mathematics

Article

Mastery of "Monthly Effects": Big Data Insights into Contrarian Strategies for DJI 30 and NDX 100 Stocks over a Two-Decade Period

Chien-Liang Chiu [1], Paoyu Huang [2], Min-Yuh Day [3], Yensen Ni [4,*] and Yuhsin Chen [5]

1 Department of Banking and Finance, Tamkang University, New Taipei City 251301, Taiwan; 100730@mail.tku.edu.tw
2 Department of International Business, Soochow University, Taipei 100006, Taiwan; hpy@scu.edu.tw
3 Graduate Institute of Information Management, National Taipei University, New Taipei City 237303, Taiwan; myday@gm.ntpu.edu.tw
4 Department of Management Sciences, Tamkang University, New Taipei City 251301, Taiwan
5 Department of Accounting, Chung Yuan Christian University, Taoyuan City 320314, Taiwan; yuhsin@cycu.edu.tw
* Correspondence: ysni@mail.tku.edu.tw

Abstract: In contrast to finding better monthly performance shown in a specific month, such as the January effect (i.e., better stock price performance in January as opposed to other months), which has been extensively studied, the goal of this study is to determine whether investors would obtain better subsequent performance as technical trading signals emitted in a specific month because, from the investment perspective, investors purchasing stocks now would not know their performance until later. We contend that our analysis emphasizes its critical role in steering investment decisions and enhancing profitability; nonetheless, this issue appears to be overlooked in the relevant literature. As such, utilizing big data to analyze the constituent stocks of the DJI 30 and NDX 100 indices from 2003 to 2022 (i.e., two-decade data), this study investigates whether trading these stocks as trading signals emitted via contrarian regulation of stochastic oscillator indicators (SOIs) and the relative strength index (RSI) in specific months would result in superior subsequent performance (hereafter referred to as "monthly effects"). This study discovers that the oversold signals generated by these two contrarian regulations in March were associated with higher subsequent performance for holding 100 to 250 trading days (roughly one year) than other months. These findings highlight the importance of the trading time and the superiority of the RSI over SOIs in generating profits. This study sheds light on the significance of oversold trading signals and suggests that the "monthly effect" is crucial for achieving higher returns.

Keywords: monthly effects; contrarian strategies; oversold signals; subsequent performance; stochastic oscillator indicators; relative strength index

MSC: 91-08; 62-07

check for updates

Citation: Chiu, C.-L.; Huang, P.; Day, M.-Y.; Ni, Y.; Chen, Y. Mastery of "Monthly Effects": Big Data Insights into Contrarian Strategies for DJI 30 and NDX 100 Stocks over a Two-Decade Period. *Mathematics* **2024**, *12*, 356. https://doi.org/10.3390/math12020356

Academic Editors: Codruta Mare and Ioana Florina Coita

Received: 23 December 2023
Revised: 17 January 2024
Accepted: 19 January 2024
Published: 22 January 2024

1. Introduction

Chasing higher profits in stock markets is an important issue for investors, including institutional and individual investors, leading to many investors investing in stocks, bonds, index ETFs, etc., based on their experience (e.g., the January effect [1–3], technical trading regulations [4–7], and investing strategies [8,9].

Regarding the January effect, it is a market phenomenon in which stock values typically rise in January. The main hypothesis proposes that this is caused by year-end tax-related selling [10], investors harvesting losses for tax purposes [11], year-end bonuses affecting investment decisions [12], and portfolio rebalancing [13].

Historically, this effect was evident, but changes in market dynamics have diminished its significance over time, as the stock market is more efficient for this effect [14]. Concerning technical trading regulations, we state that technical trading rules may work in trading financial instruments (e.g., stocks, bonds, and futures) since many charts in terms of technical analysis are shown on many financial websites (e.g., Bloomberg, Reuters, Forbes, Wall Street Journal, and Investing); otherwise, these charts may not be displayed on these famous financial websites.

As such, the above phenomena motivate us to examine if investors employing these technical trading regulations would benefit and even make profits in stock market trading. After conducting the literature survey in the next section, we find that although investing strategies and trading regulations have been extensively researched in the stock markets, focusing on trading in a particular month following the occurrence of technical trading signals appears to be understudied in the relevant research. Consequently, this study may overcome the research gap because our investigated issue of whether trading in stock markets when trading signs triggered by technical trading regulations in different months would result in different subsequent performance (hereafter referred to as "monthly effects") remains understudied in the existing literature.

We further state that our explored issue is of great originality since although the pursuit of higher profits in stock markets drives investors to explore various investment strategies and technical trading regulations, little research has focused on the impact of trading based on technical indicators in specific months (i.e., "monthly effects"). Additionally, trading range breakout (TRB) trading strategies have garnered traction among traders in diverse financial domains, such as stocks, currencies, and cryptocurrencies, since these strategies aim to capitalize on price momentum post-breakout by pinpointing breakout levels. Despite their popularity [15], the suitability and efficacy of TRB regulations remain unexplored using the DJI 30 and NDX 100 indices, indicating the performance of two representative stock indices in the US.

Regarding the novelty of this study, we argue that gauging subsequent performance is closely related to investment concepts. Since investors make investment decisions now, they will not know if they can generate profits until later. As such, different from the January effect that has been extensively researched over several decades [2,16,17], our explored issue is to examine that as oversold signals emitted by the contrarian regulations of SOIs and the RSI, investors purchases stocks in a particular month or few months would have better subsequent performances.

In this study, we purchase stocks as oversold signals instead of overbought signals because oversold phenomena often occur for stock indices when unexpected, adverse news happens suddenly, leading to the undervaluation of these stock indices.

However, we argue that our explored issue, closely related to investment notions, has been understudied in the previous research; therefore, the purpose of this study is to investigate whether as oversold signals emitted by the contrarian regulation of SOIs and the RSI in certain months instead of other months, investors purchasing stocks would result in better subsequent performance. Since investors can purchase stock index futures instead of index spots in investment practice, this study chooses the constituent stocks of the DJI 30 and NDX 100 as our investigated targets.

In other words, using big data to examine the constituent stocks of the DJI 30 and NDX 100 indices from 2003 to 2022 (i.e., two-decade data) from DataStream's data sources (including extensive data on various financial markets), this study analyzes market behavior using big data, with a focus on profit maximization in the stock market [18,19]. It investigates the understudied field of "monthly effects" using technical trading regulations, exploring the influence of trading based on indications in various months. This innovative technique fills a gap in the literature by stressing the importance of timing and demonstrating the potential benefits of using contrarian strategies (i.e., SOIs and the RSI). Additionally, we argue that "monthly effects" likely result from investor sentiment (oversold trading signals would be related to investor sentiment) and abnormity (January effect and "monthly effect" might result from anomalies [3], both of which may not support the theory of stock market efficiency [20]. As a result, we state that the theory used and the factors affecting the January effect may be proper for the "monthly effect" studied in this research.

We document that this study may contribute to the existing literature as follows. First, this study shows that no matter the oversold trading signs generated by either SOI or RSI contrarian trading rules in March, the subsequent performance for the constituent stocks of the DJI 30 and NDX 100 is at least 6% (9%) of the average holding period return (AHPR) for holding 100 (250) trading days (i.e., ranging from 6% to 18% (9% to 27%)). We infer that the "monthly effects" proposed in this study may play a significant role in generating profit. Second, following the occurrence of oversold trading signals, this study shows that RSI trading regulation outperforms SOI trading regulation and NDX 100 constituent stocks outperform DJI 30 constituent stocks. Consequently, despite both the RSI and SOI trading regulations, investors can choose the appropriate trading regulation and the appropriate constituent stocks to capitalize on the high profit. Third, this study discovers that trading the constituent stocks of the NDX for holding 250 trading days (approximately 250 trading days in a year) results in over 40% AHPRs; nevertheless, such remarkable performance is not observed in other months. The disclosed results imply that oversold trading signals generated by the SOI and RSI trading regulations in different months do matter for their subsequent performance.

2. Literature Review

2.1. Theory

Throughout the past financial literature, the concept of stock market efficiency has had significant importance, as observed in the relevant studies [20–22]. An efficient market is well-known for its capacity to quickly assimilate all the available information, resulting in challenges in terms of making abnormal profits based on past information [23]. Fundamentally, asset prices in such efficient markets reflect the best estimates formulated by market participants regarding the anticipated risks and returns associated with these assets at any given point in time [24].

Despite being closely studied in the finance field, there is evidence that many stock exchanges around the world may not exactly follow the principles of the efficient market hypothesis (EMH) [25,26]. It is worth noting that most buyers in real stock markets have doubts that the market is completely efficient [27]. Certain investors (e.g., high-frequency traders and hedge funds) consistently outperform the market (Masteika & Rutkauskas, 2012 [28]), motivating other investors who screen stocks in pursuit of higher returns.

In practical situations, the widely accepted EMH encounters a challenge from the domain of technical analysis [9,29–31]. The application of technical trading rules can be attributed to herd behavior driven by investor sentiment [32,33], or to stock price overreactions that lead to subsequent price rebounds [34–36]. Consequently, the decision to use technical analysis is influenced by a variety of academic concerns, including market inefficiencies, herding behaviors, and stock price overreaction.

2.2. Technical Trading Regulations

Although there are a variety of technical trading rules, we introduced the SOI and BB trading regulations since the trading signs generated by these regulations result from the contrarian investing strategies employed in this study. These trading regulations (i.e., SOI and RSI trading rules) imply that market participants had better adopt contrarian approaches as overreaction signs triggered by these regulations. For instance, when these trading regulations produce oversold or overbought signals, market participants are recommended to buy or sell stocks. Thus, we introduced the SOI and RSI regulations, along with investing approaches implicated by these trading regulations.

2.2.1. Stochastic Oscillator Indicators (SOIs)

Stochastic Oscillator Indicator (SOI) trading regulations employing K and D values are rather sensitive to share price changes, hence resulting in the K and D values being modified due to the changing of the highest and lowest prices during a given time (e.g., nine days). Therefore, a nine-day setting (while the standard setting for the SOI is to use a 14-day measurement period, recent relevant studies, such as those conducted by Zhou et al. and Ni et al. [36], often use 9 days. Additionally, relevant studies recommend setting technical indicators, such as SOIs, within a range of 6 to 20 days (Maratkhan et al., 2021 [37]). Moreover, using 14 days in addition to 9 days yields results comparable to those obtained using 9 days) was used to present the SOI model below:

$$\text{RSVt} = \text{CLt}/\text{HLt} \times 100\% \quad (1)$$

$$\text{Kt} = 2/3\ \text{Kt} - 1 + 1/3\ \text{RSVt} - 1 \quad (2)$$

$$\text{Dt} = 2/3\ \text{Dt} - 1 + 1/3\ \text{Kt} - 1 \quad (3)$$

where CLt is calculated by subtracting the market's lowest price at closing in the last nine days from the latest share price at market close; HLt is calculated by subtracting the lowest closing price from the highest closing price in the last nine days; RSVt is obtained by dividing CLt by HLt; Kt is determined by adding 1/3 RSVt to 2/3 Kt − 1; and D value is calculated by adding 1/3 Kt to 2/3 Dt − 1.

According to the SOI trading regulation, it is advisable to buy shares when the K value is 20 or lower ($K \leq 20$) (i.e., regarding an oversold signal). Conversely, selling shares is recommended when the K value is 80 or higher ($K \geq 80$) (i.e., suggesting an overbought signal). Relevant research shows that market participants following the oversold signals may generate better performance [38]. As such, individual and institutional investors often use the oversold trading signals to exploit profits from stock markets [39].

2.2.2. Relative Strength Index (RSI)

The Relative Strength Index (RSI) has three components, including relative strength (RS), average gain (AG), and average loss (AL), and is defined as below.

$$\text{RSI} = 100 - 100/(1 + \text{RS}) \quad (4)$$

where RS = AG/AL.

The initial AG (AL) value is based on the 14-day average. AG (AL) is measured by adding the gains (losses) over the last 14 days and then dividing by 14.

In measuring the following values for AG and AL, the prior value and the current gain (CG, which is defined as the current stock price surpassing the stock price of the previous day) or current loss (CL, which is defined as the current stock price surpassing the stock price of the previous day) should be considered. As such, AG (AL) is calculated as (Previous AG (AL) multiplied by 13 plus CG (CL) at current day) divided by 14.

Therefore, the RSI would range from 0 to 100. An RSI value of 100 (0) indicates that the price is rising (falling) without any decrease (increase). Overbought (oversold) signals are indicated by RSI values of 70 (30) or higher (lower) on the 14-day RSI [40,41]. Furthermore, Shik and Chong [42] note that RSI trading rules can boost currency market risk-adjusted returns; Chong and Ng [43] show that investors can earn higher returns utilizing the RSI trading rule compared to a buy-and-hold strategy.

2.3. Investing Strategies

Momentum and contrarian strategies are two of the most hotly discussed profit-generating investment methods [44–46]. Momentum trading can result in short-term profits depending on recent share price moves [47]. Trading stocks with slower information dissemination can be successful if momentum comes from incremental information release [48]. According to research, momentum trading is advantageous and beats the market [49,50]. Enhanced momentum strategies decrease crashes and improve risk-adjusted returns [51,52]. Removing stocks with extreme absolute strength from momentum portfolios reduces volatility and enhances returns [53]. Timing individual factors based on recent performance enhances momentum strategies, as driven by persistence in common return factors [54]. Excluding stocks with extreme payoffs improves momentum strategy returns, especially for loser portfolios [55].

Contrarian strategies, prioritizing buying losers and shorting winners, exploit stock price overreactions to generate profits [56–60]. This approach has been observed to yield contrarian profits for value and growth stocks [61,62], and it is also present in the long-term contrarian profitability of the Chinese stock market [63]. Huang et al. (2019) [64] highlight that market participants' overreaction to past performance leads to undervalued and overvalued stock values, making contrarian approaches outperform the market. In the Chinese stock market, institutional investors exhibit a contrarian trading strategy, particularly in up-markets, with positive predictability of future stock returns [65]. Shen and Shen [66] provide evidence supporting the role of the disposition effect in driving short-term contrarian profits in the Chinese stock market. Boussaidi and AlSaggaf [67] find that the representativeness-based behavioral explanation of contrarian profits is not consistent across all the MENA stock markets. Chae and Kim [68] demonstrate that residual return-based contrarian strategies outperform conventional approaches, attributing profits to negative autocovariance in individual residual returns and overreactions to good firm-specific news. Therefore, we argue that investors who employ contrarian strategies may profit from overreactions in the stock market by capitalizing on undervalued stock prices, resulting in an improvement in subsequent performance via the proposed H1.

H1. *Investors who employ contrarian strategies as contrarian trading signals emitted would have better subsequent performance.*

2.4. January Effects

The January effect, a phenomenon observed in financial markets, refers to the tendency of stock prices to rise in January. Numerous studies have explored this anomaly, attributing it to various factors. While summarizing relevant research on the January effect, traditional explanations include tax-loss harvesting [69], the influx of fresh investment capital at the beginning of the year [11], and portfolio adjustment [13]. As such, the January effect may be attributed to several factors, such as tax-loss selling that occurs as investors aim to realize losses for tax purposes at year-end, leading to a subsequent rebound in January [70]; window dressing that involves portfolio managers adjusting holdings at lower in the months preceding the tax year-end [10]; and investor sentiment, as influenced by psychological factors, also plays a role, with renewed optimism and fresh capital entering the market at the beginning of the year [71]. Furthermore, several key studies support the existence of the January effect. Rozeff and Kinney [72] find evidence of this anomaly, attributing it to tax-related selling in December followed by a January rebound. Keim [73] also supports this seasonality, suggesting investors exploit year-end tax considerations, contributing to distinct market patterns during January. Thaler [3] discusses how stock prices tend to rise in January, particularly for small firms and corporations whose stock prices have fallen significantly in recent years, most likely because these risky stocks earn more risky premiums in January.

Moreover, other factors that may influence January price movement include market sentiment shifts [74], macroeconomic indicators [75], geopolitical events [76], or unexpected news [74], all of which contribute to volatile trading patterns. We contend that macroeconomic indicators, global events, and changes in market regulations can influence tock prices by altering investor perceptions of economic health, corporate performance, and regulatory settings [77–79]. Furthermore, fluctuations in indicators such as GDP, inflation, or interest rates might reflect changes in economic conditions [80], while geopolitical events and regulatory changes add uncertainties that impact investor behavior, causing stock values to shift in response to changing market conditions [81]

Despite ongoing research, the exact mechanisms driving this phenomenon remain complex and multifaceted, making it a subject of continued interest and investigation in the financial literature. However, after reviewing the foregoing relevant studies, we found that the existing literature on contrarian strategies investigates the effectiveness of investing in stock markets, relevant studies on the January effect investigate the historical stock price rise in January, and pertinent research uses big data analytics in financial studies, employing large datasets for insights into market behavior, enhancing understanding and predictive capabilities [82–84]. However, we argue that the issue of incorporating contrarian strategies and the monthly effect (e.g., the January effect) using big data analytics is understudied in the financial research literature. Consequently, in contrast to the renowned January effect, this study investigates whether trading these stocks based on contrarian signals from SOIs and the RSI in specific months yields better subsequent performance (referred to as "monthly effects") in this study. Because investors who purchase stocks now will not know their performance until later, we contend that our research is important for investors in practice.

As such, in addition to the existing literature on momentum, contrarian strategies, and the January effect [44,59,85], relevant research has indicated that stock market overreaction could explain contrarian profits [86], as well as the relationship between sentiment and technical indicator performance [87]. However, we found that there is a gap in the literature regarding the impact of trading signals triggered by contrarian regulations of SOIs and the RSI in a particular month on subsequent performance ("monthly effects"), which differs significantly from the better monthly performance in a particular month (e.g., the January effect that has been extensively investigated in the relevant literature [2,3,69,71,74]. As a result, we argue that this research addresses the gap and aims to contribute to the existing literature by examining whether investors who employed trading signals emitted contrarian SOI and RSI trading rules in a particular month instead of other months would have better subsequent investment performance, given that the concept of investment is to invest now and derive investment performance in the future.

Moreover, contrarian trading strategies can be used to identify and capitalize on irregular stock price patterns associated with anomalies shown by the "monthly" effect (e.g., the January effect). This synergy results from leveraging anomalies that may contradict the theory of stock market efficiency. Furthermore, adopting big data analytics can provide more information with dynamic, data-driven perspectives, allowing for more accurate predictions, along with improving decision-making.

Accordingly, investors who employ contrarian trading rules based on trading signals emitted by these trading rules (SOI and RSI trading rules) in a few months, as opposed to other months, may have much better subsequent performance due to seasonal market anomalies, investor sentiment shifts [88], and socio-economic, demographic, institutional, and even macroeconomic factors [89] that produce temporary mispricing by proposing H2.

H2: *Investors who utilize contrarian strategies as contrarian trading signals emitted in special months, as opposed to other months, would achieve much better subsequent performance.*

3. Methodology and Data

3.1. The Method for Measuring Average Holding Period Returns

This study examines the potential interest of a diverse range of investors in gauging subsequent performance using trading signals generated by stochastic oscillator indicator (SOI) and relative strength index (RSI) regulations. Contrarian trading regulations are employed due to the common occurrence of stock price overreaction in stock markets, especially when negative news is unexpectedly released, triggering further overreaction in stock prices. Accordingly, the study adopts SOI and RSI contrarian trading regulations, as they are expected to exploit stock price undervaluation resulting from such overreactions and potentially lead to stock price rebounds.

As such, this study aims to examine whether the utilization of contrarian trading regulations enables investors to generate profits and to determine if any specific contrarian regulation outperforms others. Furthermore, it explores the impact of "monthly effects" on the subsequent performance of trading signals. While the existing literature extensively investigates trading performance at different times, such as the well-documented January effect [2,3], the examination of "monthly effects" remains understudied. It is noteworthy that the discussion on whether investors can generate substantial profits by employing trading signals triggered by technical regulations in specific months has been largely ignored. Consequently, this study not only investigates whether trading signals generated by various contrarian trading regulations, such as SOIs and the RSI, result in improved subsequent performance but also examines whether these signals exhibit superior performance during specific months compared to other months.

After identifying the trading buying signals produced by the contrarian trading regulations ($K \leq 20$; $RSI \leq 30$), this study proceeds by introducing the method for evaluating the subsequent performance using holding period returns (HPRs). HPRs are widely employed as a measure of investment performance [90,91]. In this context, day 0 corresponds to the occurrence of buying signals. To assess the efficacy of these signals generated by the SOI or RSI regulations, we analyze the HPRs over various holding periods, including 100, 150, 200, and 250 days, considering the approximately 250 trading days in a year.

Subsequently, Equation (5) was employed to express HPRn, which represents the total holding period return. The equation is given as follows:

$$\text{HPRn} = [(1 + \text{R1}) \times (1 + \text{R2}) \times (1{+}\text{R3}) \times \ldots (1 + \text{Rn})] - 1 \quad (5)$$

where R1, R2, R3. . .... ., Rn denote the daily holding period returns from day 1 to day n.

According to Equation (5), the holding period return for n days (HPRn) can be calculated by substituting 100, 150, 200, or 250 for n. Following that, we measure the average holding period return ($AHPR_{n,m}$), since numerous buying signals (i.e., m buy signals) are generated by either of these two contrarian trading regulations. As such, we can measure $AHPR_{n,m}$ using the following equation (i.e., Equation (6)).

$$AHPR_{n,m} = \left(HPR_{\,n,1} + HPR_{n,2} \ldots\ldots\ldots + HPR_{n,m}\right)/\text{m} \ldots\ldots\ldots \quad (6)$$

where n represents different holding periods of 100, 150, 200, and 250 days, and m denotes the total number of trading signals generated by either the SOI or RSI trading regulation (i.e., $K \leq 20$ or $RSI \leq 30$) over the data period. Additionally, for the round-trip trading of these indices' constituent stocks, it should be noted that transaction costs must be considered. However, due to the exceptional performance displayed in this research, the transaction costs of trading these stocks may not have had a significant impact on our revealed results in this study. Additionally, the explanation of how to obtain our revealed results is shown in Appendix A.

Moreover, since the average number of trading days in a year is approximately 252 days, we are concerned with minimizing overlapping issues to avoid either over- or underestimating the results, since measuring more than one year of data (i.e., five quarters) may result in overlap issue because one-quarter data would be overlap as trading signals emitted in the same day of two consecutive years. As such, the maximum day employed for measuring the average subsequent performance is HPR250.

3.2. Data and Descriptive Statistics

For the DJI 30 and NDX 100 indices, daily data was extracted from DataStream. The data period spans from 2003 to 2022 and incorporates the 2008 financial crisis, 2012 European debt crisis, and 2020 COVID-19 epidemic (i.e., showing that both bull and bear market periods have occurred throughout our data period), as shown in Figures 1 and 2. In addition, Table 1 shows a wide range of minimum to maximum values for these indices, indicating that their movements are relatively volatile. In addition, Figures 1 and 2 show that the DJ 30 and NDX 100 indices followed a bullish trend from 2003 to 2022, with occasional corrections. Both indices showed overall market development, as driven by economic expansion and technical advancements, but with periods of volatility.

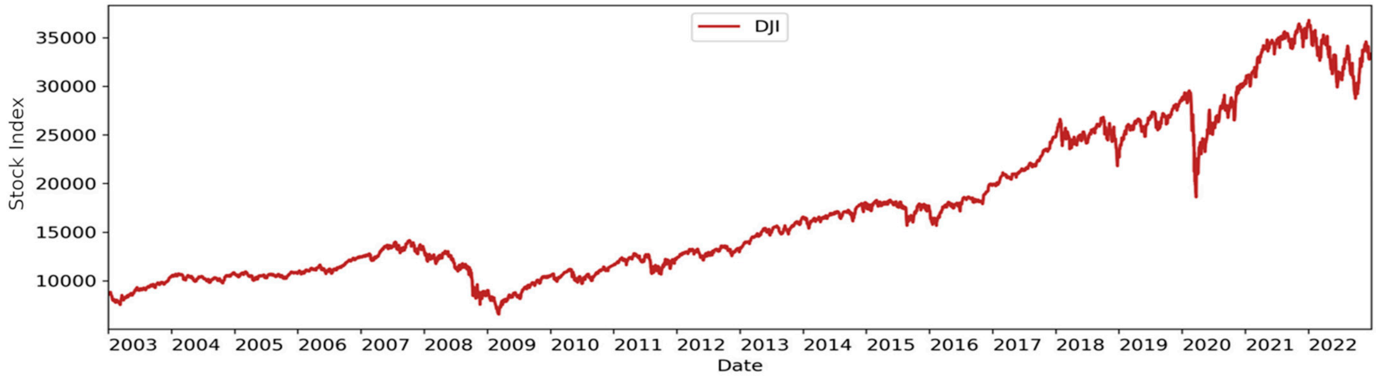

Figure 1. The DJI 30 index from 2003 to 2022.

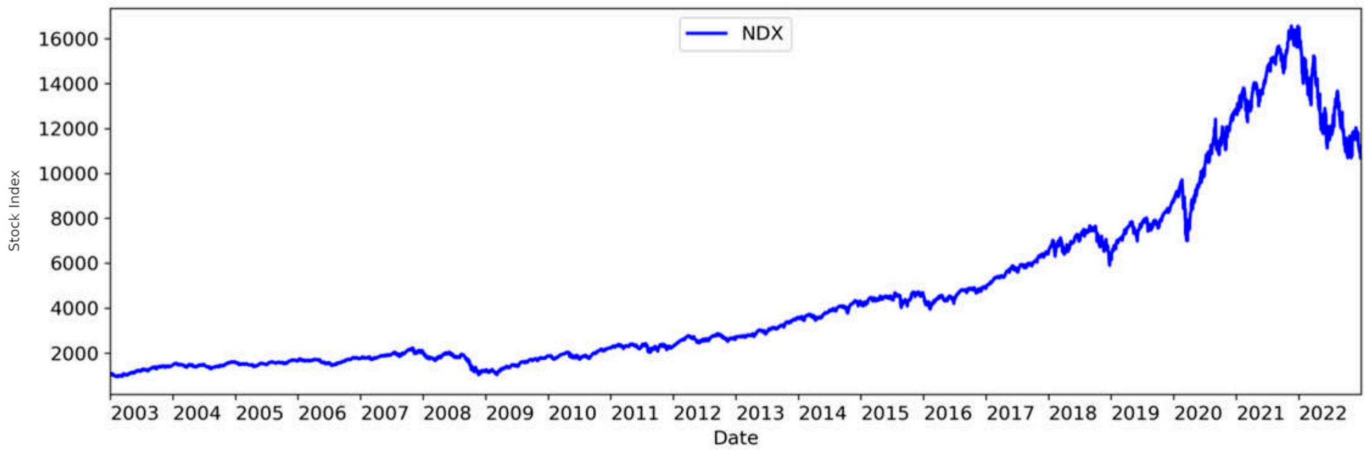

Figure 2. The NDX 100 index from 2003 to 2022.

Table 1. Statistics summary. Table 1 shows the mean, standard deviation (SD), median (Med), minimum (Min), and maximum (Max) for the DJI 30 and NDX 100 indices from 2003 to 2022.

Stock Indices	Obs.	Mean	Med	SD.	Min	Max
DJI 30 index	5035	17,224.14	13,895.63	7812.81	6547.05	36,799.65
NDX 100 index	5035	4586.517	2771.75	3891.036	951.9	16,573.34

4. Results

4.1. Subsequent Performance without Concerning Trading Timing

Due to the concern of comparison, we first present the subsequent performance as trading signals emitted by contrarian SOI and RSI regulations without concerning the trading timing for the constituent stocks of the DJI 30 and NDX 100 in Table 2, which would be employed for comparing the performance as trading signals emitted by diverse months in this study.

Table 2. Results of the DJI 30 and NDX 100 stocks (2003–2022). By using two-decade data (i.e., 2003–2022), we evaluate the subsequent performance of the constituent stocks of the DJI 30 and NDX100 indices following oversold signs emitted by the SOI and RSI trading rules. By examining whether these diverse AHPRs would differ from zero, we display the *p* statistics (*p*) for these AHPRs, with *, **, and *** denoting significance levels (Sig.) of 10%, 5%, and 1%, respectively.

		DJI 30				**NDX 100**			
Strategy	Day	Sample	AHPR	*p*	Sig.	Sample	AHPR	*p*	Sig.
K20	100	8540	7.86%	0.000	***	25,644	10.54%	0.000	***
K20	150	8475	10.81%	0.000	***	25,225	15.85%	0.000	***
K20	200	8152	14.29%	0.000	***	24,199	21.67%	0.000	***
K20	**250**	**8044**	**18.14%**	**0.000**	***	**23,930**	**27.95%**	**0.000**	***
Strategy	Day	Sample	AHPR	*p*	Sig.	Sample	AHPR	*p*	Sig.
RSI30	100	6013	6.88%	0.000	***	18,227	9.00%	0.000	***
RSI30	150	5995	10.60%	0.000	***	18,104	14.44%	0.000	***
RSI30	200	5776	13.60%	0.000	***	17,491	19.85%	0.000	***
RSI30	**250**	**5667**	**18.12%**	**0.000**	***	**17,289**	**26.48%**	**0.000**	***

In Table 2, while trading signals are emitted by either the contrarian SOI or the RSI trading rules on any given trading day over a year, the subsequent performance (i.e., AHPRs) of the constituent stocks of the DJI 30 and NDX 100 ranges from over 6% and 9% for holding 100 trading days to over 18% and 27% for holding 250 trading days (approximately a year). These revealed results are quite impressive since they are much higher than the one-year ten-year treasury bond rate proxied as opportunity costs (i.e., less than 5% on average during the data period). Additionally, the results derived using two-decade data might be more objective than those derived using only a few years of data.

4.2. Subsequent Performance concerning Trading Timing

Even though impressive results are shown in Table 3, we are interested in whether investors would reap much higher AHPRs concerning the trading timing for purchasing the constituent stocks of the DJI and NDX indices as oversold signals (i.e., $K \leq 20$ and $RSI \leq 30$) generated by contrarian SOI and RSI trading rules. Additionally, since we have to present the results for different months (i.e., 12 months), we then present the constituent stocks of the DJI30 and NDX 100 in different subsections.

Table 3. Results of the DJI 30 stocks as trading signals emitted in diverse months (2003–2022). We present various subsequent performances (AHPRs) of trading the DJI 30 constituent stocks following oversold signals issued by SOIs and the RSI at different months, and we test whether these AHPRs differ from zero. Additionally, we display the *p* statistics (*p*) for these AHPRs, with *, **, and *** denoting significance levels (Sig.) of 10%, 5%, and 1%, respectively.

Panel A: SOI Trading Signals Emitted (i.e., $K \leq 20$)																	
Strategy	Day	Sample	AHPR	*p*	Sig.	Sample	AHPR	*p*	Sig.	Sample	AHPR	*p*	Sig.	Sample	AHPR	*p*	Sig.
			M1				M4				M7				M10		
	100	779	7.75%	0.000	***	457	3.07%	0.000	***	627	5.32%	0.000	***	831	5.03%	0.000	***
	150	779	10.81%	0.000	***	457	6.66%	0.000	***	627	7.95%	0.000	***	831	9.98%	0.000	***
	200	779	11.74%	0.000	***	457	10.08%	0.000	***	627	10.83%	0.000	***	799	13.08%	0.000	***
	250	779	17.87%	0.000	***	457	12.41%	0.000	***	616	12.81%	0.000	***	799	16.69%	0.000	***

Table 3. *Cont.*

Panel A: SOI Trading Signals Emitted (i.e., K $\leq$ 20)																	
Strategy	Day	Sample	AHPR	p	Sig.	Sample	AHPR	p	Sig.	Sample	AHPR	p	Sig.	Sample	AHPR	p	Sig.
		M2				M5				M8				M11			
	100	652	8.73%	0.000	***	742	5.05%	0.000	***	927	10.51%	0.000	***	565	14.68%	0.000	***
	150	652	13.13%	0.000	***	742	9.79%	0.000	***	927	11.10%	0.000	***	563	15.97%	0.000	***
	200	652	20.77%	0.000	***	742	11.61%	0.000	***	883	13.77%	0.000	***	563	19.89%	0.000	***
	250	652	24.31%	0.000	***	742	16.49%	0.000	***	875	15.85%	0.000	***	563	25.28%	0.000	***
		M3				M6				M9				M12			
	100	**833**	**12.06%**	**0.000**	***	851	4.49%	0.000	***	731	8.69%	0.000	***	545	8.29%	0.000	***
	150	**833**	**13.61%**	**0.000**	***	851	8.21%	0.000	***	731	11.00%	0.000	***	482	11.27%	0.000	***
	200	**833**	**22.67%**	**0.000**	***	851	12.16%	0.000	***	484	9.15%	0.000	***	482	13.19%	0.000	***
	250	**833**	**25.76%**	**0.000**	***	762	13.24%	0.000	***	484	12.52%	0.000	***	482	23.53%	0.000	***
Panel B: RSI Trading Signals Emitted (i.e., RSI$\leq$ 30)																	
		M1				M4				M7				M10			
	100	468	5.66%	0.000	***	277	5.23%	0.000	***	544	4.79%	0.000	***	596	4.70%	0.000	***
	150	468	7.98%	0.000	***	277	8.77%	0.000	***	544	6.65%	0.000	***	596	9.54%	0.000	***
	200	468	5.73%	0.000	***	277	12.65%	0.000	***	544	11.08%	0.000	***	508	10.74%	0.000	***
	250	468	10.15%	0.000	***	277	13.13%	0.000	***	478	10.87%	0.000	***	508	16.27%	0.000	***
		M2				M5				M8				M11			
	100	683	4.34%	0.000	***	537	5.70%	0.000	***	572	9.79%	0.000	***	376	10.37%	0.000	***
	150	683	8.58%	0.000	***	537	11.91%	0.000	***	572	9.81%	0.000	***	376	12.24%	0.000	***
	200	683	13.55%	0.000	***	537	13.14%	0.000	***	572	11.27%	0.000	***	376	15.52%	0.000	***
	250	683	18.09%	0.000	***	537	16.28%	0.000	***	559	16.20%	0.000	***	376	17.84%	0.000	***
		M3				M6				M9				M12			
	100	**714**	**14.99%**	**0.000**	***	474	3.57%	0.000	***	511	7.28%	0.000	***	261	0.82%	0.498	
	150	**714**	**19.33%**	**0.000**	***	474	9.91%	0.000	***	511	11.88%	0.000	***	243	4.18%	0.006	***
	200	**714**	**29.47%**	**0.000**	***	474	11.87%	0.000	***	380	12.11%	0.000	***	243	4.32%	0.007	***
	250	**714**	**35.43%**	**0.000**	***	444	19.12%	0.000	***	380	16.31%	0.000	***	243	16.46%	0.000	***

4.2.1. Results of the Constituent Stocks of the DJI Index

Based on the trading timing of trading signals emitted by contrarian trading rules, we then present the results derived from trading the constituent stocks of the DJI index over two decades in Table 3.

We show that the results presented in Table 2 may approximate the concept of average performance. However, while we present the AHPRs for various months, we may observe that several months are above the AHPRs presented in Table 2, and we reveal that March in blue has the highest AHPRs compared to the other months, regardless of whether SOI (RSI) trading rules are used, as shown in Panel A (Panel B) of Table 3. Although the AHPRs derived from the RSI trading rules may not exceed those generated from the SOI trading rules in multiple months, the best AHPRs are exhibited in March utilizing the RSI trading rules in Table 3. Consequently, as evidenced by two-decade data, we might infer that the trading timing emitted by oversold trading signals following the SOI and RSI trading rules does matter for their subsequent performance as trading the constituent stocks of the DJI 30.

4.2.2. Results for the Constituent Stocks of the NDX Index

Like the results shown in Table 3, we also disclose that March in blue has the highest AHPRs compared to the other months, regardless of whether the SOI (RSI) trading rules are used, as seen in Panel A (Panel B) of Table 3. Additionally, when we compared the AHPRs in Table 4 to those in Table 3, we observed that the AHPRs in Table 4 are much higher than the ARHPs in Table 3, indicating that as compared with the results of investing in the constituent stocks of the DJI index, investors would have better subsequent performance when investing the constituent stocks of the NDX 100 in general (i.e., without concerning trading timing) and in the particular month that perform best (i.e., March). Also, like Table 3, Table 4 shows the best AHPR displayed in March utilizing the RSI trading rule, which is higher than the best AHPR displayed in March using the SOI trading rule in Table 3.

Table 4. Results of the NDX 100 stocks as trading signals emitted in various months (2003–2022). We present various subsequent performance (AHPRs) of trading the NDX 100 constituent stocks after oversold signals issued by SOIs and the RSI at various months, and we test whether these AHPRs differ from zero. Additionally, we display the *p* statistics (*p*) for these AHPRs, with *, **, and *** denoting significance levels (Sig.) of 10%, 5%, and 1%, respectively.

Panel A: SOI Trading Signals Emitted (i.e., K $\leq$ 20)																	
Strategy	Day	Sample	AHPR	*p*	Sig.	Sample	AHPR	*p*	Sig.	Sample	AHPR	*p*	Sig.	Sample	AHPR	*p*	Sig.
			M1				M4				M7				M10		
	100	2299	7.43%	0.000	***	1652	7.31%	0.000	***	1885	6.30%	0.000	***	2747	9.16%	0.000	***
	150	2299	13.84%	0.000	***	1652	10.85%	0.000	***	1885	10.08%	0.000	***	2747	16.32%	0.000	***
	200	2299	12.20%	0.000	***	1652	17.85%	0.000	***	1885	15.94%	0.000	***	2639	24.19%	0.000	***
	250	2299	18.17%	0.000	***	1652	22.23%	0.000	***	1871	23.00%	0.000	***	2639	32.87%	0.000	***
			M2				M5				M8				M11		
	100	1681	11.06%	0.000	***	2274	8.65%	0.000	***	2419	12.19%	0.000	***	1996	16.51%	0.000	***
	150	1681	15.86%	0.000	***	2274	15.47%	0.000	***	2419	17.77%	0.000	***	1948	21.71%	0.000	***
	200	1681	23.16%	0.000	***	2274	19.56%	0.000	***	2211	23.49%	0.000	***	1948	29.59%	0.000	***
	250	1681	30.70%	0.000	***	2274	28.19%	0.000	***	2205	28.12%	0.000	***	1948	32.02%	0.000	***
			M3				M6				M9				M12		
	100	**2242**	**21.94%**	**0.000**	***	2136	4.43%	0.000	***	2389	8.75%	0.000	***	1924	12.35%	0.000	***
	150	**2242**	**26.66%**	**0.000**	***	2136	9.63%	0.000	***	2389	13.39%	0.000	***	1553	17.28%	0.000	***
	200	**2242**	**38.30%**	**0.000**	***	2136	15.10%	0.000	***	1679	18.44%	0.000	***	1553	19.99%	0.000	***
	250	**2242**	**43.07%**	**0.000**	***	1887	19.27%	0.000	***	1679	25.66%	0.000	***	1553	28.61%	0.000	***
Panel B: RSI Trading Signals Emitted (i.e., RSI $\leq$ 30)																	
			M1				M4				M7				M10		
	100	1623	5.71%	0.000	***	901	14.11%	0.000	***	1464	4.67%	0.000	***	2344	9.85%	0.000	***
	150	1623	9.71%	0.000	***	901	16.15%	0.000	***	1464	5.67%	0.000	***	2335	17.16%	0.000	***
	200	1623	7.68%	0.000	***	901	23.03%	0.000	***	1464	13.83%	0.000	***	2116	23.76%	0.000	***
	250	1623	12.43%	0.000	***	901	29.52%	0.000	***	1332	18.05%	0.000	***	2116	32.87%	0.000	***
			M2				M5				M8				M11		
	100	1657	4.07%	0.000	***	1646	5.99%	0.000	***	1787	10.31%	0.000	***	1427	11.33%	0.000	***
	150	1657	9.77%	0.000	***	1646	13.00%	0.000	***	1787	13.51%	0.000	***	1404	19.03%	0.000	***
	200	1657	12.23%	0.000	***	1646	18.97%	0.000	***	1786	18.73%	0.000	***	1404	23.39%	0.000	***
	250	1657	19.80%	0.000	***	1646	26.00%	0.000	***	1786	26.29%	0.000	***	1404	24.73%	0.000	***
			M3				M6				M9				M12		
	100	**1460**	**24.96%**	**0.000**	***	1309	6.41%	0.000	***	1571	5.67%	0.000	***	1038	6.93%	0.000	***
	150	**1460**	**31.13%**	**0.000**	***	1309	13.92%	0.000	***	1571	12.47%	0.000	***	947	11.63%	0.000	***
	200	**1460**	**47.33%**	**0.000**	***	1309	17.91%	0.000	***	1178	13.18%	0.000	***	947	18.67%	0.000	***
	250	**1460**	**52.41%**	**0.000**	***	1239	29.69%	0.000	***	1178	21.28%	0.000	***	947	23.05%	0.000	***

In sum, the "monthly effect" is evident as the study shows positive returns from contrarian strategies, particularly in March, for the DJI 30 and NDX 100 stocks. These findings provide evidence of the importance of timing in trading, emphasizing the significance of trading signals issued in specific months, particularly for maintaining the 200 and 250 trading days. Particularly for the instance using the RSI trading rule, this study finds that RSI trading rules outperform SOI rules. Furthermore, this research enriches knowledge on the study of "monthly effects" because, based on the "monthly effects" explored in this study, investors who buy stocks now will not know their performance until later, and we thus argue that our study might be crucial for investors in practice by measuring subsequent performance. In addition, although factors like earnings reports, macroeconomic data, geopolitical events, etc., may confound "monthly effects", influencing stock performance, we assert that our finding is based on 20-year long-term big data rather than a short period of data that are likely impacted by these factors, indicating that our revealed findings are objective rather than arbitrary.

4.3. Further Investigation

Furthermore, we extend our data period to explore whether our revealed results would exist after prolonging our data period. As such, we extend our data for the DJI 30 and NDX 100 from 1993 to 2022 (i.e., three-decade data). Table 5 also shows a broad range of minimum to maximum values for these two indices, indicating volatility, as evidenced by the substantial standard deviations presented in the table.

Table 5. Statistics summary. Table 5 shows the mean, standard deviation (SD), median (Med), minimum (Min), and maximum (Max) for DJI 30 and NDX 100 indices from 1993 to 2022.

Stock Index	**Obs.**	**Mean**	**Med**	**SD.**	**Min**	**Max**
DJI 30 index	7809	13,606.63	10,939.95	8126.11	3136.60	36,799.65
NDX 100 index	8062	3292.61	1854.77	3550.94	191.68	16,573.34

Similarly, while trading signals are emitted by either the contrarian SOI or the RSI trading rules on any given trading day over a year, the subsequent performance (i.e., AHPRs) for the constituent stocks of the DJI 30 and NDX 100 ranges from more than 7% and 10% for holding 100 trading days to more than 18% and 28% for holding 250 trading days in Table 6. In other words, we may conclude that market participants would have better subsequent performance when investing the constituent stocks of the NDX 100 than those of the DJ 30 as oversold trading signals emitted by contrarian SOI and RSI trading rules.

Table 6. Results of the DJI 30 and NDX 100 stocks (1993–2022). By using three-decade data (i.e., 1993–2022), we evaluate the subsequent performance of the constituent stocks of the DJI 30 and NDX 100 indices following oversold signs emitted by the SOI and RSI trading rules. By testing whether these diverse AHPRs would differ from zero, we display the p statistics (p) for these AHPRs, with *, **, and *** denoting significance levels (Sig.) of 10%, 5%, and 1%, respectively.

		DJI 30				**NDX 100**			
Strategy	Day	Sample	AHPR	p	Sig.	Sample	AHPR	p	Sig.
$K \leq 20$	100	12,397	8.18%	0.000	***	35,413	11.85%	0.000	***
$K \leq 20$	150	12,332	11.34%	0.000	***	34,994	17.86%	0.000	***
$K \leq 20$	200	12,009	14.88%	0.000	***	33,968	23.81%	0.000	***
$K \leq 20$	**250**	**11,901**	**18.53%**	**0.000**	***	**33,699**	**30.73%**	**0.000**	***
Strategy	Day	Sample	AHPR	p	Sig.	Sample	AHPR	p	Sig.
$RSI \leq 30$	100	8668	7.75%	0.000	***	24,628	10.52%	0.000	***
$RSI \leq 30$	150	8650	12.00%	0.000	***	24,505	16.39%	0.000	***
$RSI \leq 30$	200	8431	14.99%	0.000	***	23,892	21.45%	0.000	***
$RSI \leq 30$	**250**	**8322**	**18.25%**	**0.000**	***	**23,690**	**28.09%**	**0.000**	***

We further investigate whether the results shown in Table 3 would still exist in Table 7. That is, whether the better subsequent performance would exist in March instead of other months after extending our data period from two-decade data to three-decade data. Table 7 shows that when measuring subsequent performance as oversold trading signals emitted by either SOIs (i.e., K20) or the RSI (RSI30) in March for the constituent stocks of the DJI 30, the subsequent performance would be better than the subsequent performance after oversold trading signals emitted at other months, as shown by over 27% using the SOI trading regulation and 33% using the RSI trading regulation for holding 250 trading days in March instead of other months. The revealed results (using three-decade data) are consistent with those shown in Table 3 (using two-decade data).

Table 7. Results of the DJI 30 stocks as trading signals emitted in various months (1993–2022). We present various subsequent performance (AHPRs) of trading the DJI 30 constituent stocks after oversold signals issued by SOIs and the RSI at various months, and we test whether these AHPRs differ from zero. Additionally, we display the p statistics (p) for these AHPRs, with *, **, and *** denoting significance levels (Sig.) of 10%, 5%, and 1%, respectively.

Panel A: SOI Trading Signals Emitted (i.e., K $\leq$ 20)																	
Strategy	Day	Sample	AHPR	p	Sig.	Sample	AHPR	p	Sig.	Sample	AHPR	p	Sig.	Sample	AHPR	p	Sig.
			M1				M4				M7				M10		
	100	1045	6.51%	0.000	***	711	2.57%	0.000	***	1077	6.69%	0.000	***	1102	6.87%	0.000	***
	150	1045	8.51%	0.000	***	711	6.45%	0.000	***	1077	8.72%	0.000	***	1102	13.52%	0.000	***
	200	1045	9.05%	0.000	***	711	9.04%	0.000	***	1077	12.79%	0.000	***	1070	17.05%	0.000	***
	250	1045	14.39%	0.000	***	711	12.44%	0.000	***	1066	13.52%	0.000	***	1070	19.94%	0.000	***
			M2				M5				M8				M11		
	100	961	8.24%	0.000	***	953	3.16%	0.000	***	1329	10.69%	0.000	***	693	12.95%	0.000	***
	150	961	11.92%	0.000	***	953	8.38%	0.000	***	1329	11.96%	0.000	***	691	14.70%	0.000	***
	200	961	20.06%	0.000	***	953	10.70%	0.000	***	1285	15.13%	0.000	***	691	18.04%	0.000	***
	250	961	22.89%	0.000	***	953	16.41%	0.000	***	1277	16.73%	0.000	***	691	24.00%	0.000	***
			M3				M6				M9				M12		
	100	**1121**	**12.39%**	**0.000**	***	1238	4.35%	0.000	***	1235	9.89%	0.000	***	932	13.26%	0.000	***
	150	**1121**	**14.32%**	**0.000**	***	1238	7.65%	0.000	***	1235	13.39%	0.000	***	869	16.63%	0.000	***
	200	**1121**	**23.85%**	**0.000**	***	1238	11.10%	0.000	***	988	14.43%	0.000	***	869	16.92%	0.000	***
	250	**1121**	**27.22%**	**0.000**	***	1149	14.41%	0.000	***	988	15.19%	0.000	***	869	26.79%	0.000	***
Panel B: RSI Trading Signals Emitted (i.e., RSI $\leq$ 30)																	
			M1				M4				M7				M10		
	100	625	5.10%	0.000	***	444	4.96%	0.000	***	921	6.11%	0.000	***	962	7.66%	0.000	***
	150	625	6.43%	0.000	***	444	10.58%	0.000	***	921	7.13%	0.000	***	962	15.96%	0.000	***
	200	625	4.43%	0.000	***	444	13.16%	0.000	***	921	11.55%	0.000	***	874	17.22%	0.000	***
	250	625	8.53%	0.000	***	444	14.84%	0.000	***	855	11.08%	0.000	***	874	20.59%	0.000	***
			M2				M5				M8				M11		
	100	866	4.64%	0.000	***	599	4.63%	0.000	***	830	10.02%	0.000	***	464	9.31%	0.000	***
	150	866	9.53%	0.000	***	599	11.21%	0.000	***	830	12.21%	0.000	***	464	10.47%	0.000	***
	200	866	15.48%	0.000	***	599	12.90%	0.000	***	830	15.62%	0.000	***	464	12.36%	0.000	***
	250	866	18.84%	0.000	***	599	16.00%	0.000	***	817	19.29%	0.000	***	464	14.44%	0.000	***
			M3				M6				M9				M12		
	100	**983**	**15.19%**	**0.000**	***	711	2.46%	0.002	***	844	9.88%	0.000	***	419	10.40%	0.000	***
	150	**983**	**19.55%**	**0.000**	***	711	7.45%	0.000	***	844	15.67%	0.000	***	401	13.55%	0.000	***
	200	**983**	**29.59%**	**0.000**	***	711	9.12%	0.000	***	713	16.45%	0.000	***	401	12.28%	0.000	***
	250	**983**	**33.33%**	**0.000**	***	681	16.83%	0.000	***	713	15.49%	0.000	***	401	22.02%	0.000	***

Like the results shown in Tables 3 and 4, the March results in blue have the highest AHPRs when compared to other months, as shown in Panel A (B) of Tables 7 and 8, regardless of whether the SOI (RSI) trading rules were used, indicating that the trading timing does matter for subsequent performance, as disclosed in this study. Furthermore, when comparing trading rule performance, we discover that the March results utilizing

RSI trading rules outperformed those using SOI trading rules. Moreover, when compared to trading stocks, we show that the March outcomes utilizing the constituent stocks of the NDX 100 would be better than those of the DJI 30.

Table 8. Results of the NDX 100 stocks as trading signals emitted in various months (1993–2022). We present various subsequent performance (AHPRs) of trading the NDX 100 constituent stocks after oversold signals issued by SOIs and the RSI at various months, and we test whether these AHPRs differ from zero. Additionally, we display the p statistics (p) for these AHPRs, with *, **, and *** denoting significance levels (Sig.) of 10%, 5%, and 1%, respectively.

Panel A: SOI Trading Signals Emitted (i.e., K $\leq$ 20)																	
Strategy	Day	Sample	AHPR	p	Sig.	Sample	AHPR	p	Sig.	Sample	AHPR	p	Sig.	Sample	AHPR	p	Sig.
			M1				M4				M7				M10		
	100	2898	7.71%	0.000	***	2455	11.13%	0.000	***	2790	8.49%	0.000	***	3641	14.25%	0.000	***
	150	2898	12.39%	0.000	***	2455	14.80%	0.000	***	2790	12.36%	0.000	***	3641	23.57%	0.000	***
	200	2898	11.71%	0.000	***	2455	21.81%	0.000	***	2790	18.33%	0.000	***	3533	31.84%	0.000	***
	250	2898	17.27%	0.000	***	2455	27.40%	0.000	***	2776	26.67%	0.000	***	3533	39.08%	0.000	***
			M2				M5				M8				M11		
	100	2344	10.13%	0.000	***	2936	6.05%	0.000	***	3197	13.92%	0.000	***	3641	14.25%	0.000	***
	150	2344	12.70%	0.000	***	2936	14.18%	0.000	***	3197	19.84%	0.000	***	3641	23.57%	0.000	***
	200	2344	20.33%	0.000	***	2936	18.93%	0.000	***	2989	26.52%	0.000	***	3533	31.84%	0.000	***
	250	2344	27.66%	0.000	***	2936	26.98%	0.000	***	2983	31.85%	0.000	***	3533	39.08%	0.000	***
			M3				M6				M9				M12		
	100	**3061**	**19.32%**	**0.000**	***	3150	3.82%	0.000	***	3492	13.50%	0.000	***	2850	17.22%	0.000	***
	150	**3061**	**23.28%**	**0.000**	***	3150	11.31%	0.000	***	3492	19.13%	0.000	***	2479	25.54%	0.000	***
	200	**3061**	**35.35%**	**0.000**	***	3150	16.88%	0.000	***	2782	25.68%	0.000	***	2479	26.84%	0.000	***
	250	**3061**	**41.86%**	**0.000**	***	2901	24.37%	0.000	***	2782	29.92%	0.000	***	2479	39.34%	0.000	***
Panel B: RSI Trading Signals Emitted (i.e., RSI $\leq$ 30)																	
			M1				M4				M7				M10		
	100	1900	5.26%	0.000	***	1451	15.40%	0.000	***	2301	6.95%	0.000	***	3278	14.07%	0.000	***
	150	1900	8.74%	0.000	***	1451	18.88%	0.000	***	2301	9.74%	0.000	***	3269	21.87%	0.000	***
	200	1900	7.12%	0.000	***	1451	27.16%	0.000	***	2301	17.86%	0.000	***	3050	26.60%	0.000	***
	250	1900	11.93%	0.000	***	1451	35.20%	0.000	***	2169	25.56%	0.000	***	3050	32.64%	0.000	***
			M2				M5				M8				M11		
	100	2016	3.83%	0.000	***	1986	5.27%	0.000	***	2355	11.19%	0.000	***	3278	14.07%	0.000	***
	150	2016	8.02%	0.000	***	1986	11.55%	0.000	***	2355	16.75%	0.000	***	3269	21.87%	0.000	***
	200	2016	11.88%	0.000	***	1986	18.08%	0.000	***	2354	22.04%	0.000	***	3050	26.60%	0.000	***
	250	2016	18.56%	0.000	***	1986	25.13%	0.000	***	2354	28.83%	0.000	***	3050	32.64%	0.000	***
			M3				M6				M9				M12		
	100	**1972**	**20.57%**	**0.000**	***	1974	3.77%	0.000	***	2147	15.71%	0.000	***	1506	12.37%	0.000	***
	150	**1972**	**24.58%**	**0.000**	***	1974	13.69%	0.000	***	2147	24.71%	0.000	***	1415	17.68%	0.000	***
	200	**1972**	**38.88%**	**0.000**	***	1974	16.61%	0.000	***	1754	28.09%	0.000	***	1415	20.60%	0.000	***
	250	**1972**	**43.65%**	**0.000**	***	1904	28.90%	0.000	***	1754	32.68%	0.000	***	1415	28.85%	0.000	***

5. Discussion

In this study, we present hypotheses in Section 2, and we determine whether these hypotheses will be accepted or rejected based on our results disclosed in Section 4. Concerning H1, we show that when trading signals (i.e., K $\leq$ 20 and RSI $\leq$ 30) are issued for the constituent stocks of the DJI 30 and NDX 100, these stocks would have better subsequent performance as compared with the benchmarks of either the risk-free interest rate (10-year treasury bond rate proxied for risk-free interest rate; ranging from below 1% to up to 8% for recent 30 years (https://www.macrotrends.net/2016/10-year-treasury-bond-rate-yield-chart (accessed on 15 October 2023))) or stock market performance (the average returns of the

S&P index proxied for stock market performance; close to 10% over the long term (https://www.fool.com/investing/how-to-invest/index-funds/average-return/ (accessed on 15 October 2023))), as it is shown that the 250-day AHPRs in Tables 2 and 6 are greater than the above benchmarks. Additionally, while comparing the subsequent performance of both contrarian trading rules, we show that the results using the RSI trading rules are better than those using the SOI trading rules. As such, H1 is accepted. Although our findings may contradict previous research that technical trading rules do not outperform the market in stock markets [92–94], they may be consistent with relevant studies that apply contrarian technical trading rules would result in considerable returns in stock markets. Thus, we infer that the efficacy of trading rules may be related to the investment horizon and investment instruments [5,95,96].

Regarding H2 of "utilize contrarian strategies as contrarian trading signals emitted in specific months, as opposed to other months, would achieve much better subsequent performance", we disclose that in addition to purchasing and holding constituent stocks of these two stock indices (DJI 30 and NDX 100 indices) for over 100 trading day would derive positive profits no matter the trading signals emitted in any months, investors would exploit much higher profit for holding 250 trading days (approximately one year) as trading signals emitted in some months (e.g., March and December) rather than other months, and especially impressive performance is shown for trading signals emitted by contrarian trading rules (i.e., SOI and RSI trading rules) in March, thereby accepting H2. As such, we argue that our findings may indicate that the trading timing would matter for enhancing profitability in the stock markets [32,97]. However, we would point out that the trading timing emitted in this study would be different from that trading performance that would be better in January [2,3].

Moreover, while comparing the January effect widely disclosed in the relevant studies, we would point out that the meaning of the "monthly effect" employed in this study is different from the trading timing employed in the relevant studies in several aspects. First, the trading timing is oversold trading signals emitted by contrarian SOI and RSI trading regulations, which would be different from trading stocks as the occurrence of various events (e.g., merger, acquisition, etc.). Second, the trading timing would be appropriately measured by the subsequent performance (AHPRs) following trading signals issued by contrarian trading rules, because market participants purchasing stocks now (i.e., at time t) may not know their investment performance until later (i.e., at time t + i). As a result, we believe that this study will cast light on the trading timing of trading signals emitted at specific times (e.g., a particular month, such as March) rather than trading at any time, as well as measuring subsequent performance rather than disclosing better performance in a specific month (January effect), both of which appear to be understudied in the existing literature.

6. Concluding Remarks

6.1. Conclusions

The insightful and significant findings of this study shed light on previously overlooked aspects of research, thereby adding to the existing body of knowledge. As a result, we contend that our study draws major conclusions, fills significant information gaps, and comprehends "monthly effects" that may not be examined in relevant studies. In sum, we find that using contrarian strategies with specific trading signals yields better subsequent performance compared to benchmarks (e.g., risk-free interest rates or stock index returns), RSI trading rules outperform SOI trading rules, and employing contrarian strategies in specific months leads to higher profits. This study differentiates its concept of trading timing from the widely studied January effect and highlights the significance of measuring subsequent performance after trading signals are emitted in special months (i.e., "monthly effects"), providing novel insights into trading strategies and timing considerations, all of which are illustrated below.

First, the results of this study reveal that regardless of whether oversold trading signs are generated by either SOI or RSI contrarian trading rules in March, the constituent stocks of the DJI 30 and NDX 100 consistently demonstrate an average holding period return (AHPR) of at least 12% when held for 100 trading days, with returns ranging from 12% to 20% and no exceptions. Our findings suggest that "monthly effects" could be considered for increasing profits, which is similar to previous studies on contrarian strategies and market inefficiencies [98,99]. However, before implementing the "monthly effects" disclosed in this study, investors also should consider potential risks and changing market conditions.

Second, this study finds that when subsequent performance is measured as the occurrence of oversold signals, the RSI trading rules outperform the SOI trading rules, and the NDX 100 constituent stocks outperform the DJI 30 constituent stocks, indicating the significance of using proper oversold trading rules and stock selection. Previous research has disclosed that the RSI would be a useful technical indicator in trading stock markets [100] and the importance of stock selection in investment performance [101,102]. Thus, investors may adopt contrarian strategies to improve trading results. However, it is still imperative to incorporate comprehensive risk management and market risks into investment strategies [103].

Third, this study shows significant performance differences in the NDX constituent stocks across 250 trading days (almost a year) based on oversold trading signals produced in different months. Unlike in previous months, March's oversold trading signals increased the average holding period return (AHPR) to 40%. Oversold trading signals resulting from the SOI and RSI trading regulations appear to have a significant effect on performance. As previously shown, the market timing affects the investment outcomes [104,105]. This study underlines the significance of timing in trading strategies. Thus, investors can trade these constituent stocks as oversold signals from a given month [106,107].

6.2. Research Implications

To begin, unlike the January effect, this study incorporates the "monthly effect" in stock market trading, which investigates how technical trading signals generated in different months affect performance. This research has the potential to provide insights into the importance of timing in trading strategies. In addition to enhancing knowledge of market anomalies [2–5], it contributes to a fundamental investment principle concerning the practice of investing at present without knowing the potential profit or loss until a later time.

Regarding practical implications, this study suggests investors use contrarian methods based on oversold SOI and RSI trading regulations. Trading the constituent stocks of representative stock indexes (e.g., DJ 30 and NDX 100 indices) can improve performance when oversold signals are generated, offering a practical way to increase profitability [9,108]. In addition, similar to the January effect, "monthly effects" can influence investor behavior by actively timing purchases to capitalize on potential gains. Fund managers may modify portfolio allocations to capitalize on this phenomenon. When developing economic policies, policymakers may analyze market dynamics and their implications for market efficiency and investor sentiment. As such, we argue that recognizing and navigating the "monthly effect" might have an impact on investment strategies and decision-making across the financial landscape. Even so, in today's financial markets, the relevance of "monthly effects" or the January effect is called into question by the efficient market theory, which suggests that any past patterns can be quickly absorbed into asset prices, likely limiting their predictive value for investors.

6.3. Limitations and Future Research

Although this study sheds light on the importance of oversold trading signals and suggests that the "monthly effect" is critical for increasing returns, several research limitations may remain. This study ignores external macroeconomic factors, market sentiment, and company-specific news that could dramatically affect stock prices, which could invalidate the conclusions. Historical data are used in this study, and past patterns may repeat. Future performance may not be predicted by past performance since market dynamics can change. Studying the "monthly effect" or January effect may have potential survivorship bias, reducing the data accuracy and generalizability in understanding market phenomena. The possible biases in the chosen data sources could be caused by insufficient market representation or the omission of transactional data. This research solely covers oversold trading signals and the SOI and RSI technical trading regulations. Other trading strategies and indicators that could help to a deeper comprehension of market behavior have yet to be investigated.

In addition, the findings provide a nuanced understanding of the potential profitability associated with oversold signals generated in special months (e.g., March), emphasizing the importance of timing in trading strategies. However, caution is warranted, considering the potential risks and changing market conditions. As such, we propose that the following concerns be raised for future research. First, continued research is imperative to build on the valuable insights uncovered in this study. Future research may explore risk management in technical trading strategies, assess adaptability to varying market conditions, and examine the impact of behavioral biases on the effectiveness of such strategies, providing a comprehensive understanding of market dynamics and refining trading approaches. Second, we may examine the risk associated with employing technical trading strategies and explore ways to manage and mitigate potential downside risks. Third, this study may not only focus on the adaptability of technical trading regulations in diverse market conditions (e.g., bull markets, bear markets, and high volatility periods) but also investigate the risk associated with employing technical trading strategies, including finding ways to manage downside risks and assessing the performance of these strategies during various market phases as mentioned above. Fourth, we may further examine the influence of behavioral biases, such as herding behavior, overconfidence, and loss aversion, on the effectiveness of technical trading strategies, providing a more comprehensive understanding of market dynamics. These insights will pave the way for future avenues that may contribute to refining trading strategies and addressing identified flaws in the existing literature.

Author Contributions: Conceptualization, C.-L.C., P.H., M.-Y.D. and Y.N.; methodology, C.-L.C., P.H., M.-Y.D. and Y.N.: software, C.-L.C., M.-Y.D., Y.N. and Y.C.; investigation, C.-L.C., P.H., Y.N. and Y.C.; writing—original draft, C.-L.C., M.-Y.D., P.H., Y.N. and Y. C.; writing—review and editing C.-L.C., P.H. and Y.N. All authors have read and agreed to the published version of the manuscript.

Funding: Min-Yuh Day has really appreciated the financial support from the Ministry of Science and Technology (MOST), Taiwan (110-2410-H-305-013-MY2) and National Taipei University (NTPU), Taiwan (112-NTPU-ORDA-F-003 and 112-NTPU-ORDA-F-004). Yensen Ni has really appreciated the financial support from the National Science and Technology Council, Taiwan (NSTC 112-2410-H-032-047).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The datasets used and/or analyzed during the current study are available from the first author on reasonable request at myday@gm.ntpu.edu.tw.

Acknowledgments: Thanks to Hua-Tsen Ni for assisting with data collection and processing.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. Description of the Methodological Process

This study employs big data analytics in Python to deal with large datasets and perform complex computations with the advantages of effectiveness and accuracy. We then present our process in five steps, as shown below.

Step 1. Data collection.

To begin with, we collect daily data for the constituent stocks of the Dow Jones 30 Stock Index (DJI 30) and Nasdaq 100 Stock Index (NDX 100) from the database of DataStream. Following that, we programmatically collect extensive 20-year datasets for the DJI 30 and Nasdaq 100 using Python software (https://www.python.org/).

Step 2. Identifying intervention days.

To determine the intervention days, we utilize Python to identify trade (buy) signals generated by the contrarian trading regulations (K $\leqq$ 20; RSI $\leqq$ 30). That is, determining whether any given day was an intervention day during the data period.

Step 3. Calculating HPR.

The calculation of HPRs is performed using the shift method in Pandas to compute returns over 100, 150, 200, and 250 trading periods (Equation (5)) following each intervention day.

Step 4. Presenting results of AHPRs.

The results derived from Equation (6) are presented in various tables, highlighting the AHPRs for different holding periods post-intervention.

Step 5: Statistical significance testing.

This study examines whether these AHPRs differ from 0, provides p-values for these AHPRs, and displays *, **, and *** to represent 10%, 5% and 1% statistical significance.

References

1. Cheng, L.; Shadabfar, M.; Sioofy Khoojine, A. A state-of-the-art review of probabilistic portfolio management for future stock markets. *Mathematics* **2023**, *11*, 1148. [CrossRef]
2. Haug, M.; Hirschey, M. The January effect. *Financ. Anal. J.* **2006**, *62*, 78–88. [CrossRef]
3. Thaler, R.H. Anomalies: The January effect. *J. Econ. Perspect.* **1987**, *1*, 197–201. [CrossRef]
4. Fong, T.P.W.; Wu, S.T. Predictability in sovereign bond returns using technical trading rules: Do developed and emerging markets differ? *N. Am. J. Econ. Finance.* **2020**, *51*, 101105. [CrossRef]
5. Grobys, K.; Ahmed, S.; Sapkota, N. Technical trading rules in the cryptocurrency market. *Financ. Res. Lett.* **2020**, *32*, 101396. [CrossRef]
6. Ni, Y.; Cheng, Y.; Huang, P.; Day, M.Y. Trading strategies in terms of continuous rising (falling) prices or continuous bullish (bearish) candlesticks emitted. *Physica A.* **2018**, *501*, 188–204. [CrossRef]
7. Psaradellis, I.; Laws, J.; Pantelous, A.A.; Sermpinis, G. Performance of technical trading rules: Evidence from the crude oil market. *Eur. J. Financ.* **2019**, *25*, 1793–1815. [CrossRef]
8. Capelle-Blancard, G.; Desroziers, A.; Zerbib, O.D. Socially responsible investing strategies under pressure: Evidence from the COVID-19 crisis. *J. Portf. Manag.* **2021**, *47*, 178–197. [CrossRef]
9. Ni, Y.; Day, M.Y.; Cheng, Y.; Huang, P. Can investors profit by utilizing technical trading strategies? Evidence from the Korean and Chinese stock markets. *Financ. Innov.* **2022**, *8*, 54. [CrossRef]
10. Gallagher, D.R.; Pinnuck, M. Seasonality in fund performance: An examination of the portfolio holdings and trades of investment managers. *J. Bus. Financ. Account.* **2006**, *33*, 1240–1266. [CrossRef]
11. Doran, J.S.; Jiang, D.; Peterson, D.R. Gambling preference and the new year effect of assets with lottery features. *Rev. Financ.* **2012**, *16*, 685–731. [CrossRef]
12. Easterday, K.E.; Sen, P.K.; Stephan, J.A. The persistence of the small firm/January effect: Is it consistent with investors' learning and arbitrage efforts? *Q. Rev. Econ. Financ.* **2009**, *49*, 1172–1193. [CrossRef]
13. Branch, B.; Echevarria, D.P. The Impact of Bid-Ask Prices on Market Anomalies. *Financ. Rev.* **1991**, *26*, 249–268. [CrossRef]
14. Qinqin, W.; Qalati, S.A.; Hussain, R.Y.; Irshad, H.; Tajeddini, K.; Siddique, F.; Gamage, T.C. The effects of enterprises' attention to digital economy on innovation and cost control: Evidence from A-stock market of China. *J. Innov. Knowl.* **2023**, *8*, 100415. [CrossRef]
15. Day, M.Y.; Ni, Y. Be greedy when others are fearful: Evidence from a two-decade assessment of the NDX 100 and S&P 500 indexes. *Int. Rev. Financ. Anal.* **2023**, *90*, 102856.
16. Bassiouny, A.; Kiryakos, M.; Tooma, E. Examining the adaptive market hypothesis with calendar effects: International evidence and the impact of COVID-19. *Glob. Financ. J.* **2023**, *56*, 100777. [CrossRef]
17. Baur, D.G.; Cahill, D.; Godfrey, K.; Liu, Z.F. Bitcoin time-of-day, day-of-week and month-of-year effects in returns and trading volume. *Financ. Res. Lett.* **2019**, *31*, 78–92. [CrossRef]
18. Chen, Z.; Daves, P.R. The January sentiment effect in the US stock market. *Int. Rev. Financ. Anal.* **2018**, *59*, 94–104. [CrossRef]
19. Yang, C.T.; Ni, Y.; Yu, M.H.; Chen, Y.; Huang, P. Decoding the Profitability of Insurance Products: A Novel Approach to Evaluating Non-Participating and Participating Insurance Policies. *Mathematics* **2023**, *11*, 2926. [CrossRef]
20. Fama, E.F. Efficient capital markets: A review of theory and empirical work. *J. Financ.* **1970**, *25*, 383–417. [CrossRef]

21. Chiu, C.L.; Ni, Y.; Hu, H.C.; Day, M.Y.; Chen, Y. Enhancing Crypto Success via Heatmap Visualization of Big Data Analytics for Numerous Variable Moving Average Strategies. *Appl. Sci.* **2023**, *13*, 12805. [CrossRef]
22. Phan, K.C.; Zhou, J. Market efficiency in emerging stock markets: A case study of the Vietnamese stock market. *IOSR J. Bus. Manag.* **2014**, *16*, 61–73. [CrossRef]
23. Baciu, O.A. Ranking capital markets efficiency: The case of twenty European stock markets. *J. Appl. Quant. Methods* **2014**, *9*, 24–33.
24. Daxhammer, R.J.; Facsar, M.; Papp, Z.A. *Behavioral Finance: Limited Rationality in Financial Markets*; UVK: Tübingen, Germany, 2023.
25. Al Janabi, M.A.; Hatemi-J, A.; Irandoust, M. An empirical investigation of the informational efficiency of the GCC equity markets: Evidence from bootstrap simulation. *Int. Rev. Financ. Anal.* **2010**, *19*, 47–54. [CrossRef]
26. Durusu-Ciftci, D.; Ispir, M.S.; Kok, D. Do stock markets follow a random walk? New evidence for an old question. *Int. Rev. Econ. Financ.* **2019**, *64*, 165–175. [CrossRef]
27. Guo, M.; Kuai, Y.; Liu, X. Stock market response to environmental policies: Evidence from heavily polluting firms in China. *Econ. Model.* **2020**, *86*, 306–316. [CrossRef]
28. Masteika, S.; Rutkauskas, A.V. Research on futures trend trading strategy based on short term chart pattern. *J. Bus. Econ. Manag.* **2012**, *13*, 915–930. [CrossRef]
29. Bessembinder, H.; Chan, K. The profitability of technical trading rules in the Asian stock markets. *Pac.-Basin Financ. J.* **1995**, *3*, 257–284. [CrossRef]
30. Day, M.Y.; Ni, Y.; Hsu, C.; Huang, P. Do Investment Strategies Matter for Trading Global Clean Energy and Global Energy ETFs? *Energies* **2022**, *15*, 3328. [CrossRef]
31. Day, M.Y.; Huang, P.; Cheng, Y.; Ni, Y. Investing Strategies for Trading Stocks as Overreaction Triggered by Technical Trading Rules with Big Data Concerns. *Rom. J. Econ. Forecast.* **2023**, *26*, 148–161.
32. Day, M.Y.; Yang, C.Y.; Ni, Y. Portfolio dynamic trading strategies using deep reinforcement learning. *Soft Comput.* **2023**, *2023*, 1–16. [CrossRef]
33. Ni, Y.; Wu, M.; Day, M.Y.; Huang, P. Do sharp movements in oil prices matter for stock markets? *Phys. A Stat. Mech. Appl.* **2020**, *539*, 122865. [CrossRef]
34. Chen, Y.; Huang, P.; Day, M.Y.; Ni, Y.; Liang, M.C. Using Heatmap Visualization to assess the performance of the DJ30 and NASDAQ100 Indices under diverse VMA trading rules. *PLoS ONE* **2023**, *18*, e0284918. [CrossRef] [PubMed]
35. Neely, C.J.; Rapach, D.E.; Tu, J.; Zhou, G. Forecasting the equity risk premium: The role of technical indicators. *Manag. Sci.* **2014**, *60*, 1772–1791. [CrossRef]
36. Ni, Y.; Cheng, Y.; Liao, Y.; Huang, P. Does board structure affect stock price overshooting informativeness measured by stochastic oscillator indicators? *Int. J. Fin. Econ.* **2022**, *27*, 2290–2302. [CrossRef]
37. Maratkhan, A.; Ilyassov, I.; Aitzhanov, M.; Demirci, M.F.; Ozbayoglu, A.M. Deep learning-based investment strategy: Technical indicator clustering and residual blocks. *Soft Comput.* **2021**, *25*, 5151–5161. [CrossRef]
38. Urquhart, A.; Zhang, H. The performance of technical trading rules in Socially Responsible Investments. *Int. Rev. Econ. Financ.* **2019**, *63*, 397–411. [CrossRef]
39. Ni, Y.; Huang, P.; Chen, Y. Board structure, considerable capital, and stock price overreaction informativeness in terms of technical indicators. *N. Am. J. Econ. Financ.* **2019**, *48*, 514–528. [CrossRef]
40. Ashraf, B.N. Economic impact of government interventions during the COVID-19 pandemic: International evidence from financial markets. *J. Behav. Exp. Financ.* **2020**, *27*, 100371. [CrossRef]
41. Hamdi, A.; Karimi, A.; Mehrdoust, F.; Belhaouari, S.B. Portfolio Selection Problem Using CVaR Risk Measures Equipped with DEA, PSO, and ICA Algorithms. *Mathematics* **2022**, *10*, 2808. [CrossRef]
42. Shik, T.C.; Chong, T.T.L. A comparison of MA and RSI returns with exchange rate intervention. *Appl. Econ. Lett.* **2007**, *14*, 371–383. [CrossRef]
43. Chong, T.T.L.; Ng, W.K. Technical analysis and the London stock exchange: Testing the MACD and RSI rules using the FT30. *Appl. Econ. Lett.* **2008**, *15*, 1111–1114. [CrossRef]
44. Hofmann, D.; Keiber, K.L.; Luczak, A. Up and down together? On the linkage of momentum and reversal. *Glob. Financ. J.* **2022**, *54*, 100754. [CrossRef]
45. Liao, C.C. Momentum trading, contrarian trading and smart money manipulation. *Int. Bus. Res.* **2017**, *10*, 53–62. [CrossRef]
46. Liu, Z.; Lu, S.; Li, B.; Wang, S. Time series momentum and reversal: Intraday information from realized semivariance. *J. Empir. Financ.* **2023**, *72*, 54–77. [CrossRef]
47. Hong, H.; Stein, J.C. A unified theory of underreaction, momentum trading, and overreaction in asset markets. *J. Financ.* **1999**, *54*, 2143–2184. [CrossRef]
48. Ni, Y.; Liao, Y.C.; Huang, P. MA trading rules, herding behaviors, and stock market overreaction. *Int. Rev. Econ. Financ.* **2015**, *39*, 253–265. [CrossRef]
49. Butt, H.A.; Kolari, J.W.; Sadaqat, M. Revisiting momentum profits in emerging markets. *Pac.-Basin Financ. J.* **2021**, *65*, 101486. [CrossRef]
50. Shen, D.; Urquhart, A.; Wang, P. Bitcoin intraday time series momentum. *Financ. Rev.* **2022**, *57*, 319–344. [CrossRef]
51. Hanauer, M.X.; Windmüller, S. Enhanced momentum strategies. *J. Bank. Financ.* **2023**, *148*, 106712. [CrossRef]
52. Li, Y.; Liang, C.; Huynh, T.L. A new momentum measurement in the Chinese stock market. *Pac.-Basin Financ. J.* **2022**, *73*, 101759. [CrossRef]

53. Yang, X.; Zhang, H. Extreme absolute strength of stocks and performance of momentum strategies. *J. Financ. Mark.* **2019**, *44*, 71–90. [CrossRef]
54. Gupta, T.; Kelly, B. Factor momentum everywhere. *J. Portf. Manag.* **2019**, *45*, 13–36. [CrossRef]
55. Sim, M.; Kim, H.E. Salience theory and enhancing momentum profits. *Financ. Res. Lett.* **2022**, *50*, 103274. [CrossRef]
56. Day, M.Y.; Ni, Y. Do clean energy indices outperform using contrarian strategies based on contrarian trading rules? *Energy* **2023**, *272*, 127113. [CrossRef]
57. Day, M.Y.; Cheng, Y.; Huang, P.; Ni, Y. The profitability of trading US stocks in Quarter 4—Evidence from trading signals emitted by SOI and RSI. *Appl. Econ. Lett.* **2023**, *30*, 1173–1178. [CrossRef]
58. Gopal, K. A Review of contrarian strategies in capital markets. *Int. J. Manag. Soc. Sci.* **2016**, *4*, 115–120.
59. Montgomery, W.; Raza, A.; Ülkü, N. Tests of technical trading rules and the 52-week high strategy in the corporate bond market. *Glob. Financ. J.* **2019**, *40*, 85–103. [CrossRef]
60. Wu, M.; Huang, P.; Ni, Y. Investing strategies as continuous rising (falling) share prices released. *J. Econ. Financ.* **2017**, *41*, 763–773. [CrossRef]
61. Arnott, R.D.; Harvey, C.R.; Kalesnik, V.; Linnainmaa, J.T. Reports of value's death may be greatly exaggerated. *Financ. Anal. J.* **2021**, *77*, 44–67. [CrossRef]
62. Bali, T.G.; Demirtas, K.O.; Hovakimian, A. Corporate financing activities and contrarian investment. *Rev. Financ.* **2010**, *14*, 543–584. [CrossRef]
63. Shi, H.L.; Zhou, W.X. Time series momentum and contrarian effects in the Chinese stock market. *Phys. A Stat. Mech. Appl.* **2017**, *483*, 309–318. [CrossRef]
64. Huang, W.; Goodell, J.W.; Zhang, H. Pre-merger management in developing markets: The role of earnings glamor. *Int. Rev. Financ. Anal.* **2019**, *65*, 101375. [CrossRef]
65. Blackledge, J.; Lamphiere, M. A review of the fractal market hypothesis for trading and market price prediction. *Mathematics* **2021**, *10*, 117. [CrossRef]
66. Shen, Y.; Shen, K. Short-term contrarian profits and the disposition effect. *Financ. Res. Lett.* **2022**, *46*, 102380. [CrossRef]
67. Boussaidi, R.; AlSaggaf, M.I. Contrarian profits and representativeness heuristic in the MENA stock markets. *J. Behav. Exp. Econ.* **2022**, *97*, 101820. [CrossRef]
68. Chae, J.; Kim, R. Contrarian profits of the firm-specific component on stock returns. *Pac.-Basin Financ. J.* **2020**, *61*, 101176. [CrossRef]
69. Jones, S.L.; Lee, W.; Apenbrink, R. New evidence on the January effect before personal income taxes. *J. Financ.* **1991**, *46*, 1909–1924. [CrossRef]
70. D'Mello, R.; Ferris, S.P.; Hwang, C.Y. The tax-loss selling hypothesis, market liquidity, and price pressure around the turn-of-the-year. *J. Financ. Mark.* **2003**, *6*, 73–98. [CrossRef]
71. Ciccone, S.J. Investor optimism, false hopes and the January effect. *J. Behav. Financ.* **2011**, *12*, 158–168. [CrossRef]
72. Rozeff, M.S.; Kinney, W.R., Jr. Capital market seasonality: The case of stock returns. *J. Financ. Econ.* **1976**, *3*, 379–402. [CrossRef]
73. Keim, D.B. Size-related anomalies and stock return seasonality: Further empirical evidence. *J. Financ. Econ.* **1983**, *12*, 13–32. [CrossRef]
74. Cheema, A.K.; Ding, W.; Wang, Q. The cross-section of January effect. *J. Asset Manag.* **2023**, *24*, 513–530. [CrossRef]
75. Rana, S.J. Macroeconomics and Anomalies as Determinants of Stock Returns. Master's Thesis, Southern Illinois University at Carbondale, Carbondale, IL, USA, 2022.
76. Day, M.Y.; Ni, Y. The profitability of seasonal trading timing: Insights from energy-related markets. *Energy Econ.* **2023**, *128*, 107132. [CrossRef]
77. Bezuidenhout, J.M.; Van Vuuren, G. Spectral analysis and the death of value investing. *Cogent Econ. Financ.* **2021**, *9*, 1988380. [CrossRef]
78. Huang, P.; Yang, C.T.; Chen, Y.; Ni, Y. A New Look on the Profitability of Fixed and Indexed Mortgage Products. *Mathematics.* **2023**, *11*, 3631. [CrossRef]
79. Pyo, D.J. Does geopolitical risk matter? Evidence from South Korea. *Def. Peace Econ.* **2021**, *32*, 87–106. [CrossRef]
80. Xu, Y.; Zhao, J. Can sentiments on macroeconomic news explain stock returns? Evidence from social network data. *Int. J. Financ. Econ.* **2022**, *27*, 2073–2088. [CrossRef]
81. Bouoiyour, J.; Selmi, R.; Hammoudeh, S.; Wohar, M.E. What are the categories of geopolitical risks that could drive oil prices higher? Acts or threats? *Energy Econ.* **2019**, *84*, 104523. [CrossRef]
82. Broby, D. The use of predictive analytics in finance. *J. Financ. Data Sci.* **2022**, *8*, 145–161. [CrossRef]
83. Goldstein, I.; Spatt, C.S.; Ye, M. Big data in finance. *Rev. Financ. Stud.* **2021**, *34*, 3213–3225. [CrossRef]
84. Hussain, S.M.; Ahmad, N.; Ahmed, S. Applications of high-frequency data in finance: A bibliometric literature review. *Int. Rev. Financ. Anal.* **2023**, *89*, 102790. [CrossRef]
85. Yao, Y. Momentum, contrarian, and the January seasonality. *J. Bank. Financ.* **2012**, *36*, 2757–2769. [CrossRef]
86. Lo, A.W.; MacKinlay, A.C. When are contrarian profits due to stock market overreaction? *Rev. Financ. Stud.* **1990**, *3*, 175–205. [CrossRef]
87. Feng, S.; Wang, N.; Zychowicz, E.J. Sentiment and the performance of technical indicators. *J. Portf. Manag.* **2017**, *43*, 112. [CrossRef]

88. Coita, I.F.; Belbe, S.Ș.; Mare, C.C.; Osterrieder, J.; Hopp, C. Modelling taxpayers' behaviour based on prediction of trust using sentiment analysis. *Financ. Res. Lett.* **2023**, *58*, 104549. [CrossRef]
89. Laura Dragos, S.; Mare, C.; Mureșan, G.M.; Purcel, A.A. European motor insurance demand: A spatial approach of its effects and key determinants. *Econ. Res.-Ekon. Istraživanja* **2023**, *36*, 2132348. [CrossRef]
90. Dreman, D.N.; Berry, M.A. Overreaction, underreaction, and the low-P/E effect. *Financ. Anal. J.* **1995**, *51*, 21–30. [CrossRef]
91. Higgins, C.J. Simplicity of the holding period return. *J. Financ.* **2018**, *6*, 55–57. [CrossRef]
92. Brogaard, J.; Zareei, A. Machine learning and the stock market. *J. Financ. Quant. Anal.* **2023**, *58*, 1431–1472. [CrossRef]
93. Coe, T.S.; Laosethakul, K. Applying technical trading rules to beat long-term investing: Evidence from Asian markets. *Asia-Pac. Financ. Mark.* **2021**, *28*, 587–611. [CrossRef]
94. Nti, I.K.; Adekoya, A.F.; Weyori, B.A. A systematic review of fundamental and technical analysis of stock market predictions. *Artif. Intell. Rev.* **2020**, *53*, 3007–3057. [CrossRef]
95. Jakubik, P.; Uguz, S. Impact of green bond policies on insurers: Evidence from the European equity market. *J. Econ. Financ.* **2021**, *45*, 381–393. [CrossRef]
96. Kouaissah, N.; Hocine, A. Forecasting systemic risk in portfolio selection: The role of technical trading rules. *J. Forecast.* **2021**, *40*, 708–729. [CrossRef]
97. Zoicas-Ienciu, A.; Pochea, M.M. What drives trend-following profits in stocks? The role of the trading signals' volatility. *Appl. Econ.* **2023**, *55*, 3788–3805. [CrossRef]
98. Arumugam, D.; Prasanna, P.K. Commonality and contrarian trading among algorithmic traders. *J. Behav. Exp. Financ.* **2021**, *30*, 100495. [CrossRef]
99. Ham, H.; Cho, H.; Kim, H.; Ryu, D. Time-series momentum in China's commodity futures market. *J. Futures Mark.* **2019**, *39*, 1515–1528. [CrossRef]
100. Ye, Z.; Wu, Y.; Chen, H.; Pan, Y.; Jiang, Q. A stacking ensemble deep learning model for bitcoin price prediction using Twitter comments on bitcoin. *Mathematics* **2022**, *10*, 1307. [CrossRef]
101. Kwak, Y.; Song, J.; Lee, H. Neural network with fixed noise for index-tracking portfolio optimization. *Expert Syst. Appl.* **2021**, *183*, 115298. [CrossRef]
102. Mosavi, A.; Faghan, Y.; Ghamisi, P.; Duan, P.; Ardabili, S.F.; Salwana, E.; Band, S.S. Comprehensive review of deep reinforcement learning methods and applications in economics. *Mathematics* **2020**, *8*, 1640. [CrossRef]
103. Wen, F.; Zou, Q.; Wang, X. The contrarian strategy of institutional investors in Chinese stock market. *Financ. Res. Lett.* **2021**, *41*, 101845. [CrossRef]
104. Gunay, S.; Kaskaloglu, K.; Muhammed, S. Bitcoin and Fiat Currency Interactions: Surprising Results from Asian Giants. *Mathematics* **2021**, *9*, 1395. [CrossRef]
105. Jitmaneeroj, B. Time-varying fund manager skills of socially responsible investing (SRI) funds in developed and emerging markets. *Res. Int. Bus. Financ.* **2023**, *64*, 101877. [CrossRef]
106. Vecch, E.; Berra, G.; Albrecht, S.; Gagliardini, P.; Horenko, I. Entropic approximate learning for financial decision-making in the small data regime. *Res. Int. Bus. Financ.* **2023**, *65*, 101958. [CrossRef]
107. Zhang, X.; Liu, S.; Zheng, X. Stock price movement prediction based on a deep factorization machine and the attention mechanism. *Mathematics* **2021**, *9*, 800. [CrossRef]
108. Barroso, B.C.; Cardoso, R.T.; Melo, M.K. Performance analysis of the integration between Portfolio Optimization and Technical Analysis strategies in the Brazilian stock market. *Expert Syst. Appl.* **2021**, *186*, 115687. [CrossRef]