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Analytical Modeling and Empirical Analysis of Binary Options Strategies

Gurdal Ertek *, Aysha Al-Kaabi and Aktham Issa Maghyereh

College of Business and Economics, United Arab Emirates University,
Al Ain P.O. Box 15551, United Arab Emirates; aysha-k-alkaabi@hotmail.com (A.A.-K.);
a.almaghaireh@uaeu.ac.ae (A.I.M.)
* Correspondence: gurdal@uaeu.ac.ae; Tel.: +971-37135277

Abstract: This study analyzes binary option investment strategies by developing mathematical formalism and formulating analytical models. The binary outcome of binary options represents either an increase or a decrease in a parameter, typically an asset or derivative. The investor receives only partial returns if the prediction is correct but loses all the investment otherwise. Mainstream research on binary options aims to develop the best dynamic trading strategies. This study focuses on static tactical easy-to-implement strategies and investigates the performance of such strategies in relation to prediction accuracy, payout percentage, and investment strategy decisions.

Keywords: binary options; Monte Carlo simulation; knowledge discovery; visual analytics; big data

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1. Introduction

1.1. Binary Options

Binary options, also referred to as Arrow-Debreu state-contingent securities [1], are a class of financial investment instruments, specifically, a special type of exotic options within financial derivatives.

Binary options, due to their simplicity, are popular among investors. In Japan alone, the trading volume for binary options was above 23 billion yen in 2015 (https://www.financemagnates.com/forex/brokers/binary-options-trading-volume-in-japan-jumps-42-77-yoy/ accessed on 22 May 2022). The number of registered users in the binary options trading platform IQ Option increased nearly 50-fold, to more than 48 million users, from 2014 to 2020 (https://iqoption.com/en/numbers accessed on 22 May 2022). Binary options are also gaining increasing attention in the academic literature: a literature search on Google Scholar with the Publish or Perish software yielded approximately 100 finance-related research studies from 2010 onwards that had "binary options" in their title. Thus, binary options is a topic within finance that deserves further attention and objective research. Further discussions on the research motivation are described in Supplementary File S1.

During each period wherein an investment in binary options can be made, the investor predicts and bets on whether the value of the predicted parameter—typically the price of an underlying instrument—will be higher or lower than a defined target value (price) by a certain specified *expiry time* [2]. Without loss of generality, the predicted parameter in this study is referred to as *price*.

For binary options, the investor selects one of two—call (long) or put (short)—based on their prediction of whether the price will be higher or lower than the target *strike price*. If the prediction is correct, the investor receives a positive *payout percentage* on the investment; otherwise, they receive zero payout. If the option expires in the money, the payout is a fixed amount, calculated as a certain payout percentage of the investment. If the option expires out of the money, the payout is zero, and the initial investment is lost, hence the term *binary option*—there is either payout or no payout [3]. In summary, the investor is rewarded with a payout percentage of the investment if the prediction is correct, and the entire investment is forfeited if the prediction is incorrect.

As an illustration of binary options, Figure 1 displays a typical trading user interface for the following binary option: "The EUR/USD exchange rate will be higher than 1.083260 at 18:05 today". In Figure 2, the elements of the user interface are highlighted and mapped to the corresponding finance terms, namely Asset, Option, Investment Amount, and Payout Percentage.

Figure 1. Typical user interface for binary options trading.

Figure 2. Components of typical user interface for binary options trading.

1.2. Literature Review Methodology

The literature on binary options is growing. To identify the research in the field and identify the most significant studies, a systematic approach was followed. Publish or Perish software was used to search all results in Google Scholar that have the term "binary options" within the paper title. Then, the results of this search, which generated approximately 100 results, were exported to a spreadsheet database, labeled consecutively as S001, S002, and so on, and investigated one by one. For each paper in the search results, four new data columns were added. The Rating column assigned, for each paper, a relevance score, between 0 and 10, that summarized how relevant the paper is to our research. The Research Topic column described the research topic of the paper. The Contribution column described the main contribution of the paper to the literature. The Comparison column compared the paper to our research in terms of topic, results, and contributions. Then, only papers with a Rating greater than or equal to 6 were filtered and chosen to be included in the literature review. In addition to the results obtained from Publish or Perish, additional papers found throughout the research were also evaluated and labeled as R001, R002, and so on. The most relevant papers among these were also included in the literature review.

1.3. Literature Review

This paper builds on prior studies that describe and analyze various aspects of binary options. This section begins with a review of the research papers that introduce binary options. Then, studies that focus on the working principles of binary options systems, particularly in the context of exchanges, are described. Much of the research on binary options is focused on trading algorithms, options pricing, and portfolio analysis. These categories of research on binary options are in line with the research categories of other types of investment instruments.

1.3.1. Exotic and Binary Options

In [4], binary options are defined as fixed-odds financial bets. Furthermore, the book describes the applications of binary options and studies the value of binary options decisions on the basis of volatility, the passing of time, and the price of the instrument. Ref. [5] presents recommendations for exotic options investments and suggests that binary options are more suitable for speculation than they are for hedging because the fixed payment compensates for the hedging. Ref. [6] presents binary options' characteristics and payoffs and certain trading strategies for these options. The analysis in the paper was performed after the Chicago Board Options Exchange's (CBOE) announcement to list binary option contracts on the SPX and the VIX. Other relevant research includes [7,8].

1.3.2. Operational Mechanisms

Binary options' operational mechanisms and inventions for novel mechanisms can be found in a multitude of patents [9–12], which are detailed in Supplementary File S2.

Regarding academic research on binary options' operational mechanisms, ref. [2] discusses methods for traders who aim to create a binary options trading system using algorithmic trading. An extension of the Black–Scholes model is provided in [13] that recaptures, from market prices, the real drift of binary call options. The results show that the proposed approach can verify the presence of arbitrage opportunities in a binary options transaction.

1.3.3. Trading Algorithms

A considerable bulk of research on binary options focuses on trading algorithms, which are discussed in this section. All the research works cited require the application of algorithmic computations, thus making them inappropriate for the average retail investor seeking intuitive, easy-to-implement investment strategies. Earlier research on trading algorithms for binary options is detailed in Supplementary File S3. Ref. [14] presents a trading system developed for binary options that can configure several indices and then compare their relative rates of return. Ref. [15] illustrates how algorithmic optimization can improve the performance of binary options trading systems using the BB-RSI (Bollinger bands-Relative strength index) strategy. Ref. [16] presents a candlestick prediction methodology for binary options traders by using a support vector machine (SVM) classifier. Ref. [17] combines the news and social sensing with historical stock price to enhance the trading forecast.

1.3.4. Options Pricing

Earlier research in pricing exotic options includes [18–23], which is detailed in Supplementary File S4. Ref. [24] uses fuzzy set theory to price binary options, and the proposed model is reportedly feasible. Ref. [25] considers the pricing of binary options using stochastic analysis by assuming a Markov-modulated geometric Brownian motion of the basic price dynamics. The study uses the "Black–Scholes–Merton" formula. Ref. [26] discusses binary options in detail, particularly "British binary options", including their option pricing mechanics. A protective feature that enables investors to protect themselves against adverse stock price shifts characterizes these options. While applying a quantum mechanics formalism in the pricing of binary options and thus addressing the challenges in using the Black–Scholes model and Monte Carlo simulations, ref. [27] also builds a portfolio of binary options based on S&P 500 stocks.

Ref. [1] develops a new method to estimate how much public and private information is reflected in prices in assets in binary options markets. The authors estimate that 90% to 100% of public information, versus only 0% to 30% of private information, is reflected in prices, suggesting that prices may be very far from strong-form efficiency.

1.3.5. Portfolio Management

Another stream of research studies the management of a portfolio of binary options. Ref. [28] suggests the Haar hedging strategy for a portfolio of binary options, which is more advantageous than the benchmark delta hedging approach. Ref. [29] presents the study and improvement of hedging performance of the DEK static replication approach by developing a portfolio of European and binary options with convergence. Ref. [30] proposes a static hedging method for European, Barrier, and Geometric Asian options by using binary options based on a vector lattice approach. Ref. [31] presents the application of "discrete entropic portfolio optimization" on the basis of the expected growth rate and relative entropy of a portfolio of binary options. The method developed is compared with strategies that are based on the Kelly criterion. Ref. [32] uses the deep learning features to create candlestick-based portfolio. Under various parameter settings, the proposed portfolio outperformed top funds in China. Research on the variations of binary options is provided in Supplementary File S5.

1.3.6. Risks and Mitigation

The risks and mitigation methods of binary options are researched in the following stream of studies. Ref. [33] discusses the provisions in EU law on binary options and suggest improvements, particularly concerning capital requirement estimations. Ref. [34] presents a methodology to reduce risks in trading with binary options, potentially reducing losses for investors. Ref. [35] presents systems to detect the manipulation of binary options, particularly for mobile device trading platforms. Ref. [36] examines the risks associated with CFD spread bets and binary options. Ref. [37], while conducting an extensive joint estimation analysis of option-pricing models, extracts the expected risk premium associated with each risk factor and reveals the significance of idiosyncratic risk. Ref. [38] investigates how various financial derivatives, such as binary options, can be used to transfer information security risk.

Regarding the perception of binary options and their risks, ref. [39] studies the binary options market, particularly that in Russia. The possibilities of financial frauds and the difficulties in exercising legal options in the case of Internet-based brokers are discussed, thus presenting the need for strong regulations. Further discussions on the risks relevant to binary options can be found in Supplementary File S6.

1.4. Research Motivation, Design, and Contribution

1.4.1. Motivation

Despite the numerous existing research studies in the literature, this study's review of binary options literature revealed the following three notable research gaps, which motivated the research presented in this paper. First, no prior research work was found that formally and mathematically represents binary options and their payouts as functions of the parameters of the option and decision variables of intuitive investment strategies. Second, no prior work was found that provided an extensive empirical analysis of binary options payouts with respect to prediction accuracy, payout percentage, and decision variables. Finally, a gap (and opportunity as well) was identified regarding the demonstration of how visual and other data analytics techniques that are applied increasingly in finance and other fields can be applied to the analysis of binary options and proposed investment strategies. Further discussions on the research motivation are described in Supplementary File S1.

1.4.2. Design

To fill the gap in the existing literature, the presented paper develops a mathematical model that enables the performance evaluation of binary options investment strategies. The research literature focuses mostly on trading strategies for binary options, with a specific focus on the varying actions to take in each trade, with varying values for decision parameters. In other words, the bulk of the research on binary options is focused on trading and pricing; for each trade decision, extensive computations are required. Such trading and pricing strategies are not easy to implement and update for the average investor. In contrast, what is more applicable in practice would be trading and investment strategies that are (1) easy to express, (2) easy to understand, (3) simple, involving few parameters with static/fixed values over time, (4) easy to compute, and (5) easy to implement at a tactical level rather than having to continuously update them at an operational level. We can and will refer to strategies with these five characteristics as *easy to implement* in the remainder of the paper. This paper is the first of its kind and researches such easy-to-implement investment strategies. The strategies introduced and analyzed in this paper can be expressed through simple decision rules on how to invest in and out of a series of trades over a period. Order of events in each period assumed in the research study are displayed in Figure 3. The results, insights, and conclusions obtained in this paper serve as guidance for stakeholders in the finance sector, including investors, exchanges, trading software, expert advisor developers, and policymakers of regulatory bodies.

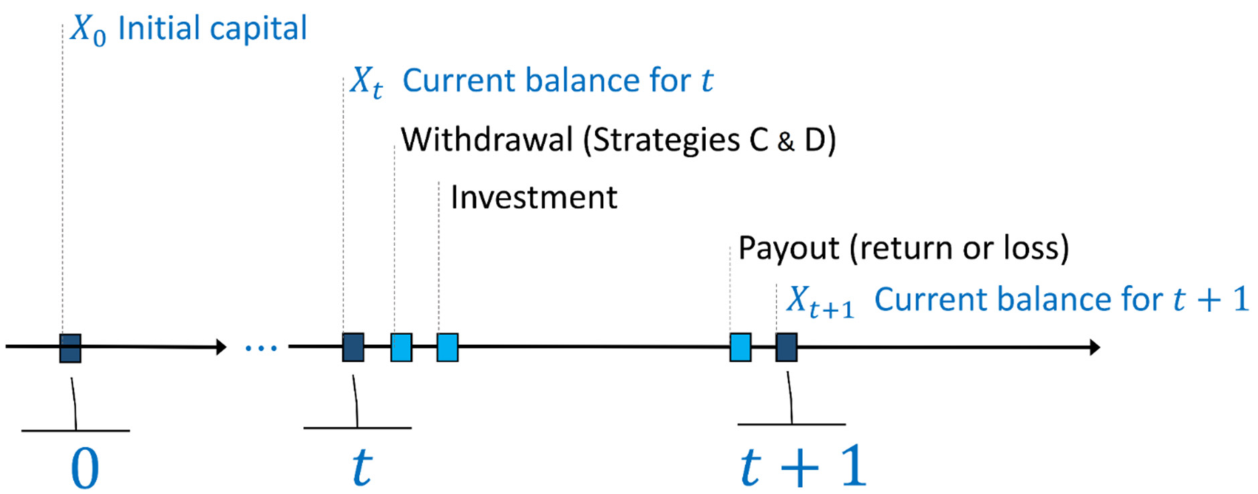

Figure 3. Order of events in each period assumed in the research study.

1.4.3. Contributions

Our study makes the following contributions to the literature. First, the binary options and various intuitive investment strategies are formulated as mathematical functions of the option parameters and decision variables. Second, extensive (more than 120,000) Monte Carlo simulation experiments are conducted, resulting in the creation of a reference database for the performance of binary options under various parameter settings. The presented work includes the most extensive empirical analysis on binary options strategies in the literature to date. Finally, visual analytics and regression are applied to analyze the results of simulation experiments for knowledge discovery. To the best of our knowledge, the analyzed data in this paper is the largest ever data analyzed in binary options research and can be considered as *big data* in this field. The objective is to gain insights into how option parameters and decision variables affect performance and how the introduced investment strategies compare.

The remainder of this paper is organized as follows: Section 2 introduces the methodologies used in this study, illustrates the mathematical model, and defines and explains the four proposed investment strategies. The section also describes the details of applying the computational modeling through Monte Carlo simulation and experiments. Section 3 presents an analysis of the experimental results through visual analytics. Finally, Section 4 concludes with a summary of the presented work and an outline of possible future research.

2. Materials and Methods

This section introduces the methods employed in the study, namely, the Monte Carlo simulation methods and measures, statistical measures, visual analytics, and regression.

2.1. Monte Carlo Simulation

The Monte Carlo simulation is an empirical computational method used to generate approximations for measures/metrics of interest. In a Monte Carlo simulation, multiple simulations are carried out, and statistics are computed for the measures of interest. This method is particularly applicable when the calculations involve inherent randomness or computational complexity that make exact calculations impossible or impractical [40]. In our research work, the Monte Carlo simulation is needed because binary options have probabilistic outcomes in each trading period.

Ref. [40] describes in detail the theoretical aspects and practical applications of Monte Carlo simulation in financial engineering. Refs. [41–44] employ the Monte Carlo simulation when evaluating various trading, portfolio, and risk management strategies. Ref. [41] employs the Monte Carlo simulation to substantiate a new profitable trading and risk management strategy, and it is used by [42] to confirm that a novel, agent-based model replicates the essential aspects of financial markets. Ref. [43] presents a Monte Carlo simulation-based mechanism to solve the constrained dynamic mean-variance portfolio management problem. In [44], Monte Carlo simulations of a rigorous optimal pair-trading strategy model are performed to test its applicability in the real world. Monte Carlo simulation is also utilized in pricing mechanisms [45].

2.2. Statistical Measures

In this paper, multiple statistical measures (metrics) are calculated to summarize the experimental results. Such statistical measures summarize the vast amount of data succinctly and enable easier interpretation, comparisons and discussions. The measures computed in the computational experiments include mean, median, standard deviation, interquartile range (IQR) [46], skewness [47], and kurtosis [48]. These are some of the most basic and widely used measures in descriptive statistics, as recommended in the literature [46] and found in the summary statistics analysis of popular statistical software, such as SPSS (https://www.ibm.com/docs/en/spss-statistics/26.0.0?topic=statistics-summary-scale-variables-categorical-custom-totals#table_builder_scale_sumstats accessed on 22 May 2022).

Although the values of these statistical measures have been computed in an experimental analysis, only a subset of the statistical measures are reported in this section, given the limitations on paper length. These selected measures are (average of) median (for example, as in Figure 4) and (median of) standard deviation. Each measure includes a "median" component to eliminate the disrupting effects of outliers because the median is insensitive to extreme values in a dataset and thus is robust.

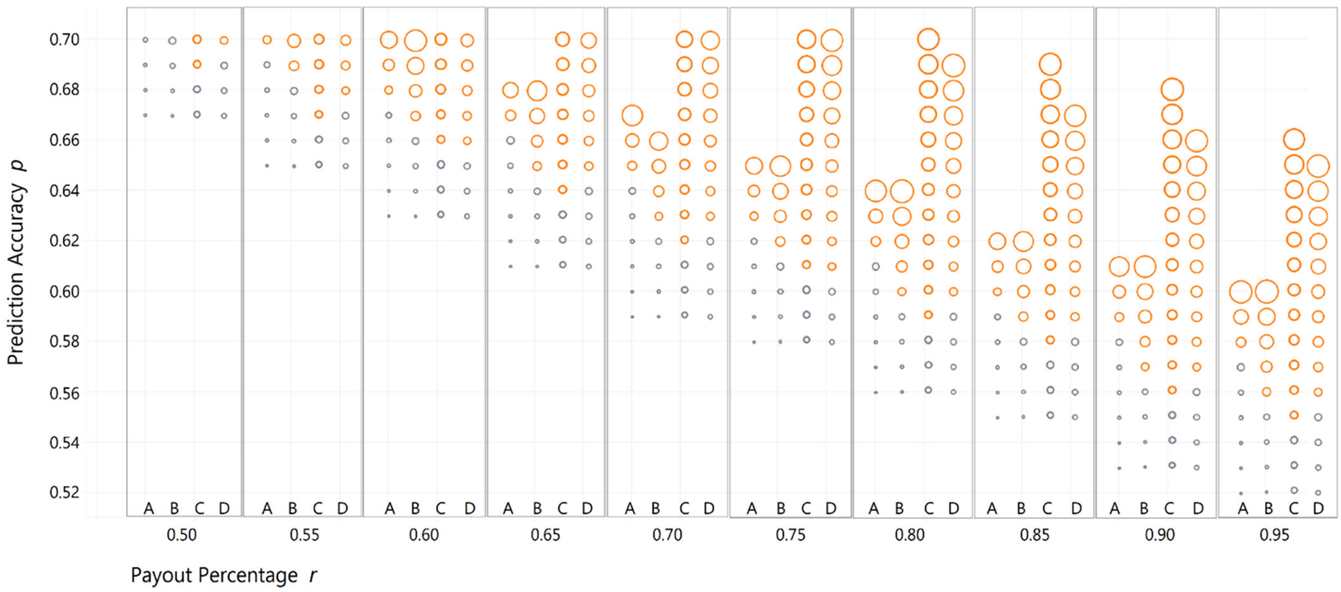

Figure 4. Relation between binary option parameters and return on investment (*roi*) across all four strategies.

2.3. Visual Analytics

(Data) analytics refers to the mathematical and computational analysis and modeling of data. In this paper, the primary analytics method used to analyze the experimental results for knowledge discovery is visual analytics, that is, data analysis through graphical visualizations. Visual analytics was chosen in this research (Figures 4–11) as the primary analytics method due to its many advantages and benefits [49]. Visual analytics (a) is based on human intuition and creativity and is easy to use; (b) does not require the user to develop or understand any computational algorithm; (c) has a relatively flat learning curve; (d) is ideal for purposes of generating and visually testing hypotheses and detecting any errors in the data; (e) allows different visual patterns to be directly observed on the screen, and the perception can be enhanced through color, size, and other visual clues [50].

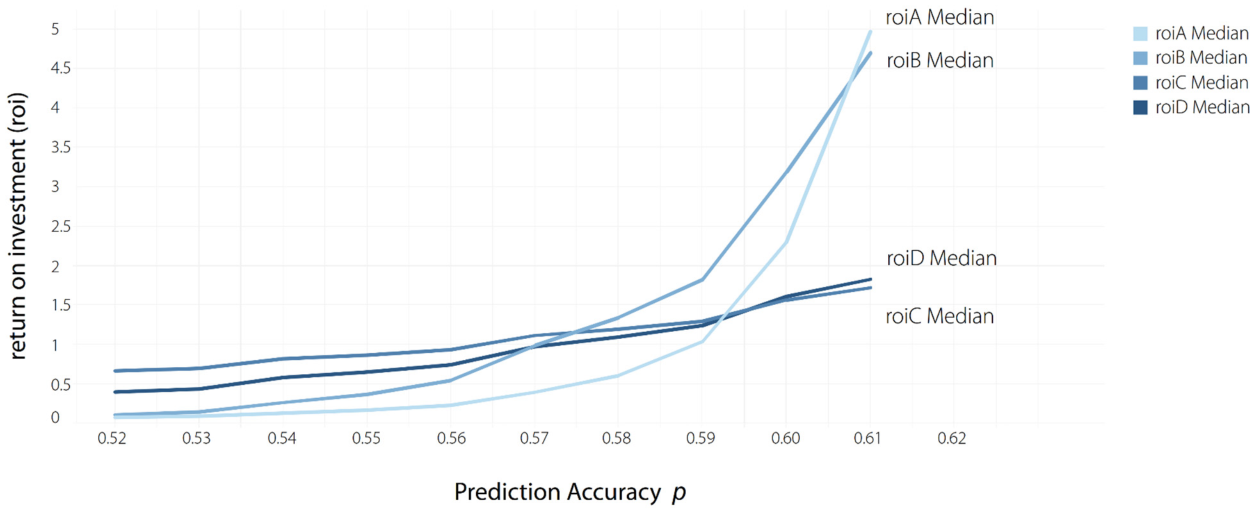

Figure 5. Change in (average of median) *roi* of the strategies in relation to prediction accuracy *p* on the *x*-axis.

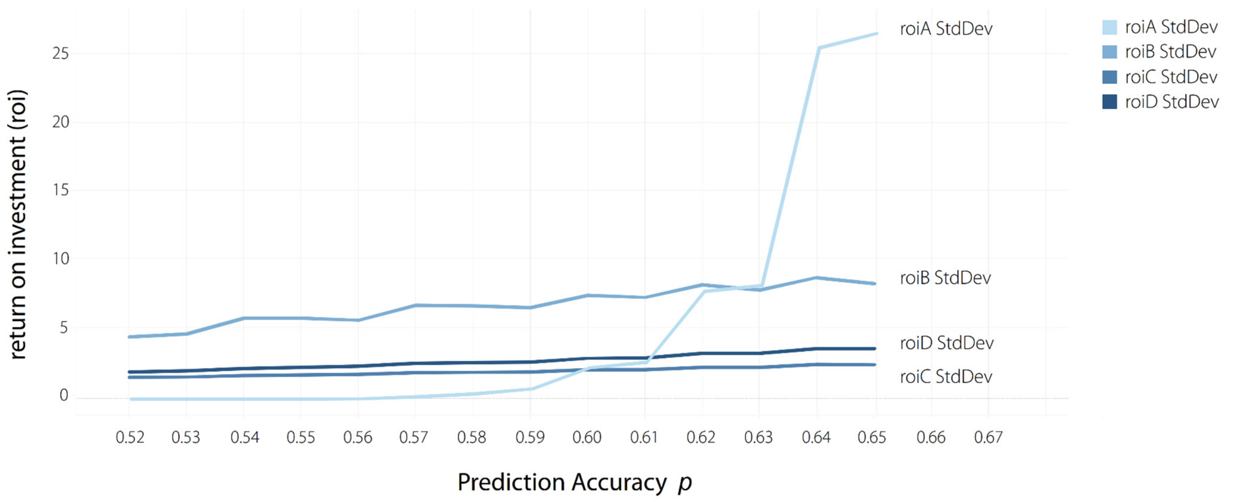

Figure 6. Change in (median) *roi StdDev* of the strategies in relation to prediction accuracy p on the x-axis.

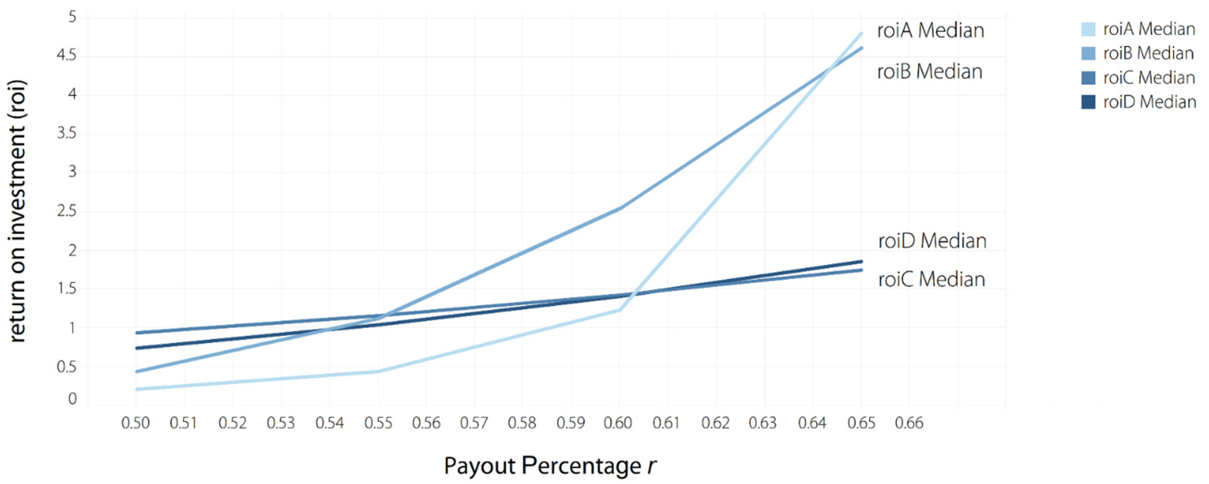

Figure 7. Change in (average of median) *roi* of the strategies in relation to payout percentage r on the x-axis.

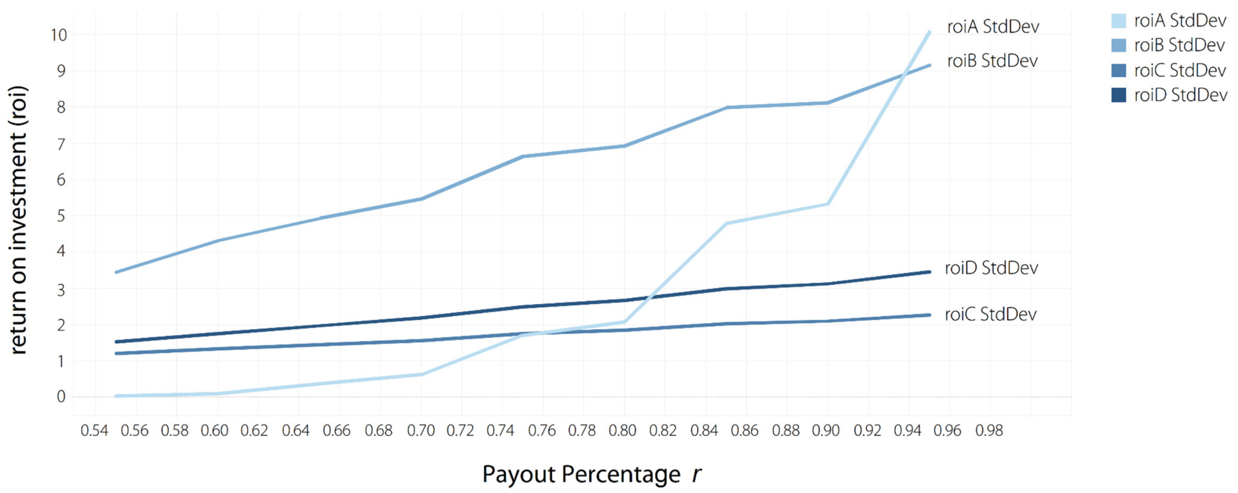

Figure 8. Change in (median) *roi StdDev* of the strategies in relation to payout percentage r on the x-axis.

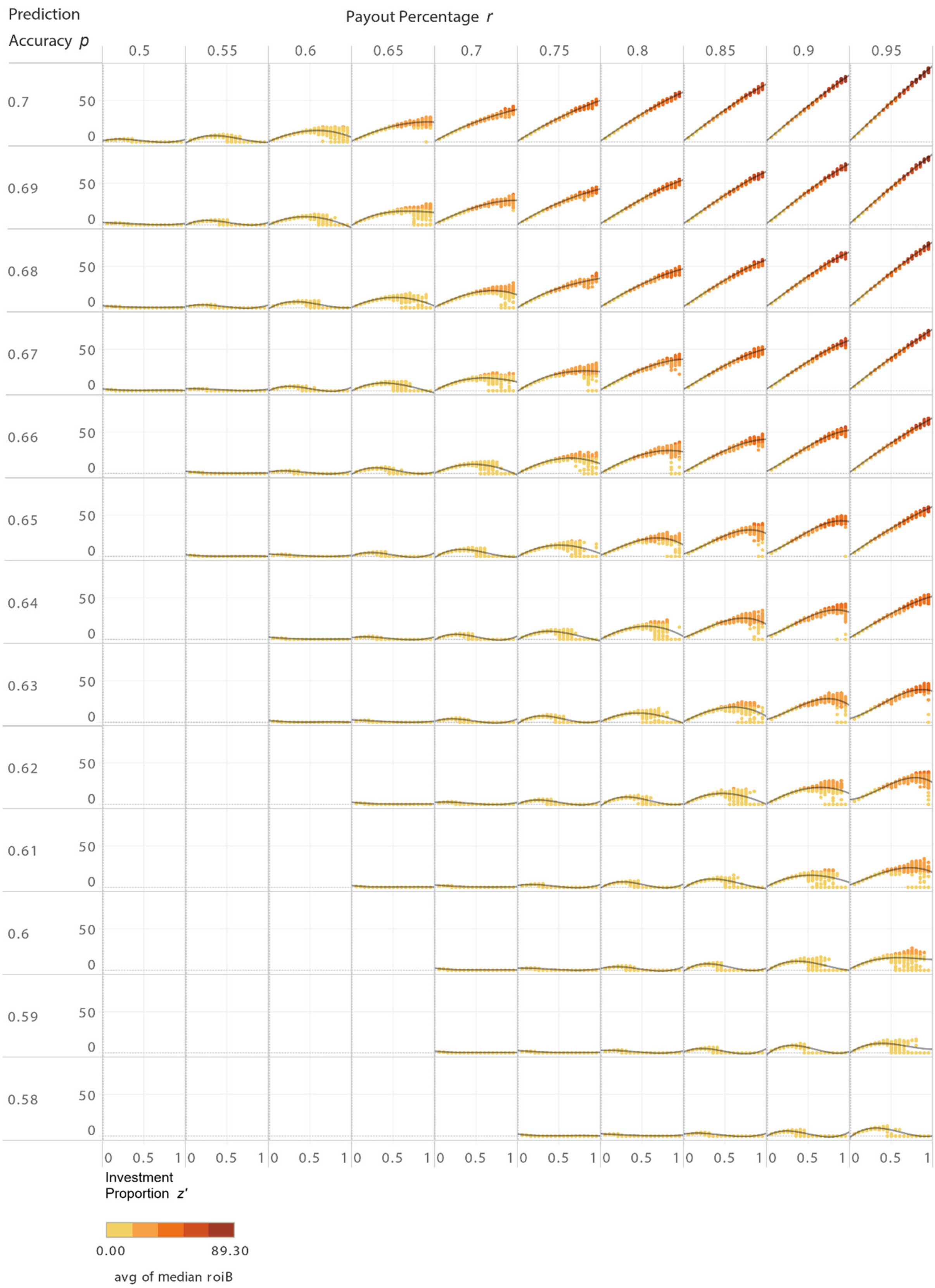

Figure 9. Impact of prediction accuracy p, payout percentage r, and investment proportion z' on (average of median) *roiB* for Strategy B.

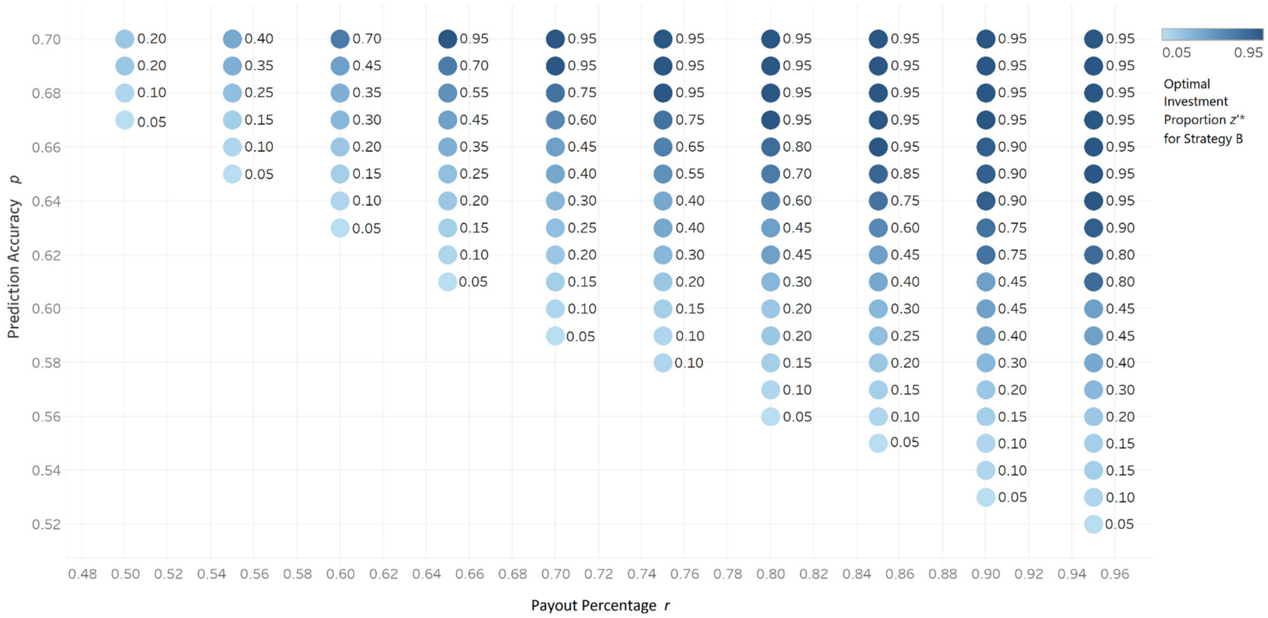

Figure 10. Relation between binary options parameters (p, r) and near-optimal investment proportion z'^* values of strategy B.

The first type of visualization used in the analysis is the simple line chart, which displays and compares changes in the values of a metric against changes in a parameter's values for the different strategies. For example, Figure 5 shows the change in (average of) median roi (y-axis) for each strategy (denoted by each line) for different values of prediction accuracy (x-axis).

The second type of visualization employed is the scatter plot matrix, which allows the effects of two or more factors on a response measure of interest to be observed.

- In Figure 4, the scatter plot matrix shows the effects of prediction accuracy p (y-axis) and payout percentage r (x-axis) on (average of median) roi for each of the four strategies (columns in each box). Each circle's (bubble's) size linearly represents roi, and the color denotes whether the strategy results in $roi \geq 1$ (orange) or $roi < 1$ (gray);
- Similarly, the scatter plot matrix in Figure 9 analyzes the impact of prediction accuracy, payout percentage, and investment proportion on (average of median) $roiB$ for strategy B. As a further visual clue, $roiB$ for strategy B is also mapped to color, and darker colors denote higher returns. To strengthen the results and insights, Figure 9 also displays best-fitted nonlinear regression curves for each plot in the matrix, where a mathematical equation is established between the factor on the x-axis and the response on the y-axis. For each (p, r) pair, the equations for the curves in Figure 9 are provided in full in Supplementary File S7.
- For more than two factors, the scatter plot matrix can still be constructed by setting constant values for the additional factors. The scatter plot matrix in Figure 11 sets fixed values for prediction accuracy and payout percentage ($p = 0.65$, $r = 0.65$). It also analyzes the impact of other factors—investment proportion ($z = 0.05, \ldots, 0.95$), on the y-axis of the matrix, the withdrawal multiplier ($w = 1, \ldots, 2$) on the x-axis of the matrix, and the proportion withdrawn ($v = 0.1, \ldots, 0.9$) on the x-axis of each plot—on (average of median) $roiC$ for strategy C. This impact is displayed on the y-axis of each plot and is denoted by color.

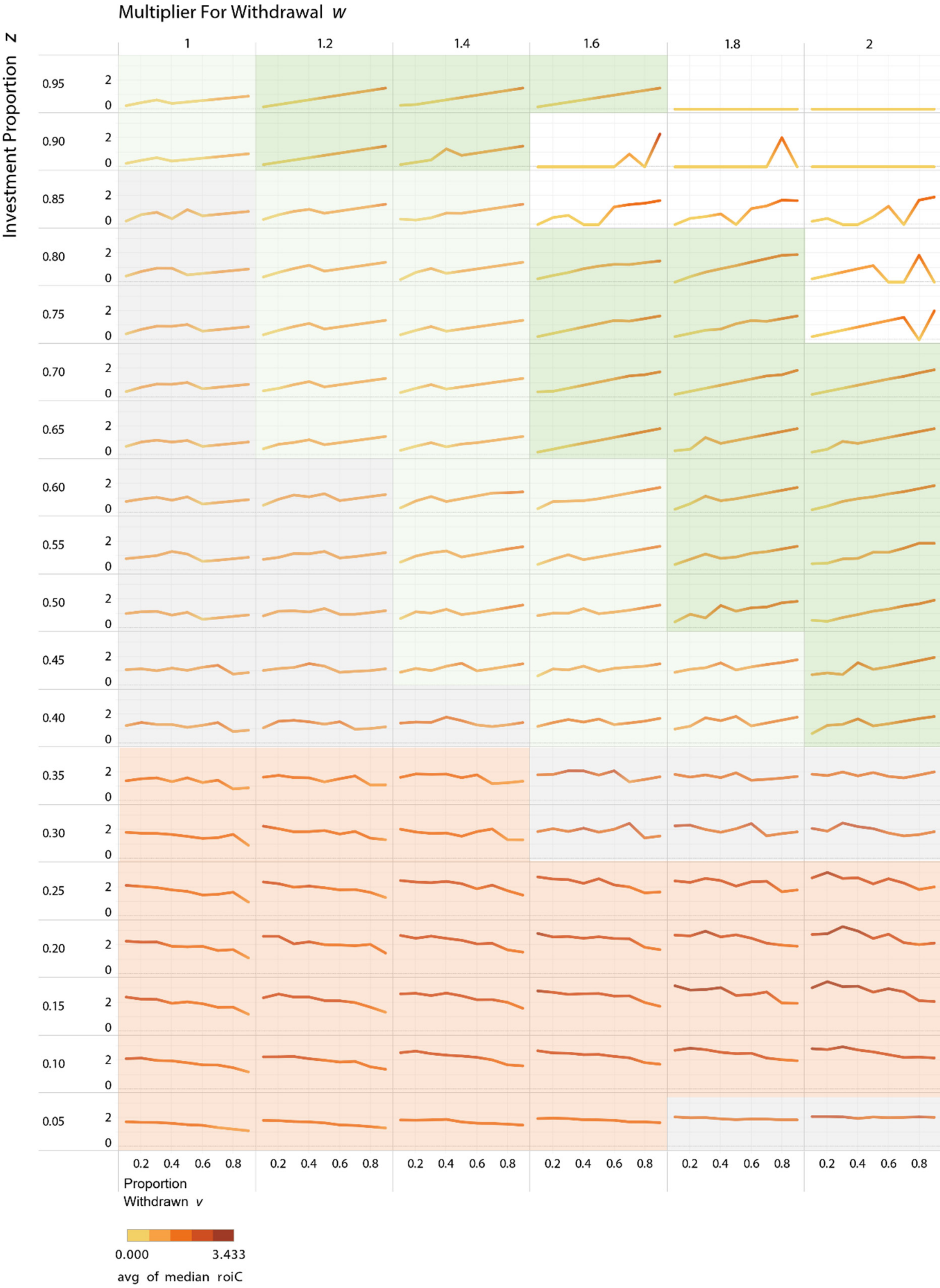

Figure 11. Relation between decision variables (z, w, v) of Strategy C and return on investment ($roiC$) under constant ($p = 0.65,\ r = 0.65$).

2.4. Regression Modeling

Regression is also used to predict the values of the response variable, given the values of the factors. In a nonlinear regression, the response variable is modeled as a nonlinear function of the factors [51]. A multitude of different nonlinear functions can be fitted in a nonlinear regression, including polynomial functions, exponential functions, logarithmic functions, and trigonometric functions.

According to the "State of Machine Learning and Data Science 2021" report by Kaggle [52], regression modeling is the most widely used data analytics method, hence justifying its application in this research.

In the regression analysis in this study for strategy B, polynomial (nonlinear) functions were found to be most robust across different (p, r) value pairs. The results of the regression model are presented visually in Figure 9 and as regression equations in Supplementary File S7.

2.5. Modeling Binary Options

In this section, mathematical formalism is presented for modeling binary options and various proposed investment strategies for binary options. Then, the introduced formalism is put to work, where a series of trades over multiple periods is assumed, and mathematical equations for computing the values of performance metrics in each period are presented for the strategies.

2.5.1. Metrics, Parameters, and Decision Variables

The primary metric of *return on investment (roi)* is expressed as a multiple of the initial investment. For example, $roi = 4$ means that the ending balance (at the end of the trading horizon T) is four times that of the initial balance (before the series of trades).

The binary option parameters are *prediction accuracy* p and *payout percentage* r.

The decision variables for the investment strategies include *investment proportion*, *withdrawal proportion*, and *withdrawal multiplier*.

2.5.2. Assumptions

Before the development of mathematical equations that model each strategy, the assumptions of the order of events in each period, as illustrated in Figure 3, should be clarified. The assumption that the order of events is the same for each investment strategy is necessary when comparing the performance of the different strategies. In Figure 3:

- dark blue boxes indicate the beginning of each period;
- light blue boxes indicate events during a period;
- X denotes the *balance* at the beginning of each period: X_0 is the *initial investment* ($X_0 = X_1$), X_t is the balance at the beginning of period t, X_{t+1} is the balance at the beginning of period $t + 1$, and so on;
- *withdrawals* (for investment strategies C and D) occur right when period t begins and before any other event;
- *investments* for trade in each period t can occur in the beginning or after any withdrawals;
- *payout* for each period t occurs right before the end of that period and before the next period $t + 1$ begins; and
- balance after the period t payout results in the beginning balance X_{t+1} for period $t + 1$.

2.5.3. Mathematical Notation

The mathematical notation for formally modeling binary options and the introduced investment strategies is as follows:

Sets

- $\mathcal{T}$: set of periods, $t \in \mathcal{T} = \{1, \ldots, T\}$, where T is the *trading horizon*.

Parameters

- X_0: initial capital available in period 0 before the series of successive investments begins.

- p: prediction accuracy, $0 \leq p \leq 1$; probability that a prediction (put or call) correctly predicts the future.
- r: payout percentage, $0 \leq r \leq 1$; percentage of initial investment received if the prediction is correct.
- T: trading horizon, number of periods for which successive investments are made.

State Variables

- X_t: balance available at (beginning of) period t.

Decisions

- z: investment proportion (proportion of the current balance invested in each period) in Strategies A, C, and D, $0 \leq z \leq 1$;
- z': investment proportion (proportion of the initial balance invested in each period) in Strategy B, $0 \leq z\prime \leq 1$;
- w: multiplier for withdrawal; multiplier of initial capital X_0 in deciding whether to withdraw money in Strategies C and D, $w \geq 0$;
- v: withdrawal proportion (proportion of current balance withdrawn) in Strategy C, $0 \leq v \leq 1$;
- y: withdrawal proportion (proportion of surplus withdrawn) in Strategy D, $0 \leq y \leq 1$.

2.5.4. Feasibility Condition

For a binary option to be feasible, the expected return should be more than the investment. In other words, if the amount of a single investment in binary options is denoted by I, the expected return is

$$E(return) = pI + prI + (1-p) \times 0 \times I = pI + prI = p(1+r)I \quad (1)$$

In the first line of this expected return equation, $pI + prI$ refers to the return for a correct prediction, which is the probability p of keeping the initial investment I and receiving a return of rI. In the first line, $(1-p) \times 0 \times I$ refers to the return for an incorrect prediction. For the investment/trade to be feasible, one should have expected a return higher than the investment, $E(return) = pI(1+r) > I$, which translates into

$$p > 1/(1+r)$$

This inequality is referred to as the feasibility condition. This condition, which can be found in similar forms in [53,54], can be an important guiding principle for investors. Importantly, note that the payout percentage r in this inequality is the net value, which is the payout percentage mentioned in the user interface of the trading platform minus any other fees/costs associated with trading on the platform.

As an example of the feasibility condition, if the payout percentage (including the effects of any trading and other fees/costs) is $r = 0.75$, the prediction accuracy should be at least $p > 1/(1+0.75) \Rightarrow p > 0.5715$.

2.6. Investment Strategies

In this paper, the performance of four easy-to-implement investment strategies for binary options, namely Strategies A, B, C, and D, was introduced and empirically analyzed. These strategies are based on two popular investment principles in practice, *dollar cost averaging (DCA)* [55] and *taking profits* [56].

The *dollar-cost-averaging (DCA)* principle suggests investing regularly over time, regardless of the price of the asset. This principle is represented in our proposed strategies through *proportional investment*, which is reflective of investing consistently and regularly over time. The *taking profits* principle suggests regularly taking profit as profits are made. This principle is represented in our proposed strategies through *proportional withdrawals* in strategies C and D.

The description of each strategy, expression of the strategy as a rule, and the formula for balance X_{t+1} in each period $t+1$ are provided. The balance at the beginning of period $t+1$ is the ending balance at the end of period t and is a function of the balance X_t at the previous period t, as well as the parameters of the binary options and the decision variables of the investment strategy.

Strategy A: Proportional Investment of Current Balance

In this strategy, in each period t, the investor invests a certain proportion z of the current balance X_t. In other words, strategy A is

"At each period t, invest $A_t = zX_t$".

For strategy A,

$$X_{t+1} = \begin{cases} X_t + rzX_t & \text{with probability } p \\ X_t - zX_t & \text{with probability } 1-p \end{cases} \tag{2}$$

$$X_{t+1} = \begin{cases} (1+rz)X_t & \text{with probability p} \\ (1-z)X_t & \text{with probability } 1-\text{p} \end{cases} \tag{3}$$

Strategy B: Proportional Investment of Initial Capital

In this strategy, in each period t, the investor invests a certain proportion $z\prime$ of the initial balance X_0. In other words, strategy B is

"At each period t, invest $B_t = z\prime X_0$".

For strategy B,

$$X_{t+1} = \begin{cases} X_t + rz\prime X_0 & \text{with probability p} \\ X_t - z\prime X_0 & \text{with probability } 1-\text{p} \end{cases} \tag{4}$$

Strategy C: Proportional Withdrawal and Investment from Current Balance

In this strategy, in each period t, if the balance is higher than a certain w multiple of the initial balance X_0, the investor withdraws a certain percentage v of the current balance X_t and then invests a certain proportion z of the remaining balance after the withdrawal. In other words, strategy C is

"At each period t, if the balance X_t equals or exceeds wX_0 $(w \geq 1)$, withdraw vX_t at the beginning of t. Then, invest C_t as a portion z of the remaining available balance".

For strategy C,

$$C_t = \begin{cases} z(1-v)X_t & \text{if } X_t \geq wX_0 \\ zX_t & \text{if } X_t < wX_0 \end{cases} \tag{5}$$

$$X_{t+1} = \begin{cases} X_t + rz(1-v)X_t \text{ if } X_t \geq wX_0, \text{ with probability p} \\ X_t - z(1-v)X_t \text{ if } X_t \geq wX_0, \text{ with probability } 1-\text{p} \\ X_t + rzX_t \quad \text{if } X_t < wX_0, \text{ with probability p} \\ X_t - zX_t \quad \text{if } X_t < wX_0, \text{ with probability } 1-\text{p} \end{cases} \tag{6}$$

$$X_{t+1} = \begin{cases} (1+rz(1-v))X_t \text{ if } X_t \geq wX_0, \text{ with probability p} \\ (1-z(1-v))X_t \text{ if } X_t \geq wX_0, \text{ with probability } 1-\text{p} \\ (1+rz)X_t \quad \text{if } X_t < wX_0, \text{ with probability p} \\ (1-z)X_t \quad \text{if } X_t < wX_0, \text{ with probability } 1-\text{p} \end{cases} \tag{7}$$

Strategy D: Proportional Withdrawal of Surplus from Initial Capital and Investment from Remaining Current Balance

In this strategy, in each period t, if the balance is higher than a certain w multiple of the initial balance X_0, the investor withdraws from the current balance X_t a certain percentage y of the surplus $(X_t - X_0)$ higher than the initial balance X_0 and then invests a certain proportion z of the remaining balance after the withdrawal. In other words, strategy D is as follows:

"At each period t, if the balance X_t equals or exceeds wX_0 $(w \geq 1)$, withdraw y portion of the surplus $(X_t - X_0)$ from X_0—in other words, withdraw $y(X_t - X_0)$—at the beginning of t. Then, invest D_t as a portion z of the remaining available balance".

For strategy D,

$$D_t = \begin{cases} z(X_t - y(X_t - X_0)) & \text{if } X_t \geq wX_0 \\ zX_t & \text{if } X_t < wX_0 \end{cases} \quad (8)$$

$$D_t = \begin{cases} z(yX_0 + (1-y)X_t) & \text{if } X_t \geq wX_0 \\ zX_t & \text{if } X_t < wX_0 \end{cases} \quad (9)$$

$$X_{t+1} = \begin{cases} X_t + rz(yX_0 + (1-y)X_t \text{ if } X_t \geq wX_0, \text{ with probability } p \\ X_t - z(yX_0 + (1-y)X_t \text{ if } X_t \geq wX_0, \text{ with probability } 1-p \\ X_t + rzX_t \quad \text{if } X_t < wX_0, \text{ with probability } p \\ X_t - zX_t \quad \text{if } X_t < wX_0, \text{ with probability } 1-p \end{cases} \quad (10)$$

$$X_{t+1} = \begin{cases} rzyX_0 + (1 + rz(1-y))X_t \text{ if } X_t \geq wX_0, \text{ with probability } p \\ -zyX_0 + (1 - z(1-y))X_t \text{ if } X_t \geq wX_0, \text{ with probability } 1-p \\ (1+rz)X_t \quad \text{if } X_t < wX_0, \text{ with probability } p \\ (1-z)X_t \quad \text{if } X_t < wX_0, \text{ with probability } 1-p \end{cases} \quad (11)$$

2.7. Experimental Setup and Computations

The equations for the strategies previously presented do not lend themselves to a closed-form expression for the balance X_{T+1} at the end of investment period T. To this end, a Monte Carlo simulation needs to be conducted to calculate the ending balance, return on investment ($roi = X_{T+1}/X_0$), and other performance metrics for each scenario, where a scenario is defined as a given combination (set) of parameter and decision variable values.

To carry out the computations, a spreadsheet model was first constructed. In the spreadsheet model, for each scenario, the balance X_t in each period is computed for each strategy up to the end of the trading horizon, that is, the end of period T. The trading horizon was taken as $T = 260$, approximating the number of weekdays within a year. The actual number of trading days in a year is smaller for traditional stock markets and represents a full year for cryptocurrency trading and most binary options platforms. The static spreadsheet model was subsequently extended into a full Monte Carlo model through coding, where multiple simulation runs ($N = 500$) were conducted for each scenario (combination of parameter and decision values). Furthermore, more than 120,000 experiments were carried out to analyze a diverse collection of scenarios and to compute performance metrics. Table 1 displays the values of the parameters and the decision variables used in the experiments.

Table 1. Experimental settings.

Symbol	Name	Parameter or Decision	Min Value	Max Value	Increment	Number of Values
p	Prediction Accuracy	Parameter	0.50	0.70	0.01	21
r	Payout Percentage	Parameter	0.50	0.95	0.05	10
z, z'	Investment Proportion	Decision	0.05	0.95	0.05	19
w	Multiplier For Withdrawal	Decision	1.00	2.00	0.20	6
v, y	Withdrawal Proportion	Decision	0.10	0.90	0.10	9

prz, $z'wv$, y A custom-developed Visual Basic for Applications (VBA) code was run to conduct the Monte Carlo experiments and statistical computations. The code was developed through unit testing [57] and progressively organized within modules. The source code for the developed program, as well as the results database, can be obtained from the corresponding author. Several techniques inherent to the programming language were implemented (https://professor-excel.com/15-ways-to-speed-up-excel/, https://www.microsoft.com/en-us/microsoft-365/blog/2009/03/12/excel-vba-performance-coding-best-practices/ accessed on 22 May 2022) to accelerate the computations. Although 215,460 scenarios ($21 * 10 * 19 * 6 * 9 = 215,460$) were possible, only 124,137 feasible scenarios for which the feasibility condition $p > 1/(1+r)$ was satisfied were analyzed in total. The experiments were run on a personal computer (PC) with an Intel Core i7 chip and six processors dedicated to running the code. A 1 ms (millisecond) waiting time was allocated toward updating the formula cells with computed values. $N = 500$ simulations runs were carried out for each scenario, totaling to 62,068,500 simulations ($124,137 * 500 = 62,068,500$). The experiment runs took 292 h.

3. Results

This section presents an analysis of the computational experiments' results and insights. These results and insights characterize the conclusions resulting from the application of the proposed strategies. Visual analytics (described in Section 2.3) and regression modeling (described in Section 2.4) were the two main analytics methods applied. In addition to spreadsheet software, Tableau analytics software (https://tableau.com accessed on 22 May 2022) was used throughout the data analysis. It is important to note that the *roi* in each figure is actually the average of the median for *roi*. As mentioned in Section 2, the median is used to obtain robust results.

The following is a summary of the conducted analysis.

All strategies

- Figure 4 analyzes the relation between the binary option parameters (p, r) and *roi* across all four strategies.
- Figures 5 and 6 analyze the relation between *roi* and prediction accuracy p.
- Figures 7 and 8 analyze the relation between *roi* and payout percentage r.

Strategy B

- Figure 9 analyzes the relation between the binary option parameters (p, r) and investment proportion in Strategy B as factors versus return on investment (*roiB*) as the response. For each (p, r), the figure also plots the best-fit nonlinear regression model, for which *roiB* is a function of investment proportion z'. Supplementary File S7 of the Supplement document provides in full a nonlinear regression model and equations for the best-fit curves in Figure 9 for each (p, r) pair.
- Figure 10 analyzes the relation between the binary options parameters (p, r) and near-optimal values z'^* for the decision variable z' of Strategy B. The equations of the regression models of Figure 9 are used to calculate these near-optimal values.

Strategy C

- Figure 11 considers a specific binary option parameter value pair ($p = 0.65$, $r = 0.65$) as constant and subsequently analyzes the relation between the decision variables (z, w, v) of Strategy C and return on investment (*roiC*). A subsequent analysis was conducted for Strategy C for each (p, r) pair, and the near-optimal values for the decision variables (z^*, w^*, v^*) of Strategy C were computed. Supplementary File S8 provides these near-optimal values for the decision variables of Strategy C for each (p, r) pair.

The remainder of this section provides the details of each analysis and the insights obtained.

3.1. All Strategies

Figure 4 illustrates the *roi* of all of the strategies in relation to prediction accuracy p and payout percentage r. The sizes of the circles denote the *roi*, and the color denotes profits/losses (orange for profits, $roi \geq 1$, and gray for losses, $roi < 1$). A change in color from gray to orange denotes the start of profits ($roi \geq 1$). The growth of the circle sizes denotes the growth in profits. Missing circles denote either infeasibility (lower-left triangle) or $roi > 10$. For example, for $r = 0.65$, Strategy B has $roi > 10$ after $p > 0.68$, and hence, there are no more circles.

Profits in Strategy C are observed to start at smaller values of p and r when compared with the values at which profits are observed to start in other strategies (circles become orange for smaller p and r values). For example, for $r = 0.65$, C starts to profit at

$p = 0.64$ (orange-colored bubble), whereas A, B, and D start to profit at $p = 0.67$, 0.65, and 0.65, respectively.

In contrast, profits in other strategies grow faster than those in Strategy C. For example, for $r = 0.65$, profits for all strategies grow for higher values of p, yet the circles for C grow the slowest.

For Strategy A, profits start the latest (for highest values of p) but also grow the fastest.

For Strategy B, profits start after C but before A. Therefore, B seems to exhibit a balance of benefits, with profits starting earlier than A yet growing faster than C.

It is to be noted that although Strategies A and B yield a much higher *roi* for high values of (p, r), these take place at the end of the trading horizon $T = 260$. The models in this study assume that the same values hold for (p, r) throughout the trading horizon, which most likely does not hold true in the real world, where prediction accuracy is never a constant or granted on average. In contrast, Strategies C and D start withdrawing profits earlier, and thus they are more robust against possible changes in (p, r) over the trading horizon.

The line charts in the following figures show changes with increasing values of p and r, revealing many inflection points, after which the behavior changes significantly.

Figure 5 displays the change in the (average of median) *roi* of the strategies in relation to prediction accuracy p on the x-axis over all considered values of payout percentage r. The figure suggests that Strategies A and B yield the highest *roi* as p increases despite their lower initial values. For Strategy B, *roiB* exhibits a higher yield until *roiA* for Strategy A eventually catches up at $p \cong 0.605$ and starts to exceed the yields of Strategy B because the prediction accuracy p is higher. Figure 5 also suggests that as the prediction accuracy increases, the *roi* increases for all strategies but unevenly.

The figure also suggests that *roiB* for Strategy B increases at a faster rate as prediction accuracy p increases, whereas *roi* for Strategies C and D increases only slightly.

An analysis of skewness can be found in Supplementary File S9.

Figure 6 exhibits the change in (the medians of) the standard deviation of *roi* for different strategies when plotted against prediction accuracy p on the x-axis. Figure 6 indicates that the *roiA StdDev* for Strategy A is substantially higher than the standard deviations of *roi* for other strategies for higher prediction accuracy values when $p > 0.63$. Strategy A *roiA* can be termed the most volatile (less clustered around the mean); hence, Strategy A could be considered the riskiest, particularly for high p values. Figure 6 suggests that standard deviations of *roi* for all strategies increase, although unevenly, with higher values of prediction accuracy p.

Figure 7 displays the change in (average of median) the *roi* of the strategies in relation to payout percentage r on the x-axis over all considered values of prediction accuracy p. Strategies A and B have the highest *roi* among all strategies, and *roiA* for Strategy A yields more than the *roiB* for Strategy B when the payout percentage parameter increases to beyond $r > 0.645$. Similar to Figure 5, this phenomenon occurs despite their lower initial values.

Figure 7, which excludes *roiA* of Strategy A because of fluctuations, also suggests that that $r \cong 0.55$; *roiB* for Strategy B starts to increase much more than its counterparts for Strategies C and D as the payout percentage r increases. In other words, an investor implementing Strategy B receives higher and earlier returns than an investor implementing Strategy C or D. Moreover, Strategies C and D exhibit only a slight increase in *roi* as the payout percentage r grows.

Figure 8 exhibits the change in the (medians of) standard deviation of *roi* for different strategies in relation to payout percentage r on the x-axis. Figure 8 indicates that *roiA StdDev* and *roiB StdDev* of Strategies A and B, respectively, are higher than those of other strategies. Strategy B is the most volatile, and hence it is the riskiest strategy for a wide range of r values as long as $r < 0.938$. Strategy A exhibits the highest standard deviations when $r > 0.938$. Furthermore, Figure 8 suggests that the standard deviation of *roi* for all strategies increases with higher payout percentage r.

3.2. Strategy B

Figure 9 analyzes the relation between the binary option parameters (p, r) and investment proportion z' in Strategy B as factors versus (average of the median) *roiB* as the response. The y-axis of the matrix denotes prediction accuracy p, the x-axis of the matrix denotes payout percentage r, the x-axis of each plot denotes investment proportion z', and the y-axis of each plot denotes roiB for Strategy B. In the visualization, the yellow color denotes lower roiB values, and the orange to red color tones denote higher roiB values. The matrix suggests that roiB increases as prediction accuracy—payout percentage and investment proportion—increases.

Figure 9 shows that the relation between z' and *roiB* can be nonlinear or (almost) linear, depending on the (p, r) values. The best value to select for z' also changes with different (p, r) value pairs. For example, for $(p, r) = (0.65,\ 0.75)$, *roiB* first increases as z' increases. Then, after a certain point ($z' \cong 0.55$), *roiB* decreases as z' increases. Therefore, the investor should use the z' value that (nearly) maximizes *roiB*, which is empirically found to be $z'^{*} = 0.55$ (also displayed in Figure 10).

Figure 9 also plots for each (p, r) the best-fit nonlinear regression model for which *roiB* is a function of investment proportion z'. In the regression analysis for Strategy B, various functional forms are tested. Eventually, polynomial functions were found to be most robust across different (p, r) value pairs with respect to fit despite simplicity and consistent statistical significance. Thus, to derive the nonlinear regression equations, a polynomial trend model of Degree 3 was computed. The model response was (average of median) *roiB* as a function of the factor investment proportion z' for each (p, r) value pair. The regression model results are presented visually in Figure 9 and provided in full as regression equations in Supplementary File S7.

During the development of the regression functions for Strategy B, two further research questions were identified, as follows: "Can (near-)optimal values z'^{*} for the decision variable investment proportion z' be derived? Are there any patterns in these (near-)optimal values?" Because the data generated in the experiments are for discrete points in continuous space, the derived values could only be near-optimal rather than optimal. To this end, for each (p, r) value pair, database queries were used to search within the experimental results for the value of z' that yields the highest *roiB* for that pair.

Figure 10 displays the near-optimal investment proportion values (z'^{*}) for Strategy B for each (p, r) value pair. Darker colors denote higher near-optimal investment proportion values z'^{*}. The visualization suggests that z'^{*} also increases (higher value captions, darker-colored circles) as payout percentage p increases. In other words, a higher percentage of the initial balance can be invested in each period as the prediction accuracy increases; that is, one can stake more as the instrument becomes safer.

3.3. Strategy C

In Figure 11, the scatter plot matrix sets fixed values for prediction accuracy and payout percentage ($p = 0.65$, $r = 0.65$). The matrix also analyzes the impact of other factors, namely investment proportion ($z = 0.05, \ldots,\ 0.95$) on its y-axis, the multiplier for withdrawal ($w = 1, \ldots,\ 2$) on its x-axis, and the proportion withdrawn ($v = 0.1, \ldots,\ 0.9$) on the x-axis of each plot, on (average of median) *roiC* for Strategy C. This impact is shown on the y-axis of each plot and denoted by color. To facilitate the observation of insights, one of five different background colors is applied for each plot. Starting from low investment proportion z values and going upwards:

- Pink background denotes scenarios in which *roiC* decreases.
- Gray background denotes scenarios in which *roiC* stays mostly constant.
- Light green background denotes scenarios in which *roiC* increases slightly.
- Darker green background denotes scenarios in which *roiC* increases considerably, with the increasing values of the proportion withdrawn v. Meanwhile, a white background denotes scenarios in which no consistent patterns exist.
- The following observations are made from Figure 11.

- Pink plots: Not making any withdrawals at all ($v = 0$) is typically more profitable (higher *roiC*) when the investment proportion has low values, less than $z < 0.40$;
- Gray plots: For certain (w, z) value ranges, *roiC* is insensitive to changes in v;
- Green plots: The return *roiC* typically increases as the values of the proportion withdrawn v increase when the investment proportion is $z \geq 0.40$, and the multiplier for withdrawal is $w \geq 1.20$. In other words, higher values of v are preferred for higher *roiC* with higher values of w and z.

After observing these patterns for Strategy C, similar to the analysis for Strategy B, two further research questions were identified: "Can (near-)optimal values (w^*, z^*, v^*) for the three decision variables (w, z, v) be derived? Are there any patterns in these (near-)optimal values?". Again, because the data generated in the experiments are for discrete points in continuous space, the derived values could only be near-optimal rather than optimal. To this end, for each (p, r) value pair, database queries were used to search within the experimental results for the values of (w, z, v) that yield the highest *roiC* for that pair. Although all near-optimal values were obtained, no pattern was directly discovered from the results. The near-optimal values for the decision variables (z^*, w^*, v^*) of strategy C, for each (p, r) pair, are provided in full in Supplementary File S8.

Figure 11 is only an illustrative example of the types of insights that can be obtained through visual analytics when analyzing the experimental results. Naturally, different insights would be gained for different combinations of factors and responses and different constant values of (p, r) assumed. Analysts can select the factors, responses, constant values, and parameter ranges that are most suitable for their investment settings and analysis needs, and subsequently, they can analyze the results to discover fresh insights and new knowledge that they can apply to reach better investment decisions.

4. Conclusions

4.1. Research Scope

A binary option is a special type of financial instrument that rewards the investor based on his/her prediction of the direction of price movements—whether higher than, or below, a pre-defined target price. This paper reports research on tactical easy-to-implement investment strategies for binary options in contrast to the extant literature that mostly focuses on trading. Several novel contributions are made in this paper, including developing four investment strategies, using time series equations to mathematically describe the strategies, identifying key binary options parameters and decision variables, conducting extensive Monte Carlo simulation experiments, empirically analyzing the performance under the developed strategies, identifying critical inflection point values for parameters with performance behavior that changes significantly, and searching for near-optimal decision variable values. A detailed visual analysis of the obtained results reveals insights for better investment decisions for binary options.

4.2. Findings

This paper makes several contributions to the body of knowledge on binary options and thus on exotic options; therefore, it also clears a path for multiple new future research areas. Several conclusions are derived in the study, as supported by the results and analysis:

First, as mentioned in Section 3, Strategies C and D start withdrawing profits earlier than Strategies A and B and thus are more robust against possible changes in (p, r) over the trading horizon. An analysis of the *roi* of the strategies over the trading horizon presents another possible topic for future research.

Second, the extensive dataset obtained through the Monte Carlo simulations can be further explored using a variety of data analytics techniques, including machine learning.

Third, in the current paper, the calculation of near-optimal values for decision variables is based on a simple grid search.

4.3. Future Work

As a possible future research topic, stochastic optimization techniques can be employed to calculate much more accurate near-optimal values for the decision variables for given parameter value sets. To this end, a variety of techniques [58] can be implemented using various open source (https://www.grasp-open.com/ accessed on 22 May 2022) and commercial (https://www.localsolver.com/ accessed on 22 May 2022) software libraries. Fourth, the performance of the presented investment strategies can be compared with that of the trading strategies that require different trading parameters over time. Fifth, new and intuitive strategies can be developed, modeled, and analyzed.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/fi14070208/s1. References [59–81] are cited in the supplementary materials.

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