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Enhancing Crypto Success via Heatmap Visualization of Big Data Analytics for Numerous Variable Moving Average Strategies

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Abstract: This study employed variable moving average (VMA) trading rules and heatmap visualization because the flexibility advantage of the VMA technique and the presentation of numerous outcomes using the heatmap visualization technique may not have been thoroughly considered in prior financial research. We not only employ multiple VMA trading rules in trading crypto futures but also present our overall results through heatmap visualization, which will aid investors in selecting an appropriate VMA trading rule, thereby likely generating profits after screening the results generated from various VMA trading rules. Unexpectedly, we demonstrate in this study that our results may impress Ethereum futures traders by disclosing a heatmap matrix that displays multiple geometric average returns (GARs) exceeding 40%, in accordance with various VMA trading rules. Thus, we argue that this study extracted the diverse trading performance of various VMA trading rules, utilized a big data analytics technique for knowledge extraction to observe and evaluate numerous results via heatmap visualization, and then employed this knowledge for investments, thereby contributing to the extant literature. Consequently, this study may cast light on the significance of decision making via big data analytics.

Keywords: VMA trading rules; cryptocurrencies; Ethereum (ETH); investing strategies; heatmap visualization; big data analytics

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1. Introduction

According to the efficient market hypothesis (EMH) [1–3], stock prices may be difficult to predict because they already reflect all available information. However, disposition effects [4,5], stock price overreaction [6,7], and even clustering behaviors [8,9] appear to challenge this viewpoint. As a result, some investors might predict future prices by taking diverse technical trading indicators into account because different approaches might be appropriate for some technical indicators due to the overreaction hypothesis [10–13], or momentum approaches might be suitable for other technical indicators because of excessive self-confidence [14–17].

In this research, we investigated cryptocurrencies as opposed to stocks because cryptocurrencies have attracted increasing investor interest due to their innovation, transparency, and growing acceptance [18,19]. Furthermore, not only has the market value of cryptocurrencies increased exponentially [20], but they have also rapidly become a significant component of the global financial market [21–27]. Moreover, because of their higher risk, expected high return, lower transaction costs, and so on, cryptocurrencies attract a variety of investors, including individual investors. Bitcoin, one of the most well-known cryptocurrencies [28], has garnered the most attention [29–36] among cryptocurrencies.

Additionally, López-Martn, Benito Muela, and Arguedas [37] demonstrated that, while the EMH has been challenged over time, changes in Bitcoin markets show a tendency to evolve from less to more efficiency, indicating that other cryptocurrencies may be less explored than Bitcoin but also appear understudied in relevant studies. Furthermore, some trading rules may create a considerable excess return for most cryptocurrencies other than Bitcoin, meaning that cryptocurrency markets may not be efficient for most cryptocurrencies other than Bitcoin [38]. We then infer that the aforementioned result may be attributable to Bitcoin's appeal to individual investors, institutional investors, and even academics, thereby enhancing the efficiency of the Bitcoin market. Moreover, Naeem et al. [27] observed a significant asymmetry in the price movement of cryptocurrencies. In light of the upward trend over the past few years, we employed another cryptocurrency, Ethereum, in this study.

We thus not only used Ethereum (hereafter referred to as ETH) instead of Bitcoin as our investigated target due to the above concern [39] but also investigated whether investors could predict the price movement of ETH by considering various technical indicators, particularly the VMA trading rule [40], as shown in Section 2. As a result, because Bitcoin seems to be well cultivated in relevant studies, this research may shed light on the usefulness of technical trading rules by using other cryptocurrencies (e.g., ETH) instead of Bitcoin, potentially increasing the added value and contribution to the cryptocurrency literature.

Furthermore, a significant proportion of investors embrace alternative trading strategies, as exemplified by the 5–20 (5–60) rule, which provides a buy signal when the weekly MA exceeds the monthly (quarterly) MA calculated over 5 and 20 (60) trading days, representing a week and a month (quarter), differing from employing the 1–100 and 1–200 rules commonly used in previous studies [41–45]. Consequently, through the incorporation of the variable-lag MA (VMA) into the approach denoted as VMA (5, 20 $\times$ N), where N varies from 1 to 9, factoring the VMA (5, 20) and VMA (5, 60) regulations into the VMA (5, 20 $\times$ N) framework, this study identifies that one specific VMA trading strategy exhibits superior returns compared to its counterparts, such as the conventional model [17,46,47]. In contrast to the conventional approach, our innovative framework generates diverse outcomes due to a variety of VMA trading regulations. Additionally, this innovative method employs a distinct short MA (SMA) and long MA (LMA), represented as VMA (n1, n2), with n1 representing the n1 days for the SMA and n2 representing the n2 days for the LMA, where n2 > n1. By adopting this approach, we are able to present the results in Table 4 (comprising a variety of outcomes from the application of a number of VMA trading rules to trading ETH index futures) or Figure 2 (illustrating a variety of outcomes in a heatmap diagram with distinct colors) in Section 3. Therefore, we can achieve some superior outcomes, denoted by the color red in Table 4, that surpass the highest outcome in Table 3 using the conventional approach.

As previously stated, we move our focus from stock markets to cryptocurrency markets as we investigate cryptocurrency dynamics. Following that, we raise the research questions of whether utilizing technical trading rules will increase profitability, whether we can derive as many outcomes as feasible by using technical trading rules via big data analytics, and whether we can screen these outcomes in a short time. Unlike the previous relevant literature that focused on popular cryptocurrencies (e.g., Bitcoin) and traditional technical trading rules (e.g., MA trading rule), we present a flexible VMA trading approach for trading ETH's potential, revealing numerous outcomes and highlighting the potential of big data analytics and heatmap visualization in shaping profitable trading strategies. This divergence from established methodologies, along with a thorough analysis of alternative cryptocurrency (ETH), positions our research to significantly contribute to the financial and cryptocurrency literature.

In other words, this study emphasizes the substantial use of VMA trading rules and heatmap visualization [48,49]. The study not only highlights the importance of evaluating the adjustability of the VMA rule, which has been neglected by previous research, but also employs the heatmap visualization technique, a technique that has been used infrequently in finance, to provide investors with useful information for choosing profitable trading strategies, which could potentially benefit the current body of literature in the fields of finance and cryptocurrency research. Moreover, the study investigates an alternative cryptocurrency, namely, Ethereum, providing a new perspective on the applicability of technical trading rules beyond the traditional focus on Bitcoin by emphasizing the significance of big data analytics in making informed investment decisions.

This study has the potential to make significant contributions to the existing body of literature on multiple fronts. First, we present a multitude of results, specifically geometric average returns (GARs), resulting from the use of a flexible VMA trading approach, a facet often disregarded in the contemporary financial literature, due to its adaptability and the use of big data analytics. Second, we provide investors with a comprehensive perspective on trading ETH index futures by presenting numerous results through an informative heatmap diagram. This useful instrument can assist investors in identifying the appropriate VMA trading rules, thereby enhancing their potential for attaining better returns. As a result, investors may realize increased returns, possibly deriving profitable trading performance, as evidenced by the wide variety of outcomes derived from diverse VMA trading rules. Third, we contend that our research framework is likely to attract the attention of a large number of investors trading ETH index futures, given our findings that investors adopting our novel approach have the potential to achieve significantly higher returns than investors adhering to the conventional design.

2. Literature Review

In Section 2.1, we review the technical trading research using MA and VMA trading rules due to their effectiveness. In Section 2.2, we survey technical analysis studies on cryptocurrency markets based on previous studies that mainly focused on stock markets. Section 2.3 introduces the heatmap visualization employed in this research.

2.1. Technical Trading Literature of MA and VMA Trading Regulations

Given the above-mentioned effectiveness of the VMA trading approach, we will now examine the pertinent literature on both MA and VMA trading rules. Prior research has demonstrated that investors employ various MA trading strategies, such as the variable-length MA (VMA) and fixed-length MA (FMA), with the aim of generating profits [41,42,50]. Notably, Brock et al. [41] identified the widely used MA trading rule of 1–200, which refers to the use of a 1-day SMA and a 200-day LMA, where buying (selling) signs are triggered when the 1-day SMA crosses above (below) the 200-day LMA, respectively. Moreover, numerous VMA trading rules, such as 1–50, 1–100, and 1–200, have been examined in previous research [41–44]. In contrast, following the FMA, when a buying sign is emitted, it is maintained for a specific time to calculate its return [51,52]. However, we contend that determining an unequivocal standard period for exiting in FMA trading rules may lack consensus, which distinguishes it from the VMA trading rules, where explicit entry (exit) signals are defined by the occurrence of the golden cross (dead cross) according to a widely accepted standard. For the preceding reasons, this study concludes that the application of VMA trading rules may be more appropriate.

Furthermore, the study conducted by Chang, Lima, and Tabak [53] provides compelling evidence of the predictive power inherent to the VMA trading strategy. Ratner and Leal [54] conducted a comprehensive analysis of the profit potential associated with different VMA regulations in Asian stock exchanges. Their findings indicated that these trading rules were profitable on the stock exchanges of Taiwan and Thailand, whereas the evidence for profitability in other markets was weaker. In a different geographical context, Ni, Lee, and Liao [55] cast light on the profitability that investors can achieve through the use of VMA trading rules, particularly as buy signals emitted by VMA trading rules proved effective on the stock markets of Brazil, Russia, India, and China (BRIC). Nevertheless, Day and Wang [56] arrived at a contrasting conclusion, suggesting that buy-and-hold returns based on VMA trading rules may not necessarily contribute to improved performance. Adding to the complexity, Heng et al. [57] noted that some investors who employ technical trading rules may realize positive returns when transaction costs are not considered. However, once these expenses are considered, positive returns might not materialize. The diverse results observed in these relevant studies have piqued our interest in investigating VMA trading rules in financial markets, especially in dynamic crypto markets.

2.2. Technical Analysis Studies of Cryptocurrency Markets

Regarding the application of technical trading principles within the cryptocurrency domain, Bitcoin has been the subject of extensive investigation using these techniques [31,38,58]. Gerritsen et al. [59] recently showed the significant predictive power of trend-following trading rules, particularly the MA trading rule, in terms of Bitcoin price dynamics, given that that technical analysis processes using historical prices can yield predicted values, according to Vijh et al. [60]. Additionally, Corbet et al. [31] not only provide strong support for Bitcoin trading via MA strategies, with the VMA approach emerging as the most effective, but also demonstrate that adopting buy signals within such trading rules generates superior returns compared to sell signals. In the meantime, Hudson and Urquhart [61] provide compelling evidence that technical trading rules offer substantially higher risk-adjusted returns than a simple buy-and-hold strategy, providing a robust hedge against cryptocurrency market fluctuations. Bouri et al. [62] explore intraday trading opportunities for Bitcoin, uncovering profitable possibilities that challenge the market efficiency hypothesis. Additionally, Corbet et al. [50] support the effectiveness of MA methods by highlighting the superiority of VMA trading regulations in cryptocurrency markets. We present the main conclusions from the relevant literature using technical trading rules in crypto markets in Table 1. Furthermore, based on a review of the above-mentioned studies, Bitcoin seems widely explored in the relevant literature. Thus, we are interested in whether using VMA regulations could help us earn from ETH futures trading. Consequently, we propose H1.

Table 1. Conclusions in the relevant literature using technical trading rules in crypto markets.

Authors	Conclusions
Gerritsen et al. (2020) [59]	Showed the significant predictive power of trend-following trading rules, particularly the MA trading rule, for trading Bitcoin.
Resta et al. (2020) [58]	Revealed that simple moving averages yield the best performance in Bitcoin markets when dealing with daily data.
Corbet et al. (2020) [31]	Provided support for Bitcoin trading via MA and VMA strategies as well as demonstrated that adopting buy signals in these trading rules generates superior returns compared to sell signals.
Hudson and Urquhart (2021) [61]	Provided evidence that technical trading rules offer substantially higher risk-adjusted returns for trading Bitcoin.
Bouri et al. (2021) [62]	Uncovered profitable possibilities for Bitcoin that challenge the market efficiency hypothesis.
Corbet et al. (2019) [50]	Highlighted the superiority of VMA trading regulations in cryptocurrency markets.
Lento and Gradojevic (2022) [38]	Revealed that Bollinger Bands and trading range breakout rules became profitable after transaction costs during the market crash resulting from COVID-19.

H1. *Investors who utilize VMA trading regulations could help them earn from ETH futures trading.*

2.3. Heatmap Visualization

A heatmap, a widely adopted data visualization method [63–65], is useful for evaluating two-dimensional data representations, which are frequently depicted as matrices, in a variety of domains, such as artificial intelligence [66–68] and big data analytics [69–72]. Van Craenendonck et al. [72] highlight the role of heatmap visualization techniques in enhancing the interpretability of deep learning within artificial intelligence and big data analytics [73]. Fearne [74] prominently utilized heatmap methodologies to develop a pricing model for identifying key variables on Airbnb sharing economy rental platforms. Despite the considerable computer science literature on heatmap visualization, empirical studies employing heatmap data visualization techniques in financial data analysis are still uncommon.

3. Design of This Study

3.1. Introduction to MA and VMA Trading Rules

In our study, we employed the VMA trading rule and introduced the MA and VMA trading strategies. These strategies take into account distinct SMA and LMA periods. The MA strategy employs a simple MA over a specific number of days, represented as an n-day SMA, computed by the arithmetic mean of the closing prices over that period. It serves to reduce price volatility. Within the MA trading strategy, we consider two critical situations (i.e., the golden cross and the dead cross). In practice, the MA trading rule entails the buying (selling) of stocks when a golden (dead) cross appears, which leads to the buying (selling) of stocks when the SMA crosses above (below) the LMA.

3.2. Research Design

In practical trading, many investors opt for the 5–20 trading rule (i.e., the 5-day MA is SMA, and the 20-day MA is LMA), which is distinct from the 1–100 and 1–200 MA rules typically proposed in the pertinent research [41–45]. Consequently, by integrating the VMA (5, 20 $\times$ N) trading rule, where N ranges from 1 to 9 as a result of the incorporation of the VMA (5, 20) and VMA (5, 60) regulations within the VMA (5, 20 $\times$ N) framework, the approach in this study can investigate whether any of these VMA trading strategies generate superior returns, similar to what is generally considered the conventional approach in relevant studies [17,39,75]. In addition to the conventional approach, our novel strategy employs different durations for the SMA and LMA, resulting in multiple outcomes, quantified as returns (Rs). This thorough investigation encompasses various VMA trading regulations, as displayed in Table 4 (with VMA configurations represented as VMA (n1, n2), where n1 (SMA) ranges from 5 to 60 days, and n2 (LMA) ranges from 10 to 180 days, with n2 exceeding n1) and in Figure 2, which depicts all findings in a comprehensive heatmap. Consequently, we argue that by using the VMA trading rule, investors may gain more profits and even satisfactory profits by trading ETH futures via the heatmap visualization approach instead of the conventional approach. Therefore, we propose the following hypothesis.

H2. *Investors may gain more profits and even satisfactory profits by trading ETH futures via the heatmap visualization approach instead of the conventional approach.*

Furthermore, the rationale behind the design of the study is as follows. From a general standpoint, it seems prudent to investigate a diverse array of combinations resulting from various VMA trading principles. This could entail adjusting the parameters for n1 and n2 to ensure that n2 is greater than n1. However, due to reservations about handling limited trading data—something that could potentially skew our findings—and the challenge of effectively presenting a multitude of results within a heatmap matrix, we made a deliberate choice. We decided to cap the highest values for n1 and n2 at 60 days and 180 days, respectively, with 5-day increments from 5 days up to the maximum value for either n1 or n2. Importantly, we complied with the MA trading rule requirement that n2 must be greater than n1. Notably, the heatmap design includes all conventional VMA (5, 20 × N) combinations (where N ranges from 1 to 9). However, the data presentation issue may limit us in conveying our findings despite our best efforts. That is, the absence of a standardized format for demonstrating our overall results might be an aspect warranting further consideration.

3.3. Measuring the Rate of Return Following the VMA Trading Rule

Initially, by adhering to the VMA trading strategy for ETH index futures, we can calculate the return on ETH futures, denoted by "R," using the following expression:

$$\mathrm{Ri} = (\alpha \mathrm{i}/\beta \mathrm{i}) - 1 \tag{1}$$

In Equation (1), αi represents the closing price of ETH futures at the i-th trade on the selling day, while βi stands for the closing price of ETH futures at the i-th trade on the buying day.

Then, we proceed to compute the cumulative returns of ETH futures prices, hereafter referred to as "CR", employing Equation (2) as delineated below:

$$\mathrm{CR} = \sum_{i=1}^{n} (1 + R_1)(1 + R_2)\ldots\ldots\ldots(1 + R_n) \tag{2}$$

In Equation (2), CR signifies the cumulative product of adding 1 to each value in the series R_1 through R_n, encompassing the entire range from 1 to n. Each R_i denotes the return associated with ETH futures, spanning from the first trade (i = 1) to the last trade (i = n), and is generated by one of the VMA trading regulations.

Following that, we use Equation (3) to calculate the geometric average of the returns associated with ETH futures, designated as "GAR".

$$\mathrm{GAR} = \sqrt[n]{CR} - 1 \tag{3}$$

Here, GAR denotes the geometric average return of ETH futures. The parameter "n" represents the total number of trades executed by one of the VMA trading regulations.

In this research framework, following the completion of the first round-trip trading, investors then process the second round-trip transaction. This sequence spans the entire data period, beginning with the first trade and ending with the last transaction. As a result, since we can examine the subsequent return after identifying the first return, we believe that the GAR is appropriate for our research.

Nonetheless, when engaging in ETH futures round-trip trading, investors must consider transaction expenses. These costs are normally limited to 1%, and in many circumstances, they are significantly lower, perhaps as low as 0.3%. Based on the geometric average returns (GARs) shown in Table 3, which represent the results of the traditional method, we see a range from 37.45% to 2.81%. Given this context, it is evident that, while the transaction costs are not insignificant, they may not be the main concern of this study. Moreover, we can establish a benchmark for the ETH index futures trading performance. The 10-year treasury bond rate is the lower benchmark for ETH investment since it presents the opportunity cost of investments, and the performance of the S&P 500 index would be used as another benchmark because it can represent the performance of stock market trading.

In summary, this study is directly related to big data analysis and modeling applications since it includes the VMA trading rule and heatmap visualization to derive and display diverse results. The study employed big data analytics approaches to observe and assess the effectiveness of various VMA trading strategies by applying various combinations of short-term and long-term moving averages. This approach allows investors to choose acceptable strategies for trading ETH index futures, which may result in higher returns than the standard design and benchmark performance. The emphasis on the average geometric mean as a measure of returns reflects the evaluation of many round-trip trades, and the research analyzed transaction costs and established acceptable benchmarks, adding to the importance of big data analytics in investment decision making.

4. Empirical Results and Analyses

4.1. Descriptive Statistics

Since our investment target is Ethereum (ETH) futures, this section explains ETH futures. ETH futures are financial contracts that derive their value from the price of ETH, the second-largest cryptocurrency by market capitalization. These futures contracts allow investors to speculate on the future price movements of Ethereum without actually owning the underlying asset. Futures contracts are a type of derivative, meaning that their value is derived from an underlying asset (i.e., Ethereum). As such, using Datastream's daily ETH futures price data as our investment target, we display the descriptive statistics in Table 2. The table indicates a large difference between the Max (i.e., 1396.42) and Min (i.e., 0.94) of the ETH futures price, suggesting that the price movement of ETH futures is highly fluctuating, as shown by a higher standard deviation (i.e., 232.05). Furthermore, the data distribution is positively skewed (i.e., 1.62), indicating that the mean is greater than the median because higher values on the right side pull the mean (i.e., 241.29) higher than the median (194.79); a high kurtosis (i.e., 3.36) indicates that the distribution has a sharper peak than the normal distribution, which might result from a coexisting sharp rise and drop, and the former may last longer than the latter across the data period due to higher value on the right side, resulting in higher variance, positive skewness, and a higher peak.

Table 2. The descriptive statistics for the ETH futures price over the data period 2016–2020.

Cryptocurrency	Sample	Mean	Standard Deviation	Coeff. of Variance	Median	Minimum	Maximum	Skewness	Kurtosis
ETH	1824	241.29	232.05	96.17%	194.79	0.94	1396.42	1.62	3.36

In addition, we plot the ETH futures price data in Figure 1, illustrating a peak near the start of 2018 as well as an upward trend at the end of the data period.

Figure 1. The trend of the ETH futures price from 2016 to 2020.

4.2. Empirical Results for Traditional Research Design

To ensure a meaningful basis for comparison, we first implemented the VMA trading rule employing VMA (5, 20 × N), where N ranges from 1 to 9, as our traditional design, with the results displayed in Table 3.

Table 3. VMA trading approaches for ETH.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
VMA Trading Rules	**No. of Trades**	**CR (%)**	**GAR (%)**	**CV**	**Avg. Duration Day**	**Max. Duration Day**
(5, 20)	90	76,491.51	7.66	9.880	20	94
(5, 40)	48	78,318.44	14.89	31.574	37	181
(5, 60)	42	24,24.45	7.99	34.317	42	186
(5, 80)	40	202.58	2.81	104.214	43	209
(5, 100)	30	3283.26	12.46	29.391	57	271
(5, 120)	22	8439.74	22.40	21.583	75	287
(5, 140)	24	10,418.40	21.41	59.823	69	415
(5, 160)	16	16,134.81	37.45	37.204	101	417
(5, 180)	18	9862.88	29.13	40.544	90	409

Table 3 reveals that the VMA (5, 160) regulation has the highest GAR, 37.45%. This amount significantly exceeds the GARs associated with other VMA trading rules, which all fall below the 30% level. The table also displays the No. of trades, their average day length, and their maxima under VMA regulations. Because of the results of applying nine VMA trading regulations in Table 3, recognized as the traditional design in this study, we then find the highest GAR derived from adopting the VMA (5, 160) trading rule, whose GAR is significantly greater than the others indicated in Column (4) of Table 3. However, we are concerned about whether we can acquire even greater GARs by utilizing a plethora of VMA trading restrictions. As a result, we conducted additional research, which is described in the following section.

4.3. Empirical Results for Numerous Outcomes with Heatmap Visualization

To offer a thorough overview of the vast range of outcomes, we have chosen to utilize a heatmap matrix to effectively communicate our overall findings, particularly the GARs. Within the matrix, the initial column contains a range of values for n2, starting from 10 at the lower bound and extending to 180 at the upper bound. In contrast, the final row contains the range of values for n1, ranging from 5 on the leftmost end to 60 on the rightmost end. Through the analysis of the interactions between different combinations of n1 and n2, valuable insights can be obtained regarding the performance outcomes associated with the utilization of diverse VMA trading rules.

Consequently, investors will be able to identify superior GARs among the multitude of GARs generated by the use of diverse VMA trading rules if they implement our novel approach. The outcomes are depicted in Table 4, which contains a 6 $\times$ 23 heatmap matrix of VMA (n1, n2) outcomes. Here, n1 (SMA) ranges from 5 to 30 days, while n2 (LMA) is between 10 and 120 days, with a 5-day interval. Figure 2 depicts the same information visually by displaying multiple GARs in a heatmap diagram. In this diagram, dark blue represents lower GARs and brilliant yellow represents higher ones to vividly depict performance differences. In this visual representation, boosted GARs are recognizable through the presence of red colors in the heatmap matrix (Table 4) or the emergence of bright colors in the heatmap visualization (Figure 2), providing investors with an easily distinguishable overview of enhanced performance.

Table 4 further provides insight into the performance, specifically the GAR, obtained by implementing the VMA (5, 160) trading rule. Notably, the GAR is 37.45%, which has been rounded to 37.5%. This corresponds to the precise GAR of 37.5% shown in Column (4) of Table 3, which corresponds to the use of the VMA (5, 160) trading rule. It is worth noting that, whereas Table 3 offers just seven findings in terms of GARs, our new approach allows us to see multiple outcomes derived from diverse VMA regulations.

Table 4. Heatmap matrix outcomes (GARs) based on various VMA trading rules.

180	29.1	38.3	32.5	60.3	47.8	–	–	–	–	–	35.1	38.9
175	34.7	34.5	42.1	60.7	52.8	–	–	–	–	–	–	37.0
170	35.0	36.0	55.2	64.4	51.9	47.3	–	–	37.7	–	–	–
165	29.8	47.5	56.2	62.4	61.4	50.7	–	–	–	–	–	–
160	37.5	69.2	61.0	66.5	61.2	48.0	43.8	–	–	35.9	–	–
155	30.3	74.0	63.1	66.3	60.6	48.8	46.3	–	–	–	45.8	–
150	21.2	45.9	45.5	70.6	56.4	56.7	35.9	52.8	–	–	–	40.7
145	18.9	54.1	38.9	44.5	57.9	57.0	46.4	53.9	–	–	–	–
140	21.4	35.6	41.2	42.7	61.2	56.9	49.4	56.7	50.9	46.7	–	–
135	19.5	35.5	40.8	48.3	63.5	60.0	53.1	57.2	48.8	49.7	40.4	–
130	20.0	26.1	35.0	40.6	48.8	46.4	52.6	54.5	63.7	50.6	42.1	–
125	17.7	26.3	32.1	33.5	50.8	47.2	48.3	43.2	46.8	32.0	34.1	28.5
120	22.4	21.0	16.7	30.2	40.2	40.2	51.5	38.7	47.2	45.3	33.8	30.3
115	18.0	13.1	13.7	31.2	41.3	46.9	48.0	44.2	47.7	39.1	32.6	37.4
110	13.2	25.3	20.4	35.2	35.0	54.3	38.6	46.9	45.0	42.3	31.2	29.3
105	20.6	23.2	20.7	29.3	28.8	56.7	45.8	38.1	27.6	29.3	22.5	16.4
100	12.5	10.6	10.1	17.3	17.3	33.6	34.2	26.8	22.2	19.1	13.6	11.1
95	4.9	5.7	6.3	13.1	10.0	15.8	20.8	19.0	18.2	25.3	18.8	10.3
90	4.2	6.4	3.3	15.3	11.4	14.4	20.3	14.8	19.8	17.4	21.7	17.2
85	3.9	3.5	4.2	5.2	2.5	8.6	14.3	13.6	18.5	11.6	19.2	13.6
80	2.8	−3.2	4.3	−5.6	0.1	2.1	4.5	12.6	14.4	16.1	14.7	15.5
75	2.7	4.2	9.8	−4.6	0.1	5.7	9.6	7.5	12.4	14.9	18.1	15.6
70	5.3	6.9	1.2	−4.0	−2.1	10.4	8.7	10.1	9.5	12.8	12.5	7.1
65	3.4	8.2	5.3	6.2	1.1	5.9	0.1	0.1	2.7	11.3	9.5	10.3
60	8.0	7.8	11.5	−0.7	5.6	2.6	6.7	7.8	5.7	10.4	7.5	
55	12.0	9.8	14.2	7.6	0.1	6.0	3.6	8.9	4.7	0.0		
50	14.6	11.1	11.6	12.0	2.7	−1.8	7.8	3.9	3.7			
45	14.5	19.1	13.0	8.7	6.8	1.5	2.7	2.7				
40	14.9	17.1	14.0	9.2	3.4	2.3	−1.1					
35	16.3	18.3	13.0	7.0	5.5	1.1						
30	12.7	16.6	11.1	9.0	6.3							
25	8.4	14.7	12.2	8.2								
20	7.7	8.7	10.3									
15	4.2	1.1										
10	2.5											
n2/n1	5	10	15	20	25	30	35	40	45	50	55	60

Note: VMA (n1, n2) denotes a range in which n1 (SMA) ranges from 5 to 60 days and n2 (LMA) ranges from 10 to 180 days, with n2 being bigger than n1. Each cell represents the GAR from diverse VMA (n1, n2) trading rules. Notably, the cells highlighted in red have GARs that surpass the 40% threshold.

Moreover, we shed light on an interesting finding in Table 4 by providing a detailed presentation of aggregate GARs created by VMA trading rules. Notably, the GARs marked in red in this table constantly reach the 40% threshold, outperforming the conventional design's highest GAR of 37.5%. Essentially, our novel approach not only provides investors with a greater amount of information to help them be more profitable in ETH futures trading but also shows that the GARs within specific segments (indicated in red) consistently outperform the highest GAR yielded by the traditional design. As a result, we feel that our innovative approach is a valuable tool for investors trading ETH futures.

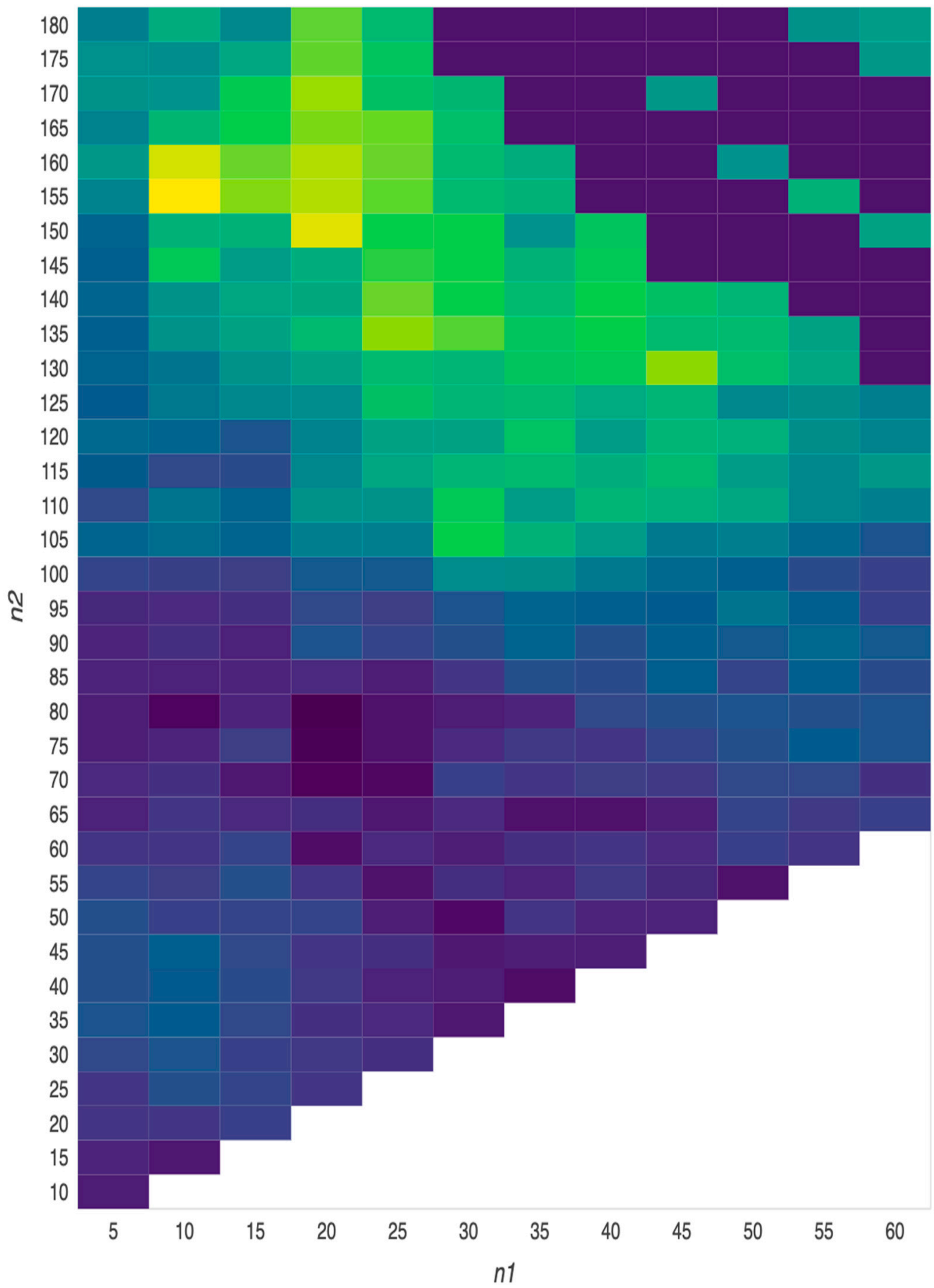

Figure 2. Heatmap visualization of trading ETH by using numerous VMA trading rules.

What is more, we argue that the following disparities should be illustrated more prominently in results tables. First, the study mentions presenting results in a "heatmap matrix" (Table 4) and a "heatmap diagram" (Figure 2), both of which use color gradients to illustrate performance differences. Clarifying the discrepancies between the data presented in these two formats could make our results more impressive to those who invest in ETH futures. Second, this study emphasizes the advantages of the novel approach over the conventional one by stating that the novel approach yields more outcomes based on varying n1 and n2 parameters. Third, this study initially specifies a 40% threshold for GARs but later highlights GARs exceeding this threshold in red. Consistently emphasizing these remarkable findings would impress ETH futures investors.

In addition to assessing geometric average returns (GARs) for ETH futures in Table 4, we also present Sharpe ratio findings for robustness in Table 5. We found that the results in Table 5 are substantially comparable to those in Table 4. In other words, our revealed results might be corroborated by utilizing risk-adjusted returns to measure performance.

Table 5. Heatmap matrix of Sharpe ratio results based on various VMA trading rules.

180	0.25	0.28	0.28	0.34	0.33	–	–	–	–	–	0.29	0.27
175	0.26	0.28	0.30	0.34	0.34	–	–	–	–	–	–	0.26
170	0.26	0.28	0.33	0.34	0.33	0.33	–	–	0.33	–	–	–
165	0.25	0.31	0.34	0.34	0.34	0.34	–	–	–	–	–	–
160	0.27	0.34	0.34	0.34	0.34	0.33	–	–	–	0.28	–	–
155	0.25	0.34	0.34	0.34	0.34	0.33	0.34	–	–	–	0.34	–
150	0.22	0.30	0.31	0.34	0.34	0.34	0.30	0.34	–	–	–	0.33
145	0.20	0.31	0.30	0.30	0.34	0.34	0.33	0.34	–	–	–	–
140	0.21	0.26	0.30	0.28	0.34	0.33	0.33	0.34	0.31	0.34	–	–
135	0.24	0.28	0.30	0.31	0.34	0.33	0.33	0.34	0.31	0.33	0.33	–
130	0.24	0.26	0.31	0.31	0.33	0.33	0.33	0.33	0.34	0.33	0.33	–
125	0.23	0.29	0.31	0.30	0.33	0.33	0.31	0.30	0.30	0.27	0.28	0.28
120	0.25	0.27	0.28	0.28	0.31	0.30	0.31	0.30	0.30	0.31	0.25	0.27
115	0.25	0.25	0.26	0.29	0.31	0.30	0.30	0.30	0.31	0.30	0.26	0.26
110	0.23	0.27	0.28	0.29	0.29	0.31	0.30	0.30	0.30	0.31	0.29	0.27
105	0.26	0.28	0.28	0.28	0.26	0.30	0.30	0.27	0.27	0.27	0.26	0.24
100	0.21	0.22	0.24	0.25	0.27	0.29	0.28	0.27	0.26	0.24	0.23	0.22
95	0.18	0.21	0.23	0.22	0.23	0.25	0.25	0.25	0.24	0.25	0.23	0.22
90	0.19	0.19	0.20	0.24	0.23	0.25	0.26	0.23	0.24	0.23	0.23	0.22
85	0.17	0.18	0.22	0.22	0.22	0.22	0.24	0.25	0.23	0.22	0.22	0.20
80	0.16	0.18	0.22	0.21	0.00	0.20	0.23	0.23	0.24	0.22	0.21	0.21
75	0.16	0.19	0.22	0.20	0.00	0.22	0.24	0.24	0.22	0.22	0.21	0.20
70	0.17	0.19	0.19	0.20	0.21	0.23	0.22	0.23	0.22	0.22	0.20	0.18
65	0.16	0.19	0.21	0.22	0.22	0.21	0.16	0.15	0.22	0.21	0.19	0.18
60	0.17	0.19	0.22	0.20	0.21	0.21	0.20	0.21	0.20	0.20	0.18	
55	0.18	0.20	0.22	0.20	0.18	0.19	0.19	0.19	0.18	0.00		
50	0.18	0.19	0.20	0.20	0.18	0.17	0.19	0.17	0.16			
45	0.18	0.21	0.20	0.19	0.18	0.17	0.16	0.14				
40	0.17	0.19	0.18	0.26	0.20	0.15	0.13					
35	0.17	0.18	0.31	0.24	0.22	0.16						
30	0.28	0.33	0.28	0.27	0.23							
25	0.24	0.31	0.30	0.24								
20	0.22	0.25	0.26									
15	0.21	0.13										
10	0.17											
n2/n1	5	10	15	20	25	30	35	40	45	50	55	60

Note: VMA (n1, n2) denotes a range in which n1 (SMA) ranges from 5 to 60 days and n2 (LMA) ranges from 10 to 180 days, with n2 being bigger than n1. The Sharpe ratio produced by utilizing different VMA (n1, n2) trading rules is represented by each cell in the heatmap matrix. Notably, the cells highlighted in red have Sharpe ratio that are above the 0.30 threshold.

5. Discussion

The present study has put forth hypotheses, which are presented in Sections 2 and 3. The subsequent stage is to ascertain the acceptance or rejection of these hypotheses. The evaluation is carried out through the analysis of the findings revealed in Section 4.

Regarding H1, this study has shown that investors using VMA regulations may earn from ETH futures trading, as shown by our results in Section 4, including the results shown in Tables 3 and 4. As a result, we can accept H1. Our findings suggest that implementing the VMA trading rules could lead to favorable outcomes in trading cryptocurrencies [31,50], implying that technical analysis could be useful in trading cryptocurrency in relevant studies [38,62]. However, such findings appear to contradict the market efficiency hypothesis [1–3] that financial prices (e.g., stock prices and future prices) may be difficult to predict because they already reflect all available information.

In terms of H2, this study proposes that investors may gain more profits and even satisfactory profits by trading ETH futures via the heatmap visualization approach [69,71] instead of the conventional approach. Table 3 shows that for investors who use VMA trading rules based on the conventional design, the highest GMA is around 37.5% using the VMA (5, 160) trading rule, which is much higher than the 10-year treasury bond rate employed as the proxy of risk-free return. However, while we use the heatmap visualization approach with the flexibility of VMA (n1, n2), where n1 (SMA) ranges from 5 to 60 days and n2 (LMA) ranges from 10 to 180 days, we also present the results in a heatmap matrix in Table 4. Among the variety of outcomes disclosed in Table 4, several outcomes exceed 40%, with two outcomes surpassing 70%, which is much higher than the highest outcome (i.e., 37.5%) using the conventional approach. As a result, H2 can be accepted. Our findings indicate that evaluating numerous outcomes using big data analytics would generate more opportunities as compared to conventional wisdom, which is consistent with the concerns of previous studies [64,72,73].

In essence, our innovative approach, which is a heatmap visualization approach, not only gives investors access to a greater quantity of information that can assist them in becoming more profitable in ETH futures trading but also demonstrates that the GARs within particular segments (which are indicated in red) consistently outperform the highest GAR that is produced by the conventional approach. In light of this, we believe that our forward-thinking strategy is an effective instrument for investors who are trading ETH futures products.

6. Concluding Remarks

6.1. Conclusions and Discussion

Given the widespread use of technical trading indicators in trading various financial instruments, such as stocks and bonds, as seen on prominent financial platforms such as Bloomberg, Market Watch, and Forbes, our research looks into the potential for investors to profit from the adoption of VMA (n1, n2) trading regulations since enabling adjustable n1 and n2 lengths makes this approach flexible, which has been understudied in previous research. Therefore, we contend that examining the effectiveness of the VMA trading rule is a worthwhile endeavor. Our inference suggests that, if historical trends can serve as a reliable guide, investors have the potential to not only generate profits but potentially gain substantial profits by analyzing historical data, particularly long-term big data analytics, to gain insights from a number of VMA trading rules.

Our research aims to obtain superior GARs from the extensive range of GARs shown in a heatmap diagram. This holistic perspective provides investors with a practical and advantageous method for determining the optimal VMA trading rules to capitalize on profit opportunities. We contend that our novel approach has an advantage over the conventional design because it consistently produces GARs in the red area of the heatmap matrix that exceed the highest GAR generated by conventional methods. The significance of this outcome for investors trading ETH futures is substantial.

This investigation makes several noteworthy contributions to the existing body of knowledge. First, our study fills a significant gap by investigating whether market participants can achieve elevated GARs through the adoption of diverse VMA trading rules, a topic that has received scant attention in prior research [76,77]. In contrast to previous research, which frequently yields limited outcomes, our method yields a vast array of results, showing the efficacy of using these VMA regulations. Moreover, our consideration of second returns following initial returns in the context of round-trip trading using VMA rules leads us to advocate for the use of the geometric mean as a more appropriate performance measure than conventional metrics, such as average holding period returns and average abnormal returns, which have been the focus of previous studies [78–80].

Second, this study distinguishes itself by not only embracing a variety of VMA trading rules and capitalizing on their flexibility but also producing a multitude of results, including improved performance within specific segments, through the application of big data analytics. These comprehensive approaches deviate from the typical conventions observed in the pertinent finance literature, which tend to provide limited findings rather than an abundance of results or particular areas demonstrating improved performance [50,74,81].

Third, our research provides investors engaged in ETH futures trading with valuable insights and a wealth of reference points via heatmap visualization. This resource aids investors in choosing suitable VMA trading rules, enabling the customization of variable SMA and LMA lengths. Consequently, we hypothesize that our novel approach will likely find favor with a diverse range of ETH market participants. By displaying a multitude of outcomes in a heatmap, market participants could instantly uncover GARs that frequently exceed those derived from conventional methods.

Although heatmap visualization techniques for comparing two-dimensional results in computer science are well established [69,82–84], their application for presenting numerous financial results is a relatively new frontier. We contend that this technique enables investors to make more informed judgments by providing them with a bird's-eye view of potential outcomes.

Fourth, this research integrates several innovations in cryptocurrency trading. Initially, this research introduces VMA (n1, n2), which enables flexible trading strategies by customizing the SMA and LMA. Following that, the study utilizes heatmaps to visualize various GARs based on the SMA and LMA parameters, making complex data accessible. Furthermore, this study emphasizes the role of big data analytics in cryptocurrency trading, demonstrating the flexibility of VMA regulations. In addition, this study provides a comprehensive range of results from diverse VMA trading rules, thereby assisting investors in making informed decisions.

Overall, this study highlights the significance of big data analysis and modeling in evaluating the profitability of VMA trading regulations for market participants. The research framework introduces a broad spectrum of combinations involving the SMA and LMA in VMA trading, a rarely investigated dimension in the existing literature. Utilizing heatmap visualization, the study provides a vast multitude of results, allowing investors to quickly identify the most profitable trading strategies. Using big data analytics techniques, this study provides investors trading ETH futures with invaluable insights, enabling more informed decision making and the potential for superior returns. The adoption of the geometric mean as a performance metric and the visualization of results via heatmap data are innovative contributions that highlight the growing significance of big data analytics in investment practices.

6.2. Research Implications

In addition, this study has several important practical implications. To begin with, investors may be able to increase their returns by thoroughly evaluating a multitude of outcomes derived from a diverse set of VMA trading rules. Investors can customize their adoption of VMA trading rules for ETH futures and other financial instruments by presenting these results in an easily consumed heatmap format and categorizing them using big data analytics. Additionally, the study provides investors with valuable information to increase profitability in ETH futures trading, emphasizing the importance of thorough preparation as a prerequisite for enhancing returns and mitigating risks, especially in the context of cryptocurrency futures with elevated leverage risks.

In addition, this research suggests that the historical performance presented here may entice some investors to engage in ETH futures trading, which offers the possibility of satisfactory profits. Given that the capital gain in ETH futures is determined by the difference between the selling and buying contract values, and returns are calculated as the capital gain (or loss) divided by the margin, trading ETH futures may result in significantly higher (or lower) returns than trading fully funded stocks.

Moreover, investors employing the strategy proposed in this study could generate greater profits during periods of rising or sharply rising trends as opposed to declining trends. Therefore, investors may be advised to use VMA trading if they can accurately predict that ETH futures or other financial instruments will experience an upward trend. In addition to GARs, the authors of this study may investigate and include the results of PnL in future research, as PnL captures the price difference and cumulative profit. PnL is regarded as one of the most important metrics. Lastly, investors can profit from a comprehensive overview of information through the adoption of a heatmap data matrix, a technique rarely utilized in the financial literature. Thus, it is suggested that investors consider incorporating beneficial tools from other fields, such as computer science, into the realm of financial investment, thereby broadening the scope of financial research and practice.

What is more, from the perspective of society, the study of variable moving-average (VMA) trading principles not only assists individual investors but also contributes to society's wealth. By integrating information from various VMA rules and employing big data analytics, investors and society gain an important channel for improving overall financial market profitability. This is consistent with a broader social purpose of supporting economic growth through educated investment decisions. This study's creative use of the geometric mean challenges standard measurements, providing a social viewpoint that improves the comprehension of market dynamics, helping investors and economic stability. The merging of heatmap visualization with big data analytics empowers investors while also serving society's goal of developing a more educated financial landscape. The proposed approach enables well-informed decision making by offering diverse findings, contributing to the societal objective of financial wellness and enabling more successful investment decisions in ETH futures trading.

6.3. Limitations and Further Research

While the strengths of this study pertain to cryptocurrency markets (specifically ETH markets), investment strategies (utilizing momentum strategies through VMA trading regulations), and the efficacy of screening trading regulations (via heatmap visualization), it is not without limitations. For example, while Ethereum is one of the cryptocurrencies, our findings may not be generalizable to other cryptocurrencies with different market dynamics. In addition, displaying numerous results in a heatmap matrix or viewing different colors in cells via heatmap visualization, simplification or oversimplification may not be avoidable. Thus, the foregoing issue is also a limitation of this study. Furthermore, another limitation is that the rapid evolution of technology and market dynamics in the cryptocurrency sector might outpace the relevance of the study's findings. Moreover, given the complexity of financial markets, it would be very challenging to obtain relevant and usable information immediately, correctly, and effectively, which is a limitation of this study as well. What is more, another limitation of this study lies in the vast number of potential VMA trading rules that could be investigated, particularly if we extend variable lag lengths or reduce intervals, such as using a 2.5-day interval as opposed to the 5-day interval used in this study.

To address these limitations, we provide several avenues for future research. First, by leveraging big data analytics, future research could broaden the scope by extending variable latency lengths and modifying intervals, thereby mitigating the issue of numerous trading rules; additionally, it would be intriguing to compare the results obtained for other cryptocurrencies, such as Ethereum, with those of Bitcoin, which has been extensively researched. Such a comparative examination could reveal both similarities and differences between the two entity types. Second, the proposed approach could be expanded to a wider range of financial instruments (e.g., stocks and currencies). This expansion may uncover additional profitable opportunities compared to conventional or alternative research designs; additionally, in contrast to previous research, such a study would not only use maximum drawdown to increase credibility but also investigate the applicability of shorter SMA intervals, including 1-, 2-, 3-, and 4-day intervals, within VMA trading rules, providing a wider array of options for investors. Third, we state that if we combine VMA strategies and other technical trading strategies, we may derive more valuable and useful information. However, due to the concern of limited samples and the objectivity of our revealed results, the preceding issue would only be considered for future research after collecting enough samples. Fourth, how different market conditions, like bear or bull markets, affect the applicability of the findings would be worthwhile for future research; moreover, factors such as regulatory changes, technological advancements, or macroeconomic variables that can significantly impact cryptocurrency markets should be considered in future studies. Last but not least, we acknowledge the need for a more thorough discussion on strategy suitability across investor types and risk profiles, thereby providing valuable avenues for future research.

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Conflicts of Interest: The authors declare that they have no competing interests.

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