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## Hjb Equation And Statistical Arbitrage Applied To High Frequency Trading

Yonggi Park  
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HJB EQUATION AND STATISTICAL ARBITRAGE APPLIED TO HIGH FREQUENCY  
TRADING

by

YONGGI PARK  
M.S. University of Central Oklahoma, 2009

A thesis submitted in partial fulfilment of the requirements  
for the degree of Master of Science  
in the Department of Mathematics  
in the College of Science  
at the University of Central Florida  
Orlando, Florida

Summer Term  
2013

Major Professor: Jiongmin Yong

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## **ABSTRACT**

In this thesis we investigate some properties of market making and statistical arbitrage applied to High Frequency Trading (HFT). Using the Hamilton-Jacobi-Bellman(HJB) model developed by Guilbaud, Fabien and Pham, Huyen in 2012, we studied how market making works to obtain optimal strategy during limit order and market order. Also we develop the best investment strategy through Moving Average, Exponential Moving Average, Relative Strength Index, Sharpe Ratio.

## **ACKNOWLEDGMENTS**

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## CHAPTER 1: INTRODUCTION

Let us begin with a classical stock trading scenario. Suppose, at time  $t_0$ , investor A wants to sell one share of a given stock and investor B wants to buy one share of this stock at time  $t > t_0$ . Investors A and B do not meet directly, and a person, called a market maker, labeled by C, will buy the stock from A at time  $t$  at price, say  $p^b$ , called a bid price, and will sell it to investor B at price, say  $p^a$ , called an ask price, with  $p^a > p^b$ . The difference  $p^a - p^b > 0$  is called the bid-ask spread. Usually traders might make several trades per day, or per week (even per month).

Nowadays, without the formal designation, any trading firms can play a role as market makers by using (swift electronic) High frequency trading (HFT, for short) system through electronic exchanges like Nasdaq's Inet, an electronic trading platform acquired by NASDAQ in 2005([26],[24],[11]).

More precisely, anyone can post the number of shares  $\ell^b$  of the stock with the bid price  $q^b$  at which she would like to buy, which is called a limit bid order and at the same time she can post the number of shares  $\ell^a$  of the stock with the ask price  $q^a$  at which she would like to sell, which is called a limit ask order. The postings are made by numerous individuals from a list which is called the limit order book (LOB, for short). People submit limit bid order and limit ask order simultaneously, and gain a possible profit from the bid-ask spread, which was the profit of market maker in classical trading. Unlike classical traders, HFT traders have information in the same level as a market maker. In other words, all traders play a role as market makers, which means that passive investors in classical trading are changed to active investors in HFT. Since trading firms are acting as market makers in HFT by making limit orders, we refer to the algorithms associated with limit orders as market making algorithms.

The introduction of some advanced tools involving computers allows the trading speed to be faster

and faster. Then, trading can be made more and more frequent. Unlike classical trading, HFT may hold an investment position for only seconds, or fractions of a second and uses the computer trading in and out of positions of thousands or tens of thousands of time a day, and the terminology of high frequency is come from these huge transaction number([45]).

Long-term investors look for chances over a period of weeks, months, or years, but HFT traders struggle on a rapid basis with other HFT traders, and struggle for very tiny, persistent profits ([29],[40]). High frequency traders aim to get only a fraction of a penny per stock or currency unit on each trade, and move in and out of short-term positions many times each day. Fractions of a penny are aggregated fast and produce vary huge profits at the end of each day ([24]). In finance, leverage means any technique to multiply gains and losses, and general ways to get leverage are borrowing money, buying fixed assets and using derivatives. High frequency trading firms do not make use of significant leverage, do not aggregate portfolios, and normally liquidate their all stock inventories on a daily basis([40]).

HFT accounts for over 70 % of stock trades in the US, 38 % in Europe by 2010, and has been very quickly expanding in popularity in Europe and Asia. Hedge funds with high frequency trading strategies manage 141 billion dollar as their assets as of the first quarter in 2009 ([18]).

The strategies for HFT are classified as Market making, Ticker tape trading, Event arbitrage, Statistical arbitrage, and so forth. The mostly used strategies are market making and statistical arbitrage according to [25].

In this thesis, I present the most successful approaches in the exciting world of high frequency trading, by introducing new concepts and applications of Hamilton-Jacob-Bellman (for short, HJB) equation and statistical arbitrage. In the rest of this Chapter, I recall some definitions. In Chapter 2, I introduce market making strategy applied to high frequency trading. In Chapter 3, I introduce statistical arbitrage strategy applied to high frequency trading. In Chapter 4, I summarize my

contribution from Chapters 2 and 3. In Chapter 5, I add the code for figure 1 through figure 5 on Chapter 5.

### Definition

We now recall some definitions.

#### *Limit order/Market order*

A limit bid order is an order to be posted to buy a specified quantity of a security at or below a specified price, called the limit bid price, and a limit ask order is an order to sell a specific quantity of a security at or above a specified price, called the limit ask price (see figure 2.1 on page 15, figure 2.2 on page 16). The execution of such kind of orders is uncertain and it has to wait until the prices are met by a counterpart market order (see 2.1 on page 19). Limit orders ensure that the trader will never pay more to buy the stock than the set limit price, and will never receive less to sell the stock than the set limit price. On the other hand, the market order is a buy or sell order at which the broker is to execute the order at the best price, called the market price, currently available. Its execution is immediate. These are often the lowest-commission trades because they involve very little work by the broker. Limit order book (for short, LOB) is a record of unexecuted limit orders maintained by the specialist (see figure 2.1 on page 16).

#### *Bid/ask price*

An ask price is the price a seller is willing to accept for a stock, also known as an offer price, and a bid price is the price at which a buyer is willing to buy a stock. Given a stock, the best bid price,

denoted by  $p^b$ , is the highest price among limit orders to buy that are active in the LOB. The best ask price, denoted by  $p^a$ , is the lowest price among limit orders to sell that are active in the LOB, and it is usually  $p^a > p^b > 0$  (see figure 2.2, table 2.1, table 2.3 on page 21). Thus, in principle, bid price is bounded below by 0, and ask price is unbounded above.

### *Market maker*

A market maker is a company, or an individual, that quotes both a bid and a ask price in a financial instrument or commodity held in inventory, hoping to make a profit from the bid-ask spread. The example of market maker are most foreign exchange trading firms, and many banks. The New York Stock Exchange (NYSE), American Stock Exchange (AMEX), the NASDAQ Stock Exchange, and the London Stock Exchange (LSE) have designated market makers.

### *The market maker's spread*

The spread at  $t$  is the difference,  $p^a - p^b > 0$  between the best ask price  $p^a$  and the best bid price  $p^b$ . For example, the market maker bought a share of stock from the investor A at the price \$9.90 and sold it to investor B at the price \$10.10. Then the spread is  $\$10.10 - \$9.90 = \$0.20$ , which is the profit of the market maker C.

### *Midprice*

The mid price at time  $t$ , denoted  $p_t$ , is the average of the best ask price and the best bid price at time  $t$ :  $p_t = \frac{p_t^a + p_t^b}{2}$ , where  $p_t^a$  is best ask price at time  $t$ , and  $p_t^b$  is best bid price at time  $t$ .

### *Quotes*

It is the latest price at which a stock or commodity is traded. In other words, it is the most recent price at which a buyer and seller agreed that certain amount of the asset was transacted.

### *Market making*

Market making is one of high frequency trading strategies that place a limit ask order or a limit bid order in order to earn the bid-ask spread. By doing so, HFT traders play a role as counterpart to incoming market orders. In 2009, total annual profit of \$10 giga (=10,000,000,000) were estimated by this strategy over all US stock market.

### *Latency and Low latency*

Latency is a measure of time delay experienced in a system. Low latency allows human-unnoticeable delays between an input being processed and the corresponding output providing real time characteristics. For example, a player with a high latency internet connection may show slow responses in spite of superior tactics or the appropriate reaction time due to a delay in transmission of game events between the player and other participants in the game session. Therefore, this gives the players with low latency connections a technical advantage and biases game outcomes, so game servers favor players with lower latency connections. Low latency is a topic within capital markets, where the proliferation of algorithmic trading requires firms to react to market events faster than the competition to increase profitability of trades.

### *Ultra-low latency*

It is the latencies of under 1 millisecond ( $= \frac{1}{1000}$ ). But, what is considered low today might be considered too slow in a near future.

### *Shelf life*

It is the length of time that a given item can remain in a good condition on a retailer's shelf. If a strategy has limited shelf life, the effectiveness of the strategy decrease over time.

### *Direct Market Access (DMA)*

It is the electronic trading facilities that give HFT investors wishing to trade in financial instruments a way to interact with the limit order book of an exchange.

## The characteristics of high frequency trading

### *The features of HFT*

According to [3], HFT has the following three main features : low latency and ultra-low latency Direct Market Access, multiple asset classes and exchanges, limited shelf life. Classical trading has a relatively high latency, no Direct Market Access, simple asset classes and exchanges, longer shelf life. Figure 1.1 shows the comparison between HFT, algorithm trading (AT), and traditional trading. We now make a little explanation.

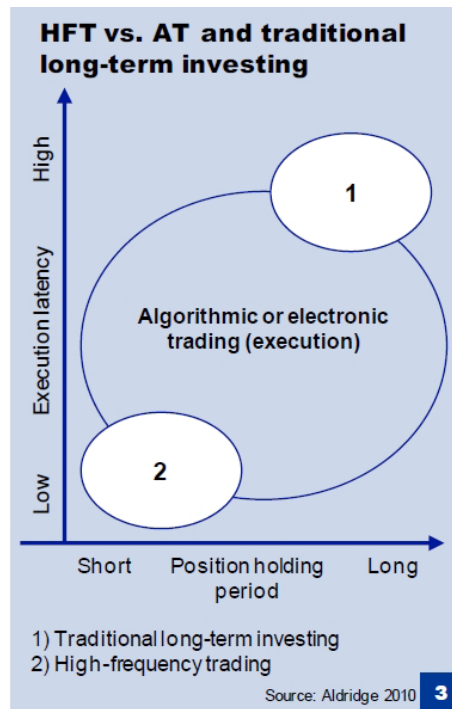


Figure 1.1: Traditional vs HFT

Low Latency, Ultra-Low Latency Direct Market Access(ULLDMA)

HFT strategies depend on ultra-low latency, which means that the reaction speed is very fast, and it is illustrated in figure 1.1. HFT trader has to have a real-time, co-located, HFT program which data is aggregated, and orders are made, directed and implemented in sub-millisecond times, to figure out any real benefit by executing these strategies.

Direct Market Access (DMA) and Direct Strategy Access (DSA) are the electronic trading facilities that give HFT investors wishing to trade in financial instruments a way to interact with the order book of an exchange and are the high speed trading systems to connect directly between trading desk and stock exchange (like NYSE, NASDAQ). They are means to implement trading flow on

a selected place by going around the brokers elective methods. In HFT the DMA should not postpone orders by more than a millisecond.

At the time of writing, market contacts suggest that some HFT participants in FX can operate with latency of less than one millisecond, compared with 10 – 30 milliseconds for most upper-tier non-HFT participants (for comparison, it is said to take around 150 milliseconds ( $= \frac{3}{20}$  seconds) for a human being to blink).

### *Multiple asset classes and exchanges*

The suitable framework is required to use long connectivity between different data places because HFT strategies handle transactions in multiple asset classes and across multiple exchanges.

### *Limited shelf life or Short holding position period*

Over time the competitive advantage of HFT strategies decrease. Thus a firm's micro-level strategies are constantly changed for two reasons even though its high level trading strategy continue persistently over time. First, HFT traders should constantly change the code to reflect tiny modification in the progressive market since HFT is dependent on very precise market interactions and stock correlations. Secondly, competitive intelligence is so smart across rival trading firms that each is exposed to the increasing susceptibility of their strategies being mimic, turning their most profitable ideas into their most risky.



## *The advantages of HFT*

In [2], the authors demonstrate the following advantages of HFT. Supporters of HFT insists the following positive points. They are the contraction of the bid-ask spread, the increase in the speed of execution, improvement in liquidity on platforms, the cushioning of volatility, reduction in trading fees, and a general increase in the efficiency of the market.

### *Bid-ask spread*

HFT traders can swiftly control the bid and ask prices to provide to new market system through the fast speed of their system. Thus, without increase of their volatility they can keep their price close to a certain standard price. The faster speed, the smaller bid-ask spread, and it causes lower trading costs for market participants and more attractive system.

### *Liquidity*

Numerous limit orders in LOB mean liquidity and HFT brings enormous liquidity in inside market. The bid-ask spread and the depth of LOB, the number of stocks for limit orders in LOB, are frequently referred as an indicator of liquidity.

### *Speed*

High speed represents less time for negative price changes between placing and executing the order. In classical trading, an adverse selection problem was big problem, and it is that 'late investor' can do transaction against the 'earlier investor' because 'late investor' can have new information when they are waiting and have a price advantage. However, HFT brings less adverse selection problem

through extremely high speed.

### Volatility

HFT can continue to set price even in volatile periods, and it means that HFT guarantee liquidity and more stable price. The fourth quarter of 2008 is a good example.

### Increased market efficiency

Market making by HFT is a kind of arbitrage, what the market deletes abnormal prices. Therefore, it brings increased market efficiency.

### Fee

As described above, the faster speed in HFT caused the smaller bid-ask spread and it decreased the transaction costs for market participants.

## CHAPTER 2: INTRODUCTION OF MARKET MAKING

Previously, specialist firms implemented the role of market maker. However, nowadays large number of HFT investors implement HFT strategy due to Direct Market Access (DMA). The reduced market spreads and the reduced indirect costs for final investors are caused by improved competition among liquidity providers.

The study shows that the new market provides ideal conditions for HFT market-making, low fees (i.e., rebates for quotes that led to execution) and a fast system, yet the HFT was equally active in the official market to remove nonzero positions. A significant improvement in liquidity supply was further brought by new market entry and HFT. The order driven markets organized most of modern stock exchanges, and in this kind markets, by posting either market orders or limit orders, any market participant can participate to with Limit Order Book (LOB).

### Features of market making strategies

Typical features of market making strategies are the following. First, market making does not benefit from stock price going up or down and so is not directional. Second, market makers do not want to hold any risky asset at the end of the trading day, which means that they do not keep overnight position. Third, during the trading day, market maker's positions on the risky asset (i.e., stock) are close to zero, and they often balance equally their positions on several different market by using high frequency order.

At [22] in 1981, Ho and Stoll studied the optimal dealer problem and applied HJB equation to the market making strategy. In [4], a structure is introduced to control inventory risk in a typical LOB, and in the context of limit orders trials happening at jump times of Poisson processes, market

maker's goal is maximizing the expected utility of her final profit. This model, called as inventory-based strategy, shows its efficiency to reduce inventory risk, measured via the variance of terminal wealth, against the symmetric strategy. This model based on HJB equation introduced by Ho and Stoll is the first one applied to HFT and is often referred in real world with the LOB model from [4].

In [19], the authors derived a simplified solution to the backward optimization problem, an in-depth discussion of its characteristics and an application to the liquidation problem. [6] provided a closely relevant model to solve a liquidation problem, and study continuous limit case.

In [10] the authors give us a method to include more exact empirical characteristics to this system by embedding a hidden Markov model for high frequency dynamics of LOB. [32] solve the Merton's portfolio optimization problem in the situation where the investor is able to select between market orders or limit orders. [44] said that in the context of market making in the foreign exchange market, it is possible to use market orders in addition to limit orders. In 2011, [20] presents a novel approach to the issue of optimal high frequency trading with limit and market order. In this paper they develop a new model to address three sources of risk : the inventory risk, the adverse selection risk, and the execution risk.

In this thesis, by choosing optimally between market and limit orders from her transactions in the LOB, and controlling the inventory, and getting rid of her inventory at the terminal date, we, as a HFT trader, maximize the expected utility function from profit over a finite time horizon  $T$ . We study in detail classical frameworks including power utility criterion and log utility criterion.

### Market-making Model

We now recall some definitions.

**Definition (Markov process, Markov chain)** *Markov process is a stochastic process satisfying the Markov property. Let  $(\Omega, \mathcal{F}, \mathbf{P})$  be probability space with a filtration  $\mathbb{F} = (\mathcal{F}_t, t \in I)$ , for some index set  $I$ . Also let  $(\mathcal{S}, \mathcal{Z})$  be a measurable space. An  $(\mathcal{S}, \mathcal{Z})$ -valued stochastic process  $P = (P_t, t \in I)$  adapted to the filtration is said to have the Markov property if, for each  $A \in \mathcal{Z}$  and each  $s, t \in I$  with  $s < t$ ,*

$$\mathbf{P}(P_t \in A | \mathcal{F}_s) = \mathbf{P}(P_t \in A | P_s).$$

*A Markov chain is a sequence of random variables  $S_1, S_2, \dots$  with the Markov property, namely that, given the present state, the future and past states are independent, Formally,*

$$\mathbf{P}(S_{n+1} = s | S_1 = s_1, S_2 = s_2, \dots, S_n = s_n) = \mathbf{P}(S_{n+1} = s | S_n = s_n).$$

*The possible values of  $S_i$  form a countable set  $\mathbb{S}$ , called the state space of the chain.*

Now remind a model from [20].

Let  $(\Omega, \mathcal{F}, \mathbb{F}, \mathbf{P})$  be a complete filtered probability space with a filtration  $\mathbb{F} = \{\mathcal{F}_t\}_{t \geq 0}$  satisfying the usual condition. We consider a fixed security. Suppose the midprice of this security is described by a Markov process  $P_t$  with infinitesimal generator  $\mathcal{P}$  and state space  $\mathbb{P}$ . For example, if

$$dP_t = \mu dt + \sigma dW_t,$$

then

$$\mathcal{P}\phi(x) = \frac{\sigma^2}{2}\phi_{xx}(x) + \mu\phi_x(x), \quad \forall \phi(\cdot) \in C^2(\mathbb{R}). \quad (2.1)$$

To describe the spread process, let  $\hat{S}_n$  be a discrete-time stationary Markov chain taking values in the finite state space

$$\mathbb{S} \equiv \{i\delta \mid 1 \leq i \leq m\},$$

where  $\delta > 0$  is a fixed constant called the tick size, and  $m > 1$  is a given (possibly large) integer (see table 2.3 on page 21). Let the probability transition matrix of  $\hat{S}_n$  be given by  $R_0 = (\rho_{ij})_{1 \leq i, j \leq m}$ , i.e.,

$$P(\hat{S}_{n+1} = j\delta \mid \hat{S}_n = i\delta) = \rho_{ij} \quad (2.2)$$

and  $\rho_{ii} = 0$ .

Next, let  $N_t$  be a Poisson process with a deterministic intensity rate  $\lambda(t)$ , which is independent of  $\hat{S}_n$ . Then, the price spread process is assumed to be

$$S_t = \hat{S}_{N_t}, \quad t \geq 0, \quad (2.3)$$

where  $N_t = (N_t^a, N_t^b)$ , with  $N_t^b$  being the number of arrivals of market bid orders matching the limit orders for quote ask  $Q^a$ , and  $N_t^a$  being the number of arrivals of market ask orders matching the limit orders for quote bid  $Q^b$ .

Also, we assume that  $\hat{S}_t$  is independent of the Poisson process  $N$ . Thus,  $S_t$  is a continuous-time Markov chain taking values in  $\mathbb{S}$ , with intensity matrix  $R(t) = \lambda(t)R_0$ , where  $\lambda(t)$  is a parameter of Poisson distribution and it is the numbers which market order hits limit order, which is the number of trading execution.

For a HFT trader, she can trade the stock by either limit orders or market orders. More precisely,

she may post at any time limit bid/ask orders at the current best bid/ask prices, and then has to wait an incoming counterpart market order engaging her limit order. She can also post market bid/ask orders to execute immediately, but, in this case obtain the opposite best quote, i.e. trades at the best-ask/best-bid price, which is less beneficial.

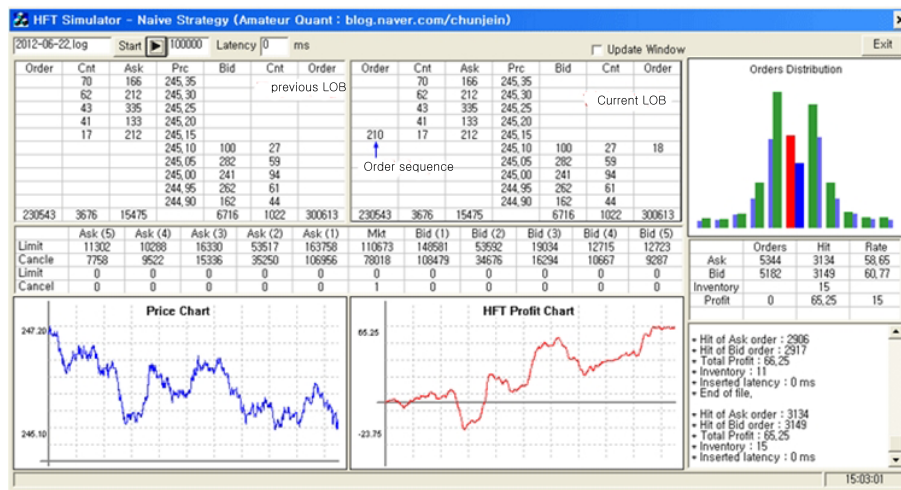


Figure 2.1: Example of Limit Order Book [35]

### Limit Order strategy

At any time the HFT trader may post limit bid/ask orders indicating the quantity and the price she want to pay/receive per stock (called limit price), and trade will be completed only when an incoming market ask/bid order ‘hits’ matching her limit bid/ask order. The HFT trader quotes the bid price  $Q_t^b$  with quantity  $L_t^b$  and the ask price  $Q_t^a$  with quantity  $L_t^a$ , and she is committed to respectively buy and sell the stock at these prices. In other words, these limit orders will be traded when a market order comes with promised quantities  $L_t^b$  or  $L_t^a$  (see figure 2.2).

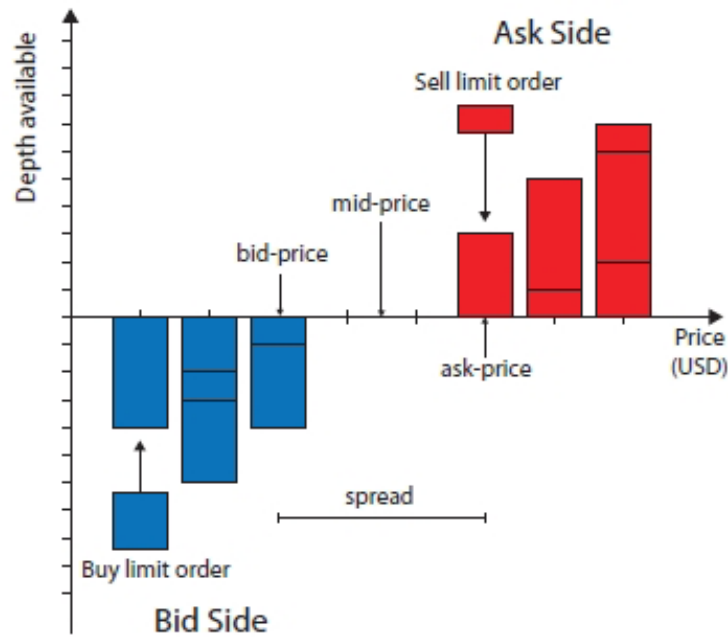


Figure 2.2: Schematic of a LOB

In stock market, consecutive event such as order flow has strong relationship with Poisson distribution and Exponential distribution in statistics. Because the events in LOB happens in very short time, in very complicated, and almost consecutively, we have to analyze them statistically. Poisson distribution focuses on how many times the events happen per unit time, while exponential distribution focuses on how long the event takes time per each event. Let us look at a concrete case to get some feeling.

Assume that a spread is  $s$  %, which is a constant. Figure 2.2 illustrates the definitions in this part and represents a schematic of LOB at some instant in time. By the definition of spread observed prices for buys, the bid prices, are lower than the actual midprices by  $0.5s$  %, but observed prices for sells, the ask prices, are higher than the actual price by  $0.5s$  % (see equation (2.4)). If we assume that the daily high price is a buyer-initiated trade, so it is grossed up by half of the spread,



but the daily low price is a seller-initiated trade, so it is discounted by half of the spread. Therefore the observed high-low price range includes both the range of the actual prices and the bid-ask spread.

We assume that the arrival market bid orders which will trade our trader's limit ask orders follow a Poisson process with an intensity rate  $\lambda^a(q_t^a, s_t)$ , where  $s_t$  is the spread,  $q_t^a$  is an ask quote. Likewise, the arrival market ask orders which will hit the trader's limit bid orders follow a Poisson process with an intensity rate  $\lambda^b(q_t^b, s_t)$ , where  $q_t^b$  is a bid quote.

Suppose that  $p_t^b$  and  $p_t^a$  are current best bid price and current best ask price respectively, and  $\delta_t^b$  should be an integer multiple of the so-called tick sizes  $\delta$  for bid,  $\delta_t^a$  should be an integer multiple of the so-called tick sizes  $\delta$  for ask, the smallest increment (tick) by which the price of stocks can move.

HFT trader try to defeat with the other trader, and it means that the trader could post limit ask order at  $p_t^a$  or  $p_t^a - \delta$ , the improved ask price, and post limit bid order at  $p_t^b$  or  $p_t^b + \delta$ , the improved bid price, to sell/buy as soon as possible. Let  $Y_t$  be the stock inventory process and  $X_t$  be the cash process at time  $t$ . If a bid limit order is made at  $t$ , we denote the limit bid price by  $Q_t^b$  and limit bid order size by  $L_t^b$ . Thus,  $(Q_t^b, L_t^b)$  determines a limit bid order. Likewise, we may let  $(Q_t^a, L_t^a)$  represent a limit ask order. We restrict  $Q_t^b$  and  $Q_t^a$  to be the following form:(see figure 2.2, table 2.1, table 2.3)

$$\begin{aligned} Q_t^b &= P_{t-} - \frac{S_{t-}^b}{2} + \delta_t^b = P_{t-}^b + \delta_t^b, \\ Q_t^a &= P_{t-} + \frac{S_{t-}^a}{2} - \delta_t^a = P_{t-}^a - \delta_t^a, \end{aligned} \tag{2.4}$$

with

$$\delta_t^b, \delta_t^a \in \{0, \delta\},$$

and assume that

$$|L_t^b|, |L_t^a| \leq L_0,$$

for some  $L_0 > 0$ , a bound for the limit order sizes. Since limit orders can be updated at high frequency with no cost, we denote a continuous time control process as

$$\alpha_t = (\delta_t^b, L_t^b, \delta_t^a, L_t^a),$$

where  $L = (L^b, L^a)$  valued in  $[0, L_0]^2$ ,  $L_0 > 0$ , and call it a limit order control.

Under any control  $\alpha_t = (\delta_t^b, L_t^b, \delta_t^a, L_t^a)$ , the cash and stock inventory are stochastic and depend on the arrival of market ask and bid order. Thus, we have a regular dynamic control system :

$$dY_t = L_t^b dN_t^b - L_t^a dN_t^a, \quad (2.5)$$

$$dX_t = -[P_{t^-} - \frac{S_{t^-}}{2} + \delta_t^b] L_t^b dN_t^b + [P_{t^-} + \frac{S_{t^-}}{2} - \delta_t^a] L_t^a dN_t^a, \quad (2.6)$$

where  $N_t^b$  and  $N_t^a$  are independent Cox processes with the intensity rates  $\lambda^b(Q_t^b, S_t)$  and  $\lambda^a(Q_t^a, S_t)$ , depending on  $(Q_t^b, S_t)$  and  $(Q_t^a, S_t)$ , respectively.  $dY_t$  represents the process of the increment of number of stock after limit order,  $L_t^b dN_t^b$  means total number of stock after limit bid order,  $L_t^a dN_t^a$  represents total number of stock after limit ask order,  $dX_t$  represents the process of the increment of the cash after limit order.

Here  $\lambda^b(q, s)$  and  $\lambda^a(q, s)$  are deterministic continuous functions having the following properties:

$$\left\{ \begin{array}{l} q \mapsto \lambda^b(q, s) \text{ is increasing,} \\ q \mapsto \lambda^a(q, s) \text{ is decreasing.} \end{array} \right. \quad (2.7)$$

We let  $\mathfrak{A}[t, T]$  be the set of all limit order controls on  $[t, T]$ .

In Table 2.1, let us consider a simple LOB having five limit orders, namely, sell 150 shares stock of SAMSUNG at \$10.11, sell 150 shares stocks of SAMSUNG at \$10.08, buy 100 shares stocks of SAMSUNG at \$10.05, buy 200 shares stocks of SAMSUNG at \$10.01.

Table 2.1: Before two market orders

	Price	Ask Size
	\$10.11	150
	\$10.08	100
300	\$10.05	
200	\$10.01	
bid Size	Price	

Orders to buy/sell are orders on the bid/ask side. The prices are \$10.11, \$10.08, \$10.05, \$10.01. \$10.05 is the highest bid price and it is called the best bid, and \$10.08 is the lowest ask price and it is named the best ask, and they consist of the inside market. The difference between the best bid and best ask is called the spread ( $= \$10.08 - \$10.05 = \$0.03$ ). The average of the best bid and best ask is called the midprice ( $\frac{\$10.08 + \$10.05}{2} = \$10.065$ ).

HFT traders can submit four kinds of messages to an LOB, and they are add, cancel, cancel/replace, and market order. A trader can add and cancel(remove) a limit order in to the LOB. Suppose a trader needs to reduce the size of her order, then she can submit a cancel/replace. So the current order will be canceled and be replaced with the order with a lower size at the same price.

Let us start to have two market orders. First, every orders have ‘timestamps’ representing the time accepted into the LOB, and they bring the time priority of an order. In other words, before later orders earlier orders will be traded. For example, in Table 1 let us assume that the order buying 200 stocks at \$10.05 was submitted after the order buying 100 stocks at \$10.05, and then LOB has 300

bid size for \$10.05. Assume that a HFT trader submit a market bid order to sell total 200 stocks to LOB. Then 100 shares of the order with 200 total shares will be traded after the limit order for 100 stocks is executed because the earlier 100 stocks was the first in the queue and 100 shares of the order with 200 total shares was the second in the queue. After this market order of 200 shares, 100 stocks will stay in the LOB at price \$10.05.

Second, if a market order has more stocks than the size at the inside market, it will trade at worse price until it end. For example, if a HFT trader submit a market order buying 200 stocks, then the order at \$10.08 would be completely traded because \$10.08 is the best ask price currently. Next 100 stocks of \$10.11 will be executed to finish the market order. An order to sell 50 stocks at the price level of \$10.11 will be in the LOB. The following LOB is the one after we executed above two market orders.

Table 2.2: After two market orders

	Price	Ask Size
	\$10.11	50
100	\$10.05	
200	\$10.01	
bid Size	Price	

Now we consider more complicated LOB, and assume that all tick sizes are same in Table 2.3. Let us consider the LOB of table 2.3. In the left table, spread = best ask ( $p^a$ ) - best bid ( $p^b$ ) = \$150 - \$130 = \$20, and mid-price =  $\frac{p^a+p^b}{2} = \frac{\$150+\$130}{2} = \$140$ . Tick size  $\delta$  = increment = \$10. If a HFT trader submit limit bid order by \$130 an limit ask order by \$150, and these contracts happen, then \$150 - \$130 = \$20 would be the profits (= spread). If a HFT trader submit limit bid order by \$120 an limit ask order by \$160, and these trades happen, then \$160 - \$120 = \$40 would be the profits (= spread + 2  $\delta$ ). In the right table, equation (1) - equation (3) = bid-ask spread  $s$  by definition.

Table 2.3: Example of LOB

\$180		$p + \frac{s}{2} + 3\delta$	$p^a + 3\delta$
\$170		$p + \frac{s}{2} + 2\delta$	$p^a + 2\delta$
\$160		$p + \frac{s}{2} + \delta$	$p^a + \delta$
\$150	Best Ask	$p + \frac{s}{2}$ (1)	$p^a = \text{possible } q^a$
\$140	Mid-price	$p$ (2)	$p^a - \delta = \text{possible } q^a(4), p^b + \delta = \text{possible } q^b(5)$
\$130	Best Bid	$p - \frac{s}{2}$ (3)	$p^b = \text{possible } q^b$
\$120		$p - \frac{s}{2} - \delta$	$p^b - \delta$
\$110		$p - \frac{s}{2} - 2\delta$	$p^b - 2\delta$
\$100		$p - \frac{s}{2} - 3\delta$	$p^b - 3\delta$

If limit ask order occur by  $p^a - \delta$  and limit bid order happen by  $p^b$ , equation (4) - equation (3) =  $s - \delta =$  HFT trader's profit.

### Market order strategies

The HFT trader may submit market orders to have an immediate execution reducing his inventory. Unlike limit orders, market order (strategy) takes liquidity in the market because market orders take incoming limit orders, and have fees.

Also, a market order strategy can be described by an impulse control, called  $\beta$ . More precisely, we may let  $\{\tau_n\}_{n \geq 1}$  be an increasing sequence of  $\mathbb{F}$ -stopping times, representing the moments at which market orders are posted, and for each  $n \geq 1$ ,  $\{\zeta_n\}_{n \geq 1}$  is a sequence of  $\mathcal{F}_{\tau_n}$ -measurable random variables valued in  $[-\bar{z}, \bar{z}]$ ,  $\bar{z} > 0$ , representing the amount traded at the moments. While submitting a market order  $\zeta_n$  at  $\tau_n$ , the cash and stock inventory jump dynamic control system at time  $\tau_n$  as follows.

$$Y_{\tau_n} = Y_{\tau_n^-} + \zeta_n, \quad (2.8)$$

$$X_{\tau_n} = X_{\tau_n^-} - c(\zeta_n, P_{\tau_n^-}, S_{\tau_n^-}), \quad (2.9)$$

where

$$c(\zeta_n, P_{\tau_n^-}, S_{\tau_n^-}) = P_{\tau_n^-} \zeta_n + \left(\frac{S_{\tau_n^-}}{2} + \rho\right) |\zeta_n| + \epsilon$$

Here,  $z$  is order size,  $\epsilon > 0$  is a fixed transaction cost and  $\rho \in (0, 1)$  is a proportional transaction cost rate. Any such a sequence  $\beta = \{(\tau_n, \zeta_n)\}_{n \geq 1}$  is called a market order (impulse) control. If  $-\bar{z} \leq \zeta_n < 0$ , then  $Y_{\tau_n} (< Y_{\tau_n^-})$  is the number of stock after market ask order, and  $X_{\tau_n} (> X_{\tau_n^-})$  is cash amount after market ask order. Also if  $0 \leq \zeta_n \leq \bar{z}$ , then  $Y_{\tau_n} (> Y_{\tau_n^-})$  is the number of stock after market bid order, and  $X_{\tau_n} (< X_{\tau_n^-})$  is cash amount after market bid order.

It is seen that  $c(\zeta_n, P_{\tau_n^-}, S_{\tau_n^-})$  is the immediate cost paid for buying  $\zeta_n$  shares of the stock (when  $\zeta_n < 0$ , it means selling  $|\zeta_n|$  shares of the stock). Different from the limit order case, for the current market order, the trader has to pay the best ask price  $P_{\tau_n}^a$  to get to stock and can only receive the best bid price  $P_{\tau_n}^b$  to sell the stock. If a proportional cost needs to be considered, we will have

$$\begin{aligned} c(\zeta_n, P_{\tau_n^-}, S_{\tau_n^-}) &= P_{\tau_n^-} \zeta_n + \left(\frac{S_{\tau_n^-}}{2} + \rho\right) |\zeta_n| + \epsilon \\ &= \begin{cases} (P_{\tau_n^-} + \frac{S_{\tau_n^-}}{2}) \zeta_n + \rho \zeta_n + \epsilon, & \zeta_n > 0 \\ (P_{\tau_n^-} - \frac{S_{\tau_n^-}}{2}) \zeta_n - \rho \zeta_n + \epsilon, & \zeta_n < 0 \end{cases} \end{aligned} \tag{2.10}$$

Note that  $\zeta_n > 0$  implies market bid order, and  $\zeta_n < 0$  implies market ask order.

We let  $\mathfrak{B}[t, T]$  be the set of all market order controls on  $[t, T]$ . Now, suppose we start at time  $t^-$  with the initial position

$$(X_{t^-}, Y_{t^-}) = (x, y).$$

Then under any pair  $(\alpha, \beta) \in \mathfrak{A}[t, T] \times \mathfrak{B}[t, T]$ , let  $(X_{T^-}, Y_{T^-})$  be the position at time  $T$  before clearing the stock inventory. Thus, the total market value of the cash is  $X_{T^-} + Y_{T^-} P_{T^-}$ . After

clearing the stock inventory, the cash becomes

$$X_T = X_{T^-} + Y_{T^-} P_{T^-} - |Y_{T^-}| \left( \frac{S_{T^-}}{2} + \rho \right) - \epsilon. \quad (2.11)$$

### Optimal control problem

The goal of the HFT trader is to maximize the expected utility from revenue over a finite time horizon  $T$ , by choosing optimally limit and market orders.

We now introduce the following payoff objective functional:

$$J(t, x, y, p, s; \alpha, \beta) = \mathbb{E} \left[ U(X_T) - \int_t^T g(Y_t) dt \right], \quad (2.12)$$

where  $U(\cdot)$  is a utility function, a level of satisfaction, and  $g(Y_t) : \mathbb{R} \rightarrow (0, \infty)$  is a continuous penalty function. The second term on the right hand side of the equation (2.12) represents a penalty on the stock inventory, and we can select it arbitrarily. Our optimal control problem can be stated as follows.

**Problem (C).**  $\forall (t, x, y, p, s) \in [0, T] \times \mathbb{R} \times \mathbb{R} \times \mathbb{P} \times \mathbb{S}$ , find a pair  $(\bar{\alpha}, \bar{\beta}) \in \mathfrak{A}[t, T] \times \mathfrak{B}[t, T]$  such that

$$J(t, x, y, p, s; \bar{\alpha}, \bar{\beta}) = \sup_{(\alpha, \beta) \in \mathfrak{A}[t, T] \times \mathfrak{B}[t, T]} J(t, x, y, p, s; \alpha, \beta) \equiv V(t, x, y, p, s), \quad (2.13)$$

where  $(\alpha, \beta)$  is limit and market order trading strategies, respectively. The function  $V(t, x, y, p, s)$  is called the value function of Problem (C), and problem (C) is a mixed regular and impulse control problem in a regime switching jump-diffusion model.

*Dynamic programming equation (DPE)*

The dynamic programming principle (DPP) is a fundamental principle in optimal stochastic control theory. It gives a relationship among dynamic control systems, problem (C), via value function. For the above problem (C), we have the following dynamic programming principle.

**Theorem.** For any  $(t, x, y, p, s) \in [0, T) \times \mathbb{R} \times \mathbb{R} \times \mathbb{P} \times \mathbb{S}$ ,

$$V(t, x, y, p, s) \geq \sup_{z \in \mathbb{R}} V(t, x - c(z, p, s), y + z, p, s) \equiv \mathfrak{M}[V](t, x, y, p, s), \quad (2.14)$$

and

$$V(t, x, y, p, s) \geq \sup_{\alpha \in \mathfrak{A}[\hat{t}, T]} \mathbb{E} \left[ V(\hat{t}, X_{\hat{t}}, Y_{\hat{t}}, P_{\hat{t}}, S_{\hat{t}}) \right], \quad \forall \hat{t} \in (t, T]. \quad (2.15)$$

If the strict inequality holds in the (2.14), then there exists a  $\sigma > 0$  such that

$$V(t, x, y, p, s) = \sup_{\alpha \in \mathfrak{A}[\hat{t}, T]} \mathbb{E} \left[ V(\hat{t}, X_{\hat{t}}, Y_{\hat{t}}, P_{\hat{t}}, S_{\hat{t}}) \right], \quad \forall \hat{t} \in [t, t + \sigma]. \quad (2.16)$$

Note that  $V(t, x, y, p, s)$  is all kind of possible strategies, and  $V(t, x - c(z, p, s), y + z, p, s)$  is one market order strategy, and  $V(\hat{t}, X_{\hat{t}}, Y_{\hat{t}}, P_{\hat{t}}, S_{\hat{t}})$  is one limit order strategy.

From the above. we have



**Theorem.** If  $V(t, x, y, p, s)$  is smooth, then it satisfies the following HJB quasi-variational inequality:

$$\begin{cases} \min \{ -V_t(t, x, y, p, s) - \mathfrak{H}[V](t, x, y, p, s), V(t, x, y, p, s) - \mathfrak{M}[V](t, x, y, p, s) \} = 0, \\ (t, x, y, p, s) \in [0, T) \times \mathbb{R} \times \mathbb{R} \times \mathbb{P} \times \mathbb{S}, \\ V(T, x, y, p, s) = U(x + yp - |y|(\frac{s}{2} + \rho) - \epsilon), (x, y, p, s) \in \mathbb{R} \times \mathbb{R} \times \mathbb{P} \times \mathbb{S}, \end{cases} \quad (2.17)$$

where the second order nonlocal operator :

$$\begin{aligned} \mathfrak{H}[V](t, x, y, p, s) &= [\mathcal{P}V](t, x, y, p, s) + [\mathcal{R}V](t, x, y, p, s) \\ &+ [\Lambda^b V](t, x, y, p, s) + [\Lambda^a V](t, x, y, p, s) - g(y), \end{aligned} \quad (2.18)$$

with  $\mathcal{P}$  is the infinitesimal generator of the midprice process  $P$ ,

$$[\mathcal{R}V](t, x, y, p, i\delta) = \lambda(t) \sum_{j=1}^m \rho_{ij} [V(t, x, y, p, j\delta) - V(t, x, y, p, i\delta)], \quad i = 1, 2, \dots, m, \quad (2.19)$$

$$\begin{aligned} [\Lambda^b V](t, x, y, p, s) &= \sup_{\delta^b \in \{0, \delta\}, |l^b| \leq L_0} \left\{ \lambda^b(p - \frac{s}{2} + \delta^b, s) \left[ V(t, x + (p - \frac{s}{2} + \delta^b)l^b, y + l^b, p, s) \right. \right. \\ &\quad \left. \left. - V(t, x, y, p, s) \right] \right\}, \end{aligned} \quad (2.20)$$

$$[\Lambda^a V](t, x, y, p, s) = \sup_{\delta^a \in \{0, \delta\}, |l^a| \leq L_0} \left\{ \lambda^a \left( p - \frac{s}{2} + \delta^a, s \right) \left[ V(t, x + (p - \frac{s}{2} + \delta^a)l^a, y + l^a, p, s) - V(t, x, y, p, s) \right] \right\}, \quad (2.21)$$

and the impulse operator associated to obstacle market order control :

$$\mathfrak{M}[V](t, x, y, p, s) = \sup_{z \in \mathbb{R}} V(t, x - zp - |z|(\frac{s}{2} + \rho) - \epsilon, y + z, p, s). \quad (2.22)$$

In the case that  $V$  is not smooth, it will be the viscosity solution to the quasi-variational inequality. On the right hand side of (2.18), the first term is the infinitesimal generator of the diffusion mid-price process  $P$ , (2.19) is the generator of the continuous time spread Markov chain  $S$ , and (2.20) correspond to the nonlocal operator induced by the jumps of the cash process  $X$  and (2.21) is the nonlocal operator induced by the jumps of inventory process  $Y$  when applying an instantaneous limit order control  $(Q_t, L_t) = (q, l)$ .

**Lemma** Suppose  $V(t, x, y, p, s)$  is found. If we holds

$$V(t, x, y, p, s) = \mathfrak{M}[V](t, x, y, p, s) = V(t, x - \bar{z}p - |\bar{z}|(\frac{s}{2} + \rho) - \epsilon, y + \bar{z}, p, s), \quad (2.23)$$

for some  $\bar{z} \in \mathbb{R}$ , then

$$V(t, x - \bar{z}p - |\bar{z}|(\frac{s}{2} + \rho) - \epsilon, y + \bar{z}, p, s) > \mathfrak{M}[V](t, x - \bar{z}p - |\bar{z}|(\frac{s}{2} + \rho) - \epsilon, y + \bar{z}, p, s) \quad (2.24)$$

proof. We observe the following:

$$\begin{aligned}
& \mathfrak{M}[V](t, x - \bar{z}p - |\bar{z}|(\frac{s}{2} + \rho) - \epsilon, y + \bar{z}, p, s) \\
&= \sup_{z \in \mathbb{R}} V(t, x - \bar{z}p - |\bar{z}|(\frac{s}{2} + \rho) - \epsilon - zp - |z|(\frac{s}{2} + \rho) - \epsilon, y + \bar{z} + z, p, s) \\
&< \sup_{z \in \mathbb{R}} V(t, x - (\bar{z} + z)p - (|\bar{z} + z|)(\frac{s}{2} + \rho) - \epsilon, y + \bar{z} + z, p, s) \\
&= \mathfrak{M}[V](t, x, y, p, s) \\
&= V(t, x - \bar{z}p - |\bar{z}|(\frac{s}{2} + \rho) - \epsilon, y + \bar{z}, p, s). \tag{2.25}
\end{aligned}$$

This proves (2.24).

From the above result, we see that in the case

$$\begin{aligned}
& V(t, X_{t-}, Y_{t-}, P_{t-}, S_{t-}) = \mathfrak{M}[V](t, X_{t-}, Y_{t-}, P_{t-}, S_{t-}) \\
&= V(t, X_{t-} - \bar{z}P_{t-} - |\bar{z}|(\frac{S_{t-}}{2} + \rho) - \epsilon, Y_{t-} + \bar{z}, P_{t-}, S_{t-}), \tag{2.26}
\end{aligned}$$

by making a market order of size  $\bar{z}$  at market price  $P_{t-} + \frac{S_{t-}}{2}$ , we obtain a new cash position:

$$\begin{aligned}
X_t &= X_{t-} - \bar{z}P_{t-} - |\bar{z}|(\frac{S_{t-}}{2} + \rho) - \epsilon, \\
Y_t &= Y_{t-} + \bar{z}. \tag{2.27}
\end{aligned}$$

At this new position, we have

$$V(t, X_t, Y_t, P_t, S_t) > \mathfrak{M}[V](t, X_t, Y_t, P_t, S_t). \tag{2.28}$$

This means that if the obstacle  $\mathfrak{M}[V]$  is touched at  $t$  by value function, then right after a market order is realized,  $V(t, X_t, Y_t, S_t, P_t)$  will be off the obstacle  $\mathfrak{M}[V]$ . Therefore, there will be no im-

mediate market order right after. Hence, right after, we may assume that the above strict inequality holds for  $t \in (\tau_1, \tau_2)$ . Then the trader will not make market orders during this time period. Let us look how she will make limit orders in the time period.

Suppose we have  $(\bar{\delta}^b, \bar{l}^b)$  and  $(\bar{\delta}^a, \bar{l}^a)$  with

$$\begin{cases} \bar{\delta}^b = \bar{\delta}^b(t, x, y, p, s), & \bar{l}^b = \bar{l}^b(t, x, y, p, s), \\ \bar{\delta}^a = \bar{\delta}^a(t, x, y, p, s), & \bar{l}^a = \bar{l}^a(t, x, y, p, s), \end{cases}$$

such that

$$\left\{ \begin{array}{l} [\Lambda^b V](t, x, y, p, s) = \sup_{\delta^b \in \{0, \delta\}, |l^b| \leq L_0} \left\{ \lambda^b \left( p - \frac{s}{2} + \delta^b, s \right) \left[ V(t, x + \left( p - \frac{s}{2} + \delta^b \right) l^b, y + l^b, p, s \right) \right. \\ \qquad \qquad \qquad \left. - V(t, x, y, p, s) \right] \Big\} \\ = \lambda^b \left( p - \frac{s}{2} + \bar{\delta}^b, s \right) \left[ V(t, x + \left( p - \frac{s}{2} + \bar{\delta}^b \right) \bar{l}^b, y + \bar{l}^b, p, s) - V(t, x, y, p, s) \right], \\ \\ [\Lambda^a V](t, x, y, p, s) = \sup_{\delta^a \in \{0, \delta\}, |l^a| \leq L_0} \left\{ \lambda^a \left( p + \frac{s}{2} - \delta^a, s \right) \left[ V(t, x + \left( p + \frac{s}{2} - \delta^a \right) l^a, y + l^a, p, s \right) \right. \\ \qquad \qquad \qquad \left. - V(t, x, y, p, s) \right] \Big\} \\ = \lambda^a \left( p + \frac{s}{2} - \bar{\delta}^a, s \right) \left[ V(t, x + \left( p + \frac{s}{2} - \bar{\delta}^a \right) \bar{l}^a, y + \bar{l}^a, p, s) - V(t, x, y, p, s) \right] \Big\}. \end{array} \right.$$

Then during the time period that the obstacle  $\mathfrak{M}[V]$  is not touched, the investor can set up two limit orders:

$$\left\{ \begin{array}{l} Q_t^b = P_{t^-} - \frac{S_{t^-}^b}{2} + \delta_{t^-}^b(t, X_t, Y_t, P_t, S_t) = P_{t^-}^b + \delta_{t^-}^b(t, X_t, Y_t, P_t, S_t), \\ \bar{L}_t^b = \bar{l}^b(t, X_t, Y_t, P_t, S_t), \\ Q_t^a = P_{t^-} + \frac{S_{t^-}^a}{2} - \delta_{t^-}^a(t, X_t, Y_t, P_t, S_t) = P_{t^-}^a - \delta_{t^-}^a(t, X_t, Y_t, P_t, S_t), \\ \bar{L}_t^a = \bar{l}^a(t, X_t, Y_t, P_t, S_t). \end{array} \right.$$

This will lead to an optimal policy on the time interval in which the obstacle is not touched. Combining the above, we have the following result.

**Theorem.** *The value function  $V(t, x, y, p, s)$  is the unique viscosity solution to the quasi-variational inequality (2.17) and through which an optimal trading strategy can be constructed.*

## CHAPTER 3: STATISTICAL ARBITRAGE

### Definition

Statistical arbitrage is to use predictable temporary deviations from stable statistical relationships among stocks, and it is actively used in all liquid stocks, stocks that is easily sold due to the fact that there is a large volume of shares traded every day, like equities, bonds, futures, foreign exchange, etc. Classical arbitrage may also be involved with such strategy. One example of classical arbitrage is the covered interest rate parity, a no-arbitrage condition representing an equilibrium state under which investors will be indifferent to interest rates available on bank deposits in two countries, in the foreign exchange market. It gives a connection between the prices of a domestic bond, a bond denominated in a foreign currency, the spot price of the currency, and the price of a forward contract on the currency.

Statistical arbitrage used for HFT uses very complicated models containing many more than four stocks. The TABB Group obtains now annual total profits over *US*\$21 billion by this strategy.

### *Pairs trading*

To exploit the long-term statistical relationships that often exist between assets statistical arbitrage trading strategies are commonly applied in industry. The most well-known application in finance is an investment strategy known as ‘pairs trading’, and it is the simplest form of statistical arbitrage. It is a market neutral trading strategy who makes HFT traders to earn returns from any market conditions: uptrend, downtrend, or sideways movement, (neither an uptrend nor a downtrend). Also it is classified as a statistical arbitrage and convergence trading strategy.

Gerry Bamberger developed this pairs trading and Nunzio Tartaglias quantitative group at Morgan Stanley applied more to market in the 1980s. Pairs trading compares the results of two historically correlated stocks. When the two stocks correlated weakly, i.e. one stock going up when the other going down, the strategy of pairs trading will be to short (= sell) the outperforming security and to long (= buy) the underperforming one, expecting the convergence of the spread between the two stocks in the future.

When there are temporary supply (or demand) changes, large buy (or sell) orders for one security, reaction for important news about one of the companies, and so on, the divergence within a pair occurs.

The opportunity is rare even though pairs trading strategy does not have much downside risk, an estimation of a security's potential to suffer a decline in value if the market conditions change, or the amount of loss that could be sustained as a result of the decline. So the HFT trader should be one of the first to gain a profit. It is hard to anticipate individual stock prices but it might be easy to anticipate the price (or the spread series) of certain stock portfolio. To anticipate the price (or the spread series) of certain stock portfolio, the first step is establishing the portfolio so that the spread series is a stationary process, a stochastic process whose joint probability distribution does not change when shifted in time or space. As the second step, the stationary process is achieved by finding a cointegration relationship, a statistical property of time series variables, between the two stock price series. We say that two or more time series are cointegrated if they share a common stochastic drift. As long as the spread series is a stationary processes no matter how portfolio is established, then it can be modeled, and subsequently anticipated, using techniques of time series analysis such as Ornstein-Uhlenbeck models, autoregressive moving average (ARMA) models and (vector) error correction models.

HFT traders consider forecastability of the portfolio spread series to be important by the following

reasons : First, by buying and selling the shares the spread can be directly traded. Second, The return and risk of the trade can be measured by the forecast and its error bounds given by the model.

Financial engineers has been interested in figure out the outcome of statistical arbitrage for two reasons. First, [14] said that in the debate over whether financial markets are efficient, such strategies violate the weakest form of market efficiency. Second, the market frictions (anything preventing markets from developing and working properly) or behavioral biases cause prices to deviate from fundamental values, and statistical arbitrage make financial engineers to understand it ([23])

Now many researchers have studied to understand the source of profitability in these strategies because there are many papers about the profitability of these strategies. [16] said that the unexpected change of trading volume also captures informational effects due to increased visibility of the equities, the profits from pairs trading may be negatively affected by the change of trading volume.

A paper said that a pairs trading strategy generates annual returns of 11 percent and a monthly Sharpe ratio of four to six times more than that of market returns between 1962 and 2002 ([17]).

In 2007, [42] compares the efficacy of the Relative Strength Index (RSI) versus the Moving Average (MA) trading rules on the daily exchange rates of six currencies. The results indicate that the trading rules can yield positive risk-adjusted returns, and the profitability of these trading rules is positively related to central bank interventions. It is also found that the impact of interest rate differentials on the trading rule return is not important.



## Moving Average (MA)

### **Definition**

$$MA(N)_t = \frac{1}{N} \sum_{i=0}^{N-1} P_{t-i}, \quad (3.1)$$

where  $N$  is the length of the moving average, and  $P_t$  is the stock price at time  $t$ .

The MA method is defined as the Simple Moving Average (SMA), which is the unweighted mean of the previous  $N$  data points.

### **Trading strategy:**

a) Long stock if  $P_t \geq MA(N)_t$

b) Short stock if  $P_t < MA(N)_t$

If the stock price is above or equal to the MA, then the trading should long (buy) the US dollar, and if the stock price is below the MA, then the trading is going to short (sell) it.

There are several advantages for MA. First, they smooth out fluctuations in data and show the trend. Second, time horizon of the trend, a fixed point of time in the future at which point certain processes will be evaluated or assumed to end, is determined by the period of the MA. Third, it can be used to generate buy and sell signals using the crossover of several averages. Fourth, it can save trader from fake-outs. Fifth, SMAs work well for longer-term situations that do not require a lot of sensitivity.

Disadvantages of MA are the followings. First, because they average the data, they lag the turns

in the underlying data. Second, reducing the period of the average reduces the lag but increases whipsaws, a condition where a security's price heads in one direction, but then is followed quickly by a movement in the opposite direction (i.e., false signals). Third, SMA provides a smoother slope and responds slower to price actions.

### Exponential Moving Average (EMA)

EMA is a type of infinite impulse response filter, a filter with a property of signal processing systems who have an impulse response function that is non-zero over an infinite length of time, that applies weighting factors which decrease exponentially.

#### **Definition :**

$$EMA(N)_t = \alpha P_t + (1 - \alpha)EMA(N)_{t-1}, \quad (3.2)$$

where the coefficient  $\alpha$  is the degree of weight decreases, and  $\alpha = \frac{2}{N+1}$  with  $0 < \alpha < 1$ . A higher  $\alpha$  discounts older observations faster.

We need to define the value of  $EMA(N)_0$ , the first value of the EMA. The choice of  $EMA(N)_0$  is not unique. To calculate  $EMA(N)_0$  some professionals may use the asset price at the time when they first implement the strategy, and some may use a SMA of the prior N data points.

#### **Trading Strategy:**

a) Long stock if  $P_t \geq EMA(N)_t$

b) *Short stock if  $P_t < EMA(N)_t$ .*

If the stock price is above or equal to the EMA, then the trading should long the US dollar, and if the stock price is below the EMA, then the trading is going to short it.

There are several advantages for EMA. First, the EMA best suits to the trader if the trader want a MA that will quickly respond to price movements, because EMA tends to catch trends very early and it would yield higher profit for a HFT trader. Second, the earlier the trader see a trend, the longer the trader will be able to take advantage of it. Third, the EMA weighs current prices more heavily than past prices. Fourth, EMA respond quicker to short-term situations than long term situation.

Disadvantages of EMA are the followings. First, trader may get superficial readings during consolidation periods, periods of the movement of an asset's price within a well-defined pattern or barrier of trading levels. Because EMA tends to catch trends quickly, it can be so fast that you may pick up a trend which could just be a sudden price change. Second, EMA is more prone to whipsaws. Third, since EMA respond quicker to short-term situations, it may also be prone to giving false signals.

However, every HFT trader should weigh the pros and the cons of the EMA and decide in which manner they will be using MA. Nevertheless, MA remain the most popular and is the most effective technical analysis indicator out on the market today.

Let us compare between MA and EMA. First, SMA work well for longer-term situations that do not require a lot of sensitivity. Second, the EMA is more sensitive and better for shorter time periods as it can capture changes quicker.

## Relative Strength Index (RSI)

### **Definition :**

$$RSI(N)_t = 100 - \frac{100}{1 + RS}, \quad (3.3)$$

where  $RS = \frac{Average(U,t)}{Average(D,t)}$ , and  $Average(U,t)$  represents the average of  $N$  days (usually 250 days) up prices and  $Average(D,t)$  is average of  $N$  days down prices.

The RSI ranges from zero to 100. It gives a reading of zero if there are pure downward price movements, and a reading of 100 if there are pure upward price movements. The threshold value is the middle point of the oscillator, 50. The RSI computes momentum, the rate of the rise or fall in price, as the ratio of higher closes (closing price) to lower closes: stocks which have had more or stronger positive changes have a higher RSI than stocks which have had more or stronger negative changes. The RSI is measured on a scale from 0 to 100, and is considered overbought when above 70 and oversold when below 30.

### **Trading strategy:**

a) Long the USD if  $RSI(N)_t \geq 50$

b) Short the USD if  $RSI(N)_t < 50$

There are several advantage for RSI. First, it is very elegant indicator, whose movements are smooth, and so it can fit into a simple package between 0 and 100. Second, it is not only a testa-

ment to its abilities, but it also makes its signals self-fulfilling prophecy, a prediction that causes itself to become true due to positive feedback between belief and behavior, at times. People who believe in the importance of the 50-day moving average, for example, closely monitor their stocks as they approach that average. Third, when used to indicate divergences, it can be quite powerful.

Disadvantages of RSI are the followings. First, it doesn't take into account how many up days vs. down days there are in the range, so one single big decline could offset a large number of gain periods and only one single big increase could offset a large number of loss periods. Second, the RSI is also notoriously weak in strongly trending markets, a market that is trending in one direction or another, because it can remain oversold/overbought for a long time during strong trends and so HFT traders avoid using RSI in strongly trending markets unless trading in the direction of the trend.

### Sharpe Ratio

The Sharpe ratio or Sharpe index or Sharpe measure or reward-to-variability ratio is a measure of the excess return (or Risk Premium) per unit of risk in an investment asset or a trading strategy, named after William Forsyth Sharpe (1966). High-frequency traders compete on a basis of speed with other high-frequency traders, not long-term investors, and compete for very small, consistent profits. As a result, high-frequency trading has been shown to have a potential Sharpe ratio thousands of times higher than the traditional buy-and-hold strategies.

Since its revision by the original author in 1994, it is defined as:

**Definition :** Let  $X \sim f(x)$  with  $E(X) = \mu$  and  $Var(X) = \sigma^2$ ,

where  $X$  is random variable and  $f(x)$  is distribution function. Then, the value

$$Sharpe = \frac{r - r_f}{\sigma} \quad (3.4)$$

is called the Sharpe ratio of  $X$ , where  $r$  is rate of return,  $r_f$  is a risk-free (interest) rate, and  $\sigma$  is standard deviation, which is a risk.

Thus, the higher the Sharpe ratio, the higher the risk-adjusted return.

### **Example :**

Suppose that portfolio A have a 10 % rate of return with a volatility of 0.10. US treasury bills are frequently considered as the criterion for risk free (interest) rate. Assume average return of the treasury bills during the 20 th century is about 0.9 %. Then, the sharpe ratio for portfolio A is  $\frac{0.10-0.009}{0.10} = 0.91$  by equation (3.4). But to evaluate this number we have to have the other sharpe ratio to compare together.

Now, assume portfolio B has bigger standard deviation, 0.15, than portfolio A and the same rate of return, and same risk free rate. Then by the equation (3.4) sharpe ratio is  $\frac{0.10-0.009}{0.15} = 0.66$ . Thus, portfolio B have a smaller sharpe ratio than portfolio A. This result is understandable because both investment have the same return but portfolio B have a bigger risk. In obvious, we prefer the investment whose risk is less if the given return is same. Suppose two investments have the same risks and one of two gives us a bigger return. Then obviously we prefer the portfolio with the bigger return by the most basic principles of investment, and it can be showed by sharpe ratio in mathematically.

Suppose that portfolio C gives the same volatility as portfolio B but has higher return of 20 %. Then  $\frac{0.20-0.009}{0.15} = 1.91$  would be Sharpe ratio. As a result, the ratio of portfolio C, 1.27, is much higher than the one of portfolio B, 0.61.

It gets a bit more complicating when portfolio A is compared to portfolio C. Portfolio A has a lower rate of return, but it is also very low risk. Portfolio C offers higher returns for higher risk. Simply glancing at the details of the two portfolios is not enough to determine which one is a better investment. This is where the Sharpe ratio comes into play. Portfolio A has a ratio of 0.91 and portfolio C has a ratio of 1.27, indicating that the risk of portfolio C is well worth the returns as compared to A.

When comparing two portfolios with the same risk or return, it is easy to see which one is a better choice. However, when looking at two options with completely different details it can be hard to determine which one provides the better return for risk. By plugging the numbers into the simple equation known as the Sharpe ratio, the return versus risk factor can easily be determined.

The Sharpe ratio is used to characterize how well the return of an asset compensates the HFT investor for the risk taken, and therefore the higher the Sharpe ratio number the better. When comparing two assets each with the expected return against the same benchmark with return, the asset with the higher Sharpe ratio gives more return for the same risk.

HFT investors are often advised to pick investments with high Sharpe ratios. However like any mathematical model it relies on the data being correct. When examining the investment performance of assets with smoothing (standardization) of returns, the Sharpe ratio should be derived from the performance of the underlying assets rather than the fund returns. Some Sharpe ratios are often used to rank the performance of portfolio or mutual fund managers.

But we should note that if one were to calculate the ratio over, for example, three-year rolling periods, then the Sharpe ratio could vary dramatically.

There are several advantages by [36]. First, it is a simple measure because it is very easy to calculate. Second, it can be used to compare long and short strategies, bond and stock strategies, leveraged and unleveraged strategies. Leveraged investing strategy is a technique that seeks higher investment profits by using borrowed money.

The disadvantage of Sharpe Ratio are the followings. First, a negative Sharpe ratio tells us that the strategy or stock analyzed is performing worse than the risk free rate. Second, the Ratio formula assumes that the risk free rate is constant, but we all know this is false. Third, the Sharpe Ratio uses only the standard deviation as a measure of risk. Fourth, the Ratio is based on historical data, and because past performance is not always an indicator of future results, we should not rely only on this measure to assess trading strategies.

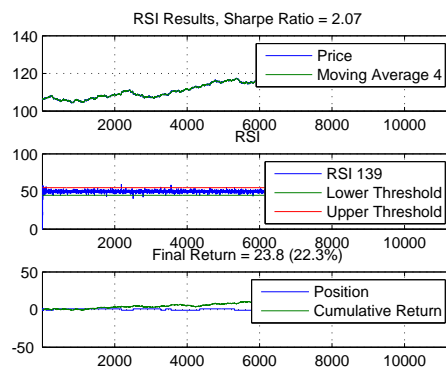


Figure 3.1: Indicators (a)



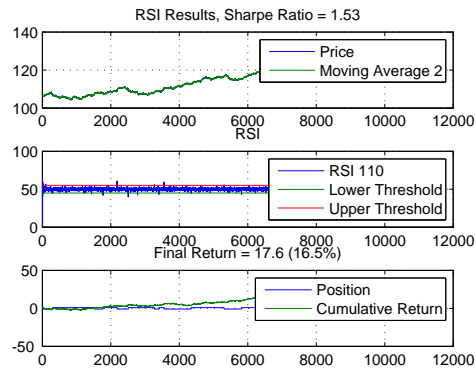


Figure 3.2: Indicators (b)

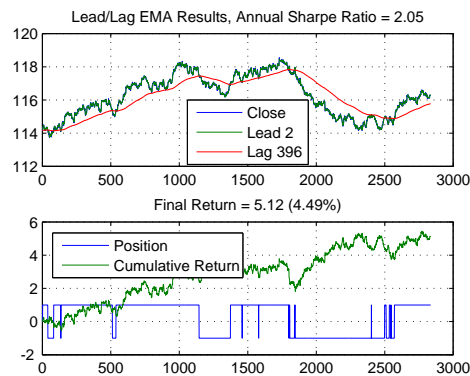


Figure 3.3: Indicators (c)

The indicator (a) has 139 for RSI, and it is higher than 50, we take long (buy) US dollar, and Sharpe ratio of 2.07 is considered as high, and finally we have the risk-adjusted annual return of 23.8 percent. In (b), it has RSI of 110, which is greater than 50, and so strategy would long US dollar, and it shows high sharpe ratio and high return, which is proportional between sharpe ratio and annual return.

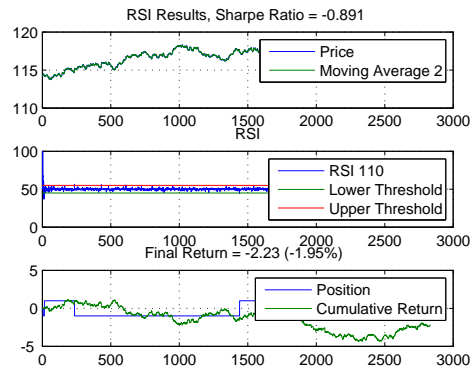


Figure 3.4: Indicators (d)

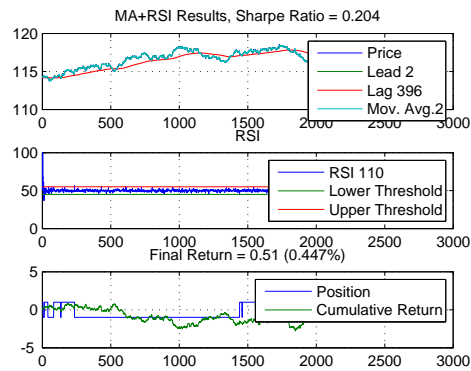


Figure 3.5: Indicators (e)

The indicator (d) shows negative sharpe ratio and negative return, and in figure 11, we have lower sharpe ratio and lower return than ones of figure 1 through (e). It demonstrate that the higher sharpe ratio is equivalent to higher annual return, which is corresponding.

In (c), we have annual sharpe ratio of 2.05 but final return of 5.12 percent, which is lower than

the others with sharpe ratio close to 2.05. It means that even though we have good sharpe ratio, we can have lower profits, and it means that one indicator cannot be perfect to anticipate optimal investment strategy. So we collect and analyze the pros and cons of all indicators, we have to apply the best investment strategy. The results is Table 4.1.

## CHAPTER 4: CONCLUSION

In optimal control and HJB equation section, we found Lemma (Obstacle) on page 27, and it shows that in mathematically how market making should work to attain optimal strategy.

In statistical arbitrage section, we found the strategy of Table 4.1.

Table 4.1: investment strategy

Indicators	MV	EMA	RSI	Sharpe
response to price fluctuation	slow	quick	middle	middle
suitable investment time	long	short	short	middle
error	middle	high	middle	middle
past data connection	middle	strong	middle	middle
calculation	middle	middle	middle	easy
trending market needed	middle	middle	weakly trending	strongly trending

The indicator (c) has its investment time interval of 3000 minutes, but the other figures have investment time of 12,000 minutes. Table 4.1 shows that EMA and RSI are suitable for short investment time and MV is ideal indicator for long investment time. Thus, for 3000 minutes it is better to use EMA or RSI to find more exact analysis.

## **APPENDIX : CODE FOR FIGURES OF CHAPTER 3**

```

load bund1min testPts = floor(0.8*length(data(:,4))); step = 30; BundClose = data(1:step:testPts,4);
BundCloseV = data(testPts+1:step:end,4); annualScaling = sqrt(250*60*11/step); cost = 0.01;

rs = rsindex(BundClose,14); plot(rs), title('RSI')

rs2 = rsindex(BundClose-movavg(BundClose,30,30),14); hold on plot(rs2,'g') legend('RSI on raw
data','RSI on detrended data') hold off

rsi(BundClose,[15*20,20],65,annualScaling,cost)

range = 1:300,1:300,55; rsfun = @(x) rsiFun(x,BundClose,annualScaling,cost); tic [ ,param] =
parameterSweep(rsfun,range); toc rsi(BundClose,param(1:2),param(3),annualScaling,cost)
rsi(BundCloseV,param(1:2),param(3),annualScaling,cost)

N = 10; M = 394; [sr,rr,shr] = rsi(BundClose,param(1:2),param(3),annualScaling,cost)
; [sl,rl,shl,lead,lag] = leadlag(BundClose,N,M,annualScaling,cost);

s = (sr+sl)/2; r = [0; s(1:end-1).*diff(BundClose)-abs(diff(s))*cost/2]; sh = annualScaling*sharpe(r,0);

figure ax(1) = subplot(2,1,1); plot([BundClose,lead,lag]); grid on legend('Close','Lead ',num2str(N)]
,['Lag',num2str(M)],'Location','Best')
title(['MA+RSI Results, Annual Sharpe Ratio = ',num2str(sh,3)]) ax(2) = subplot(2,1,2)
; plot([s,cumsum(r)]; grid on legend('Position','Cumulative Return','Location','Best')
title(['Final Return = ',num2str(sum(r),3),' (' ,num2str(sum(r)/BundClose(1)*100,3),'linkaxes(ax,'x')

marsifun(BundClose,N,M,param(1:2),param(3),annualScaling,cost)

range = 1:10, 350:400, 2:10, 100:10:140, 55; fun = @(x) marsifun(x,BundClose,annualScaling,cost);

tic [maxSharpe,param,sh] = parameterSweep(fun,range); toc

```

param

marsi(BundClose,param(1),param(2),param(3:4),param(5),annualScaling,cost)

marsi(BundCloseV,param(1),param(2),param(3:4),param(5),annualScaling,cost)

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