly those associated with trade volume, such as the overconfidence bias (Prosad et al., 2017). The epidemic period when the market turbulence peaked in Asian countries is taken from January 2020 to December 2021. The impact of uncertainty related to the SARS-Covid-19 restrictions on stock markets was predominately noticeable during this period, referred to as the first and second wave. However, during the third wave, businesses were operating in hybrid mode, the vaccination drive worldwide started, and investors were less uncertain. Therefore, the actual effect of the pandemic on investors' behaviour can be observed in a shorter time frame.

Further, we take the day of the invasion, i.e., February 24, 2022, as the starting period of the Russia-Ukraine war till April 2023 (Izzeldin et al., 2023). During this period, a significant impact of Russia-Ukraine was reported in the market returns across the globe (Yousaf et al., 2022; Boubaker et al., 2022). These periods served as a stark reminder of the vulnerability of markets to behavioural biases in times of recent global crisis. In comparison, no market shocks were reported before Covid-19, such as the global financial crisis of 2008, which impacted the whole region. Therefore, the period from January 2013 to December 2019 is considered as tranquil.

Table 1: Sample Description

Country	Stock Exchange	Index	Economic outlook

China	Shanghai Stock Exchange	Shanghai Composite	Rapidly Growing Emerging
Hong Kong	Hong Kong Stock Exchange	Hang Seng	Advanced
India	Bombay Stock Exchange	BSE Sensex	Rapidly Growing Emerging
Indonesia	Indonesia Stock Exchange	IDX Composite	Emerging
Japan	Tokyo Stock Exchange	Nikkei-225	Advanced
Malaysia	Bursa Malaysia	FTSE Bursa Malaysia KLCI	Emerging
Singapore	Singapore Exchange	Straits Times Index (STI)	Advanced
Taiwan	Taiwan Stock Exchange	Taiwan weighted (TAIEX)	Advanced
Thailand	Stock Exchange of Thailand	SET	Emerging

5. Analysis of Results

5.1. Descriptive statistics

Table 2 presents the descriptive statistics for all the variables used throughout the analysis. The ADF[1] test indicates that all series are stationary at level. India and Japan achieved the greatest average market return in the last ten years. In comparison Malaysia and Hong Kong record negative returns. Further, Singapore and Malaysia reported the least standard deviation in returns. China reported the highest standard deviation (0.013) in returns. China (mean volatility of 0.014) and Hong Kong (0.13) are the most volatile markets in the sample countries. Additionally, the majority of the pertinent distributions have skewed and heavy tails with kurtosis values greater than 3.

Table 2: Descriptive Statistics

Country	Variable	Mean	Median	Standard deviation	Skewness	Kurtosis
Taiwan	Volatility	0.00938	0.008016	0.005750	3.884611	32.56051
	Return	0.00027	0.000687	0.009465	-0.56029	8.189458
	Volume	14.7449	14.65380	0.406492	0.946106	5.261109
Singapore	Volatility	0.00821	0.007221	0.004774	3.535829	26.94768
	Return	6.99E-0	2.90E-06	0.008219	-0.098976	16.83747
	Volume	19.2692	19.25788	0.331861	0.042908	4.710851
Thailand	Volatility	0.01028	0.008726	0.007173	7.919256	149.8532
	Return	0.00004	0.000363	0.009812	-1.369679	21.62254
	Volume	23.3239	23.27505	0.496174	0.029381	2.628108
Malaysia	Volatility	0.00746	0.006206	0.004932	3.144667	22.31129
	Return	-0.00006	0	0.006845	-0.15480	11.32738

[1] The results of ADF test in not reported here for the conciseness of article and are available on request

	Volume	18.72042	18.69002	0.375270	0.603011	4.631750
Indonesia	Volatil-ity	0.010970	0.009080	0.007427	3.438748	25.22882
	Return	0.000171	0.000651	0.010165	-0.25279	10.23257
	Volume	22.70242	22.57487	0.681852	0.311475	2.013111
Japan	Volatil-ity	0.011426	0.009320	0.008225	3.332811	22.75354
	Return	0.000395	0.000757	0.013094	-0.252264	7.206841
	Volume	18.31555	20.35174	3.773990	-1.070207	2.191253
Hong Kong	Volatil-ity	0.013136	0.011275	0.007478	2.605204	15.17045
	Return	-0.00006	0.000300	0.012640	0.0355754	6.622474
	Volume	21.34030	21.31659	0.328266	0.3771228	3.745429
China	Volatil-ity	0.014700	0.011660	0.010677	3.065657	17.19076
	Return	0.000144	0.000505	0.013207	-1.03557	10.41197
	Volume	12.26293	12.26623	0.542866	-1.126075	17.83266
India	Volatil-ity	0.011807	0.009997	0.008084	5.86379	75.96678
	Return	0.000450	0.000639	0.010780	-1.223007	21.78249
	Volume	12.68334	9.965992	3.589324	0.1113952	1.100679

5.2. Market-wide VAR

The VAR coefficients for Asian economies in both the tranquil and the stressed market periods are displayed in Tables 3-5. The market volume of respective countries is arranged in columns, whereas lagged values of the market return, constant, and exogenous/control variable are arranged in rows in each table.

As shown in Table 3, For the first three lags, market trade volume is autocorrelated with highly significant coefficients for all the stock markets except Malaysia. However, the coefficients show reductions after the first lag in all the markets. In China and Malaysia, a positive serial connection is consistently seen in the detrended market volume. In contrast, inconsistent trends were noted in other markets. Investors are said to be confident in the stock market when the market return lags are positively correlated with the log transaction volume of the respective market index while controlling the relationship between market volatility and volume.

The results show that the investors from China (Lags = 1, 2, 3, 4, 5, 7, 8, 9, and 13 days), Hongkong (Lags = 1, 7, 8, and 9 days), Indonesia (Lags = 1, 3, 4 and 5 days), Singapore (Lags = 1, 2, 4, 5, 9, 10 and 19 days), Taiwan (Lags = 1, 2, 3, 4, 5, 6, 7, 9, 10, 11 and 15 days) and Thailand (Lags = 1, 2, 3, 4 and 5 days) shows overconfidence bias in stock markets. Negative and insignificant results were reported in the Indian, Japanese, and Malaysian markets in the overall sample period, showing insufficient overconfidence bias among investors. Despite possible variations in market structure and regulatory settings in advanced, rapidly developing emerging and emerging economies. Investors in these markets exhibit similar behavioural tendencies. Shrotryia and

Kalra (2020) mentioned lower liquidity as the primary reason for investors' delayed stock market reaction. Lower trading costs and minimum information asymmetry can be the possible reasons behind investors' quick reaction in advanced stock markets (Shrotryia & Kalra, 2020).

Further, to see how one endogenous variable is affected by a shock to another endogenous variable. Ten days, IRFs have been plotted for all the countries to determine the overconfident trading among investors. In Figure 1-3, the X-axis indicates the time (in days), and the Y-axis represents the effects of residual shock. The solid black line indicates how market trading volume reacts to the market return. This indicates that a market return shock of one standard deviation causes a rise in volume. Orange dotted lines show uncertainty bands surrounding the predicted IRF functions. Figure 1 shows a positive reaction for the second day in Taiwan, Hong Kong, Thailand, China, India, and Indonesia. These results confirm the VAR estimations and indicate traders' overconfident outlook. Additionally, Taiwan, Hong Kong, Thailand, and China markets have shown consistent positive response functions for ten days.

Table 3: VAR estimation for overall sample period

Parameters	CHINA	HONGKONG	INDIA	INDONESIA	JAPAN	MALAYSIA	SINGAPORE	TAIWAN	THAILAND
Volt-1	0.29***	0.402***	-0.82***	0.516***	-0.799***	0.37***	0.5***	0.414***	0.517***
Volt-2	0.153***	0.118***	-0.616***	0.096***	-0.587***	0.077***	0.08***	0.104***	0.082***
Volt-3	0.103***	0.047**	-0.526***	0.069***	-0.489***	0.027	0.098***	0.106***	0.102***
Volt-4	0.081***	0.034*	-0.477***	0.084***	-0.43***	0.075***	0.071***	0.024	0.076***
Volt-5	0.028	0.017	-0.412***	0.12***	-0.356***	0.064***	0.007	0.088***	0.008
Volt-6	0.031	-0.026	-0.361***	-0.037	-0.295***		-0.002	-0.019	0.007
Volt-7	0.046**	0.003	-0.297***	0.013	-0.22***		0.023	0.003	0.023
Volt-8	0.041**	0.023	-0.319***	0.009	-0.235***		0	0.018	-0.003
Volt-9	0.021	0.027	-0.303***	0.041*	-0.205***		0.026	0.048**	0.029
Volt-10	0.026		-0.248***	0.019	-0.131***		-0.005	0.007	0
Volt-11	0.029		-0.201***	0.02	-0.062**		0.027	0.032	0.035
Volt-12	0.014		-0.225***	-0.004	-0.058***		-0.014	0.03	0.004
Volt-13	0.022		-0.205***	-0.007			0.066***	0.036*	0.087***
Volt-14	0.027		-0.181***	0.043**			-0.015	0.036*	
Volt-15			-0.145***				0.032	0	
Volt-16			-0.078***				-0.033		
Volt-17			-0.008				-0.011		
Volt-18							0.041*		
Volt-19							0.084***		
Rt-1	4.468***	1.133***	2.779	0.993***	2.477	-0.235	2.105***	1.202***	1.945***
Rt-2	2.78***	0.221	-0.841	-0.181	-1.153	0.326	1.873***	3.151***	1.779***
Rt-3	2.899***	0.492	-1.655	0.985***	-2.068	0.986	0.724*	1.201***	0.731*
Rt-4	1.04***	0.163	-0.307	1.353***	-0.25	-0.063	1.652***	1.456***	1.563***
Rt-5	1.027***	0.492	0.389	0.813**	0.258	0.679	1.67***	1.504***	1.607***
Rt-6	0.031	0.235	2.307	0.475	2.244		0.605	1.153***	0.588
Rt-7	0.818**	0.862**	-0.174	0.461	0.178		0.563	1.797***	0.459
Rt-8	0.82**	0.956***	1.258	0.488	1.505		0.555	0.37	0.488
Rt-9	0.837**	0.783**	-0.932	-0.091	-0.609		0.618*	0.555*	0.5
Rt-10	0.344		2.554	0.312	2.48		0.764**	0.92***	0.597
Rt-11	0.416		-0.973	-0.556	-1.499		0.534	1.107***	0.402
Rt-12	-0.244		0.641	0.326	1.088		0.595	-0.275	0.537

Rt-13	0.82**		0.34	-0.017			0.642*	-0.069	0.564
Rt-14	-0.639*		-1.283	0.311			0.151	0.268	
Rt-15			-2.23				0.098	1.276***	
Rt-16			2.903				0.266		
Rt-17			6.288***				0.487		
Rt-18							0.616*		
Rt-19							1.25***		
Constant	7.162***	15.756***	12.069***	3.395***	11.195***	24.577***	7.714***	11.522***	7.403***
Volatility	0.962***	7.372***	-0.132***	0.338**	-0.122***	7.043***	0.536***	0.975***	0.672***

This table reports the estimated VAR coefficients of model in equation 1 on Daily data from January 2013 to April 2023. ***, **, and * shows statistical significance at 99, 95, and 90% level respectively.

Further, table 4 presents the results of VAR estimations during the Covid-19 pandemic. Market trading volume is autocorrelated with highly significant coefficients for all the stock markets. The detrended market volume constantly displays a positive serial connection in all the markets except India and Singapore. There seems to be a strong positive correlation between detrended market volume and lag market return for China (Lags = 1 and 2 days), Hongkong (Lags = 1 and 3 days), Singapore (Lags = 2 and 5 days), Taiwan (Lags = 2, 3, 4, 5, 6 and 7 days), and Thailand (Lags = 1, 2, 4 and 5 days) markets. Investors in emerging markets, except China and Thailand, show a lack of confidence in stock markets. This could indicate that participants are not applying the rule of feedback trading, which is predicated on good returns (Shrotryia and Kalra, 2020). The herding behaviour of investors could be the reason behind this. Ten days of IRF function during the Covid-19 pandemic were plotted (Figure 2), a persistent positive reaction was noted in Hong Kong, Thailand, India, Indonesia, and Malaysia after day two. However, negative reactions to market returns were reported after day five in the Indian market. Since the values are so close to zero on the first day, the market volume response to the market return shock is not reflected. The results contradict the VAR estimations during the Covid-19 pandemic and suggest the probability of optimistic behaviour in other markets. Additionally, it has been noted that market return shocks cause a decline in market volume in Taiwan, Singapore, Japan, and India.

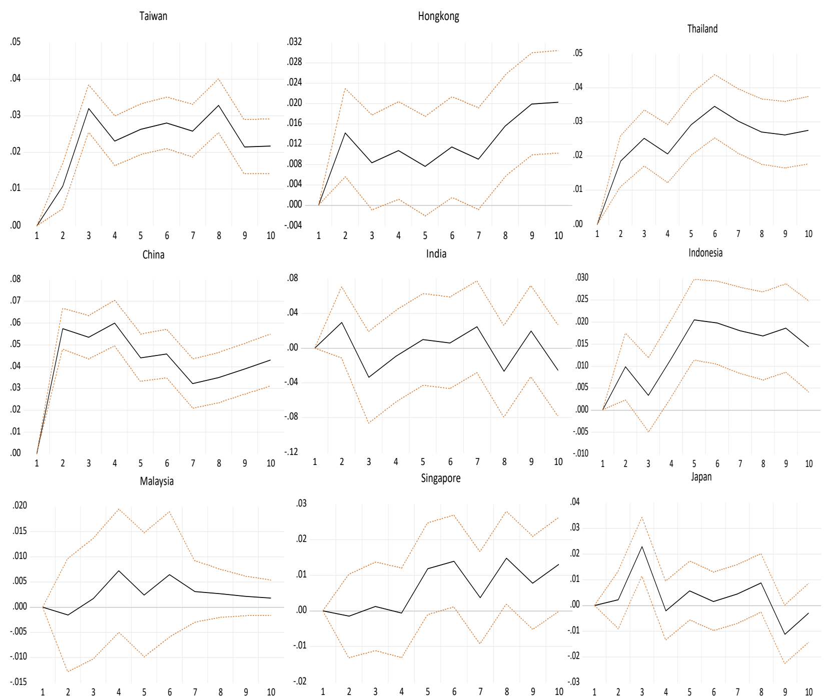

Figure 1: Market volume's reaction to a market return in overall sample period

Table 4: VAR estimation for Covid-19 period

Parameters	CHINA	HONGKONG	INDIA	INDONESIA	JAPAN	MALAYSIA	SINGAPORE	TAIWAN	THAILAND
Volt-1	0.667***	0.391***	0.252***	0.565***	0.475***	0.37***	0.385***	0.286***	0.549***
Volt-2	0.212***	0.241***	0.38***	0.146***	0.002	0.167***	0.155***	0.045	0.077
Volt-3		0.07*	-0.051	0.109*	0.121***		-0.033	0.171***	0.083*
Volt-4			-0.078	0.099*			0.024	0.088*	0.076
Volt-5			0.22***	0.06			0.08	0.188***	0.192***
Volt-6			0.081					0.059	
Volt-7			-0.332***					0.073*	
Volt-8			0.142***						
Volt-9			0.178***						
Rt-1	3.573***	1.292*	4.363	0.987	-0.12	1.875	-1.013	-0.127**	1.736***
Rt-2	1.126***	0.968	0.036	-0.874	0.749	2.325	2.264*	0.335***	1.488***
Rt-3		1.826**	1.785	0.964	0.653		1.113	0.145**	0.593
Rt-4			-1.854	-0.044			0.991	0.146**	0.923**
Rt-5			-1.642	0.939			3.787***	0.182***	1.841***
Rt-6			-1.27					0.14**	
Rt-7			-0.109					0.196***	
Rt-8			-0.766						
Rt-9			-2.958						
Constant	7.435***	14.809***	7.03*	1.604**	10.947***	-0.013	16.28***	0.515***	2.699***
Volatility	1.428***	6.189***	3.269***	0.489	8.045***	-0.002	7.382***	0.236***	0.519

This table reports the estimated VAR coefficients of model in equation 1 on Daily data from January 2020 to December 2021. ***, **, and * shows statistical significance at 99, 95, and 90% level respectively.

Table 5: VAR estimation for Russia-Ukraine war period

Parameters	CHINA	HONGKONG	INDIA	INDONESIA	JAPAN	MALAYSIA	SINGAPORE	TAIWAN	THAILAND
Volt-1	0.031	0.42***	-0.036	0.4***	0.383***	0.467***	0.422***	0.555***	0.455***
Volt-2	0.015	0.157***	-0.013	0.191***	0.051	0.172***	0.089*	0.178***	0.127**
Volt-3	0.045			0.246***					0.09
Volt-4	0.138**								0.022
Volt-5	0.052								0.212***
Rt-1	-1.277	0.409	20.231	0.893	0.766	-1.648	1.753	0.049	1.61
Rt-2	6.791**	0.148	-2.05	1.323	-0.842	-4.425*	-0.827	0.012	0.776
Rt-3	16.62***			-0.881					1.256
Rt-4	1.206								2.276**
Rt-5	8.483***								2.367**
Constant	16.1***	10.228***	37.11	5.227***	15.175***	33.641***	29.139***	0.822***	14.625***
Volatility	8.879***	8.908***	15.668***	3.792***	11.399***	6.571***	9.177***	0.711***	2.106***

This table reports the estimated VAR coefficients of model in equation 1 on Daily data from February 24, 2022 to April 2023. ***, **, and * shows statistical significance at 99, 95, and 90% level respectively.

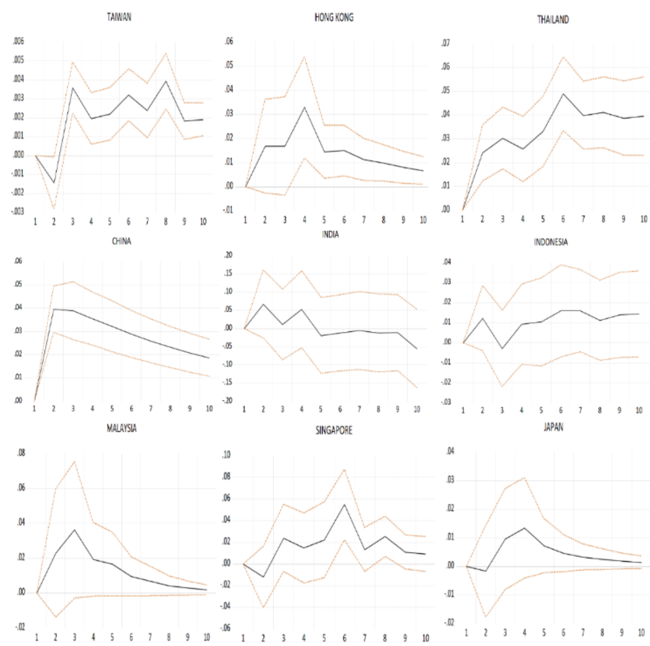

Figure 2: Market volume's reaction to a market return during Covid-19 pandemic.

Further, to provide a comparative analysis of investors' overconfidence during market stress and tranquil periods, we limit our analysis to the Russia-Ukraine conflict period. Table 5 represents the results of VAR estimations. The market volume is autocorrelated with highly significant coefficients for all stock markets except China and India. Detrended market volume and delayed market return appear to be strongly positively correlated for China (Lags = 2, 3, and 5 days) and Thailand (Lags = 4 and 5 days). The presence of geopolitical tensions and economic uncertainty appeared to induce a state of caution, resulting in decreased feedback trading. On day two, Positive impulse responses were reported in all markets except China and Malaysia. However, the response became negative on day two in India, Singapore, and Japan

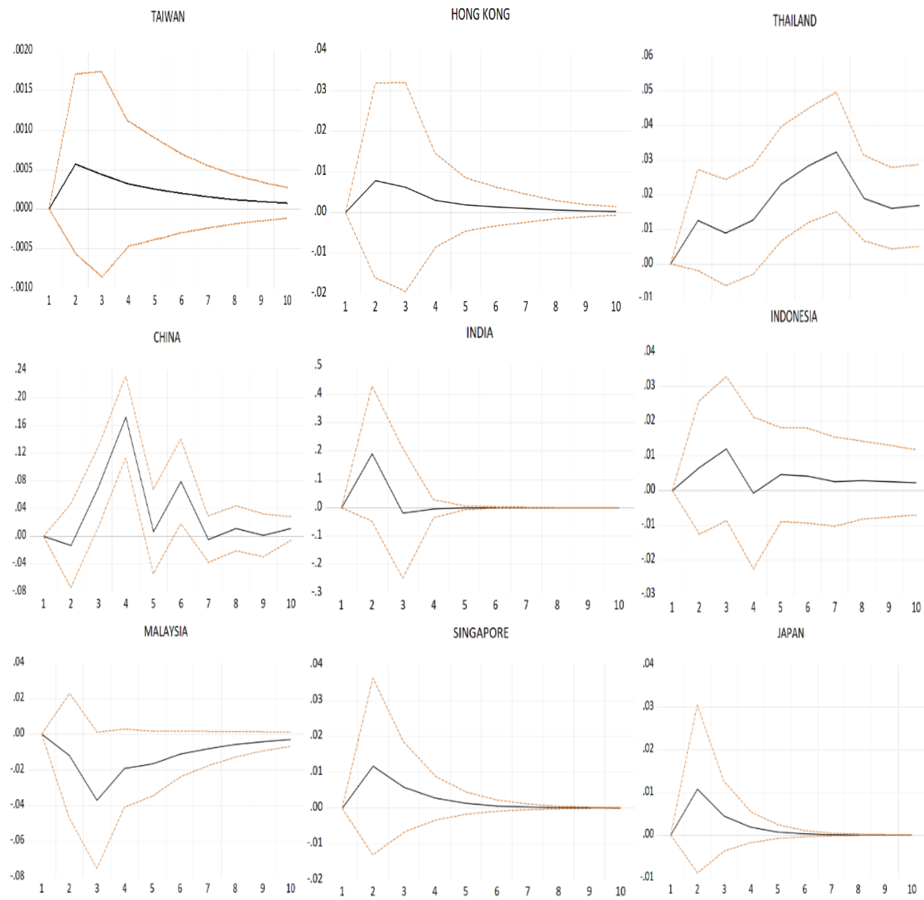

Figure 3: Market volume's reaction to a market return during Russia-Ukraine war

6. Implications

The consequences of overconfidence bias show how important it is to recognize and deal with behavioural biases in financial decision-making, as they can affect everything from investor protection to economic stability. Findings indicate a lack of trust and confidence among investors during market stress, specifically in emerging economies. The regulators and policymakers can maintain investors' confidence by enhancing financial literacy among investors and initiating recovery plans by providing tax benefits, job creation, and support for reducing transaction costs.

The tendency towards overconfidence frequently encourages investors to take on more risk, which could enhance market volatility and instability. Particularly in markets where overconfidence bias is prevalent, financial institutions and portfolio managers must create risk management strategies considering these irrational exuberances. Moreover, results reported that, investors from different economies have similar behavioural tendencies, which shows that the financial landscape is globally interconnected, impacting risk, regulation, and investment strategies. Asset managers and investors must incorporate the study's conclusions into their investment strategies. Strategies that account for behavioural biases and employ risk-adjusted returns may be more effective in emerging markets, where overconfidence bias can significantly influence investment decisions.

Further research is needed to delve into the psychological factors contributing to this bias and to explore potential interventions to mitigate its effects in the complex world of financial markets. In conclusion, this study's implications emphasize the need for a multifaceted approach to manage the effects of overconfidence bias in Asian equity markets, promoting economic stability, investor protection, and efficient market functioning.

7. Conclusion

The primary aim of this study is to reveal the striking prevalence of overconfidence bias among investors in Asian equity markets. This overconfidence bias is characterized by an unwarranted overestimation of one's knowledge and abilities and has far-reaching consequences in the investment landscape. Investors exhibit confidence in the stock market when there is a positive correlation between lagging market returns and the logarithmic transaction volume of the corresponding market index (Statman et al., 2006). The authors emphasize the highly significant contemporaneous link between market return and volume using VAR and IRFs. The daily adjusted closing prices and volume of the broad market indexes of 10 major Asian stock markets were used in this analysis for the January 2013 - April 2023 time-frame. Further, to deepen our analysis, the sample period dividend into the Covid-19 pandemic and Russia-Ukraine conflict phases. During the pandemic, we observed a heightened overconfidence bias among Chinese, Hong Kongese, Singaporean, Taiwanese, and Thai investors. Insignificant results were found in Indian, Indonesian, Malaysian, and Japanese markets.

Conversely, during the Russia-Ukraine conflict period, investors were more cautious in all Asian markets except China and Thailand. In the tranquil period, significant evidence of overconfidence bias is found in all the markets except India, Japan, and Malaysia. No significant differences were reported in Advanced, rapidly growing emerging and emerging economies. Overall, the comparative evidence highlights the significance of comprehending how various economic and geopolitical situations influence the frequency and consequences of overconfidence bias.

The key implications of this study provide valuable insights for shaping the future of financial markets and economic policies. By fostering investor education, implementing risk management strategies, enhancing regulatory oversight, and preserving market efficiency, we can pave the way for more rational and stable financial markets in the Asian region, ultimately benefiting investors and economies alike. This research is a stepping stone for further exploration of behavioural finance and its application in shaping the future of financial decision-making and market behaviour in Asian economies. Moreover, our analysis is limited to emerging and advanced Asian economies; future researchers can expand this analysis to frontier markets. Looking into this prejudice across sectors or asset classes within the markets under study will be intriguing. Further, more research needs to be done to identify the underlying causes of overconfidence bias in stock markets.

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