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Paper:

How Does High Frequency Risk Hedge Activity Have an Affect on Underlying Market?: Analysis by Artificial Market Model

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The effect of option markets on their underlying markets has been studied intensively since the first option contract was listed. Despite considerable effort, including the development of theoretical and empirical approaches, we do not yet have conclusive evidence on this effect. We investigate the effect of option markets, especially that of dynamic hedging, on their underlying markets by using an artificial market. We propose a two-market model in which an option market and its underlying market interact. In our model, there are three types of agents, underlying local agents trading only on the underlying market, option local agents who trade only on the option market, and global agents who trade both on the underlying and the option market. In this simulation, we investigate the effect of hedgers, a global agent, to the underlying market. Hedgers who have option contracts trade the underlying asset to keep a delta neutral position. This hedge behavior is called dynamic hedging. We simulate two scenarios; one is the hedge with low frequency and the other is the hedge with high frequency that hedger can send hedge order anytime when hedge miss appears. We confirmed that dynamic hedging increases or decreases the volatility of the underlying market under certain conditions.

Keywords: agent-based model, option markets, delta hedging, financial market simulation

1. Introduction

Technologies and environments surrounding current financial markets are changing drastically. High-frequency trading, trans-border transaction, and algorithmic trading can be observed at almost any financial market. The relationships among markets become more complex and elusive.

Advancements in trading technologies are often criticized as a cause of market turbulence. Especially, high frequency trading is often regarded as a major cause of the instability. For a stable and efficient economic system, regulators are expected to implement more effective and proper regulation and complicated market dynamics should be understood for this purpose. Many researches have studied market micro structure [1], however, current financial models have not come to any conclusion on the dynamics of such a complex financial system.

An alternative approach for understanding market dynamics is needed and a multi-agent based model is one of them. Many studies have focused on multi-agent modeling for financial markets. Most attempted to explain anomalies and the effects of regulations on a single stock market, which stochastic financial models fails to address.

An agent-based simulation has the possibility to become an important method, especially for evaluating market regulations. NASDAQ, a major stock market in the U.S., adopted a multi-agent simulation when they discussed the change in market tick size [2]. To understand intricate market dynamics, it is natural to consider multiple markets rather than a single market. This study focuses on the relationship between a derivative market and an underlying market. It is important to shed light on the impact of derivative markets.

As mentioned above, most of the exsisting aritificial market models consider a single market, however, actual financial makrets interact each other. The interaction between markets is the key to understand a dynamics of markets. Markets are thought to have a relationship through trading, information, and regulations. Especially, the relationship between a derivative market and its underlying market has been discussed intensively, but we have not reached to the conclusion yet.

In this study, we focused on the effect of a hedge activity of a derivative trader who has positions of option contracts. A hedge trading is regarded as one of the important activities when it comes to the market interaction, because hedgers trade both derivatives and its underlying assets to control their risk. However, the relationships through delta hedging are not fully understood because the theoretical model is defined under simple, idealized conditions. In a real market, different market conditions, such as characteristics of traders, may have different effects on the markets; thus, we investigated the effect based on an artificial market with heterogeneous agents.

We developed the artificial market which incorporates two markets and we could see a hedger's impact on the underlying market under different trading strategies by this coupling artificial market model which could not seen by a single artificial market model or other mathematical models. The multi-agent simulation can reproduce stylized facts even on a single market that past studies failed to express and the multi-agent approach would also be effective to investigate the relationship between markets.

2. Option Market and Delta Hedging

We developed a multi-agent model that incoporates both an option market and an underlying market in order to study the effects of hedging activity of a derivative trader. An option is a contract giving the right to sell or buy specific financial products at a certain price within a specific period of time. Option traders can set a wide range of conditions and they sometimes use options as risk management to protect their other assets. Different from other typical financial products, such as stocks, bonds, or futures, the profit and loss diagram of options is not a straight line and traders can make a flexible profit and loss diagram by combining different conditions.

The most prevailing pricing model for options is the Black-Sholes model (BS model) [3]. In this model, an option's price is derived from the current price of underlying asset and its volatility.

Option delta, one of the risk parameters of option trading, is the amount of change in the option premium with respect to the change in the underlying asset price. When *option delta* is 0.5, for instance, the option price will increase 50 points when the underlying price increases to 100 points. Some investors who hold or write options are motivated to make *option delta* nearly zero to avoid fluctuations on the option premium linked to underlying price changes. These trades are called delta hedging. If *option delta* is 0.5, traders can ensure a delta neutral position by selling 0.5 units of the underlying assets. *Option delta* varies according to the price of the underlying assets and the time to maturity of the option contracts. When an underlying price changes, hedge position becomes over-hedging or under-hedging.

The continuous line in **Fig. 1** shows the relationship between underlying asset and premium of European call option. S_t is the underlying price at time t. The slope of the tangent at S_t is equivalent to *option delta* at time t. Now the price of underlying asset falls and *option delta* also changes from 0.6 to 0.4 at time $t+1$, the position of underlying asset that a hedger needs decrease to 0.4 from 0.6, then the hedger needs to buy back 0.2 units of underlying assets at time $t+1$ for sustaining delta neutral position. As can be seen from the above example, traders have to trade underlying assets according to the value of *delta*. This hedging strategy is called as dynamic hedging. In this example, a hedger buy an underlying asset when the price of underlying asset falls, this hedge activity may stabilize the underlying market theoretically.

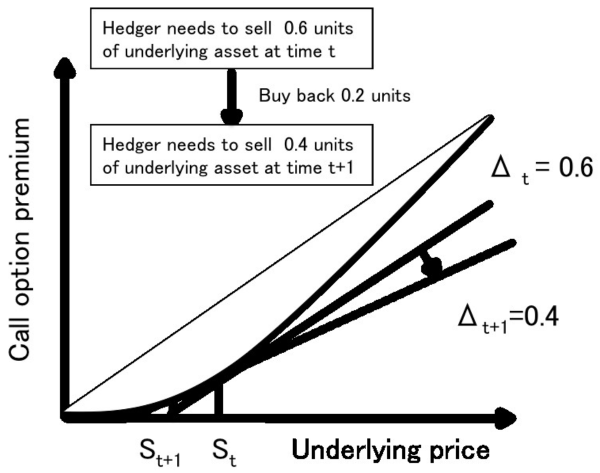


Fig. 1. The relationship between underlying price and premium of European call option.

Another important risk parameter is *option gamma*, which is the changing ratio of *delta* depending on the price of the underlying asset. *Option gamma* is positive when a trader buys options and negative when he sells options. When the price of the underlying asset increases, *option delta* decreases under a *positive gamma* position and increases under a *negative gamma* position. If the *gamma* of a trader's position is positive, he sells the underlying asset when the underlying market rises and buys the underlying asset when the underlying market falls. This activity can stabilize the underlying market. On the other hand, if the trader's position is negative, he buys the underlying asset when the underlying market rises and sells the underlying asset when the underlying market falls. This hedging trade can make the market turbulent. Theoretically, there is a mutual relationship between an option market and its underlying market through these hedge trades.

3. Related Literature

3.1. Effects of Dynamic Hedging

Frey [4] presented a simple model for evaluating the effect of delta hedging on the underlying market. In Frey's model assumption, the price process of a perfectly liquid market follows geometric Brownian motion and a large trader's hedge orders divert the underlying price from the theoretical price if the market is not perfectly liquid.

Frey's model calculates the coefficient for the volatility of the underlying assets by using Eq. (1), where ρ represents the market liquidity. When $\rho = 0$, the market is fully liquid. The term $\Gamma(t,S)$ in Eq. (1) measures the *gamma* value of hedgers and S is the current market price. If *gamma* is positive, the value of $v(t,S)$ become less than 1. If *gamma* is negative, $v(t,S)$ becomes more than 1 and increase the volatility.

$$v(t,S) = \frac{1}{1+\rho S\Gamma(1,S)}. \qquad (1)$$

In Fray's model, interactions between hedgers and other traders cannot be observed because it does not take into account heterogeneous traders who respond to market impact differently, though both Fray's model and our model are focused on the hedgers' *gamma*.

Pearson et al. [5] estimated how much delta hedgers affect the underlying market by examining daily open interest for every equity option on the Chicago Board Options Exchange (CBOE) from the beginning of 1990 through the end of 2001, which involved the positions of both public customers and firm proprietary traders. They found that there is a significant negative relationship between stock return volatility and the net *gamma* of the option positions. They estimated that 12% of the daily optioned stock return can be accounted for by hedgers. It is difficult to obtain accurate data of the hedger's position; thus, Pearson et al.'s results are a matter of speculation, although they are practically important for indicating the effects of delta hedgers on the underlying market.

3.2. Agent-Based Modeling for Option Market

Baqueiro et al. [6] compared the profit and loss of agents who can trade on both the underlying and option markets to that of agents who trade only on the underlying market. Their simulation results show that agents trading on both the underlying and option markets make a profit if the price process of the underlying market drifts. Baqueiro et al.'s simulation and our simulation have commonality in terms of considering both underlying asset and option, though Baqueiro et al.'s simulation does not take into account the relationships between a stock market and option market.

Ecca et al. [7] examined the interaction between underlying and option markets. They incorporated agents who can access the options market into an existing artificial market. In their model, bank and option traders are included in option trading. Option traders randomly choose put or call and purchase options from a bank. The asset of the bank is infinite and it issues option contracts with no limitation. On the expiration day, option traders choose a strategy favorable to them, either to exercise the option or to buy or sell underlying assets from the market. The results suggested that exercising an option slightly decreases the volatility of the underlying market. While option traders take a straddle strategy, option trading increases the volatility.

Ecca et al. focused only on the option expiration; however, the expiration date of a European-type option is usually set once a month, and the percentage of contracts actually exercised is quite low in actual markets. Traders usually close option positions before the expiration date. To study the effect of option markets on underlying markets, we focused on the daily impact for underlying markets, such as hedge and arbitrage trading.

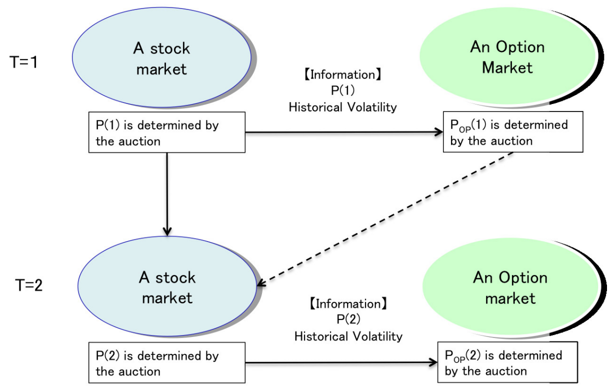


Fig. 2. Simulation steps in our model.

4. Model

There are both underlying and option markets in our model and they are connected through hedgers. In terms of information, option traders refer to an underlying asset's price and volatility to decide on their expected option return. The simulation model was developed on the basis of C. Wang et al.'s model [8] for underlying markets and Frijns et al's model [9] for option markets. C. Wang et al.'s model [8] is based on Chiarella et al [10].

We added delta hedgers in our model. An agent send an order in each time step. We assume one time step as a few minutes in an actual settings. In each session, all N agents randomly send an order; one simulation consists of 1000 sessions, and one session simulates one trading day. We use a double auction method as the matching system. In the underlying market, we use continuous double auction because underlying markets should be liquid and many orders are executed within one session. On the other hand, option markets are usually less liquid; therefore, a single price is determined within one session in our option market.

Three types of agents are involved in this model, underlying local agents trading only on the underlying market, option local agents who trade only on the option market, and global agents who are allowed to trade both on the underlying and option markets. The information flow and transaction steps are shown as **Fig. 2**. $P(t)$ is the price of underlying market and $P_{op}(t)$ is the price of option market at t. The session starts in the underlying market at time $t=1$ and the underlying price $P(1)$ is determined. Option traders compute their expected volatility and send option price $P_{op}(1)$ based on $P(1)$. At $t=2$ local agents on the underlying market compute their expected return and price based on $P(1)$ in the previous session. Global agents, who trade options at time $t=1$, also decide their hedge volume based on the delta value calculated using $P(1)$. $P(2)$ is determined by reflecting all orders through the continuous double auction system. Next, option traders decide their expected volatility based on $P(2)$ and the option price $P_{op}(2)$ is determined.

4.1. Underlying Local Agents

There are three stylized types of underlying local agents, fundamentalists, chartists, and noise traders [8]. The ratio of each type varies according to the given weights: g_1, g_2, and n^i. Each parameter is determined from a normal distribution with an average of 0 and a given variance, σ_1, σ_2, and σ_n respectively. Fundamentalists take into account the difference between the fundamental price p_t^f and the current price p_t , while chartists concentrate on the future trend $\bar{r}_t^i$. In the following equation $\bar{r}_t^i$ is the average price change inside an agent's time interval τ^i. The noise behavior is represented by a random number ε_t generated each time.

$$\hat{r}_t^i = \frac{1}{g_1^i + |g_2^i| + n^i}\left(g_1^i \log\frac{p_t^f}{p_t} + g_2^i \bar{r}_t^i + n^i \varepsilon_t\right)$$
$$g_1^i \sim |N(0,\sigma_1)|, g_{(2)}^i \sim N(0,\sigma_2), \quad . \quad . \quad . \quad . \quad (2)$$
$$n^i \sim |N(0,\sigma_n)|, \varepsilon_t \sim N(0,1)$$

The number of agents N varies from 100 to 300 and investigates the stylized facts of the underlying market, as shown in **Fig. 3**. The stylized facts are the average value of 100 simulations that contains 1,000 sessions. The autocorrelation of the square of price return is plus value and kurtosis of returns is high. These results support the validity of our model.

4.2. Option Local Agents

The option local agents in our model were developed on the basis of Frijns et al.'s model [9]. They report that there are two types of agents; fundamentalists and chartists. They examined the actual market data of the Deutscher Aktien Index (DAX) options and concluded that two heterogeneous agents can reproduce the GARCH(1,1) volatility process. Agents decide their own volatility, as expressed in the following equation.

$$E_t^F(h_{t+1}) = h_t - (1-\alpha)(h_t - \bar{h}_t) \quad . \quad . \quad . \quad . \quad . \quad (3)$$
$$E_t^C(h_{t+1}) = h_t - \beta_0(\sqrt{h_t}\varepsilon_t^+)^2 + \beta_1(\sqrt{h_t}\varepsilon_t^-)^2$$

where $E_t^F(h_{t+1})$ denotes a fundamentalists' prediction of volatility for the next session at time t, $E_t^C(h_{t+1})$ denotes that of chartists, h_t is the historical volatility, $\bar{h}_t$ is unconditional volatility, α is the speed at which fundamentalists expect the volatility process to be unconditional volatility, β_1 denotes the extent to which chartists incorporate for reacting to negative shock on volatility, β_0 denotes the coefficient for positive shock, and ε_t^- (ε_t^+) is the past negative (positive) shock on the volatility process. Frijns et al. calculated the average of α as 0.957, standard deviation as 0.043, average of β_0 as -0.242, standard deviation of β_0 as 0.101, average of β_1 as 0.240, and standard deviation of β_1 as 0.075 from the actual data of the DAX options.

We set parameters according to the normal distribution, which includes the average and standard deviations that Frijns et al. measured and give a different parameter set to each option local agent. In Frijns et al.'s model, the market price was given by the average of all agents' expectations, but the market price of our model was determined based on the best bid and ask prices, such as in an actual market.

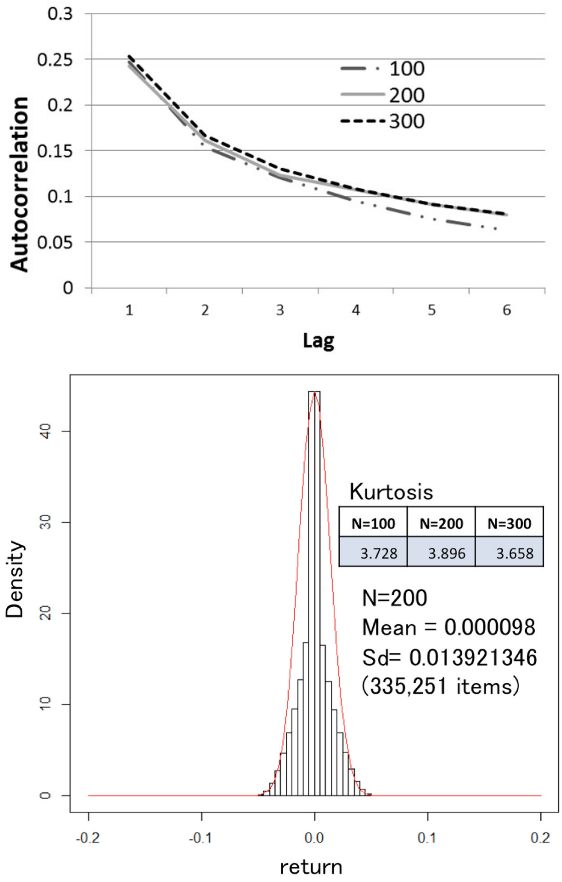


Fig. 3. Stylized facts on underlying market: autocorrelation factor (upper) and distribution of returns (bottom).

In Frijns et al.'s model, the ratio of fundamentalists to chartists varies and their model is reduced to the GARCH(1,1) volatility process; however, we do not implement the switching function because we did not focus on the mechanism of option markets in this study.

4.3. Global Agents

Global agents trade both on underlying and option markets. They are generally grouped into three types; arbitragers, hedgers, traders who protect their underlying positions, and so on. In this study, we focused on hedgers as global agents.

Global agents respond to the best bid price or best ask price on option market like market makers. Market makers often take a hedge operation because their revenue stream is from market making activities not from option trading itself. So they want to be free from the price fluctuation risk on an option market. Global agents are also motivated to maintain a delta-neutral position and send hedge orders dynamically on the underlying market. The delta value is calculated based on the underlying price at the previous session and global agents decide the hedge

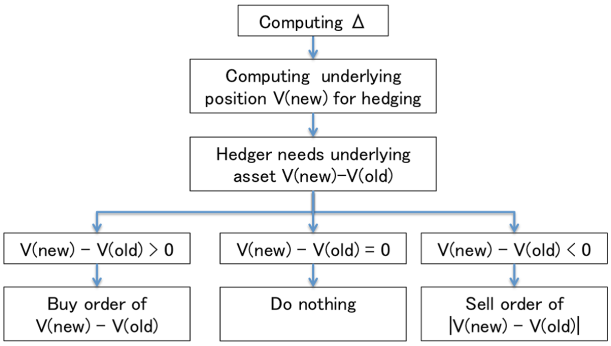


Fig. 4. Hedge flow of global agents.

volume according to the position they hold. The delta value varies with changes in the price of the underlying asset. If global agents already have underlying positions, they calculate the difference between the positions they already have and those they need. If the difference is positive, they buy the underlying asset and if the difference is negative, they sell the underlying asset. When absolute value of the difference is less than 1, they do nothing, because the volume is less than the minimum order lot of the asset (**Fig. 4**).

5. Simulation

We simulated the model 100 times. One simulation contained 1,000 sessions and all agents randomly sent orders in one session. We regarded one sesssion as one trading day in an actual market. The minimum order unit for local agents is 10 units both on underlying and option markets to observe the impact of hedge volume. If the minimum unit is small, hardly any hedge orders are submitted because the delta value is smaller than 1, and less than 1 order cannot be sent. We evaluate the impact of hedge orders by observing volatility of the underlying market. Volatility measures a price fluctuation, so high volatility means a destabilized market and low volatility indicates a stabilized market. The fundamental price of the underlying asset, the hypothetical true value of an asset, is fixed as constant value in our simulation, which means low volatility is expected because there's no bubble and crashes in our model.

5.1. Underlying Market Without Global Agents

First, we conducted a simulation for investigating the characteristics of the underlying market. The upper of **Fig. 5** shows the volatility of 20 sessions and average volume of one simulation with different number of agents (from 5 to 300).

The volatility increased as the number of agents increased. When agents were sparse, the expected price largely differed among agents; thus, the traded price significantly changed from the previous price, but when the number of agents was above 25, the volatility increased

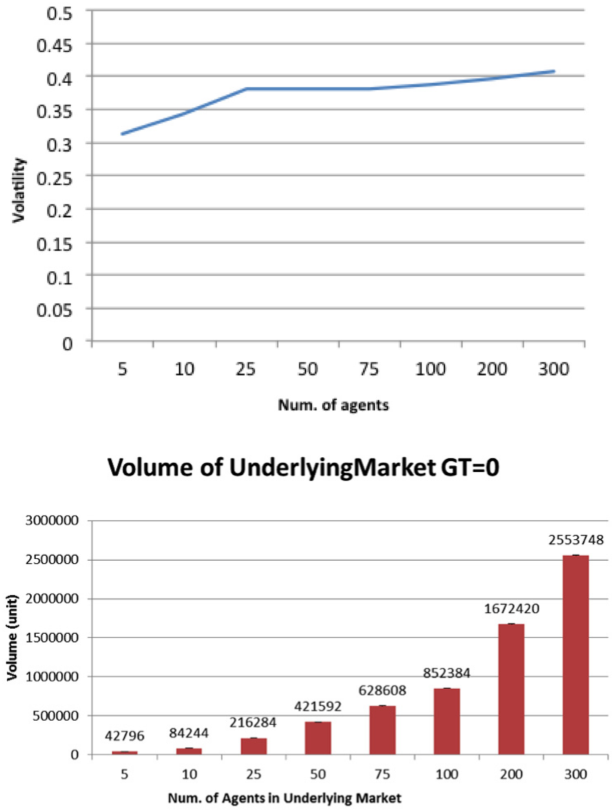


Fig. 5. Volatility (upper) and volume (bottom) of underlying market.

only slightly. The volumes also increased according to the number of agents (bottom of **Fig. 5**).

The following simulation used 200 underlying local agents because the total volume divided by the minimum order units (10 units) under this setting is close to the daily average volume of Nikkei 225 futures in 2012.

5.2. Delta Hedging with Low Frequency

In an actual markets, hedgers conduct hedging at certain times; each trading session, every trading day, or once a month. These times are usually used for volatility calculation. In the first settings of our simulation, a global agent has a chance to send a hedge order at the last trading time of each session. To investigate the basic impact of hedgers, we used one global agent who only has a buying or selling position as his portfolio in the simulation. If the global agent buys positions, the *gamma* of the global agent is positive. If he sells positions, his portfolio *gamma* is negative.

The upper of **Fig. 6** shows the volatility of underlying asset in the case of different option position sizes. A trader of *positive gamma* sells the underlying asset when the price of underlying asset rises, and buys the underlying asset when the price of underlying asset falls. A trader of *negative gamma* sells the underlying asset when the price of underlying asset falls, whereas they buys the

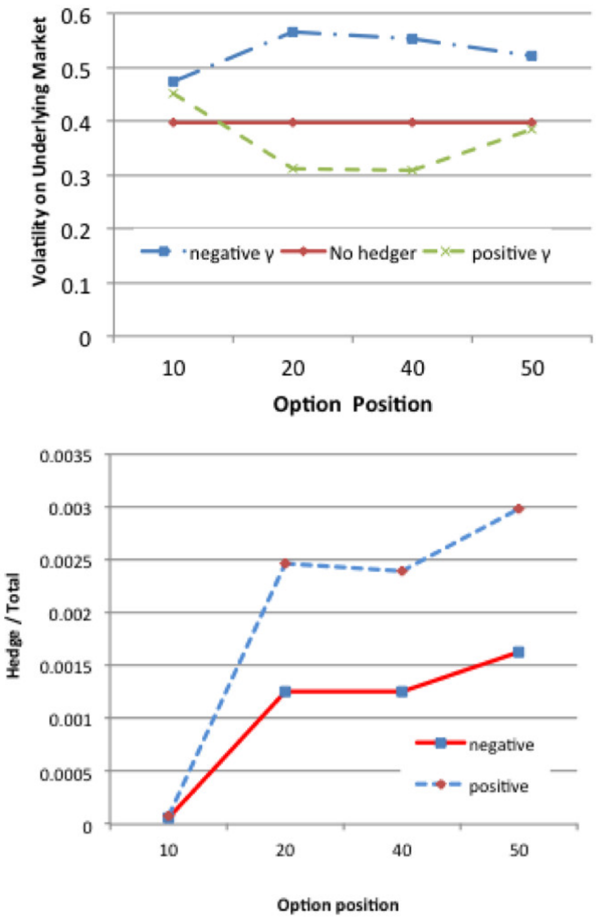
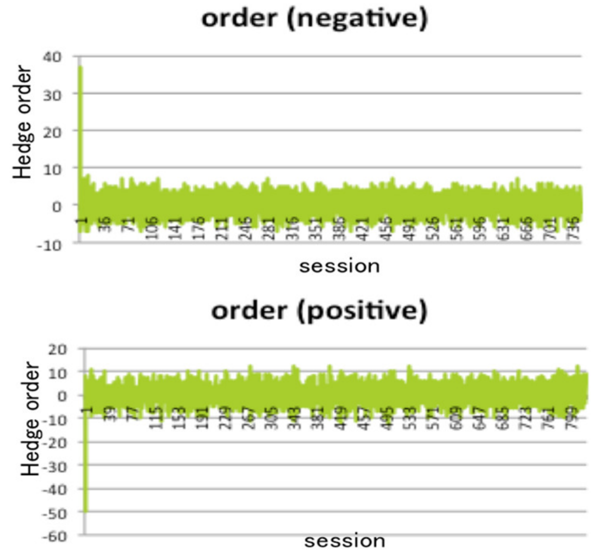


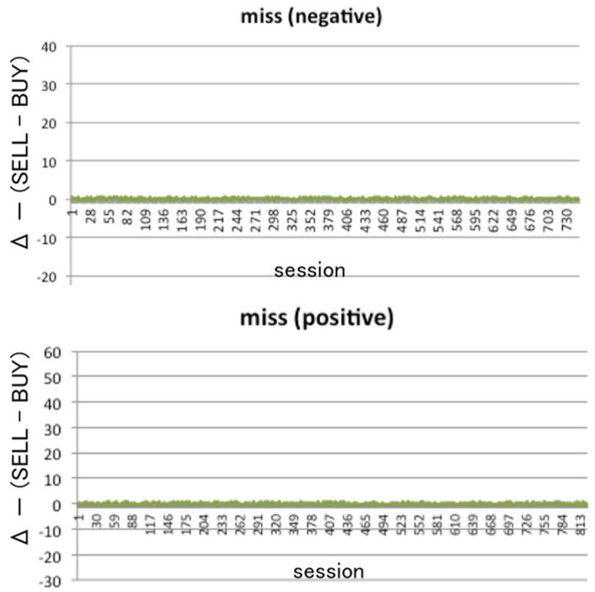
Fig. 6. Volatility of underlying markets in different number of global agents (upper); ratio of traded hedge orders to total volume (fundamental price does not change)(bottom).

underlying assets when the underlying market rises. Only in the case in which a global agent holds 10 units of a buying position, hedging activity increases the volatility compared to that of the situation without global traders (normal level). In other cases, hedge orders of a *positive gamma* position keep the volatility under the normal level. On the other hand, hedge orders of a *negative gamma* position increase the volatility over all settings. These results are predictable based on the theoretical function of hedgers.

The bottom in **Fig. 6** shows the ratio of traded volume by hedge orders to the total volume. When a global trader has 50 units of the option buying position, the hedge volume is 0.3%. The hedge volume increases according to the option positions they hold. Interestingly, the total volume of the *positive gamma* hedge is always larger than that of a *negative gamma* hedge but they stabilize the underlying market. Also, the probability of uptick and downtick in price is regarded as same, so the number of times of hedge activities should be same both on *positive gamma* and *negative gamma* theoretically. The difference in the number of times of hedge activities during the simulation indicates that it is more difficult to hold the price rather than to fluctuate it.



(a)Unit of hedge orders.



(b)Hedge miss.

Fig. 7. Unit of hedge order (upper) and hedge miss (bottom) (fundamental price does not change).

Fig. 7 indicates the order volume at each hedge time and the amount of hedge miss, which is derived from the calculation formula; Δ+underlying buy position-underlying sell position.

The volume, except in the first session, was around 5 in *negative gamma* and 10 in *positive gamma*. A hedger sends an large hedge order at the first in order to offset the risk of the option position and later, the hedger adjust his position of the underlying asset according to its price fluctuation. Hedge miss was less than 1 through all simulations, which means hedge activities were successful through all simulations.

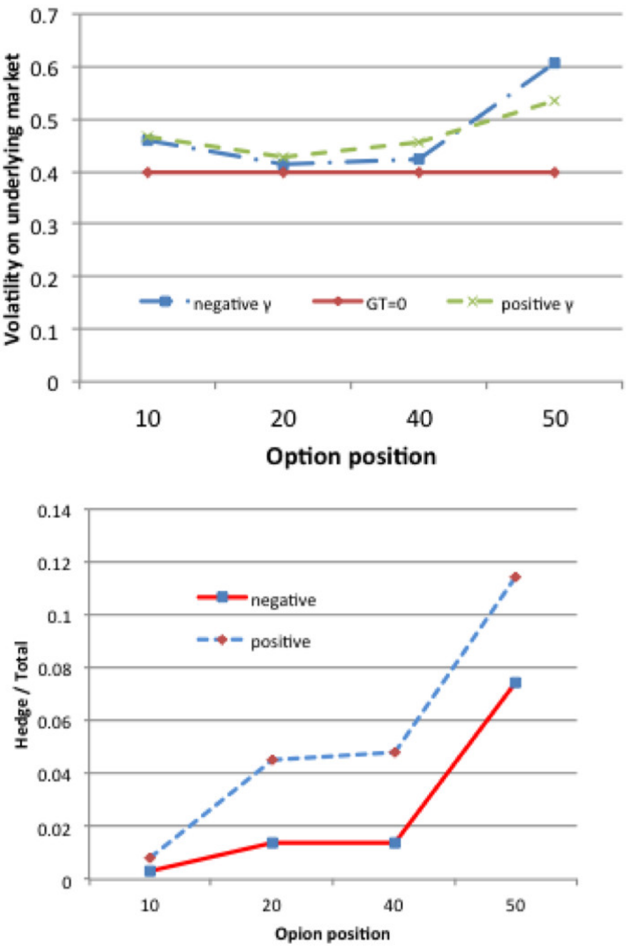


Fig. 8. Volatility of underlying markets in different number of global agents (upper) and ratio of traded hedge orders to total volume (bottom).

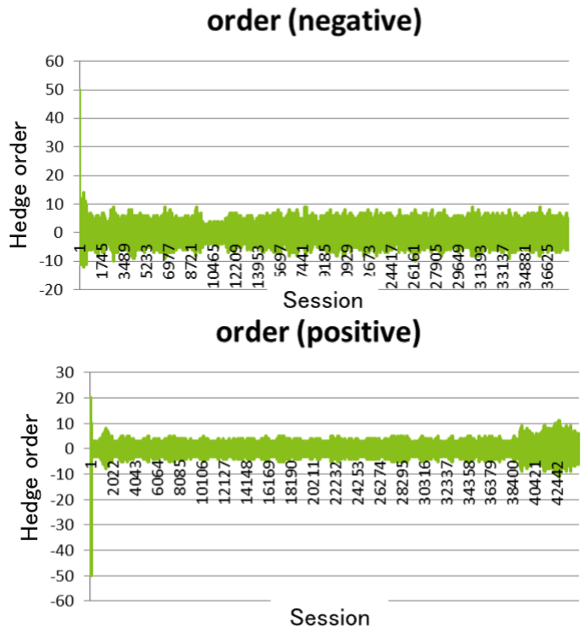
5.3. Delta Hedging with High Frequency

In the next simulation, we examined the market impact of hedge orders in which a global trader can send a hedge order at any time. It is assumed in this situation that the idealized condition on which the theoretical model introduced in Section 2 is taken into account, but real traders avoid real-time hedging by considering the matter of a trading fee. A global agent sends hedge orders when the delta value becomes more than one.

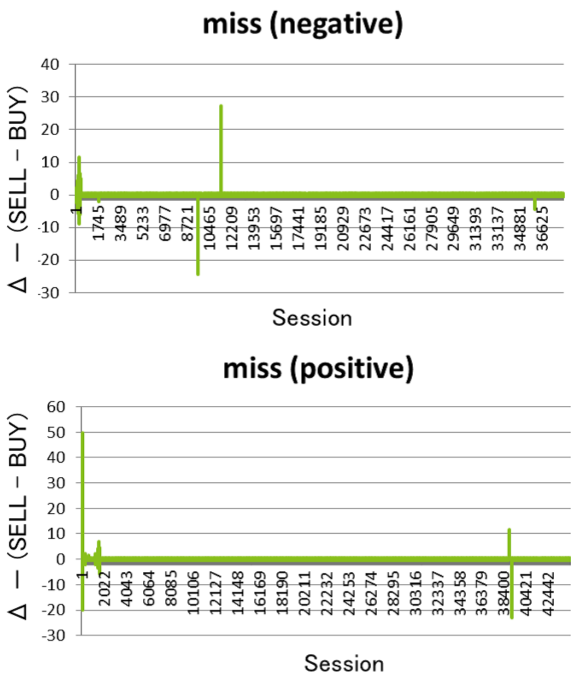
The upper of **Fig. 8** indicates the volatility value of an underlying asset when the position of global agents changes. In high frequency hedging, both *positive* and *negative gamma* positions increase the volatility of the underlying market. The percentage of the executed hedge orders increases compared to that in hedging at certain intervals at any position amount (bottom in **Fig. 8**).

For hedge volumes, there is no significant difference in hedge volumes, but some big hedge failures were observed during the simulations, as shown in **Fig. 9**.

The standard deviation of the underlying market get larger when a hedge miss appears (22.6%) compared



(a)Unit of hedge order.



(b)Hedge miss.

Fig. 9. Unit of hedge order (upper) and hedge miss (bottom) (fundamental price does not change).

to the standard deviation when there is no hedge miss (16.6%). **Fig. 10** shows the timing of hedge orders againt that of other orders. In **Fig. 10(a)**, hedge orders are sent each after the other orders from local agents, which means a hedger tried to control their risk so often by sending hedge orders at each time step. In **Fig. 10(b)**, a hedger send his order less frequently compared to the case of **Fig. 10(a)**. This result suggests that new hedge activities occur when the price of the underlying asset changes

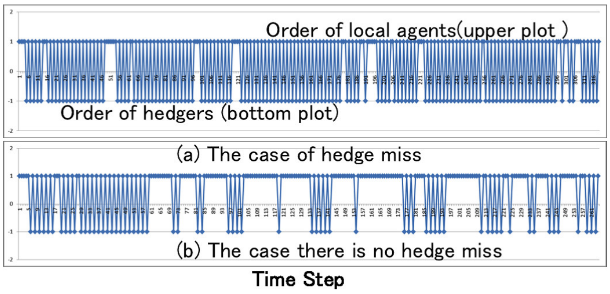


Fig. 10. The ratio of hedge orders and the other orders. The plots of 1 (the upper plots) means orders of local agents in the underlying market and the plots of -1 (the bottom plots) means orders of a hedger ((a): the ratio when a hedge miss occurs, (b): the ratio when there is no hedge miss).

because of the previous hedge orders. These hedges are caused by past hedges not by natural price changes.

In this simulation, we examine the activity of one hedger. The impact of the hedge activity with low frequency of one hedger shows the result as expected. The high frequency hedging is different from the theoretical expectation. This result can be obtained thanks to multi-agent simulation. High frequency hedge changes the condition of the underlying market that consists of local agents, and then a global agent responded to the change. An actual hedger hardly hedge so often due to the trading cost, however the effect of the high frequency hedging would realize when a number of hedgers join in the hedge trading.

6. Conclusions

Our general aim was to reveal the effect of derivative markets on their underlying assets. We specifically examined the effect of hedgers on the underlying market with our multi-agent simulation model.

When a hedge order is executed at the end of a session, we can confirm that the volatility of the underlying assets change around 25% depending on the hedgers positions, even though the hedge orders are 0.3% of all trades. Hence, the negative and positive *gamma* values increase the price volatility on the underlying market when a hedger can place an order at any time.

Under high frequent hedge settings, hedge miss sometimes widens and hedgers experience difficulty in controlling frequent hedging.

For future work, we will compare our simulation results to theoretical values obtained from Frey's model [4]. We did not examine the stylized facts on option markets in this study. Therefore, we will examine which type of agents and the percentage of strategies that reproduce option market stylized facts, such as volatility smiles, and investigate interactions between markets and the effects of option markets by focusing on the information flow between markets and interaction trading strategies.

Acknowledgements

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