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Liquidity cost of market orders in the Taiwan Stock Market: A study based on an order-driven agent-based artificial stock market

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ABSTRACT

We developed an order-driven agent-based artificial stock market to analyze the liquidity costs of market orders in the Taiwan Stock Market (TWSE). The agent-based stock market was based on the DFGIS model proposed by Daniels, Farmer, Gillemot, Iori and Smith (Daniels et al., 2003). We also improved the DFGIS model by using two average order size parameters. When tested on 10 stocks and securities in the market, the model-simulated liquidity costs were higher than those of the TWSE data. We identified some possible factors that have contributed to this result: 1) the overestimated effective market order size, which can be improved by using two average order size parameters; 2) the random market order arrival time designed in the DFGIS model; 3) the zero-intelligence of the artificial agents in our model; and 4) the price of the effective market order. We continued improving the model so that it could be used to study liquidity costs and to devise liquidation strategies for stocks and securities traded in the Taiwan Stock Market.

1. Introduction

Market liquidity, or the ability of an asset to be sold without causing a significant amount of price movement and with minimum loss of value, plays an important role in financial investment and in securities trading. One recent event that highlighted the impact of asset liquidity on financial institutions was the collapse of Bear Stearns. Bear Stearns was involved in securitization and issued a huge amount of asset-backed securities, mostly mortgage-backed assets. Due to the subprime crisis in 2007, the company issued subprime hedge funds that had very low market liquidity and subsequently lost most of their value. In March 2008, the Federal Reserve Bank of New York provided an emergency loan to try to avert a sudden collapse of the company. However, the company could not be saved and was subsequently sold to JP Morgan Chase in 2008.

In large investment institutions, the liquidation of a large block of assets within a given time constraint to obtain cash flow arises frequently. For example, a financial institution may need to liquidate part of its portfolio to pay for its immediate cash obligations. One possible liquidation strategy is to sell the entire block of assets at once. However, this high-volume trading can cause the price of the share to drop between the time the trade is decided and the time the trade is completed. This implicit cost (due to the price decline) is known as the market impact cost (MIC) or liquidity cost (the numerical definition is given in Section 3). To minimize such cost, a better strategy is to divide the block of assets into chunks and sell them one chunk at a time. However, in what way should those chunks be sold so that the liquidity cost is minimized?

In Algorithmic Trading, where computer programs are used to perform asset trading including deciding the timing, price, or the volume of a trading order, this liquidation problem is characterized as an optimization problem. With a smooth and differentiable utility function, the problem can be solved mathematically (Almgren & Chriss, 2000) (Kalin & Zagst, 2004).

However, this mathematical approach to find an optimal liquidation strategy has some shortcomings, such as the imposed assumption that risk has a linear impact on prices. In this paper, we adopt a different approach by devising an agent-based artificial stock market, which has more relaxed assumptions (explained in Section 3). By performing simulations and analyzing liquidity costs induced under different market scenarios, we hope to understand the dynamics of liquidity costs, and hence to devise a more realistic optimal liquidation strategy.

The rest of this paper is organized as follows. In Section 2, we provide the background and summarize related works. Section 3 explains the agent-based artificial stock market we developed based on the DFGIS model and the data from the Taiwan Stock Market (TWSE). In Section 4, the 10 securities and stocks that we selected to conduct our study are presented. Section 5 provides the model parameters used to perform our simulation. We analyze the simulation results in Section 6 and present our discussions in Section 7. Finally, Section 8 concludes the paper with an outline of our future work.

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2. Background and related work

This study implements an agent-based model for an order-driven double auction market, which is the most common financial market in the world. We shall first provide a brief introduction of the basic microstructure and trading mechanism of a standard order-driven double-auction market. Next, the DFGIS model (Daniels, Farmer, Gillemot, Iori, & Smith, 2003), on which our agent-based artificial stock market is based, will be presented. After that, we will summarize the work of (Guo, 2005) on agent-based models used to study liquidation strategies at the end of the section.

2.1. Order-driven double-auction markets

In an order-driven double-auction market, prices are determined by the publication of *orders* to buy or sell shares. This is different from a quote-driven market where prices are determined from *quotations* made by market makers or dealers.

There are two basic kinds of orders in an order-driven market. Impatient traders submit *market orders*, which are requests to buy or sell a given number of shares immediately at the best available price. More patient traders submit *limit orders*, which specify the limit (best acceptable) price for a transaction. Since limit orders often fail to result in immediate transactions, they are stored in a *limit order book*. As shown on the left of Table 1, limit buy orders are stored in decreasing order of limit prices while limit sell orders are stored in increasing order of limit prices. The buy limited orders are called *bids* and the sell limited orders are called *asks*. For a normal double-auction market, the best (highest) bid price is lower than the best (lowest) ask price. The difference between the two is called the *spread* of the market. In the example in Table 1 (left), the *spread* is $0.07.

When a *market order* arrives, it is matched against limit orders on the opposite side of the book. For example, when a market sell order for 30 shares arrives at the market whose order book is as that on the left of Table 1, it will first be matched against the current best bid (20 shares at $1.10 per share). Since the size of the sell order (30 shares) is larger than that of the best bid (20 shares), the remainder of the market sell order (10 shares) will be matched against the next best bid (25 shares at $1.09 per share). After the transaction is completed, the limit order book will change to the right of Table 1 and the market spread will widen to $0.08.

2.2. The DFGIS model

In the original DFGIS model (Daniels et al., 2003), all the order flows (including limit orders and market orders) are modeled as a Poisson process. Market orders arrive at the market in chunks of σ shares (where σ is a fixed integer) at an average rate of μ per unit of time. A market order may either be a buy market order or a sell market order with equal probability.

Limit orders arrive at the market in chunks of σ shares, at an average of α shares per unit price per unit of time. A limit order may either be a limit buy order or a limit sell order with equal probability. The limit prices in limit orders are generated randomly from a uniform distribution. In particular, the limit buy prices have a range between $(-\infty, a(t))$, where $a(t)$ is the best (lowest) *ask* price in the market at time t. Similarly, the limit sell prices have a range between $(b(t), \infty)$, where $b(t)$ is the best (highest) *bid* in the market at time t. In addition, the price changes are not continuous, but have discrete quanta called *ticks* (represented as dp). Tick size is the price increment/decrement amount allowed in a limit order.[1]

DFGIS also allows the limit order to expire or to be canceled after being placed in the market. Limit orders are expired and canceled according to a Poisson process, analogous to radioactive decay, with a fixed-rate δ per unit of time. Table 2 lists the parameters of the DFGIS model.

To keep the model simple, the DFGIS does not explicitly allow limit orders whose prices cross the best bid price or the best ask price. In other words, the price of a limit buy order must be below the best ask price and the price of a limit sell order must be above the best bid price.

Farmer, Patelli and Zovko (2005) implemented the model to explicitly handle this type of order. They defined *effective market orders* as shares that result in transactions immediately and *effective limit orders* as shares that remain on the order book. A limit order with a price that crosses the opposite best price is split into effective market orders and effective limit orders according to the above definition. For example, when a limit sell order of 30 shares at price of $1.10 arrives at the market (with the order book as that listed in Table 3 (left)), the order will be split into an effective market order of 20 shares and an effective limit sell order of 10 shares. After the execution of the 20 shares of the effective market order (at price $1.10), the order book is changed to that on the right of Table 3.

Table 1
An example of an order book before (left) and after (right) a transaction.

Limit buy orders		Limit sell orders		Limit buy orders		Limit sell orders	
Size	Price	Size	Price	Size	Price	Size	Price
20	$1.10	35	$1.17	15	$1.09	35	$1.17
25	$1.09	10	$1.19	35	$1.05	10	$1.19
35	$1.05	20	$1.21	10	$1.01	20	$1.21
10	$1.01	15	$1.25			15	$1.25

Table 2
Summary of DFGIS parameters.

Parameter	Description	Dimension
α	Avg. limit order rate	Share/price · time
μ	Avg. market order rate	Share/time
δ	Avg. limit order decay rate	1/time
σ	Order size	A constant share
dp	Tick size	Price

Table 3
An example of an order book before (left) and after (right) handling a limit sell order with price equal to the best bid.

Limit buy orders		Limit sell orders		Limit buy orders		Limit sell orders	
Size	Price	Size	Price	Size	Price	Size	Price
20	$1.10	35	$1.17	25	$1.09	10	$1.10
25	$1.09	10	$1.19	35	$1.05	35	$1.17
35	$1.05	20	$1.21	10	$1.01	10	$1.19
10	$1.01					20	$1.21

2.3. The Guo agent-based stock market model

Guo (2005) implemented an agent-based artificial stock market based on the DFGIS model (he called it the SFGK model) to study time-constrained asset liquidation strategies through market sell orders only. In particular, he compared the performance of two strategies. The first one uniformly divides the liquidation shares X and the time constraint T into N chunks. This "uniform rhythm" strategy instructs a trader to sell X/N shares every T/N seconds, regardless of the market condition.

[1] The range of price has $-\infty$ as the lower limit because in the DFGIS model prices are first converted to logarithms. As we shall see later in Section 3, we do not use the logarithm transformation of price. Prices and ticks are all in their original form.