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The Application of Blockchain and Robo-advisors in Wealth Management Literature Review

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Abstract: This paper aims to study the blockchain in the field of financial ecology as the carrier, optimize the consensus mechanism, and use intelligent consulting as an analytical means to provide investors with an objective, low-cost asset allocation portfolio. This article begins with an introduction to the features of blockchain decentralization and tamper-proof execution of algorithms, how proof-of-work works, and how tokens can improve welfare and reduce user base volatility. The paper then introduces how robo-advisors work and how they develop. Finally, this paper reviews existing research models on robo-advisors, from the traditional mean-variance model based on Markowitz to the jump-diffusion, regime-switching model, and the Pi portfolio management model that does not require quantifying risk preference coefficients, which this paper discusses and seeks to explore the advantages and limitations between the different models. Based on the existing research gaps, the directions that digital finance can expand in the future are discussed.

Keywords: blockchain, token, robo-advising

1. Introduction

With the rapid development of the market economy, there are more and more projects in the financial industry. The complexity of supply and demand in the financial asset market makes investing a daunting challenge, as investors in the process of selecting financial products need to evaluate factors such as portfolio risk, compliance effects, and tax implications of investment alternatives to determine the best portfolio. Some people may face additional challenges when making good investment decisions. According to the U.S. President's Advisory Council on Financial Literacy [1], a large percentage of young people don't have the basic financial skills necessary to set and sustain a budget, understand investment vehicles, or take advantage of the local banking system, which can reduce people's motivation to invest, plan retirement, etc, [2]. People with low levels of finance often make poor financial decisions. Most families have accumulated a lot of wealth in retirement, but the human analytical cognitive function has declined sharply from the age of 20, and many older people do not manage their finances well [3]. But for some groups, it is not advisable to rely on traditional investment institutions to determine the optimal portfolio. For a single small user, traditional investment institutions have a high investment threshold, and a large starting amount and financial advisors usually charge a fee of 1%-2% of the assets under management, which makes it difficult for investors to choose the best investment solution to maximize their wealth [4]. In addition, high-net-worth users have many funds, they usually require stable income and absolute security of funds, and

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the blockchain can make transactions efficient and transparent and not tampered with, which can greatly protect the rights and interests of users. But users of digital currencies usually pursue short-term benefits, and they are likely to make irrational judgments in the face of risk predictions in the secondary market [5]. Therefore, a chain based on the financial ecological field can be created, and the robo-advising can be used as an analysis means to optimize the consensus mechanism of the blockchain, diversify the smart contract, etc., and provide an objective, low-cost asset allocation solution. Through the characteristics of blockchain, the working method and the working principle of robo-advising, the algorithm iteration of robo-advisors, and other related research literature, this paper proposes that blockchain and robo-advisors can be organically combined in the future to provide customers with safe, efficient, objective, and low-cost asset allocation solutions.

2. The Characteristic of Blockchain

Cong concludes that decentralized ledger technologies such as blockchain have the characteristics of decentralized consensus and tamper-proof algorithm execution, facilitating the creation of smart contracts [6]. However, the process of reaching decentralized consensus changes the information environment on the blockchain, and promoting collusion has the potential to have the consequences of undermining welfare. In the traditional world, the assumption is that the market is perfectly competitive, and the seller excludes competitors through price competition and is the price receiver. Assuming there are no new entrants if the discount factor is low, the market price will fall, and the conspiracy will collapse into the Bertrand equilibrium. In the case where the blockchain and the seller agree on the quality of the delivery, the payment depends on the delivery, and the buyer determines the quantity of the delivery. Assuming new entrants, the market will be more competitive, and the consumer surplus will increase. Compared with the traditional model, the factor that can maintain complicity is lower. Because sellers can learn from records that the overall transaction is paid and colludes with each other, the higher the market price, the lower the consumer surplus. The solution is to separate usage and consensus generation on the blockchain so that buyers cannot use the consensus-generating information to maintain complicity.

Proof-of-work works in such a way that miners compete for the right to record new blocks, and miners can only get some native crypto-tokens as a reward if their records are approved by subsequent miners. Because decentralization removes any single point that people can attack, the blockchain is stable against cyberattacks. Nakamoto was the first to write about blockchain, arguing that there would be perfect competition between independent computer nodes around the world, but there were also pitfalls. If a pool's hash rate exceeds 50% of the global hash rate, it can in principle be manipulated. Cryptocurrency mining has two characteristics. One is that there is no additional cost when you join another pool. This does not represent there is no fee for a member of the pool. It's just that the fees are the same when miners put the consumer power in multiple pools. The second feature is that the production function of the mining industry represents an arms race. If one arm buys more computer power, another arm also has an incentive to buy more computer power. Therefore, getting more computer power per miner will directly hurt other people's expected payoff [7].

A token is essentially a proof-of-stake that represents a fungible and tradable asset that resides on its blockchain. Tokens can be used for investment purposes, stored value, or purchases, and are typically created, distributed, sold, and circulated through a standard initial coin offering (ICO) process. An initial coin offering (ICO) is a type of capital-raising activity in the cryptocurrency and blockchain environment. The ICO can be viewed as an initial public offering (IPO) that uses cryptocurrencies. Startups primarily use an ICO to raise capital. According to Cong, blockchain platforms create value by supporting special economic activities, and those tokens derive value by facilitating transactions between platform users [8]. As the productivity of the platform increases, the expected price appreciation of the token by the agent encourages early adoption and thus improves welfare. Finally, tokens can reduce the volatility of the user base as agents' long-term growth expectations for token value weaken the impact of temporary productivity shocks on the user base.

3. Robo-advisor

3.1. The Principle of Robo-advisor

The principle of robo-advisor is based on modern portfolio theory, capital asset pricing model, and behavioral finance theory, considering investors' financial status, investment needs, risk preferences, income objectives, etc., using big data, machine learning, and other technical means to provide investors with relevant asset allocation suggestions and digital and intelligent wealth management services. Robo-advisors mainly rely on automated platforms to provide investment advice to clients, less manual intervention, using mean-variance optimization to achieve low-cost and tax-efficient portfolios, and largely adopt ETFs and other passive indexation investment strategies. This model first provides a set of investment products designed in-house or purchased from third parties on the platform, provides customers with tailored analysis and combination of products based on the client's investment objectives, risk tolerance, and other factors, determines the applicability of the recommendation through the use of algorithms or heuristics, and finally communicates and interacts with the client promptly, makes a certain degree of correction promptly, and executes and trades investment decisions [9]. Robo-advisors are a relatively inexpensive and efficient way to invest in assets. Unlike traditional investment advisors, robo-advisors charge less for their services, analyze data without personal bias, and avoid agency costs.

3.2. The Development of Robo-advisory

Robo-advisors have emerged from the wave of Internet finance and the boom of financial technology. In 2008, the world's first digital financial company, Betterment, was established in New York, and in the following two years, several digital financial companies such as Wealthfront, Personal Capital, and Future Adviser were established, opening the era of intelligent wealth management. There are two main forms of robo-advisors. The first is Digital Advice Tool used by brokerage institutional practitioners to provide investment advisory analysis to clients [10]. Another is Robo-advising which exists as an investment advisor. According to the Guidance on Robo-Advisers, Robo-advisors are computer programs that use innovative technology to provide clients with discretionary asset management services through online algorithms [11]. Clients enter personal information and other data into a digital interactive platform based on which robo-advisors generate portfolios for clients and manage client accounts.

3.3. Algorithm Iteration of Robo-advisors

3.3.1. Mean-variance Optimization Model

Based on Markowitz's model of mean-variance, traditional robo-advisors assume that excess returns are independent of each other and follow a normal distribution and use a covariance matrix to measure the risk aversion coefficient of investors at a certain moment [12]. The optimal portfolio weight is then determined based on the mean and covariance matrix of asset returns. In the case of Wealthfront, for example, the platform first identifies a different set of asset classes, then selects the appropriate efts under each large class of assets to represent the asset class and uses the Mean-Variance Optimization (MVO) model for asset allocation. In the MVO model, assets assume that there are N risky assets and one risk-free asset, and investors are considered risk-averse. The r_{ft} represents the return on risk-free assets, r_t represents the return on risky assets, and the R_t is a risk premium, and it follows an Independently identical distribution, with an average of μ. γ measures the degree of risk aversion of investors. In a market with N risky assets and a risk-free as:

$$\max U(w) = w'\mu - \frac{1}{2}\gamma w' w \tag{1}$$

where 1/2 is to facilitate subsequent derivatives. When both the mean and variance are known, the optimal portfolio weighting equation and the maximum expected utility can be obtained:

$$U(w^*) = \frac{1}{2\gamma}\mu' V^{-1}\mu = \frac{\theta^2}{2\gamma} \tag{2}$$

The optimal solution is obtained using the Lagrange method, which can be simplified to obtain an algebraic formula for variance:

$$\hat{w} = \frac{1}{\gamma} V^{-1}\mu \tag{3}$$

According to different r_t can be different w, and then the corresponding V. There is a restriction here that the ownership recombination and 1, $w'\mu$ are equal to the expected return of the portfolio (R_p). In addition, $w \geqslant 0$ means that short selling is not allowed. But there are three significant problems with the MVO model, the first is the need to estimate the mean and variance of the asset, that is, there is an estimation error. Second, the portfolio is very sensitive to changes in the smile of expected returns. In the end, the result is a highly concentrated portfolio, as only a few assets are granted non-zero weights.

3.3.2. Black-litterman Model

But in practice, the mean and variance cannot be calculated. To solve the problem of the difficult application of the MVO model in practice, Wealthfront mixes the capital market model with the Black-Litterman model [13]. The portfolios involved in this model include two broad categories, portfolios that are subject to taxable accounts and retirement account portfolios. The Black-Litterman model has three main features, first, "using the composition of the global market portfolio in the reverse optimization step to obtain the implied expected return of the market for each asset class", which may simply understand as assessing the portfolio manager's views on the expected return on the asset and their confidence in those views. Second, if there is no opinion on the expected return on certain assets, the CAPM model is used to calculate the expected return. The calculated expected total return, minus the expenses, yields a pre-tax return, noting that this is not the actual return. The third step is to calculate the actual return, but before that should first calculate the tax amount corresponding to each type of asset. Here two different accounts appear, where taxable account income is taxed at the time of allocation. The head of the household in the retirement account is to pay income tax in the future, which is equivalent to the accumulation of funds in the form of deferred tax payment, from the perspective of accounting, the deferred tax here can be simply understood as a liability. Then, using the pre-tax income corresponding to each type of asset minus the tax amount of the corresponding account type can get the after-tax return, that is, the actual return. However, the issue of liquidation and amortization of investment products before the end of their life cycle should also be considered here. The actual return is then used as input to the MVO to generate an image to determine the effective boundary. Determine new ways to allocate assets over time.

However, covariance matrices, which are usually based on simple samples, are not stable, leading to extreme configurations. To solve this problem, Wealthfront uses historical data, combined with

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factor analysis and contraction, to narrow the asset class covariance matrix to a diagonal matrix. First, estimate the beta value corresponding to the N class asset, and then superimpose β into K risk factors to obtain a matrix. Second, to identify the asset's unique and non-systemic risks, estimate a regression residual covariance matrix of N*N. Finally, the covariance matrix of the historical factor benefits is calculated. The results of this approach are very clear, dividing the risk of each asset class into two parts: systemic risk and idiosyncratic risk. When the selected factors perfectly describe the economic dynamics of a group of assets, the covariance matrix is diagonally distributed.

The Risk score is derived from a questionnaire filled out by a user with a score between 0-10. The proportion of high-risk assets allocated to stocks is gradually increasing. High risk usually has high returns, and stocks not only provide high returns but are also more tax-efficient than bonds. The asset allocation in the retirement account asset allocation chart is like that of taxable accounts, but the allocation of new market bonds is in the middle of conservative and aggressive. For small accounts, Wealthfront minimizes the cash drag on uninvested assets and uses an overall optimization process to determine the most appropriate ETFs.

After that, the investment approach is to confirm the user's risk tolerance. Unlike traditional financial advisors, Wealthfront uses algorithms based on behavioral economics. Behavioral economics shows that investors are not always sane, and well-educated, overconfident men often exaggerate their true risk tolerance. Some investors are always very concerned about small probability events. The overall risk score consists of both subjective and objective components, and the higher the degree of risk aversion, the greater the proportion. The platform will contact the customer to confirm whether their financial situation and risk tolerance have changed.

3.3.3. Log-MV Model

Dai et al. built dynamic logarithmic-MV portfolio selection in complete market [14]. Based on Markowitz's model of mean-variance, traditional robo-advisors assume that excess returns are independent of each other and follow a normal distribution and use a covariance matrix to measure the risk aversion coefficient of investors at a certain moment. The optimal portfolio weight is then determined based on the mean and covariance matrix of asset returns. But there are two problems with this model. First, asset allocation is a dynamic process in which the structure of a portfolio changes as the market changes. Since at different decision-making points, investors may face different problems and the information they have may change, in addition, the preferences of decision-makers or the decision-makers themselves will also change over time intervals, which may lead to the initial optimal combination to the next point in time is not necessarily optimal. Second, Quigley uses the Q-Q plot to visually show the distribution characteristics of return rate with sharp peak, thick tail, and skew [15]. The single cycle mean-variance model does not conform to this phenomenon. The log-MV model is based on Markowitz's single cycle mean-variance, and since the returns are continuously compounded, it makes sense to consider the combined logarithmic returns [12]. Cvitanic used the values of BSDEs simulated by Monte Carlo to demonstrate the existence of an equilibrium solution and find the optimal combinatorial strategy [9]. Therefore, the log-MV is more in line with the actual distribution of yields, can produce time-consistent portfolio strategies, and the resulting portfolio strategies are in line with traditional investment wisdom. Dai et al. first assume that in a perfect market, starting from a market, there are risk-free assets and risky assets with interest rates of r, μ_t represent the drift rate, and the volatility is greater than 0. Brownian motion is used to simulate stock price changes [14]:

$$dS_t = \mu S_t dt + \sigma S_t dB_t \tag{4}$$

The process of self-financing wealth W_t can be represented by a stochastic differential equation:

$$\frac{dW_t}{W_t}= [\mathrm{r}+(\mu\text{-r})\ \pi_t]\mathrm{dt}+\sigma\ \pi_t \mathrm{d}B_t \quad (5)$$

It is assumed that the investor will not go bankrupt, so the W_t is greater than 0. Therefore, the above SDE can be rewritten as an equation that uses π_t to represent the total proportion of wealth in stocks. Then the logarithm of the return is expressed in R_t, equal to lnW_t:

$$\mathrm{d}R_t= [\ \mathrm{r}+(\mu\text{-r})\ \pi_t\text{-}\frac{1}{2}\sigma^2{\pi_t}^2]\mathrm{dt}+\sigma\ \pi_t\mathrm{d}B_t \quad (6)$$

And at any t < T, maximize the objective function:

$$E_t\ [R_t]\text{-}\ \frac{\gamma}{2}\mathrm{V}ar_t[R_t],\ \mathrm{t} \in [0,\ \mathrm{T}). \quad (7)$$

At indicates acceptable policies such as policy changes, growing user's interests and so on:

$$At = \{\pi_s=\pi(\mathrm{s},\ R_s)\text{: Et } [\int_t^T |\sigma_s\ \pi(s,R_s)|^2 \mathrm{ds}] < +\infty \quad (8)$$

The investor's risk aversion level γ > 0. Under time-consistent, the traditional HJB equation no longer applies, Bj¨ork, T., Khapko, M., and Murgoc, A. generalizes the standard HJB equations in the form of non-linear systems of equations to determine the equilibrium function [16]. The goal of Dai et al. is to seek the equilibrium solution to obtain an equation for the equilibrium strategy $\hat{\pi}$:

$$\hat{\pi}= \frac{\mu-\mathrm{r}}{(1+\gamma)\sigma^2} \quad (9)$$

In addition, the annual target returns associated with $\hat{\pi}$ are constant, resulting in an equation that γ corresponds to the expected annual target rate of return. This means that in the robo-advising, it is only necessary to quantify the investor's risk preference parameters γ by entering the answer to the question by investors and determining some fixed market parameters such as drift rate, volatility, and interest rate, etc.

3.3.4. The Jump-diffusion Model

The log-MV model created by uses Brownian motion to characterize stock price movements, which assumes that the price process of financial assets is a continuous process of time [17]. For some time, it was known that Brownian motion did not simulate the behavior of stocks very well [18]. In financial practice, the price movements of financial assets are not necessarily continuous. For example, due to the impact of major information such as sudden events, policy adjustments, etc., stock prices will fluctuate and jump, and the events and impacts of such information are random, so they can be described by poisson distribution. Heston provides a closed solution for the stochastic volatility option model, which has been generalized to model problems, following a discontinuous stochastic process. According to Carr, Fourier inversion techniques can be used to model problems involving the L$\acute{e}$vy process [19]. The paper first assumes that the volatility of stock returns σ and proportional jumps β is constant and N(t) stands for the independent Poisson process with a definite jump rate. d*Nt* is a point process that describes the jump, when d*Nt* = 0, no jump occurs, and when d*Nt* = 1, the jump occurs. An equation about the process of change in wealth can then be derived. Because the wealth process is a L$\acute{e}$vy process, it is possible to replace W with log-return. The reward function here is the same as in the log-MV model, let $\hat{\pi}$ be all participants from (t, T) on the equilibrium strategy:

$$\hat{\pi}\,(t)=\frac{\mu-r}{(1+\gamma)\sigma^2}+\frac{\beta\lambda(t)}{(1+\gamma)\sigma^2}\frac{1+\ln(1+\beta\hat{\pi}\,(t))^{-\gamma}}{1+\beta\hat{\pi}\,(t)} \tag{10}$$

The $\hat{\pi}$ given here consists of two parts, the first of which is short-sighted needs. The second term is generated by jumps, which also means that when the $\beta = 0$, the overall value of the second term is 0. The obtained optimal strategy for CRRA utility φ(t) implicit solution:

$$\varphi(t)=\frac{\mu-r}{\tilde{\gamma}\sigma^2}+\frac{\beta\lambda}{\tilde{\gamma}\sigma^2}\,(1+\beta\hat{\pi}\,(t))^{-\tilde{\gamma}} \tag{11}$$

Liu et al. studied the effects of price jumps and volatility on investment strategies and uses Duffie, Pan, and Singleton's event risk framework to present an analytical solution to the optimal portfolio problem [20]. It was also found that investors are reluctant to hold leveraged or short positions in the face of risky events. In addition to this, price jumps and volatility have an important influence on the optimal solution strategy.

3.3.5. Regime-switching Model

Many time-series data follow different dynamics over different time periods; This kind of behavior is called regime change. One model of this behavior is the regime switch model (RSM). RSMs can assign different sets of parameter values to different systems and model the probability of transfer between systems [21]. Many economists are more concerned that during recessions, many economic variables behave markedly differently, i.e., underutilization of factors of production, rather than their long-term growth trends dominating economic dynamics [22]. For example, Ang and Bekaert used the regime-switching process to solve the dynamic portfolio selection problem of US investors in the face of the time-varying investment opportunity set, proving that the correlation between international stock market returns is enhanced in a volatile bear market, but due to the many benefits of regime change and currency hedging, the cost of ignoring these mechanisms for all-stock portfolios is low, and international diversification is still valuable [19]. Dai studies the regime-switching model of a time-consistent equilibrium strategy based on the log-MV criterion [17]. $\{\alpha\,(t)\}t\geq 0$ is a stochastic process on the probability space, which is a Markov chain. I represent a discrete state of space. Combined with the conditional distribution function and the probability density transfer function, the Martens chain can be applied to characterize the price change process of an asset. The market mechanism at t-time is modeled in finite state space $\{1, \ldots, N\}$ and represents $\{\alpha\,(t)\}$ in $(q_{ij})N\times N$. P $\{a_{n+1}=j|\ a_n=i\}$ is the transfer probability of the process, representing the transition of the state of n, the probability of a shift from i to j. $\{X_t\}$ is the process of modeling the state of the market, simulated using stochastic differential equations, and the price of the stock is also given by SDE, where $\{B_t\}$ is another standard Brownian motion. Instant interest rates by r (t, Xt; $\alpha(t)$) give that for a given combination of proportions π, a log-return process can be derived, resulting in a relation to R (s; π) of the differential equation. In the objective function of state i, γ is a positive constant, where $\widehat{\pi_t}$ is the equilibrium solution of the equilibrium strategy:

$$\hat{\pi}\,(t, R, x, i) =\frac{x}{\sigma(i)(1+\gamma)} - \frac{\rho\gamma v(i)}{\sigma(i)(1+\gamma)}(2A\,(t, i)x + B\,(t, i)) \tag{12}$$

Dai then proposes Proposition 2: Suppose that the security conversion model gives an equilibrium strategy so that an equation about $\hat{\pi}(t, R, x, i)$ can be obtained. In some specific cases, the partial differential equations given in the proposition can be converted to ordinary differential equations. The first is that under the mean-variance criterion for logarithmic returns, time-varying Gaussian mean return can convert PDE into ordinary differential equations. In different regime-switching, hedging needs are expressed in terms of the density matrix of transfer probabilities. The conclusions are drawn when there is a change in institutions are consistent with actual financial markets. Investors are more willing to increase their stock investments to obtain a high-risk premium during a bull market, while in a bear market they usually reduce their stock investments to reduce risk. The second scenario is a regime switch with stochastic volatility. Optimal portfolio requirements include an intertemporal hedging component, which is negative when the relative risk factor is greater than 1, and the instantaneous correlation between volatility and stock return can be estimated based on stock return data as negative [23].

3.3.6. Pi Portfolio Management

Traditional robot-advisors take modern portfolio theory as the framework and use the mean-variance optimization model or utility function to construct asset allocation. In this process, an explicit is usually obtained, through which the optimal weights are determined to maximize the expected return of the portfolio. However, the risk aversion coefficient (γ) needs to be estimated in the display, that is, the investor's risk preference needs to be quantified. But there are some problems with this approach to quantifying investor risk appetite. First, the results based on the questionnaire are inelastic. Because the questionnaire designer will design the answer range in advance, this may limit the user's scope and even miss some deeper information. Second, γ itself is highly subjective. Finally, investor behavior in life may not strictly follow the utility function, and the tested risk appetite may not match the investor's risk-taking behavior in real life, which will be difficult to explain to investors. In addition, the average investor may not understand what the utility function is, nor do they understand what the risk aversion factor is, and investors may be more concerned about how long they need to wait to get a return from their investment and what the value of the return is.

Cvitanic et al. proposed a relatively simple single period model for calculating optimal portfolios [8].

$$\pi = c_1 P[R_1 \geq r_1] + c_2 P[R_2 \geq -r_2] \tag{13}$$

where r_1 represents the return goal, $-r_2$ is the loss limit, where r_1 and r_2 are fixed numbers. c represents the corresponding weights, and R represents the return of the portfolio, typically $c_1 + c_2 = 1$. This formula measures performance in π for portfolios that choose the appropriate weight c and R in probability vectors. In real life, the investment manager first talks to the investor and chooses the r_1 and the r_2 according to the investor's opinion. A generic formula is then given that contains one or more goal levels. In fact, we don't even need to list the specific values of c_1 and c_2, we just need to tell investors the two probabilities of each portfolio, and then let investors choose according to their preferences. Then goes on to present a general model for portfolio performance measurement. Cvitanic introduces benchmark wealth (or return) levels, goals, and downwards [9]. Wealth is represented by x, x_0=−∞, x_n=∞, interspersed with x_1, x_2, and so on. And then divide all the possible segments, I_i, from x_{i-1} to x_i. P_i is the probability that wealth will fall within these intervals. For given benchmark weights $c_1, c_2, \ldots, c_n$, the measure of $\pi = \pi(c_1, c_2, \ldots, c_n) = \sum_{i=1}^{n} c_i p_i$, Where π is a weighted average of the probabilities of obtaining a wealth benchmark level, which also includes a loss avoidance benchmark level. The goal is to maximize π, which means the weights of each probability should be determined. Investors are not completely rational economic people, and they are usually very concerned about small probability events, such as high profits or huge losses. At this time, the investor's preference is affected by the probability distortion corresponding to the function D, $\sum D(p_i) U(x_i) = \sum c_i p_i$. The same process for investment managers we mentioned earlier to list several different sets of portfolios and then let investors select is the same to enable investors to get

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the most satisfactory portfolio. Investment managers should first create questionnaires to understand the benchmark level of investors and how long they want to spend. The combined distribution of all benchmarks and asset returns over time is then estimated (or only the necessary quantiles are estimated), after which the possible portfolios are repaired and the probabilities are reported to investors, asking which vector they prefer the $\{p_i\}$. If the investor is not satisfied with the existing portfolio, repeat the above steps to obtain another portfolio.

4. Conclusion

Blockchain can make transactions more efficient and transparent, and cannot be tampered with, which can protect the rights and interests of users. In the traditional mean-variance model, the portfolio is very sensitive to changes in expected returns, and only a few assets are granted non-zero weights in the resulting portfolio results. The Black-Litterman model can solve the application of the mean-variance model in practice by pre-evaluating the investor's risk appetite coefficient and minimizing the covariance matrix. However, the model assumes that the benefits are normally distributed and do not conform to the principle of temporal consistency. Using the log-MV model, the jump-diffusion model, and the regime-switching model to allocate assets to robot consulting, the risk aversion factor can be determined according to the simple input information of investors, and the traditional asset allocation investment criteria can be met. In addition, the output is analytical and conforms to the principle of time consistency. Pi Portfolio Management then proposes a unified framework to address the risk assessment inherent in this traditional goal-based portfolio approach. This framework has two main functions. First, it enables investors to collectively measure and maximize performance on multiple targets, such as target and down. Second, directly express the risk appetite for a group of portfolio choices. But in real life, a portfolio strategy that suits investors depends not only on the target return and investment duration, but also on factors such as the investor's age and income, but these factors are not reflected in existing models. At present, there is a lack of research on the comprehensive application of blockchain and intelligent consulting in wealth management. Through the research on the working principles and characteristics of blockchain and robo-advisors, this paper proposes a new investment model, that is, using blockchain as the carrier of the financial ecology and using robo-advisors as an analysis method to provide customers with safer, more efficient, and low-cost asset allocation solutions.

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