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Human behavioral dynamics and stock return movements: Evidence from China

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Abstract: This paper develops an analysis framework based on the principle of human behavior dynamics and the jump-diffusion process. Based on empirical tests on Chinese stock markets, the paper reveals a negative correlation between jump levels in the previous month and stock returns in the following month. On average, an increase of each 1 unit in the value of the jump component results in a lower subsequent stock return of 58 basis points. Moreover, the long-short arbitrage portfolios based on jump levels perform better than the market portfolio; the Sharpe ratio is 4 times that of the market index, indicating that jump-based trading strategies have a great ability to pursue abnormal returns.

Keywords: *Chinese stock market, Human behavioral dynamics, Jump-diffusion process, Portfolio strategies.*
JEL Classifications: *C14; C53; G11; G12.*

1. Introduction

The Chinese stock market commenced its trial operations in 1989, heralding a remarkable journey spanning nearly three decades of growth. By December 2022, the Shanghai and Shenzhen stock exchanges boasted 4,917 listed companies, with a collective market capitalization of 78.8 trillion yuan. Despite this impressive progress, there remains a notable disparity in the maturity of China's securities market compared to developed economies in Europe and the United States. Nonetheless, it is evident that the Chinese stock market, in its unceasing evolution and expansion, holds vast untapped potential and will increasingly serve as a pivotal component of the financial landscape.

The stock market, a complex nonlinear dynamic system, has long been a research focus in finance, aiming to predict the fluctuating trends of stock prices. Its dynamic nature is highly intricate, influenced by a plethora of factors including economic conditions, political environments, national policies, investor behavior, and peripheral markets. Traditional time series models often struggle to address such intricate nonlinear challenges. Given the stock market's constant evolution, encompassing both significant returns and substantial risks, it can, in certain scenarios, have a profound negative impact on the real economy. Hence, accurately predicting stock price movements is of utmost importance for investors and regulatory agencies alike. By precisely forecasting stock prices, investors can reap substantial returns in trading, while regulatory agencies can effectively regulate and mitigate risks by anticipating the direction of market operations and fluctuations.

The proposed ton model has been effectively implemented in the testing of time series-based option pricing models, sparking considerable subsequent research. Ramezani and Zeng [1] introduced an asymmetric jump diffusion model as a refinement to Merton's original jump-diffusion framework. Kou [2] further advanced this concept by developing a double exponential jump diffusion model, where the logarithm of the jump quantity, derived from Poisson processes, adheres to an asymmetric double exponential distribution. This model aptly captures both peak and thick tail phenomena, as well as volatility smiles, and facilitates the derivation of closed-form solutions for European options.

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Current research on jump diffusion models primarily revolves around the outcomes of jump behavior, often assuming its occurrence to follow a Poisson process. The evolution of modern financial economics from its classical counterpart primarily revolves around the modification of several fundamental assumptions, including investor rationality, group behavior characteristics, and limited arbitrage. An effective mathematical model should not only mirror the diverse phenomena observed in financial markets, but also establish a link with the fundamental principles of financial economics.

Recent insights into human behavioral dynamics reveal that individual actions exhibit power-law characteristics. This school of thought posits that the occurrence of events is characterized by high-frequency intermittent activity, interspersed with longer intervals between two consecutive events. In contrast, Poisson processes fail to capture such patterns. The variations in behavioral dynamics among different investor groups within the market, under the general framework of human behavioral dynamics, are indeed the primary market factors that drive market differences.

This paper has the following contributions. First, the paper aims to commence by exploring the dynamics of human behavior, thereby establishing a comprehensive model that captures the intricate patterns of stock price movements. With a focus on data derived from the Shanghai and Shenzhen stock markets, it intends to dissect the temporal patterns of individual stocks, sectors, and the entire market. Second, empirical research will be undertaken to examine the dynamics of human behavior that influence the jump time interval of stock price fluctuations. Third, the analysis will delve into the similarities in the time interval of stock price fluctuations across various spatial and temporal scales, ultimately laying a solid theoretical foundation for macroeconomic predictions of stock prices.

The remainder of this paper is structured as follows: Section 2 reviews the existing literature in the field of human behavioral dynamics and stock price movement. Section 3 establishes the data and methodologies. Section 4 presents empirical results and discussion. Finally, Section 5 concludes the paper.

2. Literature Review

2.1. Human Behavioral Dynamics

In recent years, numerous research fields have shown a keen interest in studying the statistical characteristics of human behaviors. Contrary to the past belief that human behaviors occur randomly, researchers have found that these behaviors, in fact, possess unique patterns. One notable observation is that human behaviors, often described using a Poisson process, do not entirely conform to randomness. As Oliveira and Barabasi [3] and Malmgren, et al. [4] investigated the inter-event time distribution—the time intervals between consecutive events in daily life and work—they discovered that human behaviors exhibit inhomogeneous features, characterized by bursts and heavy tails. Specifically, the inter-event time distributions tend to follow a right-skewed power-law shape. Since then, human dynamics research has garnered significant attention, focusing on both temporal scaling laws [5, 6] in human communication, web access, work patterns, and circadian rhythms, as well as spatial scaling laws [7-9] in human mobility. Moreover, various dynamic mechanisms have been proposed to elucidate the genesis of this power-law distribution, including those by Brockmann, et al. [10]; Vázquez, et al. [11]; Zhou, et al. [8] and Wang and Guo [12].

In addition to the temporal-spatial scaling laws that have been explored from the standpoints of the individual, the collective, and the group, the fractal nature of human behaviors has also garnered significant attention from numerous scholars across various disciplines. For instance, Plerou, et al. [13] conducted a groundbreaking study that uncovered long-range correlations in the alterations of stock prices. In simpler terms, this implies that the trading activity tends to persist along the same trajectory as it did in the past for an extended period. Building upon this foundation, Paraschiv-Ionescu, et al. [14] delved deeper into the fundamental patterns exhibited in human physical activity and discovered a fractal structure that could potentially be disrupted by the onset of chronic pain.

Furthermore, more recent research by Rybski, et al. [15] has provided additional insights into the presence of temporal correlations within the individual activity of short-message communications. They demonstrated that the dynamics of individuals who are more active exhibit clear long-term correlations, further reinforcing the notion that human behaviors possess fractal characteristics.

All these collective findings indicate that human behaviors inherently exhibit fractal characteristics, manifesting in diverse aspects of our daily lives. Inspired by these groundbreaking studies, I have embarked on a distinctive research endeavor, exploring the fractal nature of human dynamics from a novel perspective, centered on library loans. This innovative approach enables us to delve into and comprehend the intricate relationships and patterns within human behaviors, offering a profound understanding of the intricate dynamics of human behavior. As people tend to repeat certain actions over time, the number of these events can be viewed as a time series. Defined as a set of quantitative observations recorded at specific time intervals and arranged in chronological order, time series holds significant practical and theoretical importance in various fields, including physics, biology, economics, and society. Theoretical physics serves as one of the fundamental origins of these ideas and methods, and applications of physical theories have yielded remarkable achievements in this domain. The study of time series is instrumental in discovering the underlying rules of observations and forecasting future trends. Time series analysis may serve as a powerful tool to investigate the intrinsic relationship between human behaviors across different time periods, furthering efforts in predicting and managing the intricate social system.

2.2. Behavioral Finance

De Bondt and Thaler [16] assert that investors' behaviors can significantly influence financial markets through the lens of behavioral finance. If the tenets of behavioral finance are valid, it is postulated that investors may exhibit excessive or inadequate reactions to price fluctuations or news, extrapolate past trends into future predictions, disregard the fundamental value of a stock, and be swayed by popular stocks and seasonal pricing cycles. These market factors, subsequently, shape the decision-making processes of investors in the stock market. Waweru, et al. [17] further identifies the factors that impact investors' decision-making: price variations, market intelligence, historical stock trends, consumer preferences, exaggerated reactions to price changes, and the underlying fundamentals of stocks.

Market efficiency, as defined by Trong Tuan [18] which postulates that market prices accurately reflect fundamental market characteristics and that excess returns tend to be neutralized over time, has been questioned by behavioral finance. Numerous studies have highlighted market anomalies that defy explanation through traditional financial theory, encompassing aberrant price fluctuations in relation to IPOs, mergers, stock splits, and spin-offs. Throughout the 1980s and 1990s, statistical anomalies persisted, indicating that existing standard finance models, if not erroneous, are likely incomplete. Research has shown that investors do not respond logically to new information, instead exhibiting overconfidence and altering their decisions based on superficial changes in investment information presentation [19]. In recent years, for instance, there has been significant media interest in technology stocks. Often, retrospective analysis reveals a positive bias in media assessments, potentially misleading investors into making flawed investment decisions. These anomalies suggest that the fundamental tenets of rational behavior underlying the efficient market hypothesis are not entirely accurate, necessitating a review of other models of human behavior, as explored in various social sciences [20].

Normally, changes in market information, fundamentals of the underlying stock and stock price can cause over/under-reaction to the price change. These changes are empirically proved to have a high influence on decision-making behavior of investors. Researchers are convinced that over-reaction [16] or under-reaction [21] to news may result in different trading strategies by investors and hence influence their investment decisions. Waweru, et al. [17] conclude that market information has a very high impact on making decision of investors and this makes the investors, in some way, tend to focus on popular stocks and other attention-grabbing events that are relied on the stock market information. Moreover, Barber and Odean [22] emphasize that investors are impacted by events in the stock market which grab their attention, even when they do not know if these events can result good future investment performance. Odean [23] explores that many investors trade too much due to their overconfidence.

These investors entirely depend on the quality of the market or stock information when making investment decisions. Waweru, et al. [17] suggest that stock price fluctuations influence their investment behavior to a certain extent. Odean [24] observes that investors tend to prefer purchasing stocks that have experienced higher price changes over the past two years rather than selling them. In this context, a change in stock price can be viewed as a market occurrence that captures investors' attention. Furthermore, Caparrelli, et al. [25] postulate that investors are influenced by a herding effect and are inclined to follow the trend when price changes occur. Additionally, investors may revise their inaccurate estimates of stock returns in response to price changes, thereby affecting their investment decision-making process.

Many investors often gravitate towards popular or highly sought-after stocks in the market. As Odean [24] suggests, investors typically select stocks that capture their attention. Additionally, the choice of stocks also hinges on investors' personal preferences. Momentum investors, for instance, may favor stocks with robust recent performance, while rational investors tend to dispose of past losers, a strategy that can aid in tax deferment. Conversely, behavioral investors prefer to sell their former winners to mitigate the regret associated with potential losses stemming from their stock trading decisions. Furthermore, Waweru, et al. [17] explore how past stock trends influence investors' decision-making behavior to a certain extent. In this regard, investors often analyze past stock trends through technical analysis methods before committing to an investment.

In general, market factors are not included in behavioral factors because they are external factors influencing investors' behaviors. However, the market factors influence behavioral investors and rational investors in different ways, so that it is not adequate if market factors are not listed when considering the behavioral factors impacting the investment decisions.

2.3. Herding Effect

The herding effect in financial markets is widely acknowledged as a clear tendency among investors to mimic the actions of their peers. This behavior is not taken lightly in the industry, as it is understood that excessive reliance on shared data, rather than individual insights, can significantly skew the pricing of securities from their intrinsic values. Such distortions have the potential to negate numerous promising investment opportunities that may arise in the current environment. Therefore, the implications of herding investment prospects cannot be underestimated.

In the academic world, the herding effect also garners significant attention from researchers. This is due to two primary reasons. Firstly, the herd mentality can have a profound impact on the fluctuations of stock prices, thereby altering the risk-return characteristics of investment models. These changes, in turn, have the ability to reshape the foundations of asset pricing theories. Secondly, the presence of herding can foster various emotional biases among investors, including but not limited to the desire for conformity, the need for consistency, cognitive dissonance, home country bias, and the dissemination of rumors. These factors further compound the complexity of the investment decision-making process.

Kallinterakis, et al. [26] suggest that investors may follow trends, thinking it brings insights. But financial experts' performance is assessed through subjective reviews. In this competitive environment, mimicking peers may falsely boost reputation. Less skilled investors mimic experts to strengthen their standing. In the security market, herding investors mimic mass decisions on stock trading. Conversely, informed investors disregard herd behavior, enhancing market efficiency. Herding contributes to inefficient markets marked by speculative bubbles. Herding investors resemble prehistoric men, lacking knowledge and seeking safety in groups [25]. Elements affecting herding include overconfidence and investment volume. Confident investors rely more on private information, reducing herd tendencies. High-volume investors tend to follow the crowd for perceived risk reduction. Individual investors are more prone to herds than institutional investors [27].

Waweru, et al. [17] propose that herding can drive stock trading and create the momentum for stock trading. However, the impact of herding can break down when it reaches a certain level because the cost to follow the herd may increase to get the increasing abnormal returns.

Previous studies report that investors decrease the selling decisions of assets that get a loss in comparison to the initial purchasing price, a trend called the disposition effect. Odean [23] confirms the same conclusion that individual investors tend to sell stocks which their values, in comparison to their original buying price, increase rather than sell the decreasing stocks. However, it is difficult to demonstrate this phenomenon in the rational ground. It is not really reasonable to conclude that investors rationally sell winning stocks because they can foresee their poor performance. Besides, he also recognizes that the average return of sold stocks is greater than that of the average return of stocks that investors hold on. Genesove and Mayer [28] state that investors who sell their assets at the price less than original purchase price usually expect the selling price is more than other sellers' asking price. It is not only the expectation of the sellers, but also the correction of the market decides the selling price: investors encountering a loss often do the transaction at the relatively higher price than others. Coval and Shumway [29] find that investors, according to prospect theory, having gains (losses) in the first half of trading day tend to take less (more) risk in the second half of trading day. Grinblatt and Han [30] claim that the behavior of investors which is described as the disposition effect can be considered as a puzzling characteristic of the cross-section of average returns, called momentum in stock returns. In which, investors prefer selling stock that has helped them to gain capital.

Selling pressure can slow stock prices, leading to higher returns. In contrast, stockholders facing capital losses may sell only when an expected price is met, initially raising prices but later resulting in lower returns. Odean [24] offers insights on preferred stocks for individual investors. Selling decisions prioritize winning stocks, while buying decisions consider both prior winners and losers. Buying decisions may be driven by an attention effect, where investors buy stocks that catch their interest, often due to significant past performance. According to Barberis and Thaler [31] individual investors seem to be less impacted by attention-grasping stock for their selling decisions because the selling decision and the buying decision are differently run. Because of short-sale restraints, when deciding to choose a stock for selling, they can only focus on the stocks that currently belong to them. Whereas, with a buying decision, individuals have a lot of chances to choose the wanted stocks from the wide range of selective sources, this explains why factors of attention impact more on the stock buying decisions than the selling decisions. Barber and Odean [22] already prove that the selling decisions are less determined by attention than buying decisions in case of individual investors. To give this conclusion, they create the menu of attention-grasping stocks with several criteria: unusually high trading volume stocks, abnormally high or low return stocks, and stocks including news announcements. Eventually, the authors explore that the individual investors in their sample are more interested in purchasing these high-attention stocks than selling them. As such, from the viewpoints of behavioral finance, the investor behaviors impact both selling and buying decisions at different levels, and then they also impact the general returns of the market as well as the investment performance of individuals.

3. Data and Methodologies

3.1. Theoretical Background

To explore the attributes of stock returns and risk within the context of a jump-diffusion process, I adopt the methodology outlined by Jiang and Oomen [32] to derive a continuous-time representation of return and variance. Mathematically, under the established framework, the holding-period return can be formulated as:

$$R_t = \frac{dS_t}{S_t} = \alpha_t dt + V_t^{1/2} dW_t + J_t dq_t \qquad (1)$$

where α_t is the instantaneous drift, V_t is the instantaneous variance when there is no jump, J_t is a random variable representing jumps in the asset price and q_t is a ($\mathfrak{F}_t$)-counting process with finite instantaneous intensity. Applying Ito's lemma to equation (1), I obtain the corresponding dynamics process of variance:

$$Var_t = [dlnS_t]^2 = V_t dt + J_t^2 dq_t \tag{2}$$

From the Equations (1) and (2), the dynamics of stock return and variance depend both on a continuous procedure, $\{dt, dW_t\}$ and a jump procedure dq_t, and thus both return and variance should theoretically follow certain dynamic procedures. Moreover, combine Equations (1) and (2) should generate an implied relation between return and variance as:

$$R_t = F[Var_t, \{dt, dW_t, dq_t\}] \tag{3}$$

Based on Equation (3), stock returns should be theoretically influenced by their variances under the framework of jump-diffusion process.

3.2. Data and Summary Statistics

To analyst the properties of return movement comprehensively, I obtain daily, weekly, and monthly data of close prices and holding period returns for all public-listed firms in Chinese markets form CSMAR database. The sample period covers from January 2, 2018, to December 31, 2022. The summary statistics for close prices and holding period returns are reported in Table 1.

Table 1.
Summary statistics.

	Daily		**Weekly**		**Monthly**	
	Close price (Yuan)	**Return (%)**	**Close price (Yuan)**	**Return (%)**	**Close price (Yuan)**	**Return (%)**
Mean	19.69	0.06	19.63	0.13	19.54	0.48
Std. dev.	41.52	4.33	41.51	6.83	41.53	14.35
P5	2.76	-4.53	2.75	-9.49	2.72	-0.18
P25	5.70	-1.48	5.69	-3.46	5.63	-7.62
Median	10.23	0.00	10.20	-0.19	10.12	-0.99
P75	20.06	1.35	20.00	3.06	19.86	6.48
P95	60.61	4.91	60.40	10.75	60.23	23.51
N	5,007,117		1,060,226		249,137	

Table 1 presents summary statistics of all the variables in this paper. For the close prices, the average values of daily, weekly, and monthly are similar; the average stock price in Chinese market is nearly 20 yuan. Moreover, comparing the average prices to the percentiles, the mean prices are much larger than median prices, and almost equal to the 75th percentiles, indicating the closing prices are heavily positively skewed. There are few firms with high stock prices and lots of firms with low stock prices.

On the other hand, the return distributions are less skewed, but still unsymmetric. The average stock returns are all positive (although very small), but the median returns are all non-positive; the mean returns are all larger than median returns. Furthermore, the standard deviation of returns is around 50 times of mean returns, indicating stocks price occur small growth but large volatiles in the past five years.

4. Empirical Results

4.1. Data Fitting and Simulation

In this section, I firstly fit the real data of closing prices and returns into the structure of jump-diffusion process and summarize the parameters and properties of the procedures. Table 2 shows the parameters of jump-diffusion process using the daily, weekly, and monthly returns of all stocks in Chinese market, as well as the errors of fitting.

Table 2.
Fitting of stock returns in jump-diffusion process.

	α_t (%)	V_t (%)	J_t	Fitting error (%)
Monthly return				
Market index	0.52	0.88	0.42	1.45
Individual average	0.66	1.81	1.52	9.59
Weekly return				
Market index	0.13	0.23	1.02	1.66
Individual average	0.17	0.40	2.49	7.72
Daily return				
Market index	0.03	0.05	3.22	2.83
Individual average	0.04	0.08	5.43	5.85

In Table 2, the fitting errors for all returns are relatively small; below 3% for the market index and 5%-10% for the individual stocks on average. The result suggests that the jump-diffusion process captures most parts of the return movements for Chinese stocks.

Furthermore, the parameters of continuous procedure, $\{\alpha_t, V_t\}$ increase as the data frequency becomes smaller, while the parameter of jump procedure, J_t reduces as the data frequency becomes smaller. For example, the average return of the market index increases from 0.03% in daily return to 0.52% in monthly return, but the jump of market index reduces from 3.22 in daily return to 0.42 in monthly return. The result suggests that the continuous procedure has long-run impacts, and the results are cumulated as the statistic window becomes longer. However, the jump procedure is stochastic, and the long-run effects are smaller due to the offset of long-run results.

To investigate the fitting results clearly, I plot the cumulative density function of market returns. Figures 1 to 3 represent the cumulative density function of real data and fitting data based on monthly, weekly, and daily data, respectively. In all figures, the real distributions and fitting distributions are very close; the real return increases a little faster in the middle range of the cumulative density functions.

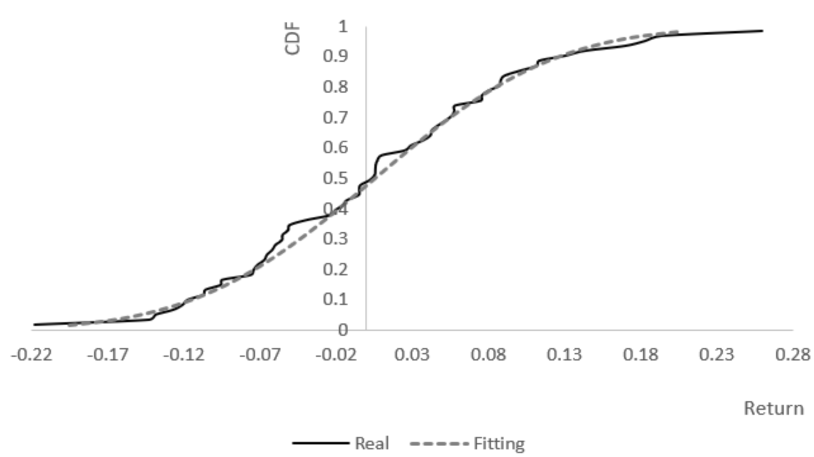

Figure 1.
Fitting for monthly return of market index.

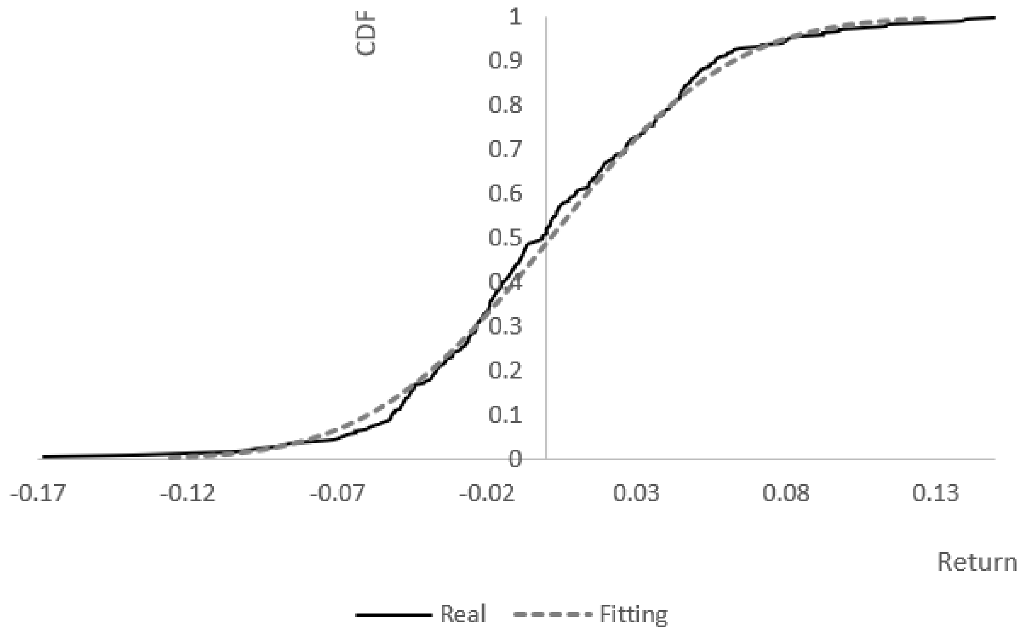

Figure 2.
Fitting for weekly return of market index

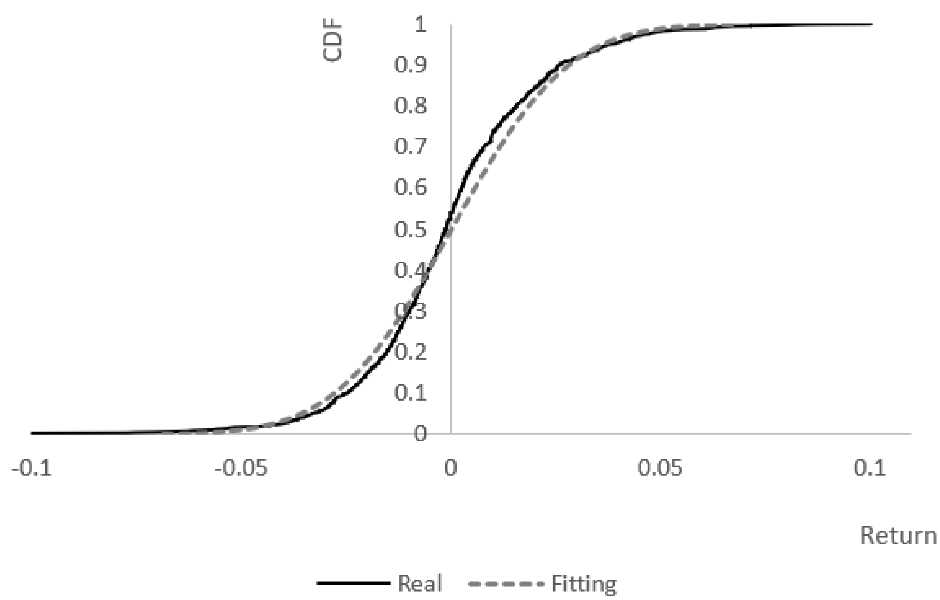

Figure 3.
Fitting for daily return of market index.

4.2. Return Predictability of Jumps

To delve into the predictability of returns associated with the jump components in estimated returns, I initially adopted a singular sorting methodology to construct equal-weighted quintile portfolios. At the conclusion of each month, individual stocks are systematically categorized into five distinct groups, contingent upon their respective jump components. The comprehensive findings are concisely presented in Table 3. The data in the designated column meticulously outlines the portfolio returns during the formation month as well as the subsequent month, which are derived from the sorting criteria encompassing both the aggregate daily jump within the formation month and its average. It is imperative to note that due to the inherent variation in trading days among individual stocks, the outcomes derived from these two sorting methodologies are not entirely congruent. Specifically, the row labeled "5-1" encapsulates the disparity in average monthly returns between portfolio 5 and portfolio 1. Additionally, the t-statistics are presented within square brackets for further statistical analysis.

Table 3.
Post-one-month returns and variations of jump-sorted portfolios.

Rank	By mean of jump	In-sample return	Out-of-sample return	By sum of jump	In-sample return	Out-of-sample return
1		-1.44	0.52		-1.43	0.53
2		-1.59	0.81		-1.61	0.80
3		-1.02	0.71		-1.02	0.70
4		1.04	0.57		1.02	0.57
5		5.78	-0.06		5.80	-0.05
5-1		7.22***	-0.58*		7.23***	-0.58*
		[9.86]	[-1.65]		[9.91]	[-1.66]

In Table 3, with the increase in jump values, the average monthly returns in the formation month significantly increase, especially from portfolio 4 to 5. The main reason is that the jump is usually positive for the region of positive return, while it is negative for negative return area for daily frequency (shown in Figure 3). For the out-of-sample performances, the portfolio returns significantly decreased as the jump components increase in the previous month, although the magnitudes are smaller than those in the in-sample analysis. The results indicate that the stocks with large jumps tend to reverse in the following month.

4.3. Portfolio Applications

In portfolio management, market timing and arbitrage are two equally valuable strategies. In this section, I employ empirical findings pertaining to the correlations between jumps and returns to devise portfolios that adhere to these two strategies, with the aim of achieving superior returns.

Our market timing portfolio strategy involves constructing a portfolio by taking long positions in stocks that fall within the bottom quantile, based on their jump levels (portfolio 1). Additionally, I consider an arbitrage strategy for portfolio construction. When examining the relationship between jumps and returns, I devise a long-short trading strategy that addresses the influence of jump levels. Specifically, I simultaneously take short positions in the quantile with the highest jump levels (portfolio 5) and long positions in the quantile with the lowest jump levels (portfolio 1). Both of these trading strategies involve rebalancing the portfolios at the conclusion of each month within our sample period.

Figure 4 depicts the evolution of the net portfolio value over time. Initially, all portfolios were evaluated at $100 in January 2018. The solid black line depicts the value trajectory of the long-short arbitrage portfolio, the solid gray line represents the pure-short market timing portfolio, and the black dashed line illustrates the value of the market portfolio. According to the graphical representation, the long-short portfolio exhibits a higher value than the market portfolio, while simultaneously demonstrating the lowest volatility. Additionally, the pure-long portfolio also surpasses the market portfolio in terms of value, albeit with a higher degree of volatility compared to the long-short strategy. It is noteworthy that, prior to the inclusion of costs, the effective annual returns for the long-short portfolio, the pure-long portfolio, and the market portfolio are 6.34%, 4.40%, and 0%, respectively. This trend underscores the potential of a jump-based investment strategy to create a high-performing portfolio and generate abnormal returns.

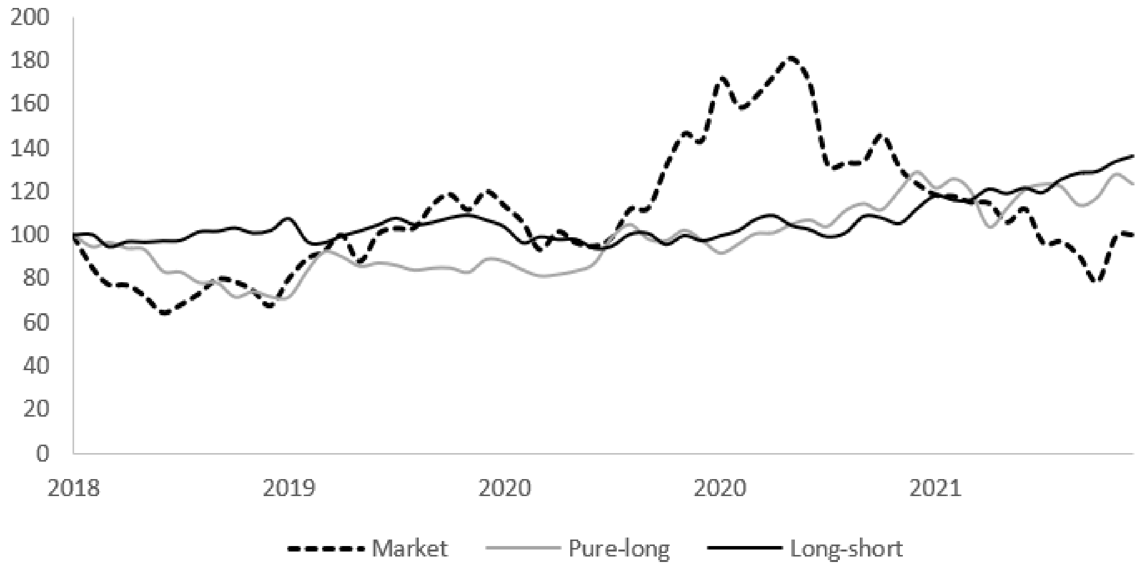

Figure 4.
Values of jump-sorted and market portfolios.

I also compare the mean return, standard deviation, and Sharpe ratios of our jump-based portfolios and market index in Table 4. Both pure-long and long-short portfolios show larger average returns and lower standard deviations than the market portfolio; the Sharpe ratio of long-short portfolios are four times as that of market index, and the Sharpe ratio of pure-long portfolios are also twice as that of market index.

Table 4.
Return, risk, and Sharpe ratios of ESG trading strategies.

	Average return (%)	Standard deviation (%)	Sharpe ratio
Mean-jump pure-long portfolio	0.52	5.70	0.06
Mean-jump long-short portfolio	0.58	3.36	0.12
Sum-jump pure-long portfolio	0.53	5.70	0.06
Sum-jump long-short portfolio	0.58	3.37	0.12
Market	0.44	9.38	0.03
3-month government bond rate (Risk-free)	0.17		

To conclude, our empirical analyses have uncovered significant practical insights. Firstly, I have scrutinized the post-one-year returns of jump-sorted portfolios, confirming a markedly negative correlation between jumps and subsequent returns. Secondly, these findings hold immense potential for portfolio strategies, enabling the construction of arbitrage portfolios that outperform traditional benchmarks, including market indices.

5. Conclusion

The stock market transforms into a convoluted nonlinear dynamic system, predicting the fluctuations of stock prices remaining a pivotal area of research within the financial realm. The market is intricately influenced by a myriad of factors, including economic conditions, political landscapes, national policies, investor sentiments, and adjacent markets, resulting in exceptionally intricate dynamic characteristics. Conventional time series models struggle to adeptly tackle such intricate nonlinear challenges. Consequently, this paper harnesses the principle of human behavior dynamics and constructs an analytical framework rooted in the jump-diffusion process, aiming to discern the nuances of stock returns.

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Theoretically, the process of stock price fluctuations is discontinuous, characterized by jumps rather than continuous flow. The volatility of financial asset returns constitutes a pivotal aspect of asset pricing and financial risk management, with jumps being a crucial component of yield volatility. The economic rationale behind this jump component is intimately tied to the diverse market behaviors exhibited by investors. This contribution is two-pronged. Firstly, the paper endeavors to embark on an exploration of human behavior dynamics, thereby constructing a comprehensive model that encapsulates the intricate intricacies of stock price movements. Secondly, the analysis delves into the similarities observed in the time intervals of stock price fluctuations across various spatial and temporal dimensions, ultimately laying a robust theoretical foundation for macroeconomic predictions pertaining to stock prices.

On the empirical front, I demonstrate the existence of a reversal jump-return relationship and its significant predictive capacity for next-month portfolio returns. Drawing from the data of the Chinese stock markets, several notable regularities emerge. Firstly, a high jump level predicts lower returns in the subsequent month. Secondly, portfolios constructed based on jump levels, including pure-long and long-short portfolios, outperform the market portfolio. As a result, this finding is highly beneficial for practitioners due to its low implementation requirements and substantial potential for generating abnormal returns.

Transparency:

The author confirms that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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