Analysis of the Impact of Leveraged ETF Rebalancing Trades on the Underlying Asset Market Using Artificial Market Simulation

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Abstract. Financial markets occasionally become highly volatile, as a result of a financial crisis or other factors. Previously, index futures trading and program trading have been singled out as direct causes of market destabilization, but more recently it has been suggested that leveraged ETFs (funds aimed at amplifying several-fold the movement of a price index such as the Nikkei Stock Average or underlying assets) rebalancing trades may also be a factor. This study uses a financial market simulation (artificial market) constructed virtually on a computer to assess the impact of leveraged ETF rebalancing trades on the underlying assets market. Analysis results showed that a larger amount of the managed assets of leveraged ETFs corresponds to a higher volatility of the underlying securities market. They also demonstrated that leveraged ETF trading can destroy the underlying assets market, if the leveraged ETF trading impact on the market is greater than that of ordinary volatility of the underlying assets.

1 Introduction

Over recent years, there have been repeated periods of high market volatility as a result of events such as the Global Financial Crisis and the Greek financial crisis. It was widely suggested that the direct cause of this market instability may have been index trading (e.g., the Nikkei 225 futures and S&P 500 futures) or automated (program) trading. More recently, however, leveraged exchange-traded fund (ETF) rebalancing trading has also been put forward as a possible cause for such instability.

A leveraged ETF is an ETF that aims at achieving a rate of return several times greater than that of the underlying asset (e.g., Nikkei 225). These kinds of ETFs invest in financial market indexes, so they are generally less risky than individual stocks, but through their use of leveraging, they are able to provide high returns, so the volume of assets under their management has dramatically expanded[3]. Leveraged ETFs have to execute rebalancing trades on a daily basis—that is, buy the underlying asset when its price goes up and sell it when it goes down—in order to maintain their level of leverage (i.e., to maintain the net asset value of the ETF at a predetermined multiple of the underlying asset exposure). For this reason, it is thought that this kind of trading causes destabilization in the prices of underlying assets[1][4].

To give an example, suppose a leveraged ETF based on the Nikkei 225 (Nikkei Stock Average) aims at achieving a return that is several times higher than that of the Nikkei average itself by means of trading in Nikkei futures. The rebalancing trades of this leveraged ETF are likely to be executed between the close of trading of the stock market and the close of trading of the Nikkei futures market[5]. The suggestion is that volatility becomes high during this period, resulting in market instability. It is feared that due to the price comovement between the Nikkei 225 and Nikkei futures, whenever a large volume of trading in Nikkei futures drives up volatility, the volatility of the Nikkei 225 will rise similarly, resulting in market instability.

A number of previous studies have tried to demonstrate the impact of leveraged ETFs on the underlying index. Cheng et al.[2] suggested that if the base index of an ETF moves 1% in one day, then the volume of rebalancing trading of a leveraged ETF may account for 16.8% of total trading in the index at the close of trading on that day. It has also been reported that volatility tends to become much higher than normal in times of economic recession and after a significant slump in share prices, and that this tendency increases with increases in the volume of rebalancing trading[3]. Since leveraged ETFs have become increasingly popular investment products in recent years, categorically stating that leveraged ETFs are the cause of increasing market volatility on the basis of these findings is not easy. On the other hand, Deshpande et al.[4] concluded that since leveraged ETFs accounted for a mere 0.0079% of trading in the S&P 500, their impact on the market is limited. Furthermore, Trainor Jr.[5] examined the impact of leveraged ETF rebalancing on the volatility of the S&P 500 by comparing the volatility before the close of trading on the previous day to the volatility after the start of trading on the following day but was unable to draw any firm conclusions.

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[3] In fact, the ETFs trade financial market index futures as underlying assets, as we cannot invest financial market indexes directly.

[4] Many Japanese and American leveraged ETFs invest financial market index futures and OTC options as underlying assets, respectively. Issuers of OTC options hold the index futures on behalf of leveraged ETFs and trade the futures to maintain their level of leverage. Therefore, even if the leveraged ETFs invest OTC options as underlying assets, the performance impacts on futures price formations as well as when the leveraged ETFs invest futures as underlying assets. The movement of financial market indexes such as the Nikkei 225 and S&P 500 is similar to the movement of the index futures due to the trade of arbitrage traders. Thus, whenever the volatility of index futures increases, the volatility of the indexes also increases.

[5] The closing time of the stock market is 15:00 and that of the Nikkei futures is 15:15.

Thus, previous studies that have focused on verification have come to very different conclusions regarding the impact of leveraged ETFs on the market. In addition, the various phenomena and factors involved in financial markets are many and complex, making it difficult to extract and analyze isolated factors in a verification analysis.

In light of this, one way of analyzing financial markets is to use an artificial market. An artificial market is a financial market multi-agent system that is simulated on a computer[6–8]. Agents are each assigned their own trading method and made to engage in trading financial assets as investors. It is then possible to observe how the market behaves. Conversely, by modeling and incorporating certain market-side restrictions (e.g., mechanisms to enhance market stability or efficiency), it is possible to observe how these affect the behavior of investors and how in turn this behavior impacts the market. Up to now, however, no study on leveraged ETFs based on this kind of market simulation has been conducted.

In view of all this, this study attempts to verify the impact of leveraged ETF balancing on the movement of underlying asset prices by implementing a leveraged ETF trading model in the artificial market developed by Yagi et al.[9][6]. The results show a greater value of assets managed by the leveraged ETF corresponds to a greater volume of rebalancing trading in the underlying asset and a higher volatility in the market. They also demonstrate that leveraged ETF trading has the potential to destroy the market of the underlying asset if it has a greater impact on the market than volatility.

2 Artificial Market Model

In this study, we constructed a model based on the artificial market model of Yagi et al.[9]. In this model only one risk asset, corresponding to an underlying security, is traded. The method used by the model to determine market prices is described, followed by a description of the investor agents participating in the simulated market.

2.1 Method for Determining Market Prices

The general investor agents described in Sect. 2.2 determine the order price and number of shares to order according to their own method and then issue orders accordingly. Trading in the market is conducted by matching the sell orders and buy orders of all the agents at period t. On the buyer side, the priority of transactions is in order from agents offering the highest order price; on the seller side, the highest priority is given to agents offering the lowest order price. If a buyer's order price exceeds or matches the order price of a seller, a trade is executed. This method of determination is generally referred to as the itayose (bid/offer) method.

On the other hand, leveraged agents trading underlying assets in order to operate a leveraged ETF conduct rebalancing trading at the close of market

[6] In this study, a leveraged ETF has an index future as underlying assets.

trading in order to achieve a return on the underlying asset that is several times higher than the prevailing return on the underlying asset, as explained above. To simulate the trading method of these leveraged agents, we extended the above mentioned itoyose method as follows. First, a tentative price is determined for the underlying asset at the present time, by tentatively matching the orders of general investors. The leveraged agents calculate their needed asset exposure based on this tentative price and then place an order for a certain number of assets (shares) corresponding to the difference between their needed exposure and their current exposure. Finally, the underlying share price is determined by matching the orders of the leveraged agents with the orders of the general investor agents mentioned above.

2.2 Agents

There are four types of agents participating in the market: fundamentalists, chartists, noise traders, and leveraged agents. All agents except leveraged agents are referred to as general investor agents.

Fundamentalists Fundamentalists predict current market prices based on theoretical prices[7] and control the number of shares that they hold to maximize their Net Asset Value (NAV) (= (expected stock price) × (the number of shares) + (their cash)). The theoretical price is a given value.The initial theoretical price is set to 10,000. Let the expected asset price of agent i at period t be $\tilde{P}_{i,t}$, and let the theoretical price be $\mathcal{P}_t$. Then, $\tilde{P}_{i,t}$ is determined according to $N((1+\epsilon_{i,t})\mathcal{P}_t, (\alpha(1+\epsilon_{i,t})\mathcal{P}_t)^2)$, where $\epsilon_{i,t}$ denotes the degree of bullishness[8] of i at t according to

$N(0, \sigma_\epsilon^2)$, and α is a coefficient that describes the degree of spread of expected prices. Let $C_{i,t-1}$ denote the amount of cash that i holds before a transaction at t, $q_{i,t-1}$ denote the number of shares that i holds before a transaction at t, and P_{t-1} denote the market price at $t-1$. The assets of agent i before a transaction at t are

$$W_{i,t-1} = C_{i,t-1} + P_{t-1} \cdot q_{i,t-1}. \tag{1}$$

Let the number of shares held by i at t that maximizes the subjective expected utility under condition (1) be $\tilde{q}_{i,t}$. Then, $\tilde{q}_{i,t}$ is as follows:

$$\tilde{q}_{i,t} = \frac{(1+\epsilon_{i,t})\mathcal{P}_t - P_{t-1}}{a(\alpha(1+\epsilon_{i,t})\mathcal{P}_t)^2}$$

Note that constant $a(>0)$ is a coefficient of risk aversion and the larger the value of a is, the smaller the number of shares that fundamentalists hold to avoid risk. Fundamentalists attempt to determine their trading rules based on $\tilde{q}_{i,t}$. If

[7] A theoretical price is calculated by using the value of a company, which is intrinsic or contained in the company itself.

[8] Since a bullish agent expects a higher price than the theoretical price, this value is positive for a bullish agent. However, for a bearish agent, who expects a lower price than the theoretical price, this value is negative.

Table 1. Rebalancing to maintain daily leverage ratio for a 2x Leveraged ETF

	Underlying Asset		2x Underlying Asset		2x Leveraged ETF			
Period	(1) Value	(2) Return	(3) Return	(4) Exposure (×(2))	(5) NAV (leverage) (×(3) (= (4)/(5))	(6)Needed Exposure (= (5)×2)	(7) Change in Exposure (= (6)-(4))	(8) # of Needed Underlying Asset (= (7)/(1))
0	100			2,000	1,000 (2)	2,000		
1	110	10%	20%	2,200	1,200 (1.83)	2,400	200	1.81
2	99	-10%	-20%	2,160	960 (2.25)	1,920	-240	-2.42

Table 2. Volatility and stylized facts for each trial

		Ratio of initial cash of leveraged agent to initial cash of general investor agents											
		No participation	×1	×10	×100	×1,000	×1,500	×1,600	×1,700	×1,800	×1,900	×2000	×5000	×10000
Volatility($\times 10^{-2}$)		1.13	1.16	1.18	1.40	1.47	1.39	6.42	29.5	31.8	13.5	22.3	39.0	39.1
Kurtosis		4.64	4.35	4.34	2.56	6.29	19.2	15.8	3.41	131	10.4	8.07	-1.87	-1.87
	Lag													
	1	0.518	0.507	0.493	0.379	0.391	0.562	0.481	-0.488	-0.522	0.137	-0.111	-0.997	-0.997
Autocorrelation	2	0.707	0.709	0.704	0.722	0.637	0.452	0.480	0.789	0.959	0.400	0.310	0.999	0.999
of the squared	3	0.521	0.513	0.500	0.416	0.345	0.313	0.266	-0.554	-0.543	0.144	0.149	-0.997	-0.997
rate of return	4	0.647	0.650	0.643	0.656	0.519	0.213	0.281	0.725	0.939	0.214	0.0318	0.999	0.999
	5	0.528	0.522	0.510	0.440	0.314	0.129	0.110	-0.601	-0.560	0.0691	0.280	-0.997	-0.997

$\tilde{q}_{i,t} > q_{i,t-1}$, i places an order to buy $\tilde{q}_{i,t} - q_{i,t-1}$ shares at $\tilde{P}_{i,t}$. If $\tilde{q}_{i,t} < q_{i,t-1}$, i places an order to sell $q_{i,t-1} - \tilde{q}_{i,t}$ shares at $\tilde{P}_{i,t}$. If $\tilde{q}_{i,t} = q_{i,t-1}$, i does not trade at period t.

Chartists Chartists trade based on the moving averages of stock prices. They consist of market followers and contrarians. Let $n_{i,t}$ be a number that satisfies $1 \leqq n_{i,t} \leqq 25$. Let the $n_{i,t}$ period moving average at t used by agent i be

$$MA_{t,n_{i,t}} = \frac{1}{n_{i,t}} \sum_{j=1}^{n_{i,t}} P_{t-j},$$

and let $\Delta MA_{t,n_{i,t}} = MA_{t,n_{i,t}} - MA_{t-1,n_{i,t}}$. Market followers place orders based on the following rules.

- If $\Delta MA_{t,n_{i,t}} > 0$, then i places an order to buy $q^T_{i,t}$ shares at price $(1 + \alpha_T)P_{t-1}$.
- If $\Delta MA_{t,n_{i,t}} < 0$, then i places an order to sell $q^T_{i,t}$ shares at $(1 + \alpha_T)P_{t-1}$.
- If $\Delta MA_{t,n_{i,t}} = 0$, then i does not trade.

Contrarians place orders based on the following rules.

- If $\Delta MA_{t,n_{i,t}} > 0$, then i places an order to sell $q^T_{i,t}$ shares at $(1 + \alpha_T)P_{t-1}$.
- If $\Delta MA_{t,n_{i,t}} < 0$, then i places an order to buy $q^T_{i,t}$ shares at $(1 + \alpha_T)P_{t-1}$.
- If $\Delta MA_{t,n_{i,t}} = 0$, then i does not trade.

Let the initial $n_{i,t}$ be a random number that satisfies $1 \leqq n_{i,t} \leqq 25$, and let α_T be a random number distributed according to $N(\mu_P^T, (\sigma_P^T)^2)$. Further, let $q_{i,t}^T$ be a random number distributed according to $N(\mu_V^T, (\sigma_V^T)^2)$.

Noise Traders Noise traders place orders to buy, sell, and wait with equal probabilities. At t, agent i places an order to buy $q_{i,t}^N$ shares at price $(1+\alpha_t)P_{t-1}$, where $q_{i,t}^N$ and α_N are random numbers distributed according to $N(\mu_V^N, (\sigma_V^N)^2)$ and $N(\mu_P^N, (\sigma_P^N)^2)$, respectively. At t, i places an order to sell $q_{i,t}^N$ shares at $(1+\alpha_t)P_{t-1}$.

Leveraged Agents Leveraged agents are agents that manage leveraged assets with the aim of achieving L times the return of the underlying asset. If the share price increases or decreases, the leverage value[9] of the leveraged shares of each agent will also change. Thus, leveraged agents must conduct rebalancing trades in the asset such that the rate of return on their holding NAV is L times the rate of return of the underlying asset[10].

Suppose, for example, that a leveraged agent who holds an amount of 1,000 in cash is trading in an asset A priced at 100 with a leverage of 2x (refer to Table 1). To begin, the leveraged agent purchases 20 shares of A (assuming the cash deficit of 1,000 is borrowed). At this point, the leveraged agent's NAV is 1,000 (= 100 × 20 - 1000) and the leverage is 2 (= (100 × 20)/(100 × 20 - 1000). If the share price rises to 110, then the leveraged agent's NAV becomes 1,200 (= 110 × 20 - 1000), and the return achieved on the shares is 2 (= ((1200 - 1000)/1000)/((110 - 100)/100)). Now, however, the leverage has dropped to 1.83 (= (110 × 20)/(110 × 20 - 1000)), so the agent must purchase 1.81 additional shares to maintain a leverage of 2.

Leveraged agents that conduct trading as described above are modeled as follows.

The time period in which a trade is made in this artificial model is expressed as t. Let the tentative share price be determined solely by the trading of general investor agents at period t be P'_t, the market price of the share at t be P_t, and the number of shares and cash held by agent i at period t be S_t^i and C_t^i , respectively. In addition, trading is started under conditions that satisfy the target leverage L. In other words, the initial number of shares S_0^i is given by $S_0^i = L \cdot C_0^i / P_0$, and the initial cash C_0^i is given by $C_0^i = C_0^i - P_0 \cdot S_0^i$. At period t, the leveraged agent's NAV NAV_t^i and leverage L_t^i of agent i are expressed as follows:

$$NAV_t^i = P'_t \cdot S_t^i + C_t^i$$

[9] Leverage = (Underlying asset exposure) / (Leveraged agents' holding NAV), where Underlying asset exposure = (Asset price) × (total number of assets held), and NAV = (Asset price) × (total number of assets held) + Cash.

[10] This is because each time the asset price changes, if the leverage is not corrected to maintain its value of L, the rate of return on total asset exposure will no longer be L times the rate of return on their holding NAV.

$$L_t^i = \frac{P_t' \cdot S_t^i}{NAV_t^i}$$

The number of shares ordered by agent i at period t, V_t^i, is expressed by the following equation[11]. Note that if the number of shares ordered turns out to be fractional, it is rounded off.

$$V_t^i = \lfloor \frac{(L-1)P_t' \cdot S_t^i + L \cdot C_t^i}{P_t'} \rfloor$$

The orders of this leveraged agent can only be executed if matched with other offers. This means that in the case of buy orders, the order price has to be higher than that of any general investor agent, and in the case of sell orders, the order price must be lower than that of another general investor agent. When NAV_t^i is below 0, the agent is assumed to be bankrupt, and after returning to the initial state, the agent can participate in the market again from the next time period (after bankruptcy).

2.3 Modeling of an Agent Influenced by the Trading Rules of High-performance Agents

After a transaction at period t, all agents evaluate their performances. Each agent whose performance is lower than that of any other agent attempts to learn the trading rules of the high-performance agents. Fundamentalists learn the degree of bullishness and Chartists learn the period moving average. However, noise traders do not evaluate their performance or learn the trading rules of other agents. In actual markets, there are some participants who attempt to improve their performance further by trial and error, although their performances are comparatively high. To model them, a genetic algorithm whose selection is elitism is applied to learning the trading rules. Thus, comparatively high-performance agents who do not rank in the top $N_H(=20)\%$ also improve trading rules.

Agents cannot change their trading strategies to other strategies, because the ratio of the three strategies is fixed. For example, a low-performance fundamentalist attempts to learn the trading rule of a high-performance fundamentalist, not that of a high-performance chartist.

Let the ratio of change in the asset of an agent i from period $t-1$ to t be $R_{i,t} = W_{i,t}/W_{i,t-1}$ and let the mean ratio of change in the assets of i in the past N periods be $\overline{R}_{i,t} = \sum_{j=1}^{N} R_{i,t-(j-1)}/N$.

[11] V_t^i is determined by the following equation.

$$L = \frac{P_t'(S_t^i + V_t^i)}{P_t'(S_t^i + V_t^i) + (C_t^i - P_t' \cdot V_t^i)}$$

Table 3. Correlation between the initial cash of the leveraged agent and market impact

	Ratio of initial cash of leveraged agent to initial cash of general investor agents						
	No participation	×1	×10	×100	×1,000	×1,500	×1,600
(1) No. of orders	0.0	0.76543	7.5734	71.5162	88.3309	90.4669	6341.36
(2) MI($\times 10^{-2}$)	0.0	0.000505	0.00493	0.0396	0.0539	0.0785	2.18
(3) Volatility($\times 10^{-2}$)	1.13*1	1.16	1.18	1.40	1.47	1.39	6.42
(4) Rate(= (2)/(*1 in (3)))	0.00	0.000445	0.00434	0.0349	0.0476	0.0692	1.92
	×1,700	×1,800	×1,900	×2,000	×5,000	×10,000	
(1) No. of orders	57616.9	72786.2	23741.6	47638.40	256003	512158	
(2) MI($\times 10^{-2}$)	12.5	13.2	4.59	8.15	16.5	16.5	
(3) Volatility($\times 10^{-2}$)	29.5	31.8	13.5	22.3	39.0	39.1	
(4) Rate(= (2)/(*1 in (3)))	11.0	11.6	4.05	7.19	14.5	14.5	

Fundamentalists When $\overline{R}_{i,t}$ ranks in the bottom $N_L\%$ of all fundamentalists, $\epsilon_{i,t}$ is changed with probability

$$p_i = \frac{\text{Rank of performance of agent } i}{\text{Total number of fundamentalists}}.$$

An agent i' whose $\overline{R}_{i',t}$ ranks in the top $N_H\%$ of all fundamentalists is chosen at random, and $\epsilon_{i,t+1} = \epsilon_{i',t}$ is set

To implement a change in the trading rules of agents who would like to improve their performance, for agents whose $\overline{R}_{i,t}$ does not rank in the top $N_H\%$, their degree of bullishness is changed with probability P_ϵ at random.

Chartists When $\overline{R}_{i,t}$ ranks in the bottom $N_L\%$ of all chartists, the moving average period, $n_{i,t}$, is changed with the following probability.

$$p_i = \frac{\text{Rank of performance of agent } i}{\text{Total number of chartists}}.$$

An agent i' whose $\overline{R}_{i',t}$ ranks in the top $N_H\%$ of all chartists is chosen at random, and $n_{i,t+1} = n_{i',t}$ is set.

To implement a change in the trading rules of agents who would like to improve their performance, for agents whose $\overline{R}_{i,t}$ does not rank in the top $N_H\%$, their trading rules (market followers and contrarians) and/or their moving average periods are changed with probability P_n at random, under the restriction that their moving average periods must fall within $[1, 25]$.

3 Experiment

In this study, we determined the price movement in an underlying asset market and the volatility of the rate of return for different values of the initial cash held by leveraged agents, in order to assess the impact of leveraged ETF balancing trades on underlying assets.

3.1 Experiment environment

We ran experiments with the initial cash amount of leveraged agents set to 1, 10, 100, 1,000, 1,500, 1,600, 1,700, 1,800, 1,900, 2,000, 5,000, and 10,000 times that of general investor agents. Other parameter settings for the simulated market are as follows. The number of general investor agents was set to 10,000, and these general investors comprised 4,500 fundamentalists, 4,500 chartists, and 1,000 noise traders. The initial number of assets was set to 1,000,000. The number of leveraged agents was set to 1. The agent parameters were set as $\alpha = 0.02$, $a = 0.001$, $\sigma_\epsilon = 0.1$, $\mu_P^T = 0$, $\sigma_P^T = \sqrt{0.02}$, $\mu_V^T = 2$, $\sigma_V^T = 0.1$, $\mu_P^N = 0$, $\sigma_P^N = \sqrt{0.02}$, $\mu_V^N = 2$, $\sigma_V^N = \sqrt{0.1}$, $N = 5$, $N_H = N_L = 20\%$, and $P_\epsilon = P_n = 0.05$.

The experiment was configured to run over 10,000 time periods, but sampling of market volatility was only performed for the latter 5,000 periods (periods 5,001 to 10,000). In addition, the trading of the leveraged agent was only commenced from period 3,001, to allow sufficient time for the trading of general investor agents to stabilize.

3.2 Validity of model

On initiating the simulation, we verified the validity of the artificial market model proposed by this study. As a method of verification, we determined whether the two typical statistical properties (stylized facts) below, obtained previously by verification analysis[10], were satisfied.

- The kurtosis of the rate of return is positive.
- The autocorrelation of the squared rate of return is positive.

Table 2 shows the stylized facts for the case in which only general investor agents participate in asset trading. These results show that the stylized facts are satisfied for the proposed model, so we can conclude that the model serves as a valid simulation environment.

4 Experiment results and discussion

The second and lower columns of Table 2 show the rate of return volatility of the asset market for different values of the initial cash of the leveraged agent. These results reveal that a higher amount of initial cash corresponds to a higher degree of volatility, which can be explained as follows. If the tentative price P'_t is higher than the market price in the previous time period, P_{t-1}, then the leveraged agent issues a buy order to increase the number of shares; if P'_t is lower than the market price P_{t-1}, then the agent issues a sell order to reduce the number of shares held. At this time, the leveraged agent may buy the underlying asset at a very high price or sell it at a very low price in order to secure the number of shares needed. In addition a greater amount of initial cash implies a greater quantity of shares is necessary to restore the leverage, and so a higher likelihood that shares are bought or sold at an unforeseen price. Accordingly, the market impact of this buying and selling by the leveraged agent appears to be an increase in volatility.

Table 3 shows the correlation between the leveraged agent's initial amount of cash and market impact, MI. (Note that here, the market impact at period t, MI_t, is given by $\mathrm{MI}_t = |P_t - P'_t|/P_t$, whereas MI denotes the average market impact for each trial.) These results reveal that a larger amount of initial cash held by the leveraged agent corresponds to a greater average number of shares being ordered per transaction. From this we can conclude that volatility also increases.

Furthermore, the results shown in Table 2 also reveal that if the initial cash becomes excessively high (in this experiment, when the initial cash of the leveraged agent is 1,700 times or more greater than that of a general investor agent), the autocorrelation of the squared rate of return becomes negative. Although this phenomenon cannot be observed in actual markets, this result suggests that the market of the asset would have been destroyed. The point to take note of here is that MI becomes greater than the market volatility when the leveraged agent does not participate. This suggests that if the initial cash amount is large and leveraged agents impact the market more than ordinary volatility, a market may be destroyed. For example, Table 2 and Table 3 show that the market may be destroyed when MI is greater than seven times the market volatility, because the autocorrelation of the squared rate of return of the leveraged agent whose initial cash is 2,000 times that of a general investor agent is negative.

5 Conclusion

The aim of this study was to use an artificial market simulation to verify the impact of leveraged ETF rebalancing trades on the price movement of market assets. It was found that a higher amount of initial cash held by a leveraged ETF corresponds to a higher volume of rebalancing trading in the underlying asset and a greater volatility in the market for that asset. Furthermore, it was observed that if the leveraged ETF trading impact on the market is greater than that of ordinary volatility, then the market may be destroyed. A further challenge to take up is a detailed investigation to estimate what level of leveraged ETF trading would have sufficient impact to destroy a market.

DISCLAIMER

It should be noted that the opinions contained herein are solely those of the authors and do not necessarily reflect those of SPARX Asset Management Co., Ltd.

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