Asian Economic and Financial Review
ISSN(e): 2222-6737
ISSN(p): 2305-2147
DOI: 10.55493/5002.v15i9.5585
Vol. 15, No. 9, 1395-1405.

URL: www.aessweb.com

Relation between discontinuous variation and stock return movement based on poisson process: Evidence from China

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Article History
Received: 8 May 2025
Revised: 17 July 2025
Accepted: 15 August 2025
Published: 16 September 2025

Keywords
Chinese stock market
Discontinuous variation
Poisson distribution
Portfolio strategies
Return predictability
Sharpe ratio.

JEL Classification:
C14; C53; G11; G12.

ABSTRACT

This study constructs an analytical framework grounded in the principles of Poisson distribution and the process of discontinuous variation. Through empirical examinations conducted on all publicly listed firms in Chinese stock markets, the research uncovers an inverse relationship between the discontinuous variance of stock returns from the preceding month and the stock returns of the subsequent month. Statistically, the average monthly return of the portfolio with the lowest discontinuous variation is 1.32%, and the average monthly return of the portfolio with the highest discontinuous variation is 0.30%, indicating that an increase in discontinuous variance by 1 unit is associated with a subsequent decrease in stock returns of 1%, on average. Furthermore, portfolios engaged in long-short arbitrage, which are formulated based on sorting portfolios of different discontinuous variances, exhibit superior performance compared to the market portfolio. The effective annual return of this long-short portfolio is 1.44%, which is larger than that of the market index (1.19%). Also, the Sharpe ratio of the long-short portfolio is 0.19, which is almost double that of the market index (0.10). The results of portfolio performance suggest that trading strategies based on Poisson distribution and discontinuous variation sorting possess a significant capacity to generate abnormal returns.

Contribution/ Originality: The contribution of this paper is threefold. First, I developed a comprehensive model to capture the stock return's complex movement based on the principles of human behavioral dynamics. Second, using return data from the Chinese stock market, I empirically tested the pattern of return movement of individual stocks and market indices, based on the approach of Poisson distribution simulation. Third, according to my empirical results, I developed pure long and long-short trading strategies and demonstrated that these strategies could generate superior portfolio returns.

1. INTRODUCTION

Since its inception in 1989, China's stock market has operated under a provisional framework, witnessing nearly three decades of significant progress. As of December 2022, the Shanghai and Shenzhen stock exchanges collectively host 4,917 listed companies, boasting a combined market capitalization of RMB 78.8 trillion. Despite these notable accomplishments, the Chinese securities market lags behind its mature counterparts in Europe and the United States in terms of development. Nevertheless, it is evident that China's stock market, as it continues to develop and grow, harbors substantial unrealized potential and is set to emerge as a pivotal element of the financial ecosystem. However, forecasting stock returns within the Chinese market presents formidable challenges, primarily due to two factors: firstly, the market is subject to unique influences such as governmental policies, regulatory shifts, and the conduct of retail investors, which may contravene the assumptions of classical asset pricing theory regarding independence;

secondly, the market's high volatility and frequent interventions complicate the modeling of events through simplistic models like the Capital Asset Pricing Model (CAPM).

To address these two problems, this paper examines the properties of stock returns for Chinese publicly listed companies, drawing on the theory of human behavioral dynamics and the approach of Poisson distribution simulation. The fundamental postulates of the Poisson distribution include the independence of events from one another, the constancy of the average occurrence rate over time, and the assumption that the probability of multiple events occurring within an extremely brief period is insignificant. Consequently, the simulation of the Poisson distribution has been applied in financial domains for purposes such as risk management, where it is used to estimate the probability of rare events; algorithmic trading, for modeling the flow of orders or the arrival of trades; and derivative pricing, through the integration of asset price fluctuations that include jumps, as facilitated by Poisson-based models.

The delineation of asset market price behavior is imperative not only for accurate investment decisions by investors in the underlying assets but also constitutes the foundation for valuing derivatives. The progression of stock price volatility is discontinuous, manifesting as a series of jumps. The volatility of financial asset returns is a pivotal element in asset pricing and financial risk management, with jumps being a significant component of return volatility. Kou (2002) introduced a bi-exponential jump-diffusion model, wherein the logarithm of the magnitude of jumps, composed of Poisson processes, adheres to an asymmetric bi-exponential distribution. This model adeptly captures the peak and heavy tail phenomena, as well as the volatility smile, and is capable of furnishing closed-form solutions for European options. In existing research concerning jump-diffusion models, the emphasis has predominantly been on the outcomes of jump behavior, typically presumed to be governed by a Poisson process.

Using the Poisson process to analyze Chinese stock markets offers several advantages. First, the Poisson process can examine the properties of transactions and returns within a specific period. Second, it can capture extreme events in the stock markets, which aligns with the jump-diffusion process. Third, the Poisson process can be applied to analyze intra-day transactions, providing a foundation for high-frequency data analysis.

The following sections are organized as follows: Section 2 summarizes the existing literature on human behavioral dynamics and behavioral biases in the stock market. 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 and Poisson Distribution

Systems theory posits that humans constitute a complex system, divided into two subsystems: individuality and sociality. The interconnectedness of the entire world is a fundamental concept within systems theory. The application of systems theory and complexity science to elucidate human behavior has emerged as a popular research area. In recent times, many fields have shown a strong interest in analyzing the statistical patterns of human behavior. Contrary to the previous notion that human behavior is random, studies have revealed that these behaviors display distinct patterns. A significant finding is that human behavior, commonly modeled by a Poisson process, does not fully align with randomness. Oliveira and Barabási (2005) and Malmgren, Stouffer, Motter, and Amaral (2008) examined the distribution of inter-event times the gaps between successive events in daily activities and work and found that human behavior exhibits heterogeneous patterns, with bursts and heavy tails. Specifically, the distribution of inter-event times tends to be right-skewed and power-law shaped. Consequently, human dynamics research has attracted considerable interest, focusing on temporal scaling laws (Dezsö et al., 2006; Gonzalez, Hidalgo, & Barabasi, 2008) in human communication, web usage, work habits, and circadian rhythms, as well as spatial scaling laws (Han, Zhou, & Wang, 2008; Song, Qu, Blumm, & Barabási, 2010; Zhou, Kiet, Kim, Wang, & Holme, 2008) in human mobility. Additionally, various dynamic mechanisms have been proposed to explain the emergence of this power-law distribution, including those by Brockmann, Hufnagel, and Geisel (2006); Vázquez et al. (2006); Zhou et al. (2008) and Wang and Guo (2010). Beyond the temporal-spatial scaling laws studied from individual, collective, and group perspectives, the fractal nature of human behavior has also drawn significant attention from scholars across multiple disciplines. For example, Plerou, Gopikrishnan, Amaral, Gabaix, and Stanley (2000) conducted a pioneering study that revealed long-range correlations in the fluctuations of stock prices. In essence, this indicates that trading activity tends to follow a similar path over an extended period. Building on this, Paraschiv-Ionescu, Buchser, Rutschmann, and Aminian (2008) explored the fundamental patterns in human physical activity and identified a fractal structure that could be disrupted by chronic pain. More recent research by Rybski, Buldyrev, Havlin, Liljeros, and Makse (2009) has shed light on the presence of temporal correlations within the individual activity of short-message communications. They showed that the behavior of more active individuals exhibits clear long-term correlations, further supporting the idea that human behavior has fractal properties.

Over an extended period, the absence of contemporary statistical tools and methodologies, coupled with the simplification of complex issues, has led to widespread acceptance of the notion that human behavior occurs uniformly. This perspective posits that lengthy periods of inactivity and brief bursts of activity are negligible. In essence, human behavior has been characterized as adhering to Poisson processes, where the time intervals between behaviors follow a negative exponential distribution, and the frequency of events aligns with a Poisson distribution. Yang and Zhang (2005) employed the Poisson distribution to examine three fundamental characteristics of financial time series data: the presence of fat tails, excess kurtosis, and the phenomenon of volatility clustering. Zhao (2012) conducted an analysis of the dynamic properties of Chinese stock prices, utilizing dynamic Poisson procedures, and provided empirical evidence that supports the practices of portfolio management and asset pricing within the Chinese financial markets. Liu and Zeng (2013) proposed that, given a specific number of stock market participants, the number of investors who place buy orders can be modeled using the Poisson distribution. Tang (2018) applied the principles of Poisson distribution theory to ascertain that, under a 5% blow-out threshold, the likelihood of a single business day experiencing a significant downturn in Chinese stock markets is relatively small. However, this probability substantially increases once the cumulative number of trading days reaches 208, and it is highly probable that at least one such event will occur, with a 99% confidence level.

2.2. Behavioral Bias in Stock Markets

De Bondt and Thaler (1995) posited that the conduct of investors exerts a substantial influence on financial markets when examined through the framework of behavioral finance. They contended that if the principles of behavioral finance are valid, it is postulated that investors may exhibit responses to price volatility or news that are either excessively exaggerated or inadequately responsive. They tend to forecast stock returns based on historical movement trends, ignoring the stock's intrinsic value, and emphasize cyclical patterns in stock returns, such as the seasonal effect and the week effect. Waweru, Munyoki, and Uliana (2008) further discuss the asset pricing factors in decision-making, which include return volatility, information asymmetry, historical trends, consumer tendencies, and the firm's other fundamental properties. Due to cognitive and emotional biases, investors might make decisions that are inconsistent with traditional investment theories.

Under normal market conditions, investors might overreact or underreact to certain market information. Empirical results show that this information has a significant impact on investors' decision-making. Existing literature indicates that overreacting (De Bondt & Thaler, 1995) and underreacting (Lai, Low, & Lai, 2001) towards news lead to different trading strategies. Waweru et al. (2008) demonstrate that market information has essential impacts on investors' decision-making, which causes popular stocks and worthy events to draw more attention. Additionally, Barber and Odean (2001) emphasized that investors are swayed by stock market events that capture their attention, even when they are uncertain about the potential for favorable investment outcomes in the future. Odean (1999) has explored the phenomenon that numerous investors engage in excessive trading due to their overconfidence in their capabilities.

Investors frequently exhibit a propensity to select stocks that are popular or in high demand within the market, as these securities tend to attract the collective focus of the investment community. Odean (1999) posits that investors typically choose stocks that have garnered their attention, which is often a consequence of the stocks' prominence or the fervor surrounding them. Moreover, the selection of stocks depends on investors' personal inclinations and their distinct investment methodologies. For example, momentum investors always prefer stocks with historical gains and believe that the historical winners have a higher probability of generating higher returns in the future. On the other hand, long-term and conservative investors tend to sell underperforming stocks, which allows for tax deferral. However, behavioral investors often sell stocks that have positive returns, which guarantees gains and helps avoid potential losses.

Other literature proposes that investors perform a technical analysis of a stock's historical performance before making decisions. Therefore, decision-making heavily relies on the quality of market and stock information data. Waweru et al. (2008) demonstrate that stock volatility significantly influences investment behaviors. Odean (1999) suggests that investors prefer stocks with significant price changes in the previous two years. Caparrelli, D'Arcangelis, and Cassuto (2004) show that investors tend to follow trends when price changes occur, which is consistent with the herding effect. The possible reason is that the cluster decision is always labeled as an unbiased estimation. Also, investors may adjust their inaccurate estimations of stock returns in response to real price movements.

2.3. Prospect Properties in Stock Markets

The prospect theory was initially developed by Kahneman and Tversky (1979). The theory shows that investors typically evaluate their utility based on gains and losses rather than on the returns of their assets. Therefore, they develop the evaluation of investment choices based on a pre-determined reference point. The theory also discusses the concept of loss aversion, indicating that investors dislike losses rather than risks. Tversky and Kahneman (1991), Benartzi and Thaler (1995), and Genesove and Mayer (2001) empirically show that investors are risk-averse when faced with potential gains and concert to risk-seeking when threatened by potential losses. Kőszegi and Rabin (2006) and Kőszegi and Rabin (2009) propose that the reference point is determined by the investor's expectations of future returns or a summary of recent past returns. The underlying assumption is that investors consistently execute an optimal strategy and subsequently compare their actual outcomes against the distribution of potential investment results. The utility derived by investors is contingent upon the disparity between the realized outcome and the anticipated outcome. Within this research paradigm, such utility is termed reference-dependent utility, which emerges from a modification to quadratic utility: above the reference point, a concave utility curve is observed, whereas below the reference point, a convex utility function that deviates from the standard is noted.

Prospect Theory fundamentally challenges the assumption of perfect rationality that is typically presumed by traditional mean-variance utility maximization theorists. Consequently, this theory is considered capable of bridging the gap between empirical evidence from the perspective of behavioral finance and the portfolio selection approach developed in an idealized world. One such idealized model is the CAPM. However, this model has a significant limitation: it is inconsistent with empirical evidence. Numerous empirical studies have indicated that, in comparison to the theoretical intercept predicted by the CAPM, the real-life security market line should exhibit a higher intercept and a lower slope. This discrepancy was noted by researchers such as Friend and Blume (1970), Black, Jensen, and Scholes (1972), and Blume and Friend (1973). To address this shortcoming of the CAPM, the asset pricing literature has developed more advanced asset pricing models in various directions. Merton (1973) introduced the Intertemporal CAPM (ICAPM), which aimed to incorporate an investor's decision-making behavior beyond the current period. Building on the ICAPM, numerous multi-factor empirical models have been proposed to better capture the covariance in security returns and relevant future-state variables, as seen in the works of Fama and French (1993); Fama and French (1996), and Carhart (1997). Other extensions of the CAPM include models that consider higher moments of return distributions, such as those proposed by Kraus and Litzenberger (1976), Harvey and Siddique (2000), and Dittmar (2002). Moreover, Todorov and Bollerslev (2010) and Bollerslev, Li, and Todorov (2016) develop models that include a dynamic price movement process.

To assimilate the fundamental principles of prospect theory into CAPM, Barberis, Huang, and Santos (2001) examined the influence of investors' loss aversion on fluctuations in the value of their financial wealth, predicated on the unrealistic assumption of a log-normally distributed dividend growth rate. Their study illustrated that incorporating a prospect-theoretic element into the conventional asset pricing framework could illuminate the empirically observed phenomena of high average returns, excessive volatility, and the predictability of stock returns. Barberis and Huang (2008) elaborated on the application of the probability weighting features of prospect theory to asset pricing and demonstrated the existence of a non-standard equilibrium where a security with positive skewness may be overvalued. Barberis, Mukherjee, and Wang (2016) provided empirical evidence supporting the modeling of asset prices based on the assumption that investors evaluate a stock's distribution by prospect theory. More recently, Barberis, Jin, and Wang (2021) introduced a novel asset pricing model wherein investors assess risk by prospect theory and documented its effectiveness in explaining a series of market anomalies. Although these studies aim to incorporate elements of prospect theory from various perspectives, their models are based on relatively stringent conditions, making direct empirical testing of the CAPM problematic. This body of literature establishes a prospect-based return generation process founded on a specific exponential value function (Barberis et al., 2016), thereby making the outcomes heavily dependent on the parameters of the value functions. In contrast, this paper derives the return generation process through the classical utility optimization procedure, positing a convex utility function in the context of losses.

3. DATA AND METHODOLOGIES

3.1. Theoretical Background

The theoretical setting begins with the classical Bernoulli trial, in which an experiment with two outcomes whether extreme events occur or not is conducted within a certain period. Therefore, the accumulated effects of multiple extreme events during a sample period can be simulated using repeated Bernoulli trials or the Poisson distribution.

Given stable market conditions, the probability of the stock return reaching a certain threshold is relatively stable. Therefore, whether the stock return reaches the threshold return could be considered as a Bernoulli Trial. Mathematically, assume X quantifies the number of times the stock return reaches the threshold return within n business days, and the probability of the stock return reaching the threshold return on each individual business day is p, and then.

$$P\{X = k\} = \binom{n}{k} p^k (1-p)^{n-k} \qquad (1)$$

If the threshold return is large enough and the examination window is long enough, the above distribution could be approximately estimated by a Poisson distribution with $\lambda = np$.

$$\lim_{n\to\infty} P\{X = k\} = \lim_{n\to\infty} \frac{\lambda^k}{k!}\left[\left(1-\frac{1}{n}\right)\ldots\left(1-\frac{k-1}{n}\right)\right]\left(1-\frac{\lambda}{n}\right)^n\left(1-\frac{\lambda}{n}\right)^{-k} = \frac{\lambda^k e^{-\lambda}}{k!} \qquad (2)$$

Tang (2018) shows that the estimation error is relatively small when $n \geq 20$ and $p \leq 0.05$. Furthermore, the conditional probability of the extreme return occurs one or more times (from $X = k$ to $X = k + 1$) follows.

$$P\{X = k+1 | X = k\} = \frac{P\{X=k+1\}}{P\{X=k\}} = \frac{\lambda}{k+1} \qquad (3)$$

Based on Equation 3, this conditional probability increases as λ increases and decreases as k increases. As a result, the total volatility of securities could be decomposed into a continuous part and a jump part as.

$$Var = \sigma_{con}^2 + \lambda\left[\mu_J^2 + \sigma_J^2\right] \qquad (4)$$

Where Var is the total volatility of a security, σ_{con}^2 measures the continuous variance without jumps, and $\lambda[\mu_J^2 + \sigma_J^2]$ measures the volatility caused by jumps. In the jump component, λ is Poisson parameter quantifies the frequency of extreme outcomes, μ_J^2 and σ_J^2 measures the jump magnitudes.

3.2. Data and Summary Statistics

To conduct a comprehensive analysis of the characteristics of return movements, I have undertaken the task of acquiring daily datasets that encompass the closing prices and holding period returns for all publicly traded companies listed on the Chinese markets. Following existing literature, I exclude firms in the financial sector and those that are designated as ST stocks. The daily return data is collected from the CSMAR database. To avoid the diminishment of discontinuous variation in the very long term, the sample period spans 10 years, from 2014 to 2023, and there are 8,040,190 daily observations. To facilitate a better understanding of the data, summary statistics pertaining to the closing prices and holding period returns have been meticulously compiled and are presented in a clear and organized manner in Table 1.

Table 1. Summary statistics (Raw daily data).

	Mean	Std.	Median	P5	P25	P75	P95
Closing prices	126.70	1,588.25	39.12	9.52	22.02	72.32	242.20
Return (%)	0.09	4.14	0	-4.56	-1.42	1.37	5.05

Table 1 offers a comprehensive statistical analysis, presenting the mean values, standard deviation, median, and various percentiles for both the unadjusted prices and returns of equities within the Chinese market. It is noted that the mean price of equities within this market is approximately 126 yuan per share. Upon closer inspection of the median price, it is significantly lower, at merely 39 yuan per share. This considerable disparity between the mean and median prices suggests that the distribution of equity prices within the Chinese market is characterized by a pronounced negative skewness. In essence, there exists a substantial quantity of equities with exceedingly high prices, which elevates the mean upwards, while the preponderance of equities is priced considerably lower. Additionally, the fact that the mean prices surpass the 75th percentile value highlights the positive skewness of the closing prices. This skewness implies that there is a relatively diminutive subset of entities with exceptionally high equity prices, whereas most entities have equity prices that are significantly lower. In juxtaposition to the price distribution, the distribution of returns appears to be approximately symmetrical. Nonetheless, it is imperative to recognize that the probability of encountering extreme outcomes in returns is markedly higher than what would be anticipated under a normal distribution. This asymmetry in the return distribution indicates that, although the returns may not be skewed in the same manner as the prices, they are prone to greater volatility and the potential for outliers.

To facilitate a comprehensive analysis of the dataset's attributes, I have undertaken the initiative to present summary statistics that delineate the average return and standard deviation for each stock monthly. This meticulous examination enables a more profound understanding of the dataset's temporal behavior. Specifically, Table 2 offers an exhaustive synopsis of the average values, standard deviations, medians, and various percentiles for both the average return and the standard deviation for each stock within each month. The dataset encompasses a significant number of monthly observations, totaling 403,211, thereby ensuring a rigorous analysis of stock performance trends.

Table 2. Summary statistics (Mean and std within a month).

	Mean	Std.	Median	P5	P25	P75	P95
Mean price	128.14	1,647.61	39.21	9.55	22.09	72.33	241.12
Mean return	0.18	3.04	0.01	-0.94	-0.32	0.39	1.33
Std of price	6.29	123.37	1.57	0.23	0.72	3.50	13.14
Std of return	2.90	4.48	2.43	1.08	1.73	3.42	5.64

In Table 2, the average prices show a similar pattern to raw daily returns, and the mean return still approximately follows symmetric distributions. However, the standard deviation of prices and returns within one month is positively skewed; while the mean values are larger than the median values and are located around the 75th percentiles.

4. EMPIRICAL RESULTS

4.1. Data Fitting and Simulation

In this section, I first fit the real data of closing prices and returns into the structure of a Poisson distribution and summarize the parameters and properties of the procedures. Table 3 shows the parameters of Poisson fitting using the daily returns within each month of all stocks in my sample.

Table 3. Fitting of stock prices and returns by Poisson distribution.

	σ_{Con}	λ	μ_J	σ_J
Closing price				
Mean	4.37	2.96	52.88	9.55
Standard deviation	64.26	1.26	882.64	183.97
Median	1.38	3.15	12.19	2.58
Return				
Mean	1.64	0.94	9.41	3.82
Standard deviation	3.38	0.10	18.57	1.28
Median	1.12	0.94	5.05	3.56

In Table 3, I have identified outcomes that lie beyond the range of positive and negative two standard deviations as extreme values. The rationale for this selection is to pinpoint outliers that markedly deviate from the norm. Upon meticulous examination, it becomes apparent that the average frequency of these extreme price fluctuations occurs approximately three days each month. This result implies potential patterns of extreme price movements. The frequency of extreme events is about once per month, indicating that the probability of such events is very low, but their severity is very high. Moreover, the magnitude of the jump components is significantly larger than that of the continuous components, which is consistent with the notion that jumps in financial markets always have critical impacts on asset prices.

4.2. Return Predictability of Poisson Variables

To investigate return predictability based on Poisson variables, I initially employed a single sorting methodology to construct equal-weighted quintile portfolios. At the end of each month, individual stocks are divided into five portfolios based on their Poisson variables for that month. All portfolios are rebalanced monthly. The comprehensive findings are succinctly presented in Table 4. I form monthly portfolios according to three distinct methods: by continuous variance (first row), by Poisson jump variance (second row), and by Poisson jump components (third row). I report the average portfolio returns in the holding month (t+1). 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 4. Post-one-month returns and variations of jump-sorted portfolios.

Group	1	2	3	4	5	5-1
Portfolios sorted by σ^2_{con}	1.21	1.33	1.21	1.05	0.32	-0.88* [1.90]
Portfolios sorted by $\lambda\sigma_J^2$	0.93	1.29	1.35	1.06	0.51	-0.42* [-1.81]
Portfolios sorted by $\lambda[\mu_J^2 + \sigma_J^2]$	1.32	1.32	1.21	0.98	0.30	-1.02** [2.62]

Note: ** p<0.05, * p<0.10.

Upon examination of Table 4, it becomes apparent that as Poisson variables increase, the average monthly returns throughout the holding period undergo a significant reduction. This pattern is notably accentuated during the transition from Portfolio 4 to Portfolio 5. The fundamental rationale behind this occurrence is that both continuous variance and Poisson variance are typically perceived negatively by investors. As a result, the short-term returns linked to elevated levels of variance tend to be diminished.

4.3. Portfolio Applications

In the domain of portfolio management, the methodologies of market timing and arbitrage are deemed to be of considerable significance. Market timing entails the strategic acquisition and divestment of assets to capitalize on short-term price fluctuations, whereas arbitrage concentrates on exploiting price differentials across disparate markets for identical assets. Within this specific segment, I draw upon empirical research outcomes that investigate the correlations between Poisson variables and investment returns. Through the application of these insights, I endeavor to construct portfolios that adeptly incorporate both market timing and arbitrage methodologies. The primary objective is to establish a portfolio that not only conforms to these methodologies but also aspires to attain enhanced returns by leveraging the statistical relationships identified.

Given that the return pattern in the third row of Table 4 is the most pronounced, I adopt this sorting methodology in this section. My market timing portfolio strategy entails forming a portfolio by assuming long positions in stocks that are within the lowest quantile, based on their jump levels (portfolio 1). Furthermore, I consider it an arbitrage strategy for portfolio formation. In examining the correlation between Poisson variables and returns, I developed a long-short trading strategy that accounts for the impact of $\lambda\left[\mu_J^2 + \sigma_J^2\right]$ levels. Specifically, I simultaneously establish short positions in the quantile with the highest levels of $\lambda\left[\mu_J^2 + \sigma_J^2\right]$ (portfolio 5) and long positions in the quantile with the lowest levels of $\lambda\left[\mu_J^2 + \sigma_J^2\right]$ (Portfolio 1). Both trading strategies necessitate the rebalancing of portfolios after each month within our sample period.

Figure 1 presents a detailed depiction of the evolution of the net portfolio value across various time intervals. Initially, it was observed that all portfolios were valued at 100 yuan in January 2014. The graph features a solid black line that meticulously delineates the trajectory of the long-short arbitrage portfolio's value over time. In juxtaposition, a black dashed line paired with a solid gray line illustrates the fluctuations in value of the pure-short market timing portfolio. The solid gray line on the graph signifies the progression of the market portfolio's value. Upon examination of the graphical data, it becomes apparent that both the pure long portfolio and the long-short portfolio have attained higher values than the market portfolio.

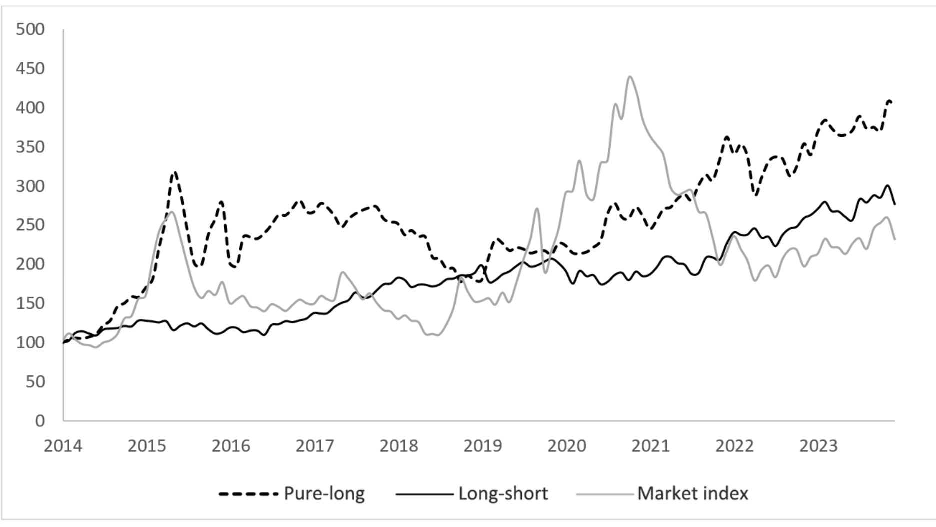

Figure 1. Values of jump-sorted and market portfolios.

However, it is particularly noteworthy that the long-short portfolio has demonstrated the least volatility among the three. Furthermore, upon closer inspection of the pure-long portfolio, it becomes evident that this portfolio has yielded the highest return in terms of portfolio value. Nonetheless, this is accompanied by a trade-off, as the pure-long portfolio also endures a greater degree of volatility compared to the long-short strategy. It is imperative to highlight 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 1.44%, 0.95%, and 1.19%, respectively.

In Table 5, I compare the average return, standard deviation, and Sharpe ratios between the Poisson-based portfolios and the market index. The results show that the pure-long portfolio, which only longs the portfolios with the smallest discontinuous variation, generates larger average returns and lower standard deviations compared to the market portfolio. Moreover, the long-short portfolio, which simultaneously longs the portfolios with the smallest discontinuous variation and shorts the portfolios with the largest discontinuous variation, generates the lowest volatility among all the portfolios, indicating that the long-short portfolio is well-diversified and exposed to low risk. Furthermore, the long-short portfolio generates the highest Sharpe ratio (0.19), almost double that of the market index, implying that the long-short portfolio earns nearly twice the risk-adjusted return compared to the market index. The Sharpe ratio of the pure-long portfolio is almost 70% greater than that of the market index, suggesting that the pure-long strategy not only provides higher average returns but also offers a more efficient return per unit of risk when compared to the market index.

Table 5. Return, risk, and Sharpe ratios of ESG trading strategies.

	Average return (%)	Standard deviation (%)	Sharpe ratio
Pure-long portfolio	1.44	7.30	0.17
Long-short portfolio	0.95	4.19	0.19
Market	1.19	9.92	0.10
3-month government bond rate (Risk-free)	0.17		

5. CONCLUSION

The stock market represents a complex nonlinear dynamic system, and the estimation of return volatility has become a critical topic in research related to financial investment. The stock price movement is affected by various factors, including economic variables, political factors, governmental policies, investor psychology, and market cointegration. Traditional time series models have difficulty effectively analyzing this complex nonlinear relationship. To address this issue, this paper introduces an analytical framework to examine the dynamics of the stock market. It is based on the Poisson process of stock return movement and establishes a theoretical approach to continuous variance and jump variance. From a theoretical viewpoint, stock price movements are not always continuous and smooth but also include discontinuous components. The Poisson process discussed in this paper, unlike the normal distribution in traditional theory, is more suitable for capturing these complex properties of price movements. The economic basis of this jump phenomenon is intricately linked to the varied behaviors exhibited by investors in the marketplace. This paper makes two significant contributions. First, it investigates the dynamics of human behavior and develops a Poisson modeling technique that encapsulates the intricate and subtle movements of stock prices and returns. Second, it examines the analogous temporal intervals observed in stock price fluctuations across various spatial and temporal scopes. This analysis aims to establish a robust theoretical foundation that can support macroeconomic forecasts related to stock returns. In the empirical domain, I substantiate the presence of an inverted Poisson volatility-return relationship and its substantial predictive power for subsequent monthly portfolio returns. Utilizing data from the Chinese stock markets, several significant patterns become apparent. Initially, the elevated levels of Poisson volatility forecast diminished returns in the ensuing month. Subsequently, portfolios established because of jump levels, encompassing both pure-long and long-short portfolios, exhibit superior performance compared to the market portfolio. Consequently, this discovery holds significant value for practitioners, as it necessitates minimal implementation efforts and offers considerable potential for generating excess returns.

Funding: This study received no specific financial support.
Institutional Review Board Statement: Not applicable.
Transparency: The author states that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
Data Availability Statement: Upon a reasonable request, the supporting data of this study can be provided by Jie Peng.
Competing Interests: The author declares that there are no conflicts of interests regarding the publication of this paper.

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