Revisiting overconfidence in investment decision-making: Further evidence from the U.S. market

Ahmed Bouteska [a], Murad Harasheh [b], Mohammad Zoynul Abedin [c],*

[a] Assistant Professor of Finance, Faculty of Economics and Management of Tunis, University of Tunis El Manar, Tunisia
[b] Department of Management, University of Bologna, Italy
[c] Department of Accounting and Finance, School of Management, Swansea University, Bay Campus, Fabian Way, Swansea SA1 8EN, Wales, UK

ABSTRACT

Investor overconfidence leads to excessive trading due to positive returns, causing inefficiencies in stock markets. Using a novel methodology, we build on the previous literature by investigating the existence of overconfidence by studying the causal relationship between return and trading volume covering the COVID-19 period. We implement a nonlinear approach to Granger causality based on multilayer feedforward neural networks on daily returns and trading volumes from 2016 to 2021, covering 1424 daily observations of the S&P 500 index. The results provide evidence of overconfidence among investors. Such behavior may be linked to the increase in the number of investors. However, there is a decline in the rate of returns during the study period, implying uncertainty caused by the COVID-19 pandemic.

1. Introduction

People exhibit overconfidence, but it can sometimes be dangerous. Psychological experts in experiments have shown that human language, memory, and thoughts are systematically positively biased (Seligman, 2015). Trivers (2000), an evolutionary biologist, identifies that self-deception has an ancient link with the evolution of the brain. Wrangham (1999) argued that natural selection favored positive illusions because they were beneficial for hunter-gatherer societies in war conditions, interpersonal combat, one-on-one disputes, negotiation, the attraction of allies, and deterrence of rivals. Furthermore, positive illusions had been related to survival, resource accessibility, and reproductive prospects. Exaggerated confidence also brings many advantages; for instance, the costs of failure from overconfidence are less significant than missed opportunities from overcautiousness, facilitating enhanced mental, social, and physical functioning and increasing performance in conflict.

Overconfidence can offer significant advantages in difficult, competitive, or combative situations (Dominic, 2004). Tuchman (2014) claims that overconfidence provides essential advantages in our ancestral environment. There are countless examples of overconfidence in diverse professional contexts, from companies to unions to governments, military commanders making decisions on the battlefield, and decision-making by political groups. Taylor and Brown (1994) argue that positive illusion leads to motivation, perseverance, better performance, and greater success.

In comparison, Dominic (2004) emphasizes that excessive confidence can bring disasters and losses. Many researchers (Dominic,

* Corresponding author.
E-mail addresses: ahmed.bouteska@fsegt.utm.tn (A. Bouteska), murad.harasheh@unibo.it (M. Harasheh), m.z.abedin@swansea.ac.uk (M.Z. Abedin).

2004; Malmendier and Tate, 2005; Neale and Bazerman, 1985; Odean, 1999; Moore and Healy, 2008) stipulate that overconfidence is a reason behind wars, strikes, litigation, entrepreneurial failures, and stock market bubbles. Overconfident people are evolutionarily stable in a wide range of environments. They may help to explain how overconfidence remains prevalent today, even if it contributes to pricing, market bubbles, financial collapses, political failures, disasters, and expensive wars (Dominic and Fowler, 2011). Skala (2008) notes that since the 1960 s, overconfidence has been employed widely in psychology, and it is a form of miscalibration widely used by economists. Most researchers attribute overconfidence to positive illusions, like the better-than-average effect, the illusion of control, and unrealistic optimism. Taylor and Brown (1994) affirm that individuals show positive illusions or overconfidence in various fields. First, they perceive unrealistic optimistic terms. Second, they think they control environmental events, leading to mistakes in judgments or decision-making, overestimating one's abilities and undervaluing an opponent, the challenge of a task, or eventual risks (Dominic and Fowler, 2011). Hence, several academics (Akerlof and Shiller, 2010; Johnson and Asher Levin, 2009; Dominic and Tierney, 2011; Dominic, 2004; Tuchman, 2014) provide evidence that overconfidence is historically blamed for high-profile disasters, namely, World War I, the Vietnam War, Iraq War, the 2008 financial crisis, and poor preparation for environmental phenomena, such as Hurricane Katrina and climate change.

Based on his hubris theory, the first pioneering study introduced the optimism and overconfidence approach to corporate finance was Roll (1986). This theory states that directors, i.e., CEOs of acquiring companies, make valuation mistakes and are overly optimistic about a takeover project's potential synergies. Consequently, they overbid target companies to the detriment of their shareholders (Brown and Sarma, 2007). Using U.S. data, Odean (1998a) (1998b) (1999) and Barber and Odean (2000, 2001) first studied overconfidence in stock markets. Recently, Qiao et al. (2022) showed that overconfidence is still evident among U.S. CFOs, and Thi Tuyet Dao et al. (2023) showed similar results among Vietnamese managers. Many works investigating developed and emerging countries' stock markets helped increase the relevant literature in recent years (Abbes, 2013; Ahmed et al., 2023a; Berg and Rietz, 2019; Deaves et al., 2010; Phan et al., 2020; Qasim et al., 2019; Şahïn and Özlem YILMAZ, 2014). However, overconfidence behavior is problematic in stock markets and has been considered at the academic level due to the evidence of market anomalies (Abdeldayem and Mahmoud, 2013; Chen et al., 2007; Metwally and Darwish, 2015; Wang and Daxue, 2008).

Regarding the role of overconfidence behavior as the most probable cause of many catastrophes, crises, and bubbles, we examine the existence of overconfidence in a developed U.S. market (S&P 500) from 2016 to 2021. It is a noteworthy case to analyze as the U.S. experienced an economic crisis in 2020 during the first period of the pandemic when the world economy experienced a synchronized slowdown driven by a public health crisis (COVID-19). We note that the number of active investors in the S&P 500 increased during this turmoil, even though COVID-19 shocked financial markets. On March 11 and 12, 2020, the S&P 500 index decreased by more than 15% in a severe decline. The index plummeted by over 30% from its closing value on March 23, 2020. Even more astonishing than the decline was the market rebound that came after, using the monetary and fiscal policies, including a rollout of programs from the Central Bank. The S&P 500 rose by about 80% compared to March's low and reached a new record on Thursday, i.e., March 26, 2020. "I think the policy response was meaningful and significant, and as a result, prevented what could have been a far worse outcome," said Tobias Levkovich in 2020.[1] Interestingly, most investments had a negative rate of return in the periods (2019–2020) during the outbreak of COVID-19. Notably, investors had negative yields despite a massive rise in the number of active investors during the relevant period, showing that behavioral motivations may have played a role.

Several methodologies have been applied to model and test overconfidence. Perhaps, the causality between return and trading volume is the prevailing approach, as appeared in Barber and Odean (2000, 2001). In this research, we build on the previous academic work by introducing two novel nonlinear modeling and forecasting techniques applied to test overconfidence studying the COVID-19 period, i.e., nonlinear Granger causality analysis based on multilayer feedforward neural networks and nonlinear impulse response analysis based on local projections. To the best of our knowledge, our study is the first to scrutinize investor overconfidence behavior on the S&P 500 index using nonlinear methodologies. We add to the behavioral finance literature by applying the artificial neural network (ANN) forecasting process to model investors' overconfidence, which includes all the past generated values and presents many advantages. Furthermore, nonlinear impulse response functions can easily differentiate trading volume responses to return shocks in various regimes. Although many studies investigate the overconfidence behavior in the U.S.stock market returns, this is the first study to use a distinguished method, i.e., impulse response analysis that was employed previously by many researchers, based on the linear approach among various stock markets (Ahmed et al., 2023b; Metwally and Darwish, 2015; Sheikh and Riaz, 2012; Statman et al., 2006; Zaiane and Abaoub, 2009).

Using novel approaches and covering COVID-19, we tested the daily returns and trading volumes from 2016 to 2021. We examine whether investors exhibit overconfidence behavior in the U.S. stock market, referring to the S&P 500 index. We document evidence of overconfidence among investors in the U.S. stock market. Such behavior may be linked to the increase in the number of investors. However, there is a decline in the rate of returns during the study period, implying uncertainty caused by the COVID-19 pandemic.

The rest of this paper is organized as follows. Section 2 provides the literature review. Section 3 mentions the methodology and data. Section 4 describes the results and discussions. Section 5 describes conclusions, implications, and further research roadmaps.

2. Literature review

Price bubbles can occur in markets and lead to financial crises if irrational prices come from investors' risky preferences because

---

[1] Tobias Levkovich, the chief U.S. equity strategist at Citi, said the quote in an interview at CNBC in March 2020 after government programs by Federal Reserve.

overconfidence is greater than the real price levels. Then, examining the factors leading to investors' irrational decisions, such as overconfidence, is imperative. Previous studies examine overconfidence behavior in decision-making for developed and developing financial markets. Regarding the U.S. market, Qiao et al. (2022) studied the U.S. listed firms from 1993 to 2019. They demonstrate that companies with overconfident CFOs are linked with greater stock crash risk, CFO overconfidence outweighs CEO overconfidence in affecting stock crash risk, and good governance practices could limit such CFO's overconfidence. Such findings are also confirmed by.

Market anomalies are not dominant in developed markets but in developing ones (Abdeldayem and Mahmoud, 2013; Chen et al., 2007; Metwally and Darwish, 2015; Wang and Daxue, 2008). Hence, investigating overconfidence behavior in a developed market may offer more interesting insights. Recently, Thi Tuyet Dao et al. (2023) analyzed the impact of executive overconfidence on the corporate cash holdings of listed Vietnamese firms, revealing that overconfident managers are more likely to hold lower cash and are associated with a low level of deviation from optimal cash holding levels. Chen et al. (2007) analyzed overconfidence behavior in the Shanghai and Shenzhen stock exchanges from 1998 to 2002 via data related to 46,969 personal and 212 institutional investor trading accounts. The results indicated a higher rate of return among individual investors and overconfidence among institutional investors. They also claim the need for testing behavioral biases in Chinese markets because different cultural or educational systems can change investors' behavior. Deaves et al. (2010) examined overconfidence based on German data from a monthly ZEW Finanzmarkttest with 350 financial market participants. The findings show that the market experience is not efficient for better-calibrating behavior.

Further, although market participants were overconfident, such behavior was not linked to self-attribution bias. Abbes (2013) tested whether overconfidence behavior was an explanatory factor for the 2008 global crisis through the closing price and trading volume data in the market index of 15 developed and developing countries. The empirical results reveal that poor news was more efficient for investors than good news. Except for Japan and Singapore, the author found an overconfidence indicator, a positive relationship between volatility and trading volume, in all countries.

In another study in Egypt by Metwally and Darwish (2015), they tested if investors trading on the stock exchange were overconfident by analyzing the period from 2002 to 2012, which they divided into four sub-periods. The findings show that the periods 2002–2004 and 2005–2007 were upward and stable; however, the periods from 2008 to 2010, i.e., the global financial crisis, and 2011–2012, i.e., the Egyptian Revolution) were downward and volatile. The relationship between return and trading volume is examined by Metwally and Darwish (2015) via a vector autoregressive model (VAR), delay selection, impulse response functions, and Granger causality testing. They suggest that investors behave overconfidently in the Egyptian stock market. Particularly, past returns achieved by investors were positively associated with current trading volume in the first lag, negatively associated in the second lag, and positively related among the third and fifth lags. This finding shows that the Egyptian stock market is characterized by overconfidence and self-attribution bias. Based on Iowa Electronics Market data, Berg and Rietz (2019) investigated the market's efficiency over two alternative behavioral finance suggestions, i.e., the longshot bias and overconfidence behavior. They found that even though the market is efficient in the short run, overconfidence behavior influences prices in the medium and long run. However, they did not find proof of the market's longshot bias. A survey on investors from Delhi was conducted by Kansal and Singh (2018), who claim that overconfidence behavior is connected with over-trading. However, no difference was noticed between the two genders in overconfidence behavior. Another survey on investors from Egypt by Metawa et al. (2019) stated that investors' intuition, age, gender, and education level positively affect investment decisions. Furthermore, the authors show that market experience does not significantly impact investment decisions; thus, investors are more susceptible to not considering emotional factors after being more experienced. Trejos et al. (2019) tested the relationship between overconfidence behavior and the disposition effect. They revealed that career, gender, and education level explain overconfidence better than age, nationality, and profit, which are insignificant. Moreover, they stated that investors under the disposition effect are more susceptible to gaining overconfidence behavior.

Investigating overconfidence behavior in the Saudi stock exchange, Alsabban and Alarfaj (2020) employed monthly return and trading volume data during 2007–2018 and found that investors were overconfident. Arifin and Soleha (2019) surveyed participants trading in the stock exchange, i.e., university students. They found that investors characterized by risk-seeking are dominant in the stock market; hence, overconfidence is widespread and linked with investors' attitudes toward risk. However, overconfidence is not affected by financial literacy. Using the Z-tree software in an experiment containing 56 subjects from the University of York in the U.K., Şahïn and Özlem Yilmaz (2014) reported the exhibition of overconfidence by most subjects; they were higher than average regarding general knowledge. However, regarding finance knowledge, they reported no difference in underconfidence among subjects with no previous investment experience. Sheng and Sabherwal (2019) analyzed overconfidence behavior in the options market, revealing that options trading volume was positively associated with past stock returns. They also found that overconfident investors are more inclined to trade options. Qasim et al. (2019) surveyed 150 subjects investing in the Pakistan stock exchange, suggesting that investors were overconfident. Zhang et al. (2019) found that investors were overconfident by testing transactions from various households investing in the Chinese stock market from 2014 to 2015. Hwang et al. (2020) analyzed the influence of overconfidence on house prices in the U.K. during 1980–2014. They showed that households in the northern region exhibited more overconfidence than those in the southern region. These authors also stated that the recent increase in house prices had been impacted directly by the overconfidence of households. Phan et al. (2020) examined stock exchanges in countries like Vietnam, Thailand, and Singapore during 2014–2018; they revealed that investors in Vietnam and Singapore were overconfident, whilethose in Thailand were underconfident.

Time series analysis and experimental research or survey techniques have been used to investigate overconfidence in stock markets. Bolaman and Yücel (2012) investigated whether return increases overconfidence behavior and whether overconfidence increased market volatility in Turkey from 1991 to 2011. They showed a significant positive causality from the return to trading volumes, while there was no evidence of an association between overconfidence and volatility. Tekçe and Yilmaz (2015) documented that individual stock market investors have overconfident behavior in Turkey. They also indicated that men were more overconfident than women; investors in developed regions showed less overconfidence than investors in poorly developed regions, and age and portfolio assets

diminished overconfidence. These results align with studies examining overconfidence in China and Taiwan. Tekin (2020) surveyed 522 students in various universities and investigated the existence of behavioral biases, such as overconfidence, control illusion, and over-optimism in their financial decision-making processes. Tekin (2020) proposed a scale for behavioral bias, which can be employed in future studies when testing the influence of behavioral biases.

Extant literature depicts overconfidence as a widespread phenomenon in financial markets. Prior research analyzed overconfidence behavior in stock markets using various periods and methodologies, confirming the existence of overconfidence. To the best of our knowledge, our model is the first to analyze overconfidence in the U.S. stock market, i.e., the S&P 500 index, using nonlinear methodologies by considering the COVID-19 period. The empirical literature shows that many studies apply the method of impulse response functions to examine overconfidence in stock markets (Ahmed et al., 2023b; Sheikh and Riaz, 2012; Statman et al., 2006; Zaiane and Abaoub, 2009). Conversely, this paper employs the novel nonlinear impulse response analysis with local projections that differentiate between the responses of trading volume and return shocks among various regimes and the new nonlinear Granger causality test that applies feedforward neural networks.

After the COVID-19 pandemic, researchers have been investigating the impact and implications of the pandemic, as a shock and crisis, on financial markets and financial commodities, concluding that markets behave differently during health crises and pandemics compared to pure financial crises. Early research on the pandemic commonly shares the impact of the pandemic on financial markets. For example, Baker et al. (2020) investigated the U.S. market reaction to the pandemic, providing that the U.S. stock market reacted so much more forcefully to COVID-19 than to previous pandemics. Similarly, Pandey and Kumari (2021) used event study methodology to test the impact of the pandemic on developed and emerging markets, showing that Asian markets were hit the most severely.

Wang and Wang (2021) investigated the efficiency in several financial markets, demonstrating a drop in efficiency measures and the existence of safe-haven investments. Akhtaruzzaman, Boubaker, and Lucey (2021) state that gold partially served as a safe haven depending on the sub-period health crisis. Contessi and De Pace (2021) studied the spillover effect from the Chinese markets to other global markets; they show evidence of transmission channels to other global markets and heterogeneous recovery patterns. In the same regard, energies were among the most affected during the pandemic. Chang et al. (2020) showed that investors behave unlike in different crises; after the global financial crisis in 2008, investors were more susceptible to present herding in the stock market, but during SARS and COVID-19, they may unwisely sell their assets. Akhtaruzzaman, Boubaker, and Chiah (2021) differentiated the risk exposure between oil supplies and users, showing that suppliers had the highest positive exposure to oil price risk. Matos et al. (2021) and Miklesh et al. (2023) studied the sectoral contagion in the U.S. and Europe, providing the strategic role of the energy sector as the first to react to the pandemic.

On the other hand, the pandemic has shown some positive environmental impacts; greenhouse gas emissions have been reduced significantly, emphasizing the role of sustainable financial instruments compared to traditional ones. In this regard, Cicchiello et al. (2022) investigated the credit spread of E.U green bonds, revealing that green bonds' credit spreads rose notably following the outbreak. However, vaccines news triggered green bonds' credit spreads to fall below conventional bonds. Overall, green bonds were riskier and less resilient to adverse events while benefiting during favorable circumstances.

In light of COVID-19-related literature, we conclude that the related literature focused only on the pandemic period. However, we contribute to the ongoing debate by investigating the overconfidence in the U.S. S&P 500 before and during the pandemic's peak using novel approaches, adding to the behavioral finance and COVID-19 literature. Our findings give evidence of overconfidence among investors in the U.S. stock market. Such behavior may be linked to the increase in the number of investors. However, there is a decline in the rate of returns during the study period, implying uncertainty caused by the COVID-19 pandemic.

Like the COVID-19 pandemic, the Russian-Ukrainian (R-U) war that started in early 2022 impacted economies and markets. Accordingly, behavioral issues could also be investigated during the war. Early research shows negative abnormal returns in global financial markets due to the war (Abbassi et al., 2022; Boubaker et al., 2022; Khalfaoui et al., 2023), revealing the investors' fear and negative expectations of global markets due to significant geopolitical tensions and wars. Tosun and Eshraghi (2022) studied the impact of the R-U war on corporate decisions and performance, showing that firms staying in Russia underperform due to investors imposing penalties, generating higher trading volumes due to selling pressures on the remaining firms.

3. Data and methodology

We analyze the daily closing prices and the trading volume for the S&P 500 index from the Bloomberg Terminal. We cover the period from January 4, 2016, to August 31, 2021, covering 1424 daily observations. This time frame is chosen due to the data availability, the change in total prices and trading volume, and providing a reliable period for the long run. Considering the COVID-19 pandemic as the crisis period, we cover the pre-crisis (from January 2016 to February 2020) and during-crisis[2] (from March 2020 to August 2021) state of the economy. In the first step in the methodological approach, daily returns were calculated using the following formula:

$$R_{i,t} = Ln\left(P_{i,t}/P_{i,t-1}\right) \tag{1}$$

Where $R_{i,t}$ is the return for a stock index i on day t, and $P_{i,t}$ is the closing price for an index i on day t. Following the return calculation, we checked the stability of variables by running the augmented Dickey-Fuller test (ADF) test as presented by the following formulas:

---

[2] Dates are chosen according to the official delcaration of the pandemic by the World Health Organization (WHO) on March 11 2020.

$$\Delta y_t = \alpha + \beta T + \varphi y_{t-1} + \sum_{i=1}^{k} \delta_i y_{i,t-1} + u_t \tag{2}$$

$$\Delta y_t = \alpha + \varphi y_{t-1} + \sum_{i=1}^{k} \delta_i y_{i,t-1} + u_t \tag{3}$$

The deterministic term T refers to the trend. The ADF (Dickey and Fuller, 1979) is based on testing the hypothesis H_0: $\delta = 0$ against the alternative hypothesis of H_1: $\delta < 0$. The null hypothesis of ADF was to check the presence of a unit root. Hence, we executed a new test, the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test (Kwiatkowski et al., 1992), which considers the variables stationary and offers more coherent results. The KPSS test depends on error terms from time series regressions with exogenous variables. We also employed the KPSS test because it is equally effective for observing the presence of the unit root for both linear and nonlinear time series. Considering the unit root test results, we calculated the logarithmic difference by adding the return series at its level and trading volume.

Granger (1969) was the first to propose the causality test. For stationary two-time series, i.e., X and Y, predicting future results of information about the Y series, are based more on X series' historical information than Y series' historical information; the X series Granger causes the Y series. Following Ren et al. (2020), the VAR model is suggested to run the Granger causality test as follows:

$$y_t = \sum_{i=1}^{p} \alpha_i Y_{t-i} + \varepsilon_{Y,t} \tag{4}$$

$$y_t = \sum_{i=1}^{p} a_i X_{t-i} + b_i Y_{t-i} + \quad \varepsilon_{Y|X_t} \tag{5}$$

Where p denotes the dimension of the VAR model, α_i, a_i, and b_i denotes the coefficients of the model, and $\varepsilon_{Y,t}, \varepsilon_{Y|X_t}$ are the error terms. Granger causality between X and Y is observed by comparing the residual terms from the above models. Following Ren et al. (2020), the Granger causality index (GCI) can be computed through this formula

$$CCI_{X \to Y} = Ln\left(\frac{Var(\varepsilon_{Y,t})}{Var(\quad \varepsilon_{Y|X_t})}\right) \tag{6}$$

When $\varepsilon_{Y|X} < \varepsilon_Y$, $CCI_{X \to Y} > 0$, indicating that X is the Granger cause of Y. The classic Granger causality tests detailed previously are applied using linear models. Linear models result in incorrect findings because real-world systems present nonlinear dependencies among the series, as Tank et al. (2018) argue. Nonlinear methods commonly employ additional models to observe interactions in time series. Applying the following additional models leads to observing other nonlinear effects in the time series. This study adopts a nonlinear Granger causality test based on multilayer feedforward neural networks following Calvo-Pardo et al. (2021) and Montalto et al. (2015). They showed that the feedforward neural network is the most common statistical tool to be applied when running non-parametric regressions. Specifically, the advantage of the artificial neural network (ANN) is that without previous knowledge of the current physical processes, it can understand the mapping from the input to the output, which explains the large-scale arbitrarily complex nonlinear optimization problems. Furthermore, all the values obtained from the past are used in (ANN) forecasting. Table 1 indicates the Brock, Dechert, and Scheinkman (BDS)[3] test results for nonlinear dependence in stock return and trading volume.

Based on Montalto et al. (2015), a neural network comprises neurons lined up among layers. Specifically, the first is the input layer, which gets external inputs, and the last is the output layer, which provides the measurement results for the entire network. The remaining layers among the input and output are known as hidden layers or neurons, and to compute their numbers, we can rely on Vujicic et al. (2016). Fig. 1 depicts the virtual picture of the nonlinear Granger causality test process based on a multilayer (variable) feedforward neural network with one hidden layer (Calvo-Pardo et al., 2021).

NlinTS, an R package for nonlinear Granger causality detection in time series, is used. Moreover, we run impulse response analysis in linear and nonlinear models employing local projections by applying the following packages *dplyr, gridExtra, ggpubr, and lpirfs* in the R software. We regressed the impulse response functions with the local projection model (LP) rather than using both vector autoregressive (VAR) and structural vector autoregressive (SVAR) models. There are several advantages to using the LP model compared to traditional models, such as VAR or SVAR. First, LP models are based on simple linear regressions, making them easier to regress. Second, it is easier to conduct points or joint-wise inferences. Finally, according to (Adämmer, 2019; Jordà, 2005), the LP approach is robust to misspecification, does not suffer from the dimensionality inherent to VARs, and is easily fit to nonlinearities. Successive to the pioneering work by to Ò. Jordà (2005), several studies employed the L.P. methodology (Adämmer, 2019; Auerbach and Gorodnichenko, 2012; Favara and Imbs, 2015; Hamilton, 2011; Jordà and Taylor, 2016; Owyang et al., 2013; Swanson, 2021; Tenreyro and Thwaites, 2016). Jordà (2005) proposed using the ordinary least squares estimation (OLS) for every forecast horizon in the first step as follows:

---

[3] BDS test for nonlinear dependence in stock return and trading volume. The null hypothesis is that the remaining residuals are independent and identically distributed. Rejection H_0 implies that the remaining structure in the time series could include a hidden nonlinearity or nonstationarity.

Table 1

Nonlinearity BDS test results.

Stock returns (S.R.)				Trading volume (T.V.)				
Standard Normal					Standard Normal			
	[0.0070]	[0.0142]	[0.0211]	[0.0283]		[0.1210]	[0.2402]	[0.3603]	[0.4804]
2	3.5037	4.0844	4.2174	4.1993	2	6.3691	6.7689	7.5737	7.9825
3	5.4671	5.6715	5.5041	5.3574	3	7.6311	8.0227	8.5660	8.8682
P-value					P-value			
	[0.0070]	[0.0142]	[0.0211]	[0.0283]		[0.1210]	[0.2402]	[0.3603]	[0.4804]
2	0.0009	0.0001	0.0001	0.0001	2	0.0000	0.0000	0.0000	0.0000
3	0.0000	0.0000	0.0000	0.0000	3	0.0000	0.0000	0.0000	0.0000

Note: Table 1 indicates the Brock, Dechert, and Scheinkman (BDS) test results for nonlinear dependence in stock return and trading volume. The null hypothesis is that the remaining residuals are independent and identically distributed. Rejection H_0 implies that the remaining structure in the time series could include a hidden nonlinearity or nonstationarity.
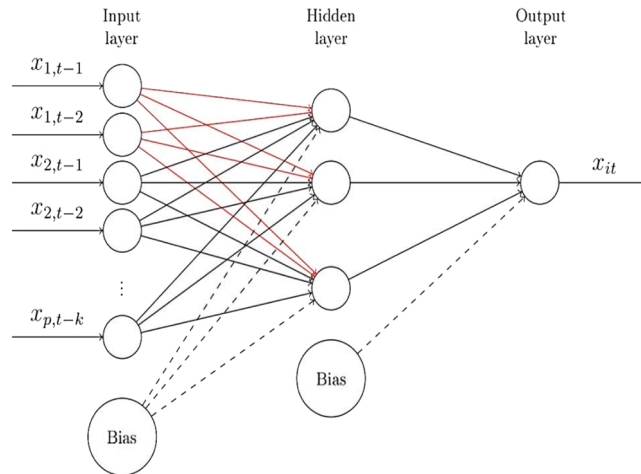

Fig. 1. Feed-forward neural network based nonlinear Granger causality.

$$y_{t+h} = \alpha^h + \beta_1^h Y_{t-1} + \cdots + \beta_p^h Y_{t-p} + u_{t+h}^h \; with \quad h = 0, 1, \ldots, H - 1 \tag{7}$$

Where α^h refers to the intercepts' vector, β_p^h refers to the coefficient matrices with lag p and forecast horizon h, and the vector elements u_{t+h}^h indicate the autocorrelated, heteroscedastic disturbances. Kilian and Kim (2011) state that these regressions are known as LPs. The slope matrix β_1^h is the response of Y_{t+h} to a reduced form shock in t, and the structural impulse responses are identified through this formula:

$$\widehat{I.R.}(t, h, d_i) = \widehat{\beta}_1^h d_i \tag{8}$$

Aiming to extend the LPs to nonlinear conceptual frameworks, we created two regimes by splitting data using a dummy variable. Adämmer (2019) and Auerbach and Gorodnichenko (2012) proposed calculating state probabilities by applying a logistic function that permits accounting for all model observations. This logistic function is provided in the following equation

$$F(z_t) = \frac{e^{(-\gamma z_t)}}{(1 + e^{(-\gamma z_t)})'} \tag{9}$$

$$var(z_t) = 1, E(z_t) = 0 \tag{10}$$

Where z_t is standardized, and ($\gamma > 0$) refers to scale-invariant. Following Auerbach and Gorodnichenko (2013), it is suggested to standardize the filter's cyclical components through the methodology of Hodrick and Prescott (1997) to obtain the variable z_t. Besides, Adämmer (2019) demonstrated that the observations for both regimes are obtained from the transition function and endogenous variables as follows:

$$Regime1(R_1) = y_{t-l} \bullet (1 - F(z_{t-1})) \quad with \quad l = 1, \ldots, p \tag{11}$$

$$Regime2(R_2) = y_{t-l} \bullet F(z_{t-1}) \quad with \quad l = 1, \ldots, p \tag{12}$$

Ahmed and Cassou (2016) applied the nonlinear impulse response forecast based on Adämmer (2019) to analyze the influences of consumer confidence on durable consumer goods in expansion and economic recession periods. Then, we regressed structural nonlinear impulse responses by applying these econometric models:

$$\widehat{I.R.}^{R_1}(t, h, d_i) = \widehat{\beta}_{1,R_1}^h d_i \quad with \quad h = 0, 1, \ldots, H-1 \tag{13}$$

$$\widehat{I.R.}^{R_2}(t, h, d_i) = \widehat{\beta}_{1,R_2}^h d_i \quad with \quad h = 0, 1, \ldots, H-1 \tag{14}$$

Where $\widehat{\beta}_{1,R_1}^0 = I$, $\widehat{\beta}_{1,R_2}^0 = I$, and $\widehat{\beta}_{1,R_1}^h$, $\widehat{\beta}_{1,R_2}^h$ refer to the parameters matrices, which are finally identified according to the LPs as follows:

$$y_{t+h} = \alpha^h + \beta_{1,R_1}^h \left(y_{t-l} \bullet (1 - F(z_{t-1}))\right) + \cdots + \beta_{p,R_1}^h \left(y_{t-p} \bullet (1 - F(z_{t-1}))\right) + \beta_{1,R_2}^h \left(y_{t-l} \bullet F(z_{t-1})\right) + \cdots + \beta_{p,R_2}^h \left(y_{t-l} \bullet F(z_{t-1})\right) + u_{t+h}^h with \quad h$$
$$= 0, 1, \ldots, H-1 \tag{15}$$

4. Results and tests

Table 2 illustrates the descriptive statistics of the variables. The mean for stock return and trading volume are 0.00056 and 3915.2610, respectively. The minimum and maximum values for returns and volumes are (-0.0714; 0.0603) and (1296.540; 9878.040), respectively. We investigate the skewness and kurtosis values to detect whether the variables are normally distributed. The kurtosis values in the two variables are higher than 3; hence, the series presents fat tail distributions.

Furthermore, the stock return is skewed to the left, while the trading volume is skewed to the right. In sum, the two variable series do not follow a normal distribution.

Fig. 2 depicts the daily change in returns and volumes, in which trading volumes appear more volatile than stock returns. Table 3 summarizes the results of the Augmented Dickey-Fuller (ADF) and (KPSS) unit root tests (Dickey and Fuller, 1979; Kwiatkowski et al., 1992). As shown in Fig. 2, the return and volume series do not exhibit a deterministic trend. Therefore, we considered one specification of the ADF and KPSS tests, i.e., neither a constant nor a deterministic trend. In this case, the ADF and KPSS tests reject (accept) the null hypothesis of a (non) unit root at 1% significance level and confirm the stock return time series stationarity. Our results show that the stock return series has no unit root at levels and is stationary. However, the ADF and KPSS reject (accept) the null hypothesis of nonstationarity (stationarity) at the first difference for the trading volume series.

We run a *VAR (p)* model with nine lags between the two-time series to analyze the dynamic evolution of each variable across days and in relation to one another and to consider some days for the propagation of the information across the market. *p* is suggested as equal to three and nine days by the Akaike information criterion (AIC) and Goodness of fit criteria (BIC). The direction of the significant relationship was only from the return to trading volume. There was almost no significant relationship for the direction from trading volume to return. We reported only the results of the relevant VAR tests because the overconfidence hypothesis test is based on the direction from the return to the trading volume. Unreported results are available from the corresponding author upon request).

Table 4 reports the VAR model results. The rows show the influence of independent variables at lags 1–9. Since we aim to determine the impacts of stock return and trading volume on trading volume, the second block of rows and the two columns should be our focus. The first part shows how the trading volume is determined by its lags. The Table demonstrates that the trading volume is negatively correlated with its past values at lag 1, 3 at 10%, and 5 at 5%. At the same time, it shows no correlation with the remaining lags. One possible explanation for this phenomenon is that we anticipate that trading volume's past information should be more impactful and easier to be captured in a young market than in mature markets such as the S&P 500. However, the second block of rows shows that the trading volume predicts itself. Most lagged values of volumes from 1–9 days are significant at 1% and 5% with negative signs. This outcome is the Granger causality concept, where the trading volume also displays strongly negative autocorrelations in the presence of

Table 2
Summary statistics.

	Stock return (S.R.)	Trading volume (T.V.)
Mean	0.0006	3915.2610
Median	0.0011	3651.7623
Min	-0.0714	1296.5401
Max	0.0603	9878.0405
Std.Dev	0.0095	1030.2530
Skewness	-0.8246	1.8326
Kurtosis	10.7552	7.9658
Jarque-Bera	3729.9340	2260.1832
Probability	0,0000	0,0000
Sum	0.7951	55753328
Observations	1424	1424

Note: Table 2 illustrates the descriptive statistics of the variables. Stock returns are skewed to the left, while the trading volumes are skewed to the right, indicating that the variables are not normally distributed.
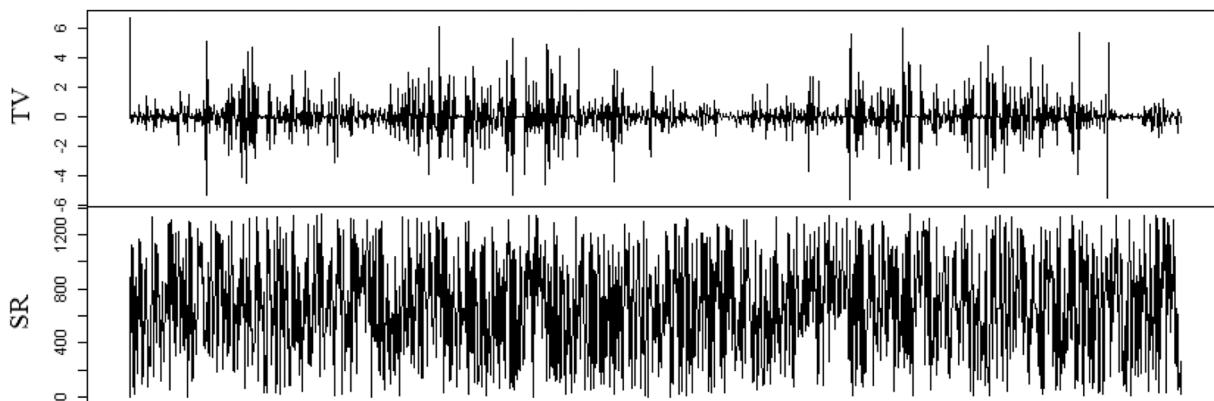
Fig. 2. Representation of the daily change of stock returns and trading volume on the S&P 500 index, January 2016 to August 2021.

Table 3
Results of the ADF and KPSS unit root tests.

ADF test			KPSS test		
Variables	(t) Statistics	P-value	Variables	(t) Statistics	P-value
S.R.	− 48.8563 *	0.0009	SR	0.0676 *	0.1023
Ln (T.V.)	− 4.95480 *	0.0009	Ln (T.V.)	3.6586	0.0104
Ln (T.V.) − 1	− 61.7132 *	0.0009	Ln (T.V.) − 1	0.0018 *	0.1006

Note: * denotes rejection/acceptance of the null hypothesis (non-stationary/ stationary variable) at 1% significance level.
The table indicates that the stock return variable is stationary in level except for trading volume, which is stationary in difference

Table 4
Results of the 9-lag VAR analysis (Stock return and Trading volume).

		Independent Variables	
Dependent Variable	Lag	S.R.	T.V.
	1		-0.0427 *
	2		0.0198
	3		-0.0152 *
T.V.	4		0.0317
	5		-0.0342 * *
	6		0.0169
	7		0.0355
	8		0.039
	9		0.011
Adjusted R-squared			0.1799
F-statistics			34.0572 * **
	1	0.2284 * **	-0.0880 * **
	2	0.3444 * **	0.0400
	3	0.2665 * **	-0.0450 * **
T.V.	4	0.2235 * **	-0.0440 * **
	5	0.2179 * **	-0.0380 * *
	6	0.7980 * **	-0.0460 * **
	7	-0.6393 * *	0.0420
	8	0.4143	-0.0280 * *
	9	-0.4316 * *	-0.0290 *
Adjusted R-squared			0.2224
F-statistics			46.3261 * **

Note: The table reports the VAR model estimations with returns and volumes. The rows show the influence of independent variables at lags 1–9 by running the following models: $y_t = \sum_{i=1}^{p} \alpha_i Y_{t-i} + \varepsilon_{Y,t}$ and $y_t = \sum_{i=1}^{p} a_i X_{t-i} + b_i Y_{t-i} + \varepsilon_{Y|X_t}$
* ** $p < 0.01$, * * $p < 0.05$, * $p < 0.1$

past information from stock returns.

Furthermore, the positive association between trading volumes and stock returns at the lags from 1 to 6 is also coherent with the prediction that rising (falling) waves of stock return lead to a transient increase (decrease) in trading volume in the short term. Likewise, the changes in the trading volume are also negatively correlated with the lagged stock return, at 5% level with lag 7, 9. Thus,

we can assume that returns could drive the movements in trading volume in the opposite direction.

To achieve Granger causality, we establish the VAR models considering two-time series of trading volumes and stock returns with length n, which are jointly stationary. Stock return time series is said to cause (Granger-cause) trading volumes if the prediction results of the future information of trading volumes based on the past information of stock returns and trading volumes are better than the results only based on the past information of trading volumes. However, we should distinguish between correlation and causality from a statistical standpoint. We should introduce the Granger causality to understand whether stock returns are useful in forecasting trading volumes.

Table 5 reports linear and nonlinear Granger causality test results. We chose lag length based on AIC values, i.e., lag lengths in stock return and trading volume are 3 and 9, respectively. This means that trading volume gradually and significantly increases with the stock return sequence length, being 2.5–3 times higher following sequences of more days. The F-statistics have probabilities lower than 0.05, indicating a causal relationship between the stock return to trading volume. i.e., we reject the null hypothesis that stock return is not Granger's cause of trading volume at the 5% level of statistical significance. This empirical result implies that investors in the S&P 500 index exhibit or suffer from overconfidence behavior. We mention that the causal relationship between stock return and trading volume is one-sided, as we do not find a statistically significant causal relationship between trading volume and stock return. As the overconfidence hypothesis test considers a causality relationship between stock return to trading volume, only the most relevant causality test findings are presented in Table 5. The results from other unreported causality tests are available upon request.

Fig. 3 displays the linear impulse response analysis results; one standard deviation shock from return affects trading volume in the panel's upper right corner. The trading volume rises by roughly 0.02 units when a standard deviation shock in returns occurs during the first and second days. While the trading volume negatively responds to return shocks from the second day to the fifth, it returns to normal and responds positively between the sixth and seventh days. Based on impulse responses over forecast horizons of 20 days, we can see that the response of the trading volume to return shocks is positive and negative, changing from one day to another.

Figs. 4 and 5 display the nonlinear impulse response analysis results and apply the logistic function to differentiate between nonlinear impulse response analysis regimes. We consider no trend exists, and the shock type equals one standard deviation shock. We can see the trading volume variation if one standard deviation return shock occurs in both low and high returns. In Fig. 4, in the first and second days, as seen in the upper right corner of the panel in the low return regime, one standard deviation return shock helps diminish the trading volume. Next, trading volume responds positively to the return shock during the second and fourth days. Then, from the fourth to the ninth day, there is a decreasing tendency in the trading volume reaction to shocks from return. We can also say that the trading volume response to shocks from the return is mainly at low levels, starting from the fourth day. To sum up, the most remarkable positive trading volume reaction to a standard deviation return shock runs from 0.025 to 0.05. However, the greatest negative reaction was 0.05.

In Fig. 5, in the first and second days, as observed in the upper right corner of the panel in the high return regime, the trading volume rises by more than 0.1 units when one standard deviation return shock occurs. Following the second day, trading volume declined by 0.15 units to a shock from return. We can also say that the trading volume reaction to shocks from the return is positive but at low levels starting from the fourth day. Overall, the first trading volume response to shocks from the return goes beyond two days, and the reaction is higher in the high regime than in the low regime. Furthermore, we notice that response intensity diminishes after the second day. The trading volume reaction to shocks from the return does not disappear and continues until 20 days. Also, comparing the two graphs related to low and high return regimes, we can see that trading volume reaction to return shocks present certain asymmetries for different regimes. We also adopt impulse responses over 60 days forecast horizons as robustness checks. The results are not significantly different from those in Figs. 3, 4, and 5, as the trading volume reaction to the return shocks does not disappear and continues. We do not report results for 60 days to conserve space—however, they are available upon request.

Based on the analysis in this section, we provide evidence of overconfidence among investors. Such behavior may be linked to the increase in the number of investors. However, there is a decline in the rate of returns during the study period, implying uncertainty caused by the COVID-19 pandemic. Our results align with three related research areas. First, notwithstanding the evolution of financial markets, the results support previous findings on the existence of overconfidence in the U.S. market and other less developed markets, as shown by Odean (1998a) (1998b) (1999) and Barber and Odean (2000, 2001) and recently, Qiao et al. (2022) and Thi Tuyet Dao et al. (2023) who document overconfidence among U.S. CFOs and Vietnamese managers. Second, from a methodological standpoint, perhaps, the causality between return and trading volume is the prevailing approach, as appeared in Barber and Odean (2000, 2001). In this research, we build on the previous academic work by introducing two novel nonlinear modeling and forecasting techniques

Table 5
Results of the linear and nonlinear Granger causality tests.

Linear Granger Causality test		Nonlinear Granger Causality test	
Proper lag order	9	Proper lag order	9
Granger causality index	0.0322	Granger causality index	0.0883
F-statistics	4.8509	F-statistics	112.8112
P-value	0.0002	P-value	0.0000
Critical value (5%)	3.1378	Critical value (5%)	4.1410

Note: In this table, we report both linear and nonlinear Granger causality test results. We chose lag length based on AIC values; i.e., lag lengths in stock return and trading volume are 3 and 9, respectively. The F-statistics have probabilities of (0.000244; 2.867e−24), which is lower than 0.05, indicating a causal relationship between the stock return to trading volume. We reject the null hypothesis that stock return is not Granger's cause of trading volume at the 5% level of statistical significance.
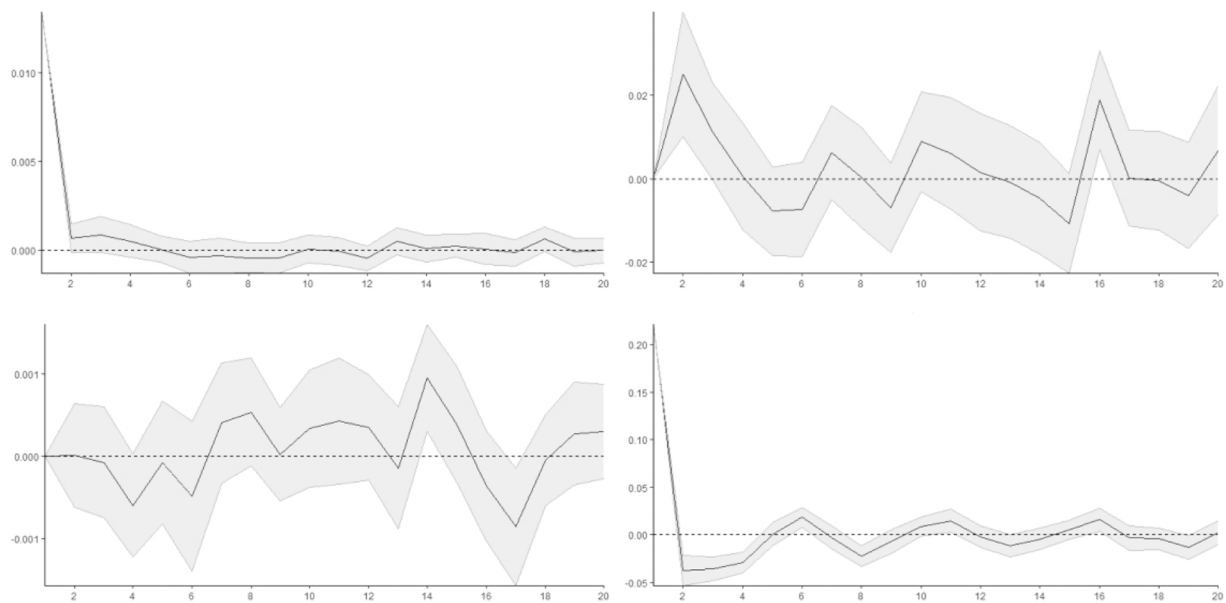
Fig. 3. Representation of the linear impulse responses. This figure plots the linear impulse responses of the trading volume to a standard deviation shock in stock return. Lines indicate the estimates, and the gray area is the 90% confidence interval. The y-axis is percentage points, and the x-axis is the days after the shock. Sample period January 2016–August 2021.
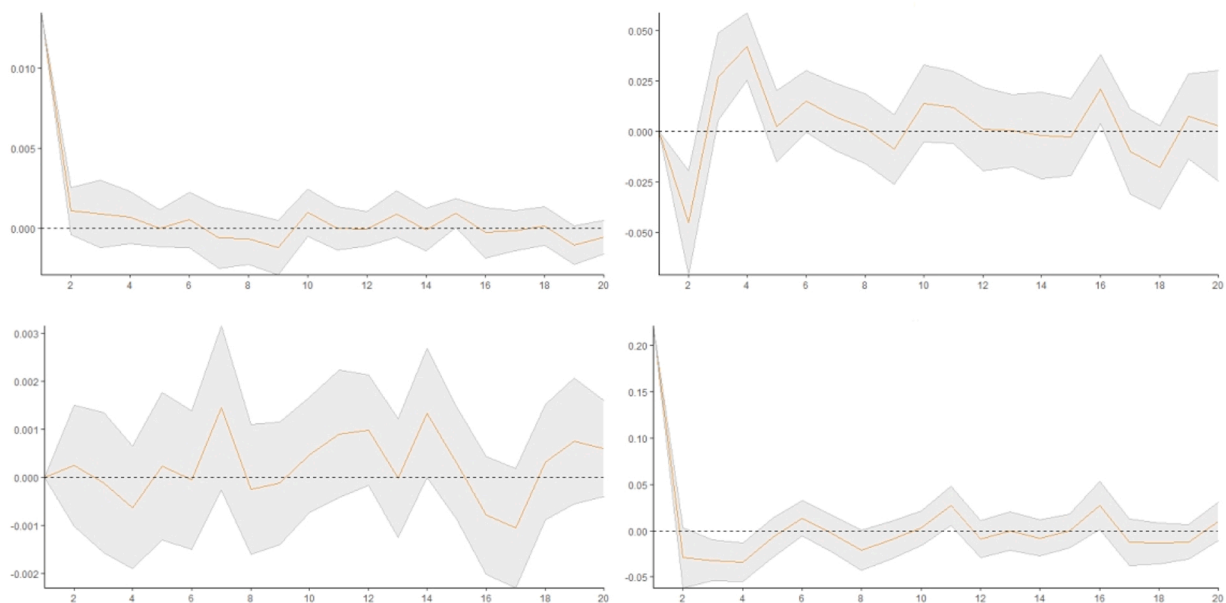

Fig. 4. Representation of the nonlinear impulse responses over the low return regime. This figure plots the nonlinear impulse responses of the trading volume to a standard deviation shock in stock return over the low return regime. Lines indicate the estimates, and the gray area is the 90% confidence interval. The y-axis is the percentage points, and the x-axis is the days after the shock. Sample period January 2016–August 2021.

applied to test overconfidence, studying the COVID-19 period. We provide that the impulse response analysis that we employed and has been previously developed is a valid method to capture overconfidence, which supports the findings by (Alsabban and Alarfaj, 2020; Metwally and Darwish, 2015; Sheikh and Riaz, 2012; Statman et al., 2006; Zaiane and Abaoub, 2009). Third, by covering part of the COVID-19 pandemic, our results align with previous research, considering the pandemic a shock to financial markets and inducing heterogeneous behaviors among different markets and asset classes due to investor behavior in discounting positive/negative information (Akhtaruzzaman, Boubaker, Chiah et al., 2021; Akhtaruzzaman, Boubaker, Lucey et al., 2021; Baker et al., 2020; Pandey and Kumari, 2021; Wang and Wang, 2021).
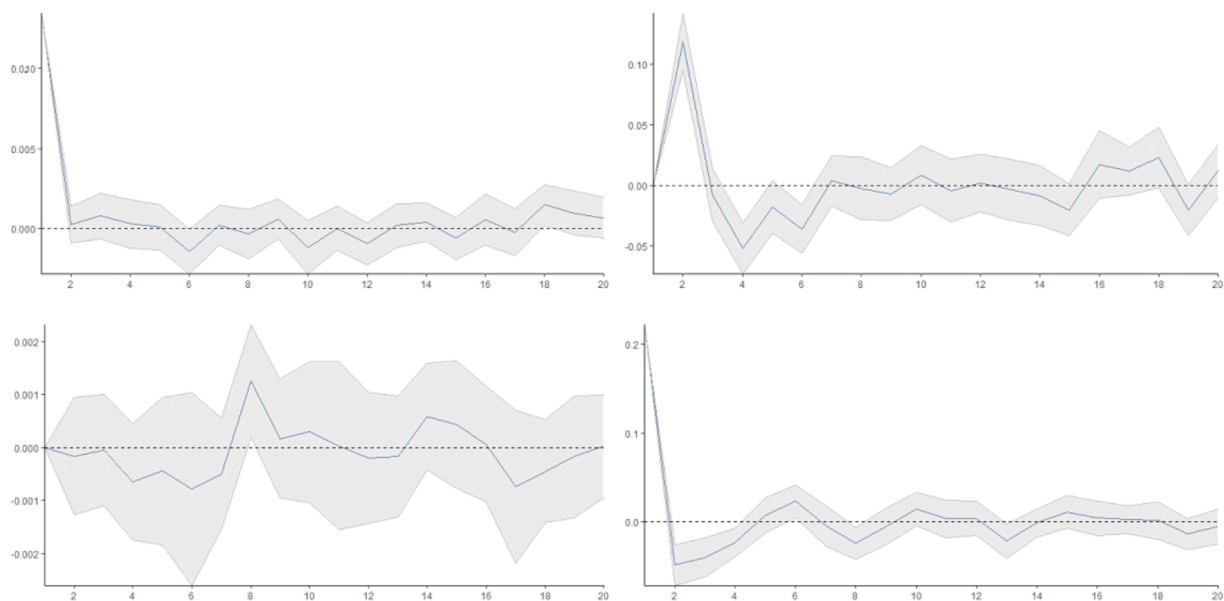
Fig. 5. Representation of the nonlinear impulse responses over the high return regime. This figure plots the nonlinear impulse responses of the trading volume to a standard deviation shock in stock return over the high return regime. Lines indicate the estimates, and the gray area is the 90% confidence interval. The y-axis is percentage points, and the x-axis is the days after the shock. Sample period January 2016–August 2021.

5. Conclusions

We investigate the relationship between stock return and trading volume to test the overconfidence behavior among investors in the U.S. stock market (i.e., the S&P 500 index) covering the COVID-19 period. In particular, we used daily data from January 4, 2016, to August 31, 2020, to examine the causal relations between the S&P 500 index return and the trading volume and the trading volume reactions to shocks from returns over various regimes. We build on the previous academic works by introducing two novel nonlinear modeling and forecasting techniques to test overconfidence studying the COVID-19 period, i.e., nonlinear Granger causality analysis based on multilayer feedforward neural networks and nonlinear impulse response analysis based on LPs developed by Calvo-Pardo et al. (2021) and Montalto et al. (2015). The methods adopted appear to capture the overconfidence among U.S. investors during the COVID-19 pandemic, contributing to the existing literature on investors' behavior and the effect of the pandemic.

Results from causality analysis are consistent with the hypothesis that stock returns cause trading volumes. We find that this causal association between return and trading volume reinforces our confidence in the existence of overconfidence behavior in the U.S. market. The two different regimes in nonlinear impulse response analysis can be related to whether the market returns are low or high. We show a fast response from trading volume to the return shocks between the two regimes. There is a stronger response from the second to the fourth day, and the response becomes lower in the coming days compared with the first days. Precisely, for a low return regime, while the first trading volume reaction to shock from the return is negative, the response is positive following the second day. For a high return regime, the reaction of the trading volume mainly increases to the return shock between the first and second day. Furthermore, we state that trading volume responses to shocks in returns present asymmetries over various regimes.

The findings of this research have direct implications for market participants. On the one hand, investors present overconfidence behavior when trading on the S&P 500 index. Moreover, this overconfidence behavior, i.e., positive trading volume reaction to shocks from the return, occurs under delay in the low return regime. The behavior is stronger for the first days in the high return regime. Alternatively, evidence of asymmetric trading volume responses suggests that investors and portfolio managers should consider the type of return regime in the market to predict which behavior is the most dominant.

The evidence of investor overconfidence in the S&P 500 index again questions why investors considering small amounts of investment undergo additional losses. These findings concur with studies from stock markets like the U.S. The result shows that trading volume reactions to shocks in return do not disappear, indicating that overconfidence is primarily dominant and persistent behavior in the U.S. market. Besides, as we find only a causal relationship supporting the direction from returns to trading volumes, we confirm that the increase in trading volume, even due to overconfidence behavior, does not lead to any significant return variation. Finally, research studies considering making important contributions to developing financial literacy will give investors the necessary knowledge and skills to make more rational decisions instead of judgments resulting from overconfidence.

In this regard, future research could be extended to cover the personal traits of investors and financial managers, distinguishing between retail and institutional investors. The Russian-Ukrainian war of 2022 is another arena where behavioral traits in financial markets could be tested, building on the early research that demonstrates negative abnormal returns in global financial markets (Abbassi et al., 2022; Boubaker et al., 2022), revealing the investors' fear and negative expectations of global markets due to significant

geopolitical tensions and wars. The impact of the R-U war on corporations could also be extended, building on Tosun and Eshraghi's (2022) work in showing that firms staying in Russia underperform due to investors imposing penalties, generating higher trading volumes due to selling pressures on the remaining firms.

Ethics approval statement

This article does not contain any studies with human participants or animals performed by any of the authors.

Funding statement

The authors received no financial support for the research, authorship, and/or publication of this article.

Declaration of Competing Interest

No conflicts of interest exist in this article or during its elaboration.

Data Availability

Data will be made available on request.

References

Abbassi, W., Kumari, V., Pandey, D.K., 2022. What makes firms vulnerable to the Russia–Ukraine crisis? J. Risk Financ. 24 (1), 24–39. https://doi.org/10.1108/JRF-05-2022-0108/FULL/PDF.

Abbes, M., 2013. Does overconfidence bias explain volatility during the global financial crisis. Transit. Stud. Rev. 19 (3), 291–312. https://doi.org/10.1007/S11300-012-0234-6.

Abdeldayem, M., & Mahmoud, M. (2013). An examination into the impact of trading motives on the dynamic relationship between stock returns and trading volume evidence from Egypt. Global Advanced Research Journal of Management and Business Studies, 2(4), 206–221. http://garj.org/garjmbs/4/2013/2/4/.

Adämmer, P., 2019. lpirfs: an R package to estimate impulse response functions by local projections. R. J. 11 (2), 421–438. https://doi.org/10.32614/RJ-2019-052.

Ahmed, B., Sharif, T., Abedin, M.Z., 2023a. Does investor sentiment create value for asset pricing? An empirical investigation of the KOSPI-listed firms. Int. J. Financ. Econ. https://doi.org/10.1002/ijfe.2836.

Ahmed, B., Petr, H., Fisher, B., Abedin, M.Z., 2023b. Nonlinearity in forecasting energy commodity prices: evidence from a focused time-delayed neural network. Res. Int. Bus. Financ. 64 (2023), 101863 https://doi.org/10.1016/j.ribaf.2022.101863.

Ahmed, M.I., Cassou, S.P., 2016. Does consumer confidence affect durable goods spending during bad and good economic times equally. J. Macroecon. 50, 1339–1351. https://doi.org/10.1016/J.JMACRO.2016.08.008.

Akerlof, G.A., & Shiller, R.J. (2010). Animal spirits: How human psychology drives the economy, and why it matters for global capitalism. In Animal Spirits: How Human Psychology Drives the Economy, and Why It Matters for Global Capitalism. Princeton University Press. https://doi.org/10.5455/ey.20020.

Akhtaruzzaman, M., Boubaker, S., Chiah, M., Zhong, A., 2021. COVID–19 and oil price risk exposure. Financ. Res. Lett. 42, 101882 https://doi.org/10.1016/J.FRL.2020.101882.

Akhtaruzzaman, M., Boubaker, S., Lucey, B.M., Sensoy, A., 2021. Is gold a hedge or a safe-haven asset in the COVID–19 crisis. Econ. Model. 102, 105588 https://doi.org/10.1016/J.ECONMOD.2021.105588.

Alsabban, S., Alarfaj, O., 2020. An empirical analysis of behavioral finance in the saudi stock market: evidence of overconfidence behavior. Int. J. Econ. Financ. Issues 10 (1), 73–86. https://doi.org/10.32479/IJEFI.8920.

Arifin, Z., & Soleha, E. (2019). Overconfidence, Attitude Toward Risk, and Financial Literacy: A Case in Indonesia Stock Exchange. Integrative Business and Economics Research, 8(4s), 115–134. http://buscompress.com/riber-8-s4.html.

Auerbach, A.J., Gorodnichenko, Y., 2012. Measuring the output responses to fiscal policy. Am. Econ. J.: Econ. Policy 4 (2), 1–27. https://doi.org/10.1257/POL.4.2.1.

Baker, S.R., Bloom, N., Davis, S.J., Kost, K., Sammon, M., Viratyosin, T., 2020. The unprecedented stock market reaction to COVID-19. Rev. Asset Pricing Stud. 10 (4), 742–758. https://doi.org/10.1093/RAPSTU/RAAA008.

Barber, B.M., Odean, T., 2000. Trading is hazardous to your wealth: the common stock investment performance of individual investors. J. Financ. 55 (2), 773–806. https://doi.org/10.1111/0022-1082.00226.

Barber, B.M., Odean, T., 2001. Boys will be boys: gender, overconfidence, and common stock investment. Q. J. Econ. 116 (1), 261–292. https://doi.org/10.1162/003355301556400.

Berg, J.E., Rietz, T.A., 2019. Longshots, overconfidence and efficiency on the Iowa electronic market. Int. J. Forecast. 35 (1), 271–287. https://doi.org/10.1016/j.ijforecast.2018.03.004.

Bolaman, Ö., & Yücel, A.T. (2012). Overconfidence Hypothesis: An Empirical Study in ISE. Ournal of Money, Investment and Banking, 26, 111–123. https://www.researchgate.net/publication/325602914_Overconfidence_Hypothesis_An_Empirical_Study_in_ISE.

Boubaker, S., Goodell, J.W., Pandey, D.K., Kumari, V., 2022. Heterogeneous impacts of wars on global equity markets: evidence from the invasion of Ukraine. Financ. Res. Lett. 48, 102934 https://doi.org/10.1016/J.FRL.2022.102934.

Brown, R., Sarma, N., 2007. CEO overconfidence, CEO dominance and corporate acquisitions. J. Econ. Bus. 59 (5), 358–379. https://doi.org/10.1016/J.JECONBUS.2007.04.002.

Calvo-Pardo, H., Mancini, T., Olmo, J., 2021. Granger causality detection in high-dimensional systems using feedforward neural networks. Int. J. Forecast. 37 (2), 920–940. https://doi.org/10.1016/j.ijforecast.2020.10.004.

Chang, C.L., McAleer, M., Wang, Y.A., 2020. Herding behaviour in energy stock markets during the Global Financial Crisis, SARS, and ongoing COVID-19. Renew. Sustain. Energy Rev. 134, 110349 https://doi.org/10.1016/J.RSER.2020.110349.

Chen, G., Kim, K.A., Nofsinger, J.R., Rui, O.M., 2007. Trading performance, disposition effect, overconfidence, representativeness bias, and experience of emerging market investors. J. Behav. Decis. Mak. 20 (4), 425–451. https://doi.org/10.1002/BDM.561.

Cicchiello, A.F., Cotugno, M., Monferrà, S., Perdichizzi, S., 2022. Credit spreads in the European green bond market: a daily analysis of the COVID-19 pandemic impact. J. Int. Financ. Manag. Account. 33 (3), 383–411. https://doi.org/10.1111/JIFM.12150.

Contessi, S., De Pace, P., 2021. The international spread of COVID-19 stock market collapses. Financ. Res. Lett. 42, 101894 https://doi.org/10.1016/J.FRL.2020.101894.

Deaves, R., Lüders, E., Schröder, M., 2010. The dynamics of overconfidence: evidence from stock market forecasters. J. Econ. Behav. Organ. 75 (3), 402–412. https://doi.org/10.1016/J.JEBO.2010.05.001.

Dickey, D.A., Fuller, W.A., 1979. Distribution of the Estimators for Autoregressive Time Series With a Unit Root. J. Am. Stat. Assoc. 74 (366), 427. https://doi.org/10.2307/2286348.

Favara, G., Imbs, J., 2015. Credit supply and the price of housing. Am. Econ. Rev. 105 (3), 958–992. https://doi.org/10.1257/AER.20121416.

Granger, C.W.J., 1969. Investigating causal relations by econometric models and cross-spectral methods. Econometrica 37 (3), 424. https://doi.org/10.2307/1912791.

Hamilton, J.D., 2011. Nonlinearities and the macroeconomic effects of oil prices. Macroecon. Dyn. 15 (S3), 364–378. https://doi.org/10.1017/S1365100511000307.

Hodrick, R., & Prescott, E. (1997). Postwar U.S. Business Cycles: An Empirical Investigation. Journal of Money, Credit and Banking, 29(1), 1–16. https://econpapers.repec.org/RePEc:mcb:jmoncb:v:29:y:1997:i:1:p:1–16.

Hwang, S., Cho, Y., Shin, J., 2020. The impact of UK household overconfidence in public information on house prices. J. Prop. Res. 37 (4), 360–389. https://doi.org/10.1080/09599916.2020.1790631.

Johnson, D., Asher Levin, S., 2009. The tragedy of cognition: psychological biases and environmental inaction. Curr. Sci. 97 (11), 1593–1603 https://doi.org/10.2/JQUERY.MIN.JS.

Jordà, Ò., 2005. Estimation and inference of impulse responses by local projections. Am. Econ. Rev. 95 (1), 161–182. https://doi.org/10.2307/1912017.

Jordà, Òscar, Taylor, A.M., 2016. The time for austerity: estimating the average treatment effect of fiscal policy. Econ. J. 126 (590), 219–255. https://doi.org/10.1111/ECOJ.12332.

Kansal, P., Singh, S., 2018. Determinants of overconfidence bias in Indian stock market. Qual. Res. Financ. Mark. 10 (4), 381–394. https://doi.org/10.1108/QRFM-03-2017-0015.

Khalfaoui, R., Gozgor, G., Goodell, J.W., 2023. Impact of Russia-Ukraine war attention on cryptocurrency: evidence from quantile dependence analysis. Financ. Res. Lett. 52, 103365 https://doi.org/10.1016/J.FRL.2022.103365.

Kilian, L., Kim, Y.J., 2011. How reliable are local projection estimators of impulse responses. Rev. Econ. Stat. 93 (4), 1460–1466. https://doi.org/10.1162/REST_A_00143.

Kwiatkowski, D., Phillips, P.C.B., Schmidt, P., Shin, Y., 1992. Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? J. Econ. 54 (1–3), 159–178. https://doi.org/10.1016/0304-4076(92)90104-Y.

Malmendier, U., Tate, G., 2005. CEO overconfidence and corporate investment. J. Financ. 60 (6), 2661–2700. https://doi.org/10.1111/J.1540-6261.2005.00813.X.

Matos, P., Costa, A., da Silva, C., 2021. COVID-19, stock market and sectoral contagion in US: a time-frequency analysis. Res. Int. Bus. Financ. 57, 101400 https://doi.org/10.1016/J.RIBAF.2021.101400.

Metawa, N., Hassan, M.K., Metawa, S., Safa, M.F., 2019. Impact of behavioral factors on investors' financial decisions: case of the Egyptian stock market. Int. J. Islam. Middle East. Financ. Manag. 12 (1), 30–55. https://doi.org/10.1108/IMEFM-12-2017-0333.

Metwally, A., Darwish, O., 2015. Evidence of the overconfidence bias in the Egyptian stock market in different market states. Int. J. Bus. Econ. Dev. 3 (3), 35–55.

Miklesh, P.Y., Sharif, T., Ashok, S., Dhingra, D., Abedin, M.Z., 2023. Investigating volatility spillover of energy commodities in the contexts of the Chinese and European stock markets. Res. Int. Bus. Financ. 65 (2023), 101948 https://doi.org/10.1016/j.ribaf.2023.101948.

Montalto, A., Stramaglia, S., Faes, L., Tessitore, G., Prevete, R., Marinazzo, D., 2015. Neural networks with non-uniform embedding and explicit validation phase to assess Granger causality. Neural Netw. 71, 159–171. https://doi.org/10.1016/J.NEUNET.2015.08.003.

Moore, D.A., Healy, P.J., 2008. The trouble with overconfidence. Psychol. Rev. 115 (2), 502–517. https://doi.org/10.1037/0033-295X.115.2.502.

Neale, M.A., Bazerman, M.H., 1985. The Effects of Framing and Negotiator Overconfidence on Bargaining Behaviors and Outcomes. Acad. Manag. J. 28 (1), 34–49. https://doi.org/10.2307/256060.

Odean, T., 1998a. Are investors reluctant to realize their losses. J. Financ. 53 (5), 1775–1798. https://doi.org/10.1111/0022-1082.00072.

Odean, T., 1998b. Volume, volatility, price, and profit when all traders are above average. J. Financ. 53 (6), 1887–1934. https://doi.org/10.1111/0022-1082.00078.

Odean, T., 1999. Do investors trade too much. Am. Econ. Rev. 89 (5), 1279–1298. https://doi.org/10.1257/AER.89.5.1279.

Owyang, M.T., Ramey, V.A., Zubairy, S., 2013. Are government spending multipliers greater during periods of slack? Evidence from twentieth-century historical data. Am. Econ. Rev. 103 (3), 129–134. https://doi.org/10.1257/AER.103.3.129.

Pandey, D.K., Kumari, V., 2021. Event study on the reaction of the developed and emerging stock markets to the 2019-nCoV outbreak. Int. Rev. Econ. Financ. 71, 467–483. https://doi.org/10.1016/J.IREF.2020.09.014.

Phan, D.T.T., van Hoang, T., Le, Nguyen, T.T.H., 2020. Overconfidence bias, comparative evidences between vietnam and selected ASEAN countries. J. Asian Financ. Econ. Bus. 7 (3), 101–113. https://doi.org/10.13106/JAFEB.2020.VOL7.NO3.101.

Qasim, M., Hussain, R.Y., Mehboob, I., Arshad, M., 2019. Impact of herding behavior and overconfidence bias on investors' decision-making in Pakistan. Accounting 5 (2), 81–90. https://doi.org/10.5267/J.AC.2018.7.001.

Qiao, L., Adegbite, E., Nguyen, T.H., 2022. Chief financial officer overconfidence and stock price crash risk. Int. Rev. Financ. Anal. 84, 102364 https://doi.org/10.1016/J.IRFA.2022.102364.

Ren, W., Li, B., Han, M., 2020. A novel Granger causality method based on HSIC-Lasso for revealing nonlinear relationship between multivariate time series. Phys. A: Stat. Mech. Its Appl. 541. https://doi.org/10.1016/j.physa.2019.123245.

Roll, R., 1986. The hubris hypothesis of corporate takeovers. J. Bus. 59 (2), 197–216. https://doi.org/10.1086/296325.

Şahìn, S., Özlem YILMAZ, ve, 2014. Overconfidence in finance with different domains: an interdisciplinary experimental approach. J. Econ. Adm. Sci. 15 (1), 253–268. ⟨http://esjournal.cumhuriyet.edu.tr/en/pub/cumuiibf/issue/4265/57380⟩.

Seligman, M.E., 2015. Authentic Happiness Age Group Occupation Group Education Level Zip Code (1st ed.). Simon and Schuster.

Sheikh, M.F., Riaz, K., 2012. Overconfidence bias, trading volume and returns volatility: evidence from Pakistan. World Appl. Sci. J. 18 (12), 1737–1748.

Skala, D., 2008. Overconfidence in psychology and finance – an interdisciplinary literature review. Bank I Kredyt 4, 33–50.

Statman, M., Thorley, S., Vorkink, K., 2006. Investor overconfidence and trading volume. Rev. Financ. Stud. 19 (4), 1531–1565. https://doi.org/10.1093/RFS/HHJ032.

Swanson, E.T., 2021. Measuring the effects of federal reserve forward guidance and asset purchases on financial markets. J. Monet. Econ. 118, 32–53. https://doi.org/10.1016/J.JMONECO.2020.09.003.

Tank, A., Covert, I., Foti, N., Shojaie, A., Fox, E., 2018. Neural granger causality. ArXiv:1802. 05842 44 (8), 4267–4279. https://doi.org/10.1109/TPAMI.2021.3065601.

Taylor, S.E., Brown, J.D., 1994. Positive illusions and well-being revisited: separating fact from fiction. Psychol. Bull. 116 (1), 21–27. https://doi.org/10.1037/0033-2909.116.1.21.

Tekçe, B., Yilmaz, N., 2015. Are individual stock investors overconfident? Evidence from an emerging market. J. Behav. Exp. Financ. 5, 35–45. https://doi.org/10.1016/J.JBEF.2015.02.003.

Tekin, B., 2020. Measurement of overconfidence, illusion of control and optimism in the context of behavioral finance: case of university students. J. Soc. Sci. Mus. Alparslan Univ. 8 (4), 1315–1322. https://doi.org/10.18506/ANEMON.615003.

Tenreyro, S., Thwaites, G., 2016. Pushing on a string: US monetary policy is less powerful in recessions. Am. Econ. J.: Macroecon. 8 (4), 43–74. https://doi.org/10.1257/MAC.20150016.

Thi Tuyet Dao, N., Guney, Y., Hudson, R., 2023. Managerial overconfidence and corporate cash holdings: evidence from primary and secondary data. Res. Int. Bus. Financ. 65, 101943 https://doi.org/10.1016/J.RIBAF.2023.101943.

Tosun, O.K., Eshraghi, A., 2022. Corporate decisions in times of war: evidence from the Russia-Ukraine conflict. Financ. Res. Lett. 48, 102920 https://doi.org/10.1016/J.FRL.2022.102920.

Trejos, C., van Deemen, A., Rodríguez, Y.E., Gómez, J.M., 2019. Overconfidence and disposition effect in the stock market: a micro world based setting. J. Behav. Exp. Financ. 21, 61–69. https://doi.org/10.1016/J.JBEF.2018.11.001.

Trivers, R., 2000. The elements of a scientific theory of self-deception. Ann. N. Y. Acad. Sci. 907 (1), 114–131. https://doi.org/10.1111/J.1749-6632.2000.TB06619.X.

Tuchman, B.W. (2014). The march of folly: from Troy to Vietnam (paperback). Random House Trade Paperbacks.

Vujicic, T., Matijevic, T., Ljucovic, J., Balota, A., Sevarac, Z. (2016). Comparative Analysis of Methods for Determining Number of Hidden Neurons in Artificial Neural Network. In Central European Conference on Information and Intelligent Systems.

Wang, & Daxue (2008). Herd behavior towards the market index: Evidence from 21 financial markets. In IESE Research Papers. IESE Business School. https://ideas. repec.org/p/ebg/iesewp/d-0776.html.

Wang, J., Wang, X., 2021. COVID-19 and financial market efficiency: evidence from an entropy-based analysis. Financ. Res. Lett. 42, 101888 https://doi.org/ 10.1016/J.FRL.2020.101888.

Wrangham, R., 1999. Is Military incompetence adaptive. Evol. Hum. Behav. 20 (1), 3–17. https://doi.org/10.1016/S1090-5138(98)00040-3.

Zaiane, S., & Abaoub, E. (2009). Investor Overconfidence And Trading Volume: The Case Of An Emergent Market. International Review of Business Research Papers, 5, 213–222. https://www.researchgate.net/publication/254158420_Investor_Overconfidence_And_Trading_Volume_The_Case_Of_An_Emergent_Market.

Zhang, X., Liang, J., He, F., 2019. Private information advantage or overconfidence? Performance of intraday arbitrage speculators in the Chinese stock market. Pac. Basin Financ. J. 58. https://doi.org/10.1016/j.pacfin.2019.101215.