Modelling Trade-Based Manipulation Strategies in Limit-Order Markets

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Abstract

Insider trading (i.e., “informed market manipulation”) use private information to illegally profit. However, it is not necessary to have trading related information to profit in a stock market. If a trader can generate false information in order to mislead other market participants, he or she can make a profit. This is commonly termed “uninformed market manipulation.”

Modelling stock markets provides a means to test market manipulation theories. This thesis presents such market models to describe different aspects of complex behaviour in stock markets and stock manipulation. This research is shown to be the first to characterise trade-based manipulation in a single realistic model of a limit order market.

We discuss the characteristics of stock manipulation by considering trading related information, and present a simple framework for manipulation. Realistic market micro-structure models are presented to characterise stock market and trader behaviour. A belief structure of a stock trader is characterised. This model allows us to control and tune trader beliefs explicitly in order to analyse their learning processes and effects on the order book. Models are then used to explain real stock market behaviour. The impacts of heterogeneous trader types on these models are considered. Finally, stock manipulation scenarios are characterised as external processes and introduced to our computational market, thus allowing stock manipulation models to be built.

Using these manipulation models, simplified formal explanations for manipulation scenarios are presented. The resulting models are used to address current theories regarding manipulation and in explaining the profitability and detectability of manipulation in liquid and illiquid markets.
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Chapter 1

Introduction

It is difficult to perform controlled experiments on real stock markets to study manipulation. There is no universal model that can be used to simulate a range of manipulation scenarios in a single environment. This thesis presents a framework to simulate stock market manipulation. This framework is useful for academic researchers to test their hypotheses on stock manipulation and improve their understanding of manipulation. Moreover, industry regulators can use this framework to generate various manipulation data samples in order to test manipulation detection mechanisms.

This thesis only considers simulation of trade-based manipulation scenarios. Manipulation scenarios are simulated in a pure limit order driven market. Via simulation, the possibility and profitability of selected known manipulation scenarios are discussed. Finding optimal manipulation strategies is beyond the scope of this thesis, however it is noted as a logical future development using this framework.

A stock market is a mechanism to facilitate trading of company stocks among market participants at an agreed price. Stock trading is fundamentally about a group of market participants competing with each other and sharing profit and loss. A major factor that affects profit and loss is the quality and the amount of information that market participants utilise for trading decisions.

Public and private information regarding future price direction, private information regarding a product that is going to come onto the market, or information regarding a new project are examples of trading related information. Information may be viewed as favourable or unfavourable signals that influence trading actions. Information associated with market properties such as price, volatility, book depth, and bid-ask spread are also important for decision making. In addition, information regarding other market participants and their beliefs can also influence trading decisions. As a result, the
trading actions of market participants (i.e., their buy and sell patterns) can also convey information to the market. Market participants with more trading related information generally have an advantage over others.

Market participants can be categorised in terms of the information that they consider when making trading decisions. Common trader categories are liquidity traders (i.e., uninformed), informed traders, and technical traders (i.e., information seekers or chartists) (Glosten and Milgrom, 1985; Allen and Gale, 1992; Harris, 2002). A liquidity trader uses no information and their actions are exogenous to market conditions. Normal Mum and Dad type traders are liquidity traders. Informed traders have private information and they utilise that information to take advantage over others. Stakeholders of a company can be informed traders. Technical traders invest on and generate information using historical trading data and are therefore influenced by their perception of market behaviour. These traders use methods such as technical analysis in order to generate trading signals. In empirical literature, there are two types of traders: fundamental traders and chartists (Beja and Goldman, 1980; Day and Huang, 1990; Zeeman, 2007). Fundamental traders use fundamental values of stocks (i.e., financial statements and forecasts of them) to make their trading decisions. They buy when they believe the stock is under valued and sell when the stock is over valued. As a result these traders push the price towards the perceived true value. Chartists use data analysis methods to generate their trading signals using past trends (i.e., they are technical traders).

Insider trading (i.e., “informed market manipulation”) uses private information to illegally gain an information advantage for profit. However, it is not necessary to have trading related information to profit in a stock market. If a trader can generate false information in order to mislead other market participants (i.e., people who extract information from the market), he or she can make a profit. This is commonly termed “uninformed market manipulation.”. Market manipulation results in loss of normal traders’ faith in stock trading and may cause inefficient markets. Based on the methods of altering trading related information, stock manipulation can be categorised under three main types: action based (e.g., not bidding in an auction or closing down an office), information based (e.g., spreading false rumours and news via various media) and trade based (e.g., performing trades in a way that it would give a misleading impression to the market) (Allen and Gale, 1992). According to Allen and Gale

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1In an “efficient market,” price is an unbiased estimate of the true or actual value (i.e., “price is right” hypothesis) (Grossman and Stiglitz, 1980; Timmermann, 1993; Malkiel, 2003).
(1992), the most commonly observed manipulation types are information and trade based manipulations.

Trade based manipulation is possible mainly due to an information asymmetry (i.e., uncertainty) in stock markets (Allen and Gorton, 1992; Allen and Gale, 1992; Aggarwal and Wu, 2006). These information asymmetries can also be considered as microstructure noise. In one form of asymmetry, buyers are considered to be more informed than sellers (Allen and Gorton, 1992). Therefore a buy transaction may contain more information than a sell, and as a result the price movement in response to a purchase is greater than a sale. Moreover, the short selling constraints in stock markets make it easier to exploit good news rather than bad news. This means that driving the price down is more difficult than driving the price up. This asymmetry allows a manipulator to buy repeatedly, thus increasing the price and sell with less overall effect on the market. This manipulation scenario is commonly termed “pump and dump” (pump and dump can also involve buying stocks and then raising the price by spreading false information before selling the stocks). Another form of asymmetry that can make trade-based “pump and dump” possible occurs in the beliefs of investors (Allen and Gale, 1992). Investors always have a problem distinguishing informed traders from manipulators. This asymmetry leads to a manipulator being able to pretend to be informed and mislead the market. Some other common trade based manipulation scenarios are “cyclic trading,” “front running,” “wash sales,” “churning,” “marking the close,” “orders without execution,” “painting the tape,” “creating a cap and creating a floor,” “insider trading,” and “cornering.”

Market participants invest their money and valuable assets via stock trading. Market participants expect fair and orderly markets. Stock manipulation is a major reason for market participants to lose faith in stock trading (Aggarwal and Wu, 2006). Stock markets compete with each other by attracting more market participants into their trading venues. If market participants lose confidence in trading due to manipulation, it is highly likely that they will switch to other markets or investment alternatives. In contrast, manipulators may prefer a market place where the chance of profitable manipulation is high. However, stock market authorities enforce rules and regulations to ensure market integrity (i.e., transparent, unbiased, and fair markets) in order to facilitate the expectations of the majority of their clients. They employ surveillance systems to detect and prevent stock manipulation (Cumming and Johan, 2008).

One way to detect possible manipulation is by past data analysis. Market attributes such as price, volume, and volatility can be used to distinguish a manipulated data
sample from a non-manipulated data sample (Pirrong, 2004; Reddy and Sebastin, 2006; Palshikar and Apte, 2008; Öğüt, Mete Doğanay, and Aktaş, 2009; Sun, Cheng, Shen, and Wang, 2010). Volume and volatility can be higher in a manipulation period than in non-manipulation periods (Aggarwal and Wu, 2006). Moreover, in manipulative periods, the behaviour of these attributes become more regular than being random. Existing manipulation detection methods involve pattern matching and classification of datasets (Cumming and Johan, 2008; Öğüt et al., 2009). Most industry level manipulation detection involves software pattern matching (Cumming and Johan, 2008). In the academic literature, statistical methods such as discriminant analysis, logistic regression and machine learning methods such as support vector machines and artificial neural networks have been used in manipulation analysis (Öğüt et al., 2009).

It has been suggested that a less liquid and less volatile (i.e., the variation of price over time is less) stock is more likely to be manipulated because most stock manipulation cases are recorded in illiquid stocks (Aggarwal and Wu, 2006). If this is wrong, “one would have to argue that a manipulator who manipulates a more liquid or more volatile stock is more likely to be caught than one who manipulates less liquid and less volatile stocks” (Aggarwal and Wu, 2006, p.1917). According to Aggarwal and Wu (2006), this is implausible because market activity is higher in more liquid stocks and as a result, in a more liquid stock, a manipulator can easily hide his activities among trades of other market participants.

1.1 Motivation

Stock manipulations are difficult to detect because manipulators can change their behaviour to avoid detection. As a result, manipulation detection systems require continuous evaluation of their detection measures. In order to design, develop and test these measures, market regulators require methods to create forms of manipulation in different stock market conditions. However, using previously detected manipulation cases (i.e., data) may be subjective and may also not represent all forms of manipulation. Moreover, it is not possible to manipulate real stock markets to produce different forms of manipulation cases.

In maintaining fair and orderly markets, it is very important to identify the normal behaviour of stock markets as well as the forces that can distort this normal behaviour. Using this normal and abnormal behaviour, market regulators can take measures to detect and prevent manipulation. These normal and abnormal forces could in principle
be studied by performing controlled experiments on stock markets and by analysing their impacts on market behaviour. However, stock markets involve highly dynamic interactions and complex theories. It is therefore not possible to perform controlled experiments on real stock markets. As a result, market manipulation theories cannot be tested on real stock markets.

Market micro-structure models that simplify and explain the behaviour of stock markets are the alternative choice of researchers to test their hypotheses on different aspects of stock trading. In this context, modelling stock markets provides a means to test market manipulation theories. Moreover, these manipulation models can be used to produce different forms of manipulations in order to design, develop, and evaluate manipulation detection methods.

In past empirical studies, agent-based simulations have been used as computational platforms for performing controlled experiments on stock markets. Agent-based simulations have been able to produce stylised features that are commonly observed with real stock markets (Samanidou, Zschischang, Stauffer, and Lux, 2007; Lye, Tan, and Cheong, 2012). However, it is difficult to extract quantitative inferences due to the large statistical fluctuations within these simulations (Lye et al., 2012). Moreover, it is difficult to distinguish the behaviour introduced by these agents from the behaviour generated by the market micro-structure. In contrast, highly simplified models developed by Bak, Paczuski, and Shubik (1997), Maslov (2000), and Iori (2002) are useful in understanding stock market behaviour in quantitative terms.

The Maslov limit order market model (Maslov, 2000) presents one simplified version of the concept of a market place for a particular stock. Maslov constructs a limit order book manipulated by an infinite pool of uninformed traders (these traders do not consider the state of the current limit order book, such as the bid-ask spread, or any past patterns of the last traded price). Due to its simple nature, the Maslov model provides a suitable platform to build a framework to study manipulation. However, until the work presented here, the Maslov model has not been used to study the effects of stock manipulation.

The Maslov model can be considered a zero-intelligence model since the model mechanics are random and the notion of information is not considered. As a result, information asymmetries are not able to be characterised in the original Maslov model, thus limiting the simulation of possible manipulations. Introduction of a notion of information to the Maslov model allows analysis of information asymmetries and how manipulators exploit these asymmetries in order to profit.
Jarrow (1992), Allen and Gale (1992), Allen and Gorton (1992), and Aggarwal and Wu (2006) have considered trade-based manipulation using micro-economic models. Using these manipulation models, they found evidence for the possibility of pump and dump type manipulation in stock markets. However, these models consider the theoretical aspects of manipulation and are far from reality. Agent-based models developed by D’hulst and Rodgers (1999) characterise manipulation scenarios such as circular trading in stock markets. However, these agent-based simulations are designed to analyse the behaviour produced by trader interactions and fail to produce quantitative inferences due to manipulations. Moreover, all these manipulation models were built on different platforms and characterise different manipulation scenarios in different types of stock markets. As a result, these manipulation models cannot be integrated and used to analyse market behaviour due to a combination of manipulation scenarios.

The novel concept of realistic market manipulation models can provide a platform to analyse the possibility, profitability, and detectability of manipulation scenarios. These manipulation models can be used to present formal explanations for manipulation. There are no such models for manipulation scenarios in the current literature.

Moreover, the information asymmetry introduced by Allen and Gorton (1992) considered the fact that a buyer is more informed than a seller. However, in the Allen and Gorton (1992) model the degree of information in buying when the price is high or low is not considered. This results in path independent price behaviour in the Allen and Gorton (1992) model. However, due to the behaviour of fundamental traders, buying or selling when the price is low or high is different.

The manipulation framework presented in this thesis provides a means to test market manipulation theories and hypotheses. For example, based on previous research, it is difficult to determine under what conditions a liquid/illiquid stock is easy to manipulate. Manipulation models can be used to test the possibility, profitability, and detectability of manipulation in different types of stock market conditions (e.g., liquid/illiquid markets). Finally, using manipulation models, it is also possible to test under what circumstances manipulation can be detected in stock markets.

Although some past work has used simulation methods to find optimal trading strategies, simulations to find optimal manipulation strategies are yet to appear in the micro-economic literature. Most past work has modeled optimal trading strategies as utility maximization problems. However, finding optimal strategies for manipulation is a logical extension and application of the framework developed in this thesis, and will be considered in future work.
1.2 Objectives

The main objective of this thesis is to build a stock manipulation framework (i.e., market manipulation models that characterise manipulation scenarios). This manipulation framework will allow controlled experiments to test hypotheses on stock manipulation.

Using the extended Maslov model, a realistic market micro-structure model to characterise trader and market behaviour is presented (i.e., the $M^*$ model). This model is used as the base model in building the market manipulation framework. The $M^*$ model is extended to represent a tunable concept of trader information. This modification allows an investigation of how manipulators can exploit information asymmetries in order to profit.

The impacts of normal and abnormal heterogeneous trading actions on the behaviour of this model are considered. These heterogeneous trading actions are then used to characterise market manipulation scenarios. Using these manipulation models, simplified formal explanations for manipulation scenarios are presented.

These manipulation models are used to test hypotheses on stock manipulation. For example, the resulting models are considered in testing hypotheses on the possibility and profitability of manipulations in liquid/illiquid markets.

Based on a set of experiments, the following questions are addressed in this thesis:

- What is the role of information in stock manipulation?
- What properties are required to build realistic market micro-structure models to characterise stock market and trader behaviour?
- What properties of manipulation can be characterised in a manipulation model?
- What types of manipulations are possible/not possible, and if so, under what circumstances?
- What are the supportive market conditions that make manipulation profitable?
- Under what circumstances can a change in market attributes be detected due to manipulation?
- Can a liquid or illiquid stock be easily manipulated? Is a manipulator strategy more profitable in liquid or illiquid stock? Can manipulation be more easily detected in liquid or illiquid stocks?
1.3 Contributions

- **Stock manipulation framework**
  A main contribution of this work is to discuss the characteristics of stock manipulation in relation to trading related information and present a simple framework for manipulation. This framework is presented in the context of a realistic computational model of a limit order market. The Maslov limit order market model is extended to present a more realistic market micro-structure model to characterise limit order market and trader behaviour (the $M^*$ model).

- **Stylised traders**
  The $M^*$ model is used to analyse the impacts of heterogeneous trading actions on the behaviour of limit order markets. These heterogeneous trading actions are characterised as external processes (i.e., stylised trader types) and are introduced to the $M^*$ model to analyse their impacts on market properties. This is a new approach to understanding the impacts of heterogeneous trading on a micro-economic model. Heterogeneous trader types such as technical traders, buyers, sellers, patient and impatient traders, order cancelling traders, pattern traders, cyclic traders, and informed traders are considered. In this analysis, a belief structure of a technical limit order trader is characterised. This belief model allows an analysis of trader beliefs in order to characterise their learning processes and effects on the limit order book. This belief model also allows a notion of information asymmetry to be introduced. Properties of these models are then used to explain normal and abnormal market behaviour. The profitability of heterogeneous trading actions are also presented.

- **Stylised manipulators and manipulation models**
  Characterisable manipulation scenarios are identified. Using heterogeneous trading actions, formal explanations of these manipulation scenarios are presented. Finally, these stock manipulation scenarios are characterised as manipulator types (i.e., external processes) and introduced to the $M^*$ model to build stock manipulation models. Manipulation scenarios such as “pump and dump,” “cyclic trading,” “wash sales,” “marking the close,” “orders without execution,” “painting the tape,” “creating a cap and creating a floor,” “insider trading,” and “cornering” are presented. These manipulation models are used to discuss what makes manipulation possible in stock markets. In this context, supportive market con-
ditions and trader behaviour that can make manipulation possible are discussed. Using the manipulation models, profitability and detectability of these manipulation scenarios are discussed. These realistic models are used to confirm the theoretical work presented in the literature. This study can be considered the first to characterise manipulation in a single realistic model of a limit order market.

A theoretical model to characterise the price responses for buy and sell transactions is introduced. This model presents a novel and path dependent approach to modelling stock price changes with respect to information in trading actions. Moreover, this model is capable of analysing the possible implications of information asymmetries on stock trading. This model is also used to show why “pump and dump” manipulation in stock markets is possible. This study can be considered the first to present an asymmetry introduced by fundamental traders (i.e., information in buying or selling when the price is low or high is different) in relation to manipulation. This model is also used to confirm the $M^*$ model results.

- **Testing manipulation theories**

  Manipulation models are used to test hypotheses on stock manipulation. For example, using the “pump and dump” manipulation model, the profitability and detectability of manipulation in liquid/illiquid markets is presented. In this analysis, models of stock manipulation are used to answer the following questions: can a liquid or illiquid stock be easily manipulated? Is a manipulator strategy more profitable in liquid or illiquid stock? Can manipulation be more easily detected in liquid or illiquid stocks?

- **Additional contributions**

  This framework is a universal model that can be used to simulate a range of manipulation scenarios in a single environment.

  This manipulation framework is useful for academic researchers to test their hypotheses (i.e., controlled experiments) on stock manipulation in order to improve their understanding of complex manipulation scenarios.

  Manipulation models can also be used to recreate manipulation scenarios and generate different forms of manipulations in different real stock market conditions. These recreated manipulation scenarios can be used by manipulation detectors...
(e.g., industry regulators) to design, develop, and evaluate their manipulation detection mechanisms.

Journals


Conferences and Workshops (published)


Conferences and Workshops (unpublished)


The thesis is organised as follows. Chapter 2 gives an overview of the concepts and state of the art related to stock markets and stock manipulation. Chapter 3 introduces the Maslov model and extensions to make it a more realistic representation of a limit order market. Based on these experiments, this chapter also presents the base model in building the manipulation framework. Chapter 4 uses the extended Maslov model (i.e., $M^*$) to analyse the normal and abnormal heterogeneous trading actions on limit order book properties. In this chapter, a notion of information is introduced to the $M^*$ model. In Chapter 5, these heterogeneous trading actions are used to build profitable manipulation scenarios. Heterogeneous trading actions are also considered for their profitability. Manipulation scenarios are characterised as external processes and are introduced to the $M^*$ model to build stock manipulation models. In this chapter, manipulation models are used to examine possibility, profitability, and detectability of manipulation scenarios. A theoretical model for manipulation is presented in Chapter 6. In this chapter, it is shown that a trade-based manipulation is possible due to an information asymmetry introduced in the behaviour of technical traders by the fundamental traders. Chapter 7 presents the implications of manipulation in liquid/illiquid markets. Finally, Chapter 8 discusses the implications of the presented work and discusses future directions for research.
Chapter 2

Background and Related Work

2.1 Overview

This chapter provides the background and related work of this thesis. In this chapter, definitions for stock markets, stock exchanges, limit order markets, market manipulation, and stock market and manipulation models are presented.

The importance of a stock market to an economy is discussed. Analysing the behaviour of a stock market is discussed in relation to market attributes and the universal properties of stock markets (i.e., stylised features). The role of information in stock market behaviour and the categories of market participants in relation to market information and motivations for trading are discussed.

The importance of micro-economic modelling is discussed. Market micro-structure models are shown to provide simplified explanations of the behaviour of stock markets and allow researchers to test hypotheses on different aspects of stock trading. Stock market modelling related work in the literature is presented.

Market manipulation is shown to be a significant issue in stock markets. Simulated manipulation scenarios are introduced as a prime method for understanding, characterising, and detecting the properties of trade-based stock manipulation. The limitations in existing manipulation models are discussed. The importance of developing realistic manipulation models to characterise manipulation scenarios is presented.

The utility of realistic manipulation models is discussed. In this aspect, using these models to simplify and explain the profitability and detectability of trade-based manipulation in different types of stock markets (e.g., liquid/illiquid markets) is presented.

This chapter concludes by presenting the limitations in current approaches and the novel contributions of this thesis.
2.2 Stock Markets

A stock market facilitates trading of company shares among market participants at an agreed price.

According to Levine (1991), stock markets play an important role in the world economy because of their involvement in: raising capital for a business, mobilising savings for investment, facilitating company growth, redistribution of wealth, facilitating corporate governance, generation of investment opportunities for small investors and businesses, helping governments to raise capital for their development projects, and providing an indicator of economic growth.

Currently there are stock markets in most countries. The world’s biggest markets are in countries such as the US, UK, Germany, India, France, Japan, and Singapore. Moreover, there are emerging markets such as Sri Lanka and Kenya.

Stock exchanges are individual corporations or mutual organisations that fulfil the purpose of a stock market. For example, trading of the stocks listed on the New York Stock Exchange (NYSE) and NASDAQ stock market represent much of the stock market in the US. Some exchanges (e.g., NYSE) have physical locations (i.e., a trading floor) to carry out trading. In these exchanges traders (i.e., investors or their agents) must be present at the trading floor physically in order to buy and sell shares. Moreover, there are virtual exchanges where trading is carried out electronically through a network of computers (e.g., New Zealand Stock Exchange (NZX)).

Ticker symbols are the common identifier for tradable entities that correspond to listed companies (e.g., AAPL and GOOG in the US and TEL.NZ and FPA.NZ in NZX). An order book is the collection of orders (i.e., normally two lists of orders) that an exchange uses to manage the interest of buyers and sellers in a particular financial symbol. There is a matching algorithm associated with an order book to determine the orders that can be executed. Execution of a buy and a sell order generates a trade and also a new last traded price. Last traded price or price of a stock is the main capital markets performance indicator of a company (i.e., a stock).

Based on the trading mechanism, stock exchanges can be categorised as auction markets, dealer markets, and limit order markets (Parlour and Seppi, 2008). A Walrasian auction is an example of an auction market and in early days the Paris Bourse had a Walrasian auction (Parlour and Seppi, 2008). The London gold fixing is also an

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1The most common matching rule is based on the order of price and then time of the buy and sell orders.
example for a Walrasian auction. The NYSE is an example of a dealer market. NZX is an example of a pure limit order driven market.

The most common stock market mechanisms are dealer and limit order markets (Parlour and Seppi, 2008). Moreover, limit order markets are amongst the fastest growing markets in the world. Most current day stock markets are either pure limit order markets or at least provide a limit order trading facility (Parlour and Seppi, 2008). For example, Euronext Paris, the successor of Paris Bourse and even the NYSE now facilitate limit order trading (Parlour and Seppi, 2008). Moreover, due to less manual human interactions for trading, limit order markets are more vulnerable to trade-based manipulation. The modelling of pure limit order markets and trading is considered in this thesis.


2.2.1 Limit order markets

Limit order trading allows patient market participants to convey their interests to the market (Glosten, 1994). In limit order markets, there are two main types of orders: limit orders and market orders. A limit order is submitted to convey an interest to buy or sell a stock at a specific price or better, and is stored in the order book for a specified time (i.e., time to live ($\text{ttl}$)). This means, a buy limit order can only be filled at the specified limit price or lower, and a sell limit order can only be filled at the specified limit price or higher. Limit orders are stored in the order book based on their price-time priority. A snapshot of the first 10 lines of each side of the limit order book for Fisher & Paykel Appliances Holdings Limited Ordinary Shares as at 14:41:20, Wednesday 12 September, 2012 (NZT) in the New Zealand Stock Exchange (NZX) is illustrated in Table 2.1. As shown in Table 2.1, buy/sell sides of the order book are arranged in descending/ascending order of the price. The highest/lowest prices to buy/sell are termed best bid/best ask. The difference between the best bid price and the best ask price is termed the bid-ask spread. There can be multiple buyers/sellers (i.e., limit orders) for one price point in an order book (see Table 2.1). Total quantities available in both bid/ask sides are called bid/ask depths. A limit order may exist in the order book until a matching market order arrives, the life time of the limit order (i.e., $\text{ttl}$) is expired, or the owner (i.e., trader) cancels the order.

Market orders are submitted to buy or sell at the current market price indicated
Table 2.1: Order book of Fisher & Paykel Appliances Holdings Limited Ordinary Shares as at 14:41:20, Wednesday 12 September, 2012 (NZT). (+u - Limit orders can be placed onto the market with an undisclosed quantity. The undisclosed quantity of the order must be of value equal to or greater than $100,000.)

by the best limit orders to buy or sell (i.e., best bid or best ask). Buy/sell limit orders with limit prices above/below the best ask/best bid prices are called marketable limit orders and are therefore executed like market orders.\(^2\)

The behaviour of limit and market orders is used to explain and characterise patient and impatient market participants in Chapter 4. In addition, these order types are used to characterise manipulation scenarios in Chapter 5. In Chapter 7, the simulation of liquid/illiquid behaviour of a market is controlled using the percentage of these order types.

A trade occurs when the matching algorithm crosses a market order with a limit order and the transaction takes place at the limit order price. Assuming sufficient depth at the best bid or ask, a buy market order always matches with the order having the lowest limit order price to sell (i.e., best ask), and a sell market order always matches with the order having the highest limit price to buy (i.e., best bid). If there is insufficient depth at the best bid or ask to fill a market order, then the order walks up the book consuming depth. After an execution, the executed price becomes the last traded price of the stock. Based on the buying quantity, a market order may execute

\(^2\)A marketable limit order is a limit order with limit price at or above the best ask (if a buy) or at or below the best bid (if a sell) So, it crosses with the contra side of the order book and is executed immediately with the contra side best bid or ask. Peterson and Sirri (2002) discussed the properties of these marketable limit orders in stock markets.
with a limit order partially or with multiple limit orders.

Market orders execute instantaneously, but a limit order is not guaranteed to be executed. The probability of execution of a limit order depends on the possible market orders that are expected to arrive in the future to clear the limit orders that have price-time priority. As a result, limit order execution depends on the status of the order book (Parlour, 1998; Parlour and Seppi, 2008).

Although limit orders are not guaranteed an execution, they guarantee that an investor does not pay more than his expected price for a stock if buying or receive less if selling. As a result, limit orders can be used to obtain better prices than market orders; however they bear a risk of non execution.


A comprehensive review of the literature on limit order markets can be found in Parlour and Seppi (2008) and Gould, Porter, Williams, McDonald, Fenn, and Howison (2011).

In this thesis, the modelling of one stock listed in a pure limit order driven market is considered. Via simulation, order book mechanics and how normal and abnormal trading affect the behaviour of the stock will be described. Due to less manual human interactions for trading, limit order markets are easy to characterise computationally.

### 2.3 Behaviour of a Stock

The behaviour of a stock (i.e., behaviour of stock market attributes such as price, bid-ask spread, and bid/ask depth) depends mainly on market related information, the behaviour of market participants, and fundamentals of the stock (i.e., financial statements and forecasts of them) (Fama, 1965; Abarbanell and Bushee, 1997). In this thesis, the behaviour of a stock in relation to market related information and the
behaviour of market participants will be considered.

2.3.1 Market related information

Bagehot (1971) presented the first study to consider market related information as a major component of market micro-structure. Public and private information regarding the future price direction, private information regarding a product that is going to come onto the market, or information regarding a new product or project are examples of market related information. Market properties such as price, volatility, book depth, and bid-ask spread also contain market related information. Stock exchanges publish market data (i.e., status of market attributes such as price, best bid price, best ask price, bid-ask spread, VWAP\(^3\)) via market data dissemination systems such as Reuters\(^4\) and Bloomberg\(^5\) to be used by their market participants. In addition, the behaviour of other market participants and their beliefs can also contain information. As a result, trading actions of market participants (i.e., buy and sell patterns) can also convey information to the market. This thesis presents a model to extract information from limit order trading in Chapter 4.

Not all market related information is known to every market participant. This is referred to as information asymmetry or uncertainty (Appendix B summarises the properties of information asymmetry or uncertainty). These information asymmetries or uncertainties can be considered as microstructure noise. Kyle (1985), Glosten and Milgrom (1985), Allen and Gale (1992), Allen and Gorton (1992), and O’Hara (1995) discussed the implications of asymmetric information in stock markets and manipulations. Aspects of asymmetric information in relation to market manipulation are simulated here in Chapters 5 and 6.

2.3.2 Efficient markets

In an “efficient market,” price is an unbiased estimate of the true or actual value (i.e., “price is right” hypothesis) (Timmermann, 1993; Malkiel, 2003). This means, in an efficient market, all the information, public as well as private, should be reflected in market attributes. Moreover, deviations from the true value are random quantities and should not be correlated with any observable variables. Thus no group of investors

\(^3\text{V}olume \text{ Weighted Average Price.}\)

\(^4\text{www.reuters.com}\)

\(^5\text{www.bloomberg.com}\)
should be able to consistently characterise stocks as under or over valued.\textsuperscript{6} Therefore, efficient markets are less vulnerable to manipulation (Qian and Rasheed, 2004; Kyle and Viswanathan, 2008; Aggarwal and Wu, 2006).

However, in reality, such “efficient” markets do not exist, because some market players are more informed than others (Grossman and Stiglitz, 1980). This superior information could be due to their positions (e.g., company directors) or due to gaining information about the true value of an asset through some means such as fundamental and technical analysis (Abarbanell and Bushee, 1997; Lo, Mamaysky, and Wang, 2002).

\subsection{2.3.3 Attributes of a limit order book and their behaviour}

The behaviour of a limit order book can be explained using the main market attributes of price, bid-ask spread, and bid/ask depth of the order book. Derived attributes such as price increments, price returns and price volatility are also used to explain the behaviour of the underlying stock.

Change in stock price or last traded price is the main capital markets performance indicator of a stock. Price may not represent the true or actual value of the stock due to information asymmetries, stock manipulations, or irrationality. In Chapter 5 and 6, via simulation it is shown that price manipulation is possible due to different forms of information asymmetries. Prices or last traded prices in this thesis are alternatively used to refer to intra day tick by tick prices and price increments are used to refer to intra day price fluctuations (i.e., first differences) between time ticks.\textsuperscript{7}

Due to information asymmetry, a stock price can be under or over valued. However, trading can push the price to its actual or true value. This is because traders hope to buy under valued stocks and sell over valued stocks. As a result of these buy and sell actions, the stock price is pushed up and down, respectively towards the true value. In other words, this can be explained as trading incorporating information and reducing information asymmetry or uncertainty (Glosten and Milgrom, 1985). In Chapter 5, the properties of under or over valued stocks with heterogeneous trader types will be examined. Moreover, a characteristic of under or over valued stocks is used in Chapter 6 to simulate a possibility of trade-based manipulation.

Price Returns are computed using the last traded price. These price returns are computed for different periods (e.g., tick by tick or daily). Moreover, daily returns

\textsuperscript{6}If price of a stock is below/above the stock’s true value, that stock is termed under/over valued.

\textsuperscript{7}Time tick refers to the lowest possible time or sampling interval.
(Equation 2.1) are commonly used in stock data analysis (Brown and Warner, 1985). In this thesis, tick by tick price returns (Equation 2.2) are used.

\[
\text{Daily return} = \frac{\text{Close price} - \text{Previous day close price}}{\text{Previous day close price}}
\]  

(2.1)

\[
\text{Price return} = \frac{p(t) - p(t - 1)}{p(t - 1)}, \text{ where } p(t) \text{ is the price at time tick } t
\]  

(2.2)

A limit order book shows a positive bid-ask spread in most trading times. The bid-ask spread could be characterised by the components of asymmetric information, inventory carrying cost, transaction cost, etc. (Huang and Stoll, 1997). Using a simple model of a dealer market, Glosten and Milgrom (1985) and Glosten (1987) showed that the bid-ask spread in stock markets can in theory occur solely due to information asymmetry. The relative bid-ask spread is computed using bid-ask spread divided by the average of the bid and ask prices. The behaviour of bid-ask spread in relation to stock manipulation is discussed in Chapter 5.

Volatility refers to the standard deviation of the price returns of a financial instrument within a specific time window (French, Schwert, and Stambaugh, 1987). It is also an indicator of risk or uncertainty of the financial instrument over the computed time period. Therefore high volatility follows large bid-ask spreads of prices, and vice versa. In a typical trading day, the bid-ask spread follows a U shape pattern representing the higher uncertainty among market players at the start and the end of the day (McInish and Wood, 2012; Chung, Van Ness, and Van Ness, 1999). As time passes (i.e., with trading), information gets revealed, bid-ask spread and volatility should be reduced (Glosten and Milgrom, 1985). Prices are more volatile during exchange trading hours than during non-trading hours (French and Roll, 1986). The behaviour of volatility in relation to stock manipulation is discussed in Chapter 5.

The other main important attribute in stock markets is liquidity. Liquidity refers to the ability for a trader to buy or sell an asset easily and immediately without disturbing the underlying prices (O’Hara, 2004). An asset is liquid if there are many sellers and buyers (i.e., liquidity traders) at all times. As a result, an order book in a liquid stock always contains positive buy and sell depths.

The main dimensions of market liquidity include:

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8Returns to an investor also include dividend yield and the effects of corporate actions (e.g., Mergers, spin-offs, stock splits, etc.).
• Depth or the ability to buy or sell large amount of stocks without disturbing the price
• Tightness or the bid-ask spread
• Immediacy or the speed a transaction can be executed
• Resilience or the speed that prices can be restored after a distortion

In Chapter 7, liquid and illiquid stocks are simulated and analysed for possibility, profitability, and detectability of manipulation.

Stock exchanges or other vendors also compute and publish market indices to summarise the performance of a group of stocks (e.g., Dow Jones Industrial Average, S&P 500, NZX 50). These attributes are available to everybody and are considered public information.

2.4 Stock Market Analysis and Stylised Attributes

With the help of real trading data, researchers identify and characterise stylised features of stock data and trading. These stylised features are the universal properties that describe the most important attributes of stock markets and are independent of country, stock exchange, stock market type, or stock (Kaldor, 1957). These stylised attributes are used to evaluate micro-economic models (Slanina, 2008; Gould et al., 2011). In this thesis, stylised attributes are used to analyse stock market and manipulation models.

Mantegna and Stanley (1995), Rydberg (2000), and Cont (2001) contain comprehensive reviews of the literature on these stylised attributes.

The following stylised attributes of financial data are considered in this thesis:

Autocorrelation of price increments

Autocorrelation of price increments (i.e., intra day price fluctuations) are negative due to the order book mechanism of fluctuating the price between best bid and ask prices (i.e., bid-ask bounce). Moreover, the amplitude of these price fluctuations have positive correlation while signs of price fluctuations show no correlation (Maslov, 2000).

Volatility clustering

The volatility of price exhibit a correlated behaviour (i.e., having regions of high amplitude data separated by relatively low amplitude regions visible in a time vs. price
increments plot). Large stock price increments tend to be followed by large increments, of either sign, and small increments tend to be followed by small increments. This is referred to as volatility clustering in stock markets (Bollerslev, Chou, and Kroner, 1992; Rydberg, 2000; Maslov, 2000; Maslov and Mills, 2001). This means, if the volatility of the market today is high, the chance of observing a more volatile market tomorrow is also high.

Volatility clustering affects the shape of the autocorrelation function of absolute price returns as a function of time. As a result, the power-law decay of the autocorrelation function of absolute values of price returns is regarded as a typical manifestation of volatility clustering (Bollerslev et al., 1992; Ding, Granger, and Engle, 1993; Cont, Potters, and Bouchaud, 1997; Guillaume, Dacorogna, Davé, Müller, Olsen, and Pictet, 1997). This means, a stationary process (with finite variance) is said to have long range dependence if its autocorrelation function decays as a power of the lag. The autocorrelation function of absolute price increments and the Fourier transform of the autocorrelation of absolute price increments also have a clear power-law decay with a similar exponent (Maslov, 2000).

In real stock markets, the autocorrelation function of absolute price returns decays according to a power law with a very small exponent in the range $\approx 0.3-0.4$ and with no apparent cut-off (Cont et al., 1997; Liu, Gopikrishnan, Stanley, et al., 1999; Maslov, 2000; Maslov and Mills, 2001). Similar behaviour is observed for the autocorrelation of squared price increments.

On one hand, the volatility clustering feature indicates that price returns are not independent across time, on the other hand, the absence of linear autocorrelation shows that their dependence is non-linear.

The volatility clustering effect is used to analyse the impacts of heterogeneous trading actions in Chapter 4. In this thesis, the Fourier transform of the autocorrelation of absolute price increments (Maslov, 2000; Maharaj, 2002) is used to analyse volatility clustering.

**Fat tails of returns**

The distribution of stock returns have tails that are heavier than the tails of a normal distribution. This was first presented by Mandelbrot (1963a) and Mandelbrot (1963b). The histogram of short time lag increments of stock price also has a non-Gaussian shape with a sharp peak and broad wings. These distributions show the characteristics of a Pareto-Levy distribution up to a certain value, with a power law exponent of $1+$
\( \alpha \approx 2.4-2.7 \), and then it crosses over either to a steeper power law with an exponent of \( 1 + \alpha \approx 3.7-4.3 \) or to an exponential decay (Maslov, 2000; Maslov and Mills, 2001).


### Asymmetry in stock returns

The distribution of stock returns is slightly negatively skewed. This attribute has been hypothesised to be caused by traders reacting more aggressively to negative information than positive information (Rydberg, 2000).

Several studies have shown that there is a significantly larger price impact due to bad news than good news (Diamond and Verrecchia, 1987; Skinner, 1994; Soffer, Thiagarajan, and Walther, 2000; Hutton, Miller, and Skinner, 2003; Anilowski, Feng, and Skinner, 2007; Kothari, Shu, and Wysocki, 2008) (see Appendix B for a detailed description of information asymmetries in stock markets).

### Aggregational Gaussianity

When the sampling frequency is decreased (e.g., from lag one to fifty, daily to monthly), the distribution of price returns tends towards the Gaussian distribution (Barndorff-Nielsen, 1997; Rydberg, 2000; Maslov, 2000).

### Hurst Exponent \((H)\)

Peters (1996) showed that stock prices have a characteristic of \( H > 0.5 \). This means that the behaviour of stock prices is distinct from that of a random walk and is not generated by a stochastic process generating non-correlated values. This is referred to as long-term memory behaviour in stock prices (Lillo and Farmer, 2004; Alvarez-Ramirez, Alvarez, Rodriguez, and Fernandez-Anaya, 2008).

The Hurst exponent is used in areas such as applied mathematics, fractals and chaos theory, long memory processes, and spectral analysis (Hurst, 1951; Mandelbrot and Van Ness, 1968; May, 1999; Corazza and Malliaris, 2002; Grech and Mazur, 2004). It has different but related meanings in different contexts.

In Fractal Geometry, fractal dimension is an indication of how rough the surface (Falconer, 2003). Fractal dimension is related to the Hurst exponent. In this
context, a small Hurst exponent has a higher fractal dimension and a rougher surface (Gneiting and Schlather, 2004).

In this thesis, the Hurst exponent of price signal is used to analyse the behaviour of stock market and manipulation models. Moreover, the behaviour of the Hurst exponent is used to analyse the roughness of stock prices.

The Hurst exponent is a measure of whether data are a pure random walk or have underlying trends. As a result, it is considered as a measure of predictability of a series. The Hurst exponent is a measure of persistence (i.e., the characteristic or tendency of the underlying series to continue in its current direction or change towards the mean). This behaviour is called “mean reversion” (Lillo and Farmer, 2004; Lento, 2009). If the Hurst exponent value is between 0.5 and 1, the process can be considered as a persistent series meaning that if the process has an increase between times $t-1$ and $t$, then there is a high possibility of having an increase between times $t$ and $t+1$. If $H$ is between 0 and 0.5, it is an anti-persistent series. In other words, if the process shows an increase between times $t-1$ and $t$, there is a high possibility of having a decrease between $t$ and $t+1$. If it is equal or closer to 0.5, this implies that it is a random and unpredictable series. Persistent and anti-persistent (i.e., $H \neq 0.5$) series are predictable (Qian and Rasheed, 2004).

A random Gaussian process with an underlying trend should have some degree of autocorrelation. If this autocorrelation has a very long (i.e., infinite) decay or long range correlations, it is referred to as a long memory process with a Hurst exponent value $0.5 < H < 1$.

There are various methods in practice to estimate the Hurst exponent. Widely used methods are re-scaled-ranged computation (Qian and Rasheed, 2004; Ellis, 2007), wavelet based method (Simonsen, Hansen, and Nes, 1998), and graphical methods (Maslov, 2000). In this thesis, the Hurst exponent value of a price signal is estimated using the re-scaled range method. The re-scaled range method was chosen after experimenting for consistency and accuracy with other available methods (Withanawasam, Whigham, Crack, and Premachandra, 2010). In the re-scaled range method, the data series is divided into sub-series of size $n$ and $(R/S)_n$ values determined. Here $R$ is the difference between the minimum and maximum of the cumulative series of the mean adjusted data series and $S$ is the standard deviation of the data series. The Hurst exponent of the data series is the slope of the plot between $\log(n)$ and $\log((R/S)_n)$. Both contiguous and overlapping sub-series selection methods are considered. In the contiguous sub-series selection method, the number of observations must
be a power of two. Furthermore, the number of sub-series that are considered in the
overlapping method is higher than the contiguous method. Therefore the overlapping
method is slower than the contiguous method. The accuracy of these two sub-series se-
lection methods is evaluated by estimating the Hurst exponent of a random walk data
series and it is observed that both these methods are equally capable of estimating
the Hurst exponent accurately. However, the standard error shown in the overlapping
method is slightly lower than the contiguous method.

A graphical summary of the behaviour of the Hurst exponent is given in Ap-
pendix C.

Stylised attributes are used to evaluate stock market and manipulation models in
Chapters 3, 4, and 7. Normal and abnormal behaviour of stock data is also considered in
relation to stylised attributes in Chapters 4 and 5. Detectability of price manipulation
is also discussed using stylised attributes such as the Hurst exponent in Chapter 7.

2.5 Market Participants and Trading

People trade for many reasons, including to invest, to borrow, to exchange, to hedge or
distribute risks, to speculate, or to deal (Harris, 2002). For some market participants
such as gamblers, the main intention for trading may not be making profits.

If transaction costs are not considered, trading is a zero sum game (i.e., total gains
of the winners are equal to the total loss of the losers). Intermediaries however, extract
transaction costs (Harris, 2002). Traders win or lose based on the information they
possess, motivations they have, and the strategies they follow.

Market participants can be categorised in terms of information that they con-
sider when making trading decisions. Common trader categories are liquidity traders
(i.e., uninformed), informed traders, and technical traders (i.e., information seekers or
chartists) (Allen and Gale, 1992). A liquidity trader uses no information and their
actions are exogenous to market conditions. Normal Mum and dad type traders are
typically liquidity traders. The role of liquidity traders is to provide liquidity to a stock
(Glosten and Milgrom, 1985; Allen and Gorton, 1992). Informed traders have private
information and they utilise that information to take advantage of others. Stakeholders
of a company can be informed traders. Sometimes trading with an informational ad-
vantage is considered illegal (i.e., abusive practice) and this scenario is termed “insider
trading.” Technical traders generate information using historical trading data. These
traders use methods such as technical analysis in order to generate trading signals. Ac-
According to Harris (2002), information-oriented technical traders can be informed and they generate trading signals by analysing whether the market price is different from the fundamental value. However, sentiment-oriented technical traders try to identify the behaviour of other traders and use that information in generating inferences about the market direction.

In another classification based on motivations for trading, market participants can be classified into three main types: utilitarian traders, profit motivated traders, and futile traders (Harris, 2002). Utilitarian traders trade because they expect to obtain some benefits other than trading profits. Borrowers, asset exchangers, hedgers, bluffers, and gamblers are utilitarian traders. Profit motivated traders trade with the sole expectation of profits from their actions. Speculators and dealers are profit motivated traders. Futile traders mistakenly believe that they are profit motivated traders. However, they have no information advantage nor capability to make profits. Utilitarian and futile traders lose on average to the profit motivated traders.

These trader classifications are used to characterise heterogeneous traders in Chapter 4. In addition, information based trader classification is used to provide a formal definition for manipulation in Chapter 5. The profitability of these heterogeneous trader types are analysed in Chapter 5 to confirm profit motivated trader strategies. These heterogeneous trader types are also used to characterise manipulation models in Chapter 5. Simulated traders only use trade to make profits and are risk neutral (i.e., no taxes, no transaction costs, or no depreciation of money is considered).

Information oriented trader categories such as informed traders, technical traders, and manipulators are profit motivated traders. Liquidity traders are utilitarian traders. However, technical traders may become futile traders if manipulators are present (Aggarwal and Wu, 2006). In Chapter 5, using a manipulation model, the behaviour of futile traders is simulated.

In empirical literature, there are two types of traders: fundamental traders and chartists (Day and Huang, 1990; Beja and Goldman, 1980; Alfarano and Lux, 2003; Zeeman, 2007; Lye et al., 2012). Fundamental traders use fundamental values of stocks (i.e., financial statements and forecasts of them) to make their trading decisions. They buy when the price is low and sell when the price is high. In this thesis, the term “technical traders” is used to refer to chartists (i.e., chartists use various data analysis methods to generate their trading signals using past trends (i.e., typically in prices and volumes)). In Chapter 6, using a theoretical manipulation model, the behaviour of fundamental traders and technical traders is used to show the possibility of trade-based
2.6 Micro-Economic Modelling

It is not possible to perform controlled experiments on a real stock market. Micro-economic models can however be used to simplify and explain the behaviour of stock markets and to test hypotheses on different aspects of stock trading.

When computer simulations were not possible, researchers widely used analytical or theoretical models to simplify and explain stock market behaviour. These analytical models were not intended to be realistic. Normally, analytical models do not consider randomness (i.e., they are deterministic), and as a result, they predict the same outcome from a given starting point. Moreover, due to the lack of simulation capabilities, these models are designed as short time period models. As a result, analytical micro-economic models fail to reproduce and simulate realistic scenarios such as the crashes and bubbles of stock markets. As a solution, simulations of microeconomic processes using electronic circuits (Morehouse, Strotz, and Horwitz, 1950) and a hydraulic machine (Phillips, 2011; Newlyn, 2007) were used to perform controlled experiments in economic settings.

However, after the invention of the computer, computational models become very popular among micro-economic studies. These computational models are used to perform probabilistic or stochastic simulations with random parameters. These probabilistic or stochastic models can be used to produce a range of realistic outcomes that are observed in real markets.

This thesis considers simulation of stock manipulation in a realistic computational model of a limit order market. In addition, a theoretical model of a limit order book is used to model a manipulation scenario.

2.6.1 Computational models for micro-economic simulations

Computational models can be used to study the behaviour of complex systems by means of a computer simulation under a set of assumptions. These models can be used to perform controlled experiments on a complex system, to study the effects of different components of a system, and to make future predictions. Computational models are required when there are no simple analytical solutions available to describe the behaviour of a system. These models can have several parameters and these parameters can be changed in order to produce different behaviours. These model outputs can
be used to derive theoretical and quantitative inferences of the system under a set of assumptions. These models are evaluated in order to test whether their behaviour is close to the behaviour often observed in the real system.

Agent-based models are a class of computational models used to simulate the actions and interactions of autonomous agents (individual or groups) with an expectation of evaluating their effects on a complex system. Agent-based simulations have been used as computational platforms for performing controlled experiments in a financial market setting (Epstein, 1999; Samanidou et al., 2007; Veryzhenko, Mathieu, and Brandouy, 2011). LeBaron (2000), LeBaron (2001), Tesfatsion (2002), Ghoulmie, Cont, and Nadal (2005), Hommes (2006), LeBaron (2006), Samanidou et al. (2007), and Gould et al. (2011) contains extensive surveys of this literature. Agent-based research has been able to produce stylised patterns in analysing stock markets. However, it can be difficult to extract quantitative inferences due to the large statistical fluctuations within the simulations (Lye et al., 2012). Moreover, it is difficult to distinguish the behaviour introduced by these agents from the behaviour generated by the market micro-structure. In contrast, highly simplified models developed by Bak et al. (1997), Maslov (2000), and Iori (2002) are useful in understanding stock market behaviour in quantitative terms. In these mechanical models, the behaviour of individual agents and their interactions are not considered.

In this thesis, an extension of a mechanical model of a limit order market, developed by Maslov (2000), is used to characterise stock market pricing and the effect of manipulation.

### 2.6.2 Analytical and computational models of stock markets

Both economists and physicists have presented analytical and computational models to characterise the behaviour of stock markets and market participants.

Stigler (1964) performed the first Monte Carlo simulation of a financial market. After some time, different trading mechanisms such as computer-assisted trading and their impact on market efficiency have been examined using simulations (Cohen, Maier, Schwartz, and Whitcomb, 1986).


Models presented in Bak et al. (1997), Maslov (2000), and Iori (2002) are designed to reproduced the stylised attributes of stock markets. Kim and Markowitz (1989) used a computational model to explain the sudden drop in the US stock market in October 1987.

A comprehensive review on the literature on micro-economic modelling can be found in O’Hara (1995), Rydberg (2000), Samanidou et al. (2007), Slanina (2008), Parlour and Seppi (2008), and Gould et al. (2011).

In this thesis, computational models are used to simulate price manipulation in limit order markets. The dynamics of three stock market models that are directly related to this thesis are now presented.
Kyle (1985) model

The “continuous auction framework” developed by Kyle (1985) derives equilibrium security prices when traders have asymmetric information. The Kyle (1985) model is a theoretical model of a dealer market. This model considers an adverse selection problem of both a market maker (i.e., specialist) and an informed trader, and shows that the equilibrium price partly reflects private information.

The specialist in this model faces information asymmetry when dealing with informed traders. As a result, the market maker faces an adverse selection problem. Informed traders also have the problem of selecting the optimal strategy (i.e., trading intensity with time) to be used with their superior information in order to get the maximum expected profit. Informed traders face this adverse selection problem because trades of informed traders may convey information to other market participants, reducing their expected profit.

Kyle (1985) models an equilibrium between these two adverse selection problems and proposed two different optimal methods to tackle these problems. The informed trader in Kyle (1985) sets his buying quantity according to his beliefs of the specialist’s pricing strategy and the noise traders’ trading quantities. The specialist observes the total order flow coming from both informed and noise traders and revises his prices accordingly.

Kyle (1985) showed that the equilibrium condition in this model lies with a linear order strategy for an informed trader and a linear pricing strategy for the specialist. By using these linear strategies, Kyle (1985) explains the behaviour of liquidity or order book depth in a stock market. According to Kyle (1985), the depth of the order book can be affected by an informed trader strategy. If the order book depth is higher, an informed trader can trade more intensely and make greater profits using his information. Using a realistic limit order book model, evidence for this theory is presented in Chapter 7.

Glosten and Milgrom (1985) model

The “sequential trade framework” developed by Glosten and Milgrom (1985) characterises a dealer market. They used the one period model developed by Copeland and Galai (1983) and proposed a multiple step deterministic model.

The Glosten and Milgrom (1985) model also addresses the adverse selection problem of a market maker. This market maker’s task is to provide liquidity to the market and
the other investors must trade with this market maker. Some traders can be more informed than the market maker and as a result the market maker faces an adverse selection problem. As a solution to this adverse selection problem, the market maker in the Glosten and Milgrom model attempts to recoup losses incurred due to informed traders from trades with uninformed traders. In doing this, the market maker revises some of his beliefs and hence his bid and offer prices based on the information extracted from the order flow (i.e., the market maker uses the trades that happen against him as an information source to change his beliefs about the true value of the asset). At each time step, using Bayes theorem, the prior probability of price going up in the future is refined with his beliefs to compute posterior probabilities (i.e., conditional probabilities) for the next time step. After observing the next trading action, the prior probability is updated using the relevant posterior probability. In this model, the bid-ask spread set by the specialist depends on the uncertainty he has about the true value of the asset and uncertainty gradually reduces as information gets revealed with time.

The Glosten and Milgrom (1985) and Kyle (1985) models have been extended in various dimensions to explain different aspects of stock trading including the studies in Diamond and Verrecchia (1987), Allen and Gorton (1992), and Chakraborty and Yılmaz (2004). Madhavan (2000) and Biais et al. (2005) contain extensive surveys of the literature.

The concept of Bayesian learning in the Glosten and Milgrom (1985) model is used to characterise a belief structure for technical traders in Chapter 4.

**Maslov (2000) model**

The Maslov (2000) limit order market model (referred to as the Maslov model henceforth) presents a simplified concept of a market place for a particular stock. This is done by constructing a limit order book with contents that are manipulated by an infinite pool of uninformed traders (these traders do not consider the state of the current limit order book, such as the bid-ask spread, or any past patterns of the last traded price). In this model, each buy order or sell order involves a single unit of a stock and all limit orders are assumed to be good till cancelled (however there are no cancellations). A new trader is drawn from this infinite pool at each execution cycle, and this trader acts as either a buyer (probability \( q_b \)), or a seller (probability \( 1-q_b \)). This trader also decides to submit either a limit order (probability \( q_{lo} \)) or a market order.

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9Maslov (2000) rationalises the trading of one unit of stock with evidence from batch trading in real stock markets.
(probability $1-q_o$). If a limit order is submitted, a value for the limit price is drawn from a distribution as an offset $\Delta$ from the last traded price $p(t)$ (trader computes buy/sell limit order price with a negative/positive $\Delta$ from $p(t)$). If a market order is submitted, it immediately matches with the contra side best price of the order book and a new $p(t)$ value is generated. If the contra side of the order book is empty, the trader may submit a limit order only.

Being a very simple model, the Maslov (2000) model has few assumptions and can be viewed as a null (neutral) model of liquidity trading in limit order markets. The Maslov model shows most of the stylised features that are commonly observed with real data (Maslov, 2000; Withanawasam et al., 2010). Slanina (2001) used the Maslov model to provide a mathematical explanation for the mechanics of limit order trading.

This thesis shows that the Maslov model also provides a suitable platform to characterise stock manipulations. In this regard, the Maslov model can be considered as a system without any external processes and the effects of external processes (i.e., stock manipulations) to the behaviour of the model can be analysed. However, the Maslov (2000) model has not been considered in the context of studying stock manipulations in the literature. An extended Maslov model is used to present realistic manipulation models in this thesis. These realistic manipulation models are a novel contribution to the micro-economics literature.

In Chapter 3, the Maslov model is developed to make it more realistic. The original Maslov price signal shows a cone-shaped repeating pattern in prices that is not often observed with real stock prices. The causes for these unrealistic cone-shaped patterns are analysed in Chapter 3 and shown to be a consequence of the pricing mechanism used in the original Maslov model. In Chapter 3, an alternative pricing mechanism based on common trader beliefs is proposed to overcome this limitation. This new pricing mechanism is a contribution to the limit order market modelling literature.

The Maslov pricing mechanism also does not allow limit orders to overlap with the contra side prices. As a result, it is not possible to submit marketable limit orders in the Maslov model. Moreover, due to the nature of the Maslov pricing logic, the last traded price of the Maslov order book cannot lie outside the bid-ask spread at any point in time. However, in real markets, the last traded price can lie outside the bid-ask spread. When compared to real order book behaviour, this is a major limitation of the Maslov model. In Chapter 3, an alternative pricing mechanism to overcome this limitation is proposed. The extended Maslov model is used to explain various aspects of limit order market dynamics and to model the behaviour of liquid and illiquid markets. Chapter 3
concludes by presenting the base model in building stock manipulation models.

In Chapter 4, the extended Maslov model is used to analyse the impacts of heterogeneous trading in limit order markets. When analysing heterogeneous trader types in Chapter 4, the Maslov traders are considered as utilitarian (liquidity) traders because their actions are exogenous to the market (i.e., random). Heterogeneous trader types such as buyers, sellers, patient and impatient traders, technical traders, cyclic traders, pattern traders, and order cancelling traders are considered. Heterogeneous traders are characterised as simple external processes and introduced to the limit order market model. This is a novel approach to characterising heterogeneous traders in a limit order book model.

The Maslov model can be considered a zero-intelligence model since the model mechanics are random and the notion of information is not considered. In Chapter 4, a notion of information is introduced to the Maslov model. This is done by introducing a technical type trader to the pool of liquidity traders. In this analysis, a belief structure of a technical trader is characterised. This belief model allows explicit control of trader beliefs in order to analyse their learning processes and its effects on the order book. The characterisation of the belief structure of a limit order trader is a novel contribution to the literature. Introduction of a notion of information to the Maslov model allows analysis of information asymmetries and how manipulators exploit these asymmetries in order to profit.

2.7 Market Manipulation

Insider trading (i.e., informed manipulation) uses private information to illegally gain an information advantage for profit. However, it is not necessary to have trading related information to profit in a stock market. If a trader can generate false information in order to mislead other market participants, he or she can make a profit. Chakraborty and Yilmaz (2004) termed this uninformed manipulation. These strategies are commonly termed “market manipulation,” which results in loss of normal traders’ faith in stock trading and may cause inefficient markets (Aggarwal and Wu, 2006). These market participants are termed “manipulators.” The commonly observed manipulation scenarios in stock markets are listed in Table 2.2.
<table>
<thead>
<tr>
<th>Manipulation Scenario</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Advancing the bid</td>
<td>Increasing the bid of a security or derivative to increase its price.</td>
</tr>
<tr>
<td>Churning</td>
<td>Frequent and excessive trading for a client’s account by a trader or brokerage.</td>
</tr>
<tr>
<td>Corner</td>
<td>Obtaining control of the bid side of both the derivative and the underlying asset. This dominant position can be exploited to manipulate the price of that derivative and/or the asset.</td>
</tr>
<tr>
<td>Cyclic (circular) trading</td>
<td>This takes place when a group of traders buy and sell shares frequently among themselves to push the stock price up/down or to generate artificial activity/volumes.</td>
</tr>
<tr>
<td>Dissemination</td>
<td>Dissemination of false or misleading market information and rumours.</td>
</tr>
<tr>
<td>Front running</td>
<td>A transaction to the detriment of the order giver on the basis of and ahead of an order, which he is to carry out for another. This is mainly performed by brokers.</td>
</tr>
<tr>
<td>Insider trading</td>
<td>This occurs when trades have been influenced by the privileged possession of corporate information or price sensitive market order that has not yet been made public.</td>
</tr>
<tr>
<td>Marking the close</td>
<td>Buying or selling securities or derivatives contracts at the close of the market in an effort to alter the closing price of the security or derivatives contract.</td>
</tr>
<tr>
<td>Marking the open</td>
<td>The placing of purchase orders at slightly higher prices/sale orders at lower prices to drive up/suppress the price of the securities when the market opens.</td>
</tr>
<tr>
<td>Matched orders</td>
<td>Transactions where both buy and sell orders are entered at the same time with the same price and quantity by different but colluding parties.</td>
</tr>
<tr>
<td>Parking or warehousing</td>
<td>Hiding the true ownership of securities/underlying by creating a set of fictitious transactions and trades.</td>
</tr>
<tr>
<td>Pre-arranged trade</td>
<td>Transactions in which the price, terms or contra-side have been pre-arranged.</td>
</tr>
<tr>
<td>Pump &amp; dump or ramping</td>
<td>Buying at increasingly higher prices. Securities are sold in the market at the higher prices.</td>
</tr>
<tr>
<td>Short Sales</td>
<td>A market transaction in which an investor sells stock he does not have or he has borrowed in anticipation of a price decline. In general, this is not manipulative but is considered manipulative in some jurisdictions in conjunction with other types of actions; for example, in Canada, under UMIR Rule 6.2(viii)(ix), a short sale cannot be at a price that is less than the last sale price.</td>
</tr>
<tr>
<td>Orders without execution</td>
<td>Placing a series of orders and cancelling them before execution is termed “orders without execution.” This strategy gives a misleading impression that there is high demand or supply at a particular price point.</td>
</tr>
<tr>
<td>(spoofing or layering)</td>
<td></td>
</tr>
<tr>
<td>Painting the tape</td>
<td>Engaging in a series of transactions reported on a public display facility to give the impression of activity or price movement in a security (e.g., misleading trading, switches, giving up priority, layering bid/asks, fictitious orders for the case of spoofing, etc.)</td>
</tr>
<tr>
<td>Squeeze</td>
<td>Taking advantage of a shortage in an asset by controlling the demand-side and exploiting market congestion during such shortages in a way as to create artificial prices.</td>
</tr>
<tr>
<td>Wash sale</td>
<td>Improper transaction in which there is no genuine change in actual ownership of the security or derivative contract.</td>
</tr>
<tr>
<td>Creating a floor and creating a cap</td>
<td>Creating a floor and creating a cap involve controlling the share price falling below or rising above a certain level (i.e., creating a price limit), and are considered as suspicious activities in stock markets.</td>
</tr>
</tbody>
</table>

Table 2.2: A list of common manipulation scenarios extended from Cumming and Johan (2008, p.462-463)

### 2.7.1 Manipulation categories

Based on the methods of altering trading related information, stock manipulations can be categorised under three main types namely: action based, information based and
trade-based (Allen and Gale, 1992). According to Allen and Gale (1992) and Öğüt et al. (2009), the most commonly observed manipulation types are information and trade-based manipulations.

In action based manipulation, manipulators perform actions such as not bidding in an auction or closing down a firm. An example of action based manipulation is the Harlem Railway corner. In another action based manipulation case, the managers of American Steel and Wire Company shorted the stock of the firm and then closed their steel mills (Allen and Gale, 1992).

Spreading false rumours and news via various media are forms of information based manipulation. Nowadays, false information can be easily disseminated via the Internet to mislead market participants. “Trading pools” that emerged in the 1920s in the US are an example of information-based manipulation (Mei, Wu, and Zhou, 2004). Pooled investors buy stocks, spread rumours to increase the price, and then sell at that inflated price. The Enron and WorldCom frauds in 2001 are information-based manipulations. Van Bommel (2003) investigated how rumours can be used to mislead the market and perform information based manipulation. Benabou and Laroque (1992) developed an information-based manipulation model. Using a model, Benabou and Laroque (1992) showed that an opportunistic trader with privileged information can profitably manipulate a market. Vila (1989) showed that there can be an information-based manipulation strategy based on shorting stock, releasing false information and then buying back the stock. Palshikar and Bahulkar (2000) analysed the problem of financial information manipulation and detected trading patterns common to the manipulators using a fuzzy temporal logic.

After the great stock market crash in 1929 (Galbraith, 2009), both information-based and action-based manipulations were categorised as illegal by the Securities Exchange Act of 1934 (Mahoney, 1999; Allen and Gale, 1992).

Performing trades in a way that gives a misleading impression to the market is referred to as trade-based manipulation (Kyle and Viswanathan, 2008). The silver market corner by the Hunt brothers of Texas in 1979-1980 is an example of a trade-based manipulation (Kyle and Viswanathan, 2008). Aggarwal and Wu (2006) presented examples of detected trade-based manipulation cases.

The methods for generating false information in action based and information based manipulations can be subjective and as a result difficult to simulate computationally. Models of trade-based manipulation will be considered in this thesis.
2.7.2 Trade-based manipulation

Hart (1977), Hart and Kreps (1986), and Jarrow (1992) showed that trade-based manipulation is profitable if unstable market equilibriums or non-linear demand functions exist. According to the studies of Allen and Gorton (1992) and Allen and Gale (1992), trade-based manipulation is possible due to an information asymmetry in stock markets. Mei et al. (2004) also analysed the possibility of trade-based manipulation and showed that a manipulator can exploit other trader behaviour in order to profit.

Buyers are considered to be more informed than sellers (Allen and Gorton, 1992). Therefore a buy transaction may contain more information than a sell, and as a result the price movement in response to a buy is greater than that in response to a sell. Moreover, the short selling constraints in stock markets make it easier to exploit good news rather than bad news. This means that driving the price down is more difficult than driving the price up. This asymmetry allows a manipulator to buy repeatedly, thus increasing the price and sell with less overall effect on the market. This trade-based manipulation scenario is commonly termed “pump and dump” (Kyle and Viswanathan, 2008). Another form of pump and dump involve buying stocks and then raising the price by spreading false information before selling.

Another form of asymmetry that can make “pump and dump” possible occurs in the beliefs of investors (Allen and Gale, 1992). Investors always have the problem of distinguishing informed traders from manipulators. This asymmetry leads to a manipulator being able to pretend to be informed and mislead the market.

In this thesis, using a trade-based manipulation model, the possibility of manipulation due to the two information asymmetries that were presented by Allen and Gale (1992) and Allen and Gorton (1992) are simulated.

Some other common trade-based manipulation scenarios are “cyclic trading,” “wash sales,” “marking the close,” “orders without execution,” “painting the tape,” “creating a floor and creating a cap,” “insider trading,” and “cornering.” These strategies can be used as separate manipulations or may be part of any other manipulation strategy. These manipulation scenarios are characterised separately as manipulation models in Chapter 5.

2.7.3 Characteristics of manipulation

Allen and Gale (1992) divided a trade-based manipulation scenario into three stages: pre-manipulation stage, manipulation stage and post-manipulation stage. Pre-
manipulation and post-manipulation periods are non-manipulation periods. These periods are used in characterising manipulation in Chapter 5.

Aggarwal and Wu (2006) presented the common characteristics of manipulated stocks. In the manipulation period, liquidity, volume, and return are higher when compared with the non-manipulation period. Short selling restrictions may make it difficult to drive the price down, so price normally rises in the manipulation period and then falls in the post manipulation period (after the true value is revealed). In general, prices are high when the manipulator sells than when he buys. Liquidity and volatility are also higher when the manipulator sells than when he buys. These characteristics have not previously been realistically simulated in a micro-economic model. This thesis presents evidence for these characteristics via simulation studies.

Aggarwal and Wu (2006) suggested that market manipulation may have impacts on market efficiency. According to Aggarwal and Wu (2006), most emerging markets are illiquid and are not efficient.\textsuperscript{10} Manipulation is a major problem in these emerging stock markets (Khwaja and Mian, 2005). Moreover, manipulation is mostly detected in illiquid markets. There are arguments that it would be easier to hide trades in more liquid and more volatile stocks so that they are more vulnerable to manipulation (Aggarwal and Wu, 2006). Moreover, it may be difficult to identify stock manipulation in more liquid stocks and efficient market places. Jiang, Mahoney, and Mei (2005) studied “stock pools” and concluded that “unlike the small and illiquid stocks studied by Aggarwal and Wu (2004), the average pool stock is of comparable size and is more liquid than other companies in its industry” (Jiang \textit{et al.}, 2005, p.168).\textsuperscript{11} Maug (2002) showed that informed trading is more profitable in highly liquid stocks. Maug (2002) assumed this was because more liquid stocks provide more opportunities to camouflage informed trades.

Based on previous research, it is difficult to determine under what conditions a liquid or illiquid stock is easily manipulated. Manipulation models are used to analyse this issue in Chapter 7. This is a novel contribution to the manipulation literature. Moreover, this application provides evidence that these manipulation models facilitate a means to test market manipulation theories and hypotheses.

\textsuperscript{10}Emerging markets are in developing countries such as Sri Lanka, Kenya, and Pakistan.

\textsuperscript{11}Stock pools are manipulative attempts, “through which groups of investors actively traded in a specified stock” (Jiang \textit{et al.}, 2005, p.148).
2.7.4 Market manipulation studies

Many studies have considered stock manipulation in both empirical and theoretical settings.


Kumar and Seppi (1992) investigated the susceptibility of futures markets to price manipulation. Gerard and Nanda (1993) examined the potential for manipulation in seasoned equity offerings. Jordan and Jordan (1996) examined Solomon Brothers’ market corner of a Treasury note auction in May 1991. Felixson and Pelli (1999) examined closing price manipulation in the Finnish stock market. Mahoney (1999) examined stock price manipulations leading up to the Securities Exchange Act of 1934. Vitale (2000) examined manipulation in the foreign exchange market. Harris (2002) presented an example of a trade-based manipulation and examined why this type of manipulation is likely to change the distribution of trades in a stock. Khwaja and Mian (2005) analysed a unique data set containing daily firm-level trades on the Karachi Stock Exchange (KSE), Pakistan. They found evidence that brokerages can be possible manipulators in a market. These brokerages trade among themselves (i.e., cyclic or circular trading) to artificially raise the price and perform pump and dump. Chakraborty and Yılmaz (2004) used the framework presented in Glosten and Milgrom (1985) and showed that when a market faces uncertainty about the existence of informed traders and if there are a large number of trading periods, long-lived informed traders can successfully manipulate a market. Aggarwal and Wu (2006) suggested that stock market manipulation may have important impacts on market efficiency and presented common characteristics of manipulated stocks. Merrick, Naik, and Yadav (2005) examined a case of manipulation involving a delivery squeeze on a bond futures contract traded in London.

2.8 Manipulation Models

Stock manipulation has been a major problem in stock markets and is difficult to detect because manipulators can use various appearances and variable strategies to avoid detection systems. As a result, manipulation detection involves continuous evaluation
and enhancement of detection mechanisms. Therefore, manipulation detection requires some mechanism to create different manipulation scenarios in order to design, develop, and evaluate their detection measures.

Stock markets involve complex and dynamic interactions between market participants. It is not possible to perform controlled experiments on stock markets to study and test hypotheses about stock markets and manipulations. Moreover, real stock markets cannot be used to generate manipulated data samples in order to test detection systems.

In this thesis, modelling manipulation strategies is developed as a prime method to study stock manipulations. Manipulation models can be used to simplify and explain manipulation scenarios. These manipulation models can be used to recreate manipulation scenarios and generate different forms of manipulations in different real stock market conditions. These recreated manipulation scenarios can be used by manipulation detectors to design, develop, and evaluate their manipulation detection mechanisms. Moreover, manipulation models can be used to test stock manipulation related hypotheses. For example, researchers can use these models to test possibility, profitability, and detectability of manipulation in stock markets. In this context, different stock market conditions can be produced and the implications of manipulation in those different market conditions can be tested.

Many studies have considered stock manipulation in both empirical and theoretical models. Using the Kyle (1985) model, Van Bommel (2003) analysed the possibilities in which the traders can spread rumours in the market about their trades. He showed that a potentially informed party can pretend to be informed and mislead the market. Van Bommel (2003) also showed that the potentially informed party would prefer to commit not to trade against their own information (i.e., buying when the true value is low).

Jarrow (1992) constructed a model that showed large traders can manipulate stock markets due to price momentum (i.e., price increase due to a trade can affect the price in the future). He finds that large traders can affect the price with their trades and profitable speculation is possible if there is price momentum. In this thesis, a technical trader who adds momentum to stock prices is introduced in Chapter 4. In Chapter 5, using the behaviour of these technical traders, it is shown that a trade-based manipulation is possible due to price momentum.

Using a simple theoretical model, Allen and Gale (1992) showed that profitable manipulation is possible even when there exists no price momentum or a price cor-
ner. They showed that a manipulation is possible when it is unclear that an action of a trader is due to his private information or due to a manipulative attempt. As a result, normal traders have problems distinguishing informed traders from manipulators. Manipulators use this dilemma in order to pretend to be informed and mislead the market. Allen and Gale (1992) model is based on simply buying and selling (i.e., only trade-based), and is not based on using public actions to mislead or spread false information. According to Allen and Gale (1992), “the model is not intended to be a realistic description of an actual stock market.” This is because, “extreme assumptions are used to make the argument more transparent” (Allen and Gale, 1992, p.508).

The possibility of manipulation due to information asymmetry introduced by Allen and Gorton (1992) has not been realistically demonstrated in the manipulation literature. The technical traders that are introduced in Chapter 4 are used to simulate and test this Allen and Gorton (1992) concept. In Chapter 5, it is shown that, although these technical traders are expected to extract information from informed trading, they can be mislead due to trade-based manipulation.

By extending the Glosten and Milgrom (1985) model, Allen and Gorton (1992) showed that manipulation is possible due to the natural asymmetry between liquidity purchases and liquidity sales. It is highly likely that buying is performed after doing a market analysis, while selling can be due to many exogenous reasons. As a result, market participants believe that a buy contains more information than a sell. This means price movement with respect to a buy transaction is higher than price movement with respect to a sell transaction. This asymmetry in price responses can make profitable manipulation possible because, due to this information asymmetry, “a manipulator can repeatedly buy stocks, causing a relatively large effect on prices, and then sell with relatively little effect” (Aggarwal and Wu, 2006, p.1919).

The possibility of manipulation due to information asymmetry between buy and sell has not been realistically demonstrated in the manipulation literature. The technical traders that are introduced in Chapter 4 are used to simulate and test this Allen and Gorton (1992) concept. In Chapter 5, using the the belief model of these technical traders, this information asymmetry is simulated and shown to play a role in profitable manipulation.

Moreover, the asymmetry introduced by Allen and Gorton (1992) considered the fact that a buyer is more informed than a seller. However, in the Allen and Gorton (1992) model the degree of information in buying when the price is high or low is not considered. This results in path independent price behaviour in the Allen and Gorton
(1992) model. However, due to the behaviour of fundamental traders, buying or selling when the price is low or high is different. A theoretical model to characterise this information asymmetry is introduced in Chapter 6.

Aggarwal and Wu (2006) also presented a mathematical model for manipulation using a comprehensive sample of manipulation cases. Aggarwal and Wu (2006) extended the framework of Allen and Gale (1992) and studied how a manipulator can trade in the presence of traders who seek information from the market. The Aggarwal and Wu (2006) model consisted of three types of market participants: informed traders (i.e., manipulators), information seekers, and uninformed (noise) traders. Information seekers increase market efficiency. When manipulators are present, the information seekers reduce market efficiency because they are being manipulated. Information seekers increase the manipulator returns. According to Aggarwal and Wu (2006), illiquid stocks are more likely to be manipulated. In general, stock price rises through the manipulation period and then falls in the post manipulation period. Prices and liquidity are higher when the manipulator sells than when the manipulator buys. Manipulation therefore increases volatility.

This model is a four period model. The first period is the pre-manipulation period and the last period is the post-manipulation period. Manipulators engage in manipulation activities in the second and third periods. Fraudulent trading by the manipulator increases trading volume and inflates the price in the second period. Information seekers may think that this activity is due to some private information and enter the market. This is what the manipulator was expecting. Demand from the information seekers will further increase the price so the manipulator can sell his shares and make a profit. The trading volume indicates the number of information seekers in the market and the volatility indicates the uncertainty they have about the price increase due to information or manipulation. Within the manipulation period, volume and volatility should be higher compared to the pre and post manipulation periods such that price (price return), volume and volatility can be used to detect manipulation in a market.

Technical traders are introduced in Chapter 4 and used to simulate and test the possibility of manipulation due to information seekers. This has not been realistically demonstrated in the manipulation literature. In Chapter 5, it is shown that a manipulation is not possible with liquidity traders. When there are information seekers (i.e., technical traders) in the market, a trade-based manipulation is shown to be profitable. In this chapter, it is also shown that increasing the percentage of these information seekers increases manipulator profit.
Other notable manipulation models include the action-based manipulation models presented by Vila (1989), Bagnoli and Lipman (1996), agent-based model for cyclic trading of goods by D’hulst and Rodgers (1999), one-period equilibrium model of profitable manipulation by Brunnermeier (2001), and manipulation in a market order model by Brunnermeier (2001).

However, most of these existing manipulation models consider the theoretical aspects of manipulation and are far from reality. As a result, these theoretical manipulation models cannot be used by the market regulators to generate different forms of manipulation scenarios in order to validate manipulation detection methods. Moreover, in the literature, agent-based simulations have been used to characterise manipulation scenarios such as circular trading. However, these agent-based simulations were designed to analyse the behaviour produced by trader interactions and fail to produce quantitative inferences due to manipulation. Moreover, all these manipulation models were built on different platforms and characterise different manipulation scenarios in different types of stock markets. As a result, these manipulation models cannot be integrated and used to analyse the market behaviour due to a combination of manipulation scenarios. This raised the requirement for a universal model that can be used to simulate a range of manipulation scenarios in a single environment.

This thesis presents a framework to characterise trade-based manipulation scenarios in a single computational model. In this framework, trade-based manipulations are considered for simulation separately in order to provide simplified formal explanations for individual manipulation scenarios. Until this work, manipulation scenarios had not been considered for simulation in a single realistic stock market model. These realistic manipulation models can be used to recreate realistic manipulation scenarios and generate different forms of manipulations in different stock market conditions. As a result, these models can also be used to study the adaptability of manipulators to detection methods. These manipulation models are a novel and important contribution to industry level manipulation detection. In addition, these realistic manipulation models can be used by the researchers to test stock manipulation related hypotheses.

In this thesis, an extension of the Maslov model is used and manipulation scenarios are introduced to build manipulation models. In Chapter 3, the Maslov model is extended to be used as the base model in building the stock manipulation framework. In Chapters 4 and 5, this base model is considered with normal and abnormal trading actions to present trade-based manipulation models. In Chapter 7, an application of manipulation models is used to test stock manipulation related hypotheses.
The following trade-based manipulation scenarios are considered for characterising in the extended Maslov model. The developed manipulation models are presented in Chapter 5.

### 2.8.1 Pump and dump

“Pump and dump” is a stock fraud which involves artificially increasing the stock price in order to sell the same stock at a higher price (SEC, 2012a; The Committee of European Securities Regulators, 2012). In a pump and dump strategy, manipulators pretend to be informed and mislead the market. There can be two main methods of performing this pump and dump strategy (Mei et al., 2004; Jiang et al., 2005; Aggarwal and Wu, 2006). In one method, a pump and dump manipulator can buy at successively higher prices, giving the appearance of activity at a higher price than the actual market value, and then sell or dump shares at an inflated price (Aggarwal and Wu, 2006). This is termed trade-based pump and dump. In another form of this manipulation, manipulators who owned some stocks can spread false information in order to raise the price and then sell their stocks to profit. In this context, means such as the Internet and telemarketing are commonly used to spread false information in these pump and dump schemes. The opposite of this pump and dump is termed “trash and cash,” which involves artificially deflating the price of a stock by means of trades and spreading false information in order to buy stocks (The Committee of European Securities Regulators, 2012). This strategy is mainly associated with short selling.\(^{12}\)

Figure 2.1 illustrates the price behaviour of a pump and dump manipulation recorded for “Universal” stock (ticker symbol UVV) between April 1999 and July 1999 in the U.S. (U.S. Securities and Exchange Commission Litigation Release No. 16621/July 6, 2000).

Allen and Gale (1992), Allen and Gorton (1992), and Aggarwal and Wu (2006) presented models to characterise pump and dump. A trade-based pump and dump is characterised as a manipulation model in Chapter 5. In this chapter, a definition of simplifying a pump and dump scenario using three periods is introduced. A theoretical model is presented to show the possibility of pump and dump manipulation in Chapter 6.

\(^{12}\)Short selling involves selling some borrowed stocks with the intention of buying them back at a lower price.
Figure 2.1: The price graph of the pump and dump manipulation recorded in Universal stock (ticker symbol UVV) in the US market between April 1999 and July 1999

2.8.2 Cyclic (circular) trading

A “cyclic trading” scenario takes place when a group of traders buy and sell shares frequently among themselves to push the stock price up or down or to generate artificial activity and/or volumes. These trades are related and do not represent a real change in the beneficial ownership of the stock. Cyclic trading is considered as a manipulation strategy. Cyclic trading is detected in stock markets by analysing trader interactions and their relationships. This is also known as “stock pools” (Khwaja and Mian, 2005). D’hulst and Rodgers (1999) developed an agent-based model for cyclic trading of goods. Palshikar and Apte (2008) used clustering algorithms to detect collusion sets (circular trading patterns) in stock trading. They used unsupervised learning algorithms to separate normal trading from fraudulent trading.

Using real manipulation cases in Pakistan, Khwaja and Mian (2005) showed the involvement of cyclic trading to the pump and dump manipulation. A trader who uses cyclic trading strategy is considered in Chapter 4. Cyclic trading is characterised as a supportive strategy for pump and dump manipulation in Chapter 5.
2.8.3 Wash sales

A “wash sale” is a sale and a purchase of a stock at substantially the same time by the same person (SEC, 2012c). This scenario is also termed as “matched orders” (Ministry of Economic Development, New Zealand, 2002). A wash sale occurs when a trader sells stocks at a loss within a short period of time before or after buying substantially identical stocks. A wash sale involves no change to the beneficial ownership of the stock. Wash sales can be used by a manipulator to create false activity and generate artificial volumes in order to attract more market participants. Aggarwal and Wu (2006) suggested that a manipulator can engage in wash sale strategy in order to increase the stock price. Grinblatt and Keloharju (2004) found empirical evidence for using wash sales to avoid taxes by Finish investors towards end of December.

A wash sale is characterised as a manipulative strategy in Chapter 5.

2.8.4 Creating a floor and creating a cap

“Creating a floor and creating a cap” involve controlling the share price falling below or rising above a certain level (i.e., creating a price limit), and are considered as suspicious activities in stock markets. Market regulators can also impose this strategy to reduce possible manipulation attempts (Kim and Park, 2010). For example, the first day of trade in Facebook stock in 2012, the underwriter propped up the stock. Chen (1993) analysed the effect of using this strategy on price volatility in Taiwan Stock Exchange. Phylaktis, Kavussanos, and Manalis (2002) performed a similar analysis for Athens Stock Exchange.

In strategies such as pump and dump, creating a floor and creating a cap can be used to support the price increase or decrease. These strategies could also be extended by the manipulators to mislead the chart pattern signals in technical analysis. In this scenario, a manipulator can generate upper or lower breakout of the price envelopes to mislead the technical traders who observe trend breaks.

Creating a floor and creating a cap strategies are characterised as supportive strategies for pump and dump manipulation in Chapter 5.

2.8.5 Marking the close

Price changes in closing are considered to be a good performance indicator of a stock (Felixson and Pelli, 1999). “Marking the close” involves buying or selling stocks at the close of a market with the intention of altering its closing price. The purpose of
doing this is to mislead outsiders who are interested in summaries of market activity (Felixson and Pelli, 1999; Hillion and Suominen, 2004). “A common indicator is trading in small parcels of the security just before the market closes” (Ministry of Economic Development, New Zealand, 2002, p.21). Kucukkocaoglu (2008) analysed the behaviour of the closing day price manipulations in the Istanbul Stock Exchange. Marking the close may take place in an individual trading day or may be associated with a series of trading days. Felixson and Pelli (1999) built a simple regression model to test closing price manipulation in the Finish stock market. Bernhardt and Davies (2005) and Carhart, Kaniel, Musto, and Reed (2002) showed that this marking the close can be a “painting the tape” strategy.

A simple method to characterise this marking the close strategy is introduced in Chapter 5.

### 2.8.6 Orders without execution

Placing a series of orders and cancelling them before execution is termed “orders without execution.” This scenario is also called “layering” or “spoofing.” In this strategy, a manipulator places orders with no intention of having them executed. Later he cancels the order after influencing others who buy or sell at an artificial price driven by his order. This strategy gives a misleading impression that there is high demand or supply at a particular price point. This could be a part of marking the close or “painting the tape” (described below) attempts and could be modelled via a manipulator who performs order cancellations.

According to the SEC, “traders placed a bona fide order that was intended to be executed on one side of the market (buy or sell). The traders then immediately entered numerous non-bona fide orders on the opposite side of the market for the purpose of attracting interest to the bona fide order and artificially improving or depressing the bid or ask price of the security. The nature of these non-bona fide orders was to induce other traders to execute against the initial, bona fide order. Immediately after the execution against the bona fide order, the overseas traders cancelled the open non-bona fide orders, and repeated this strategy on the opposite side of the market to close out the position.” (SEC, 2012b, p.1).

A trader who performs order cancellation as a strategy is considered in Chapter 4. This trader is used to characterise orders without execution manipulation in Chapter 5.
2.8.7 Painting the tape

“Painting the tape” involves carrying out a series of transactions to give a false impression of a market activity or a price movement to outside parties (Bernhardt and Davies, 2005; Cumming and Johan, 2008). Increasing the traded volume of a day and increasing the number of trades of a day are common ways of giving a false impression of activity. Cyclic trading, orders without execution, and marking the close can also be considered as painting the tape manipulation strategies. A painting the tape manipulator can also vary his order submission strategy (i.e., change the probabilities of submitting limit/market orders and hence change the number of trades) in a period of several days to show activity. This is a long-term strategy.

A simple method of charactering painting the tape strategy is introduced in Chapter 5.

2.8.8 Insider trading

“Insider trading” is an information-based manipulation scheme, which involves buying or selling securities of a company by a trader who has access to private knowledge of a company and taking advantage of that private information. This is performed by a stakeholder of a company or a person related to a stakeholder, prior to publishing market sensitive information to the public. Examples for famous insider trading cases in the US are Albert H. Wiggin case in 1929 and Levine, Siegel, Boesky and Milken case in 1980s. Kyle (1985), Glosten and Milgrom (1985), and Goettler, Parlour, and Rajan (2009) models address insider trading in stock markets.

An informed trader is characterised in Chapter 4. Insider trading manipulation is considered for modelling in Chapter 5.

2.8.9 Cornering

“Cornering” is a technique used to purchase all or most of the purchasable supply of a stock or commodity. In other words, this is a market condition that is intentionally generated when a large percentage of the company stock is held by an individual or group, who could dictate the price when a settlement is called. Examples for famous cornering cases are Harlem Railway corner in 1863 and the silver market corner by the Hunt brothers of Texas in 1979-1980. Jarrow (1992) and Allen, Litov, and Mei (2006) analysed this manipulation scenario.

A simple method to characterise cornering is introduced in Chapter 5.
2.9 Summary

Market manipulation is a significant issue in stock markets. Based on the methods of altering trading related information, stock manipulation can be categorised under three main types: action based (e.g., not bidding in an auction or closing down an office), information based (e.g., spreading false rumours and news via various media) and trade based (e.g., performing trades in a way that it would give a misleading impression to the market) (Allen and Gale, 1992). According to Allen and Gale (1992), the most commonly observed manipulation types are information and trade based manipulations.

Simulating manipulation scenarios were introduced as a prime method for understanding, characterising, and detecting the properties of trade-based stock manipulation. Stock manipulations are considered in a limit order market model. Existing manipulation models consider the theoretical aspects of manipulation and are far from reality. In addition, agent-based simulations are designed to analyse the behaviour produced by trader interactions and fail to produce quantitative inferences due to manipulations. Moreover, existing manipulation models were built on different platforms and characterise different manipulation scenarios in different types of stock markets. As a result, these manipulation models cannot be integrated and used to analyse market behaviour due to a combination of manipulation scenarios. As a solution, the importance of developing realistic manipulation models in a single framework has been presented. The following chapters address this issue by developing computational models to characterise trade-based manipulation in limit order markets.

This framework is useful for academic researchers to test their hypotheses on stock manipulation and improve their understanding of manipulation. Moreover, this framework can be used to generate various manipulation data samples in order to test manipulation detection mechanisms.
Chapter 3

Modelling Limit Order Markets

3.1 Overview

This chapter presents a limit order book model to be used as the base model in building a manipulation framework. In this chapter, the mechanics of the Maslov limit order market model (Maslov, 2000) and its properties are discussed. The Maslov model is extended to be used as the base model in building the stock manipulation framework (denoted as the M* model). The behaviour of the Maslov and M* models are compared. These models are used to evaluate the averaging methods used in estimating the limit order book properties. Based on these experiments, the null model in building the market manipulation framework is presented.

Some parts of this chapter are extensions of Withanawasam et al. (2010).

3.2 Importance of Stock Market Models

Stock markets involve complex and dynamic interactions between market participants. It is not possible to perform controlled experiments on stock markets to study and test hypotheses about stock markets and manipulation. Market micro-structure models simplify and explain the behaviour of stock markets and allow researchers to test hypotheses on different aspects of stock trading such as market manipulation. This thesis develops micro-economic models to characterise stock manipulation. These manipulation models can be used to generate different forms of manipulation in order to help design, development, and evaluate manipulation detection methods.

Agent-based simulations have been used as computational platforms for performing controlled experiments in a financial market setting (Epstein, 1999; LeBaron, 2000,
Agent-based research has been able to produce stylised results in analysing stock markets. However, it may be difficult to extract quantitative inferences due to the large statistical fluctuations within these simulations. Moreover, it is difficult to distinguish the behaviour introduced by these agents from the behaviour generated by the market micro-structure. In contrast, highly simplified models developed by Bak et al. (1997), Maslov (2000), and Iori (2002) are useful in understanding stock market behaviour in quantitative terms. In these mechanical models, the behaviour of individual agents and their interactions are not considered.

An extension of the limit order market model developed by Maslov (2000) is developed as the market model for manipulation in this thesis.

### 3.3 Maslov Limit Order Market Model

The Maslov limit order market model (referred to as Maslov) presents a simplified concept of a market place for a particular stock. This is done by constructing a limit order book manipulated by an infinite pool of uninformed (i.e., liquidity) traders (these traders do not consider the state of the current limit order book, such as the bid-ask spread, or any past patterns of the last traded price). In this model, each buy order or sell order involves a single unit of a stock and all limit orders are assumed to be good till cancelled (however there are no cancellations). A new trader is drawn from this infinite pool at each execution cycle, and this trader acts as either a buyer (probability $q_b$), or a seller (probability $1-q_b$). This trader also decides to submit either a limit order (probability $q_{lo}$) or a market order (probability $q_{mo} = 1-q_{lo}$). If a limit order is to be submitted, a value for the limit price is drawn from a distribution as an offset $\Delta$ from the last traded price $price(t)$ (trader computes buy/sell limit order price with a negative/positive $\Delta$ from $price(t)$ (see Figure 3.1)). If a market order is to be submitted, it immediately matches with the contra side best price of the order book (i.e., Best bid price or Best ask price) and a new $price(t)$ value is generated. If the contra side of the order book is empty, the trader may submit a limit order only (later in the thesis, this is referred to as the “market to limit conversion”). The Maslov model mechanism is presented in Algorithm 1.
input : Limit-Order Book L, Tick-Size t
output : Updated Limit-Order Book L

/* Buy or sell? */
if $\text{Rnd}(0,1) \leq q_b$ then
    /* Buy behaviour */
    if Sell side is Empty or $\text{Rnd}(0,1) \leq q_{lo}$ then
        /* Insert limit order to buy */
        $\text{Limit order price} = \text{price}(t) - \Delta$;
        InsertLOBuy($\text{Limit order price}$);
    end
    else
        /* Buy at lowest sell price */
        $\text{price}(t) = \text{Best ask price}$;
        RemoveAndUpdateBestAsk();
    end
else
    /* Sell behaviour */
    if Buy side is Empty or $\text{Rnd}(0,1) \leq q_{lo}$ then
        /* Insert limit order to sell */
        $\text{Limit order price} = \text{price}(t) + \Delta$;
        InsertLOSell($\text{Limit order price}$);
    end
    else
        /* Sell at highest buy price */
        $\text{price}(t) = \text{Best bid price}$;
        RemoveAndUpdateBestBid();
    end
end

Algorithm 1: Single step of the Maslov limit order book model
3.3.1 Implications of the Maslov model

The original Maslov model is initialized with \( q_b = q_o = 0.5 \) and uses the limit order price offset \( \Delta \) as a uniform discrete random number from 1 to 4 (i.e., \( \Delta = 1, 2, 3, 4 \)).

The data generated by the Maslov model complies with stylised features (Kaldor, 1957; Mantegna and Stanley, 1995; Rydberg, 2000; Cont, 2001) often observed in real stock markets (Maslov, 2000; Maslov and Mills, 2001; Withanawasam et al., 2010). Maslov compares the price vs. time (Figure 3.2) and price increments vs. time graphs (Figure 3.3) with ordinary random walks (with similar attributes) and shows that both show long-term memory effects that are significantly different from the properties of a random walk. Note that price increments refer to the first differences of price \( p(t) \) in this thesis (Equation 3.1).

\[
\text{Price increments} = p(t) - p(t - 1)
\]  

In the original Maslov paper, the Hurst exponent of the price graph is estimated using the Fourier transform of the price signal by taking the average over many runs of the model. The relationship of the Fourier transform of the autocorrelation function of the price signal (i.e., power spectral density (Liu et al., 1999)) to the value of the Hurst exponent is of the form \( S(f) \sim f^{-(1+2H)} \), where \( H \) is the Hurst exponent of prices. Maslov shows that the log-log plot of \( S(f) \) of a price signal of length \( 2^{18} \), averaged over multiple realisations, resulted in a value of the Hurst estimate approximately equal

---

\(^1\)Stylised features are the universal properties that describe the most important attributes of stock markets and are independent of country, stock exchange, stock market type, or stock. These stylised attributes are used to evaluate micro-economic models (Slanina, 2008; Gould et al., 2011).
to 0.25. This value corresponds to the decay of $S(f) \sim f^{-3/2}$. However, this Hurst exponent value differs from the short-term Hurst exponent $H \approx 0.6-0.7$, corresponding to real stock prices (Maslov, 2000; Alvarez-Ramirez et al., 2008). This Hurst exponent value also differs from $H \approx 0.5$, corresponding to a random walk (Maslov, 2000).

Maslov (2000) observed some price increment clustering in the Maslov price graphs,
where the regions with high volatility are clearly separated by some quiet regions (Figure 3.3). This effect cannot be observed with a random walk model. Maslov showed that the amplitude of price fluctuations generated from the Maslov model have long range correlations while signs of price fluctuations have short range correlations. The existence of a power-law decay of the absolute values of price increments and returns is a typical manifestation of volatility clustering. According to Maslov (2000), the autocorrelation function of the absolute values of price increments behaves according to the power law tail with an exponent of $S(t)_{abs} \sim t^{-1/2}$. The Fourier transform of $S(t)_{abs}$ also has a clear form of $f^{-1/2}$. This power-law exponent is not significantly different from 0.3, which is the corresponding value for real data such as the S&P 500 stock index (Maslov, 2000).

Maslov also analysed correlations of signs of price fluctuations using the Fourier transform of the autocorrelation function and showed that the behaviour is much closer to frequency independent forms such as white noise characteristics. Maslov compared this with real stock prices to show that real data also have similar short range (lag is less than 30 minutes) correlations of signs of price increments.

The histogram of price increments computed over time lags 1, 10, and 100 indicated strong non-Gaussian behaviour and is very close to the shape of the histogram observed with real stock prices. When the lag increases, the peak of the histogram gradually reduces and approaches a Gaussian (i.e., aggregational Gaussianity). However the tails of the distribution remain strongly non-Gaussian. The log-log plot of the histogram of lag 1 for data collected during $3.5 \times 10^7$ time steps shows the log-log plot has two distinguishable power law regions separated by a large crossover approximately around 1. According to Maslov, the reason behind this crossover is unknown. Exponents of these two regions are estimated to be $1 + \alpha = 0.6 \pm 0.1$ and $3 \pm 0.2$. A similar crossover of two power law regions was reported in real stock price fluctuations on the NYSE with the exponents in the range $1.4 - 1.7$ and $4 - 4.5$ (Maslov, 2000). The power law exponent of the tail, $1 + \alpha = 3$, stays right at the borderline, separating the Pareto-Levy region with power law exponent $1 + \alpha < 3$, where the distribution has an infinite second moment (i.e., variance). According to Maslov, although the model shows long range correlations in price fluctuations, readers can not expect any convergence of price fluctuation distribution to a Pareto-Levy or Gaussian as the lag is increased.

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2 In random walk processes, the first differences show a white noise characteristic.
3.3.2 Limitations of the Maslov model

The Maslov model only allows trading of one unit of stock at a time. Maslov (2000) rationalises this with evidence from batch trading in real stock markets. The Maslov pricing mechanism also does not allow the limit orders to overlap with the contra side prices (Figure 3.1). As a result, it is not possible to submit marketable limit orders in the Maslov model.\(^3\) Moreover, due to the nature of the Maslov pricing logic, the last traded price of the Maslov order book cannot lie outside the bid-ask spread at any point in time (Figures 3.4). However, in real markets, the last traded price can lie outside the bid-ask spread (Figure 3.5). This is a major limitation in the Maslov model when compared to real order book behaviour.

![Last traded price always lies inside the bid-ask spread in the Maslov model](image)

Figure 3.4: Last traded price always lies inside the bid-ask spread in the Maslov model

The Maslov price signal also shows a cone-shaped repeating pattern that is not often observed with real stock prices (Figure 3.6). The inset of Figure 3.6 illustrates an example cone generated in the Maslov price signal. This cone-shaped pattern is a consequence of the pricing mechanism used in the Maslov model. A Market order can remove the top most price point, increasing the bid-ask spread and causing larger

\(^3\)A marketable limit order is a limit order with limit price at or above the best ask (if a buy) or at or below the best bid (if a sell). So, it crosses with the contra side of the order book and is executed immediately with the contra side best bid or ask.
price fluctuations. As a result, a series of market orders can generate a cone-shaped pattern in the last traded price signal. Limit orders are expected to fill the bid-ask spread, increase liquidity, and reduce the effect of generating these cone-shaped patterns. However, failure to fill the bid-ask spread gap (i.e., place orders inside the bid-ask spread) by the limit orders may generate unrealistic cone-shaped patterns in the Maslov price signal.

The Maslov model can be considered a zero-intelligence model (Farmer, Patelli, and Zovko, 2005; Gould et al., 2011; Ladley, 2012). This is because the Maslov model mechanics are random and the notion of information has not been considered by the Maslov traders. As a result, information asymmetries are not able to be characterised in the original Maslov model. This limits the simulation of possible manipulation in the original Maslov model.

Being a very simple model, the Maslov model has few assumptions and may be viewed as a null (neutral) model. However, as will be shown, the model can be extended to cater for a range of trader behaviours allowing models of trading and manipulation to be considered.
3.3.3 The $M^*$ model

The Maslov model is extended here to be used as the base model in building the stock manipulation framework. An alternative (i.e., improved) pricing mechanism (denoted by $M^*$) based on contra side best prices for the Maslov model is proposed. Here the concept of a trader being more likely to refer to the contra side prices than the same side properties or the last traded price in making a decision about submitting a limit order is introduced. For example, a trader who submits a limit buy order is more likely to refer to the sell side properties such as best ask price (Parlour, 1998). The $M^*$ method computes limit buy/sell order prices with respect to the best ask/bid price of the order book. If the contra side best price is empty, the last traded price is used. The $M^*$ pricing mechanism is presented in Algorithm 2.

3.4 Comparison of the Maslov and $M^*$ Models

A comparison of the mechanics of Maslov and $M^*$ models are given in Table 3.1.

The Maslov and $M^*$ models are initialised with $price(0) = 10000$, and probabilities $q_b = q_o = 0.5$. The starting price $price(0)$ is chosen high in order to avoid negative prices.\footnote{We could alternatively have altered the model to allow for multiplicative growth in stock price, all runs commence with 1000 steps to seed the limit order book as per Maslov.
**Input**: Best ask price, Best bid price, Last traded price \( price(t) \), \( \Delta = 1, 2, 3, 4 \)

**Output**: Limit order price

```plaintext
/* Buy ? */
if (Buy) then
    /* Sell side empty ? */
    if (Sell side is Empty) then
        Limit order price = price(t) - \( \Delta \);
    end
    else
        Limit order price = Best ask price - \( \Delta \);
    end
else
    /* Sell */
    /* Buy side empty ? */
    if (Buy side is Empty) then
        Limit order price = price(t) + \( \Delta \);
    end
    else
        Limit order price = Best bid price + \( \Delta \);
    end
end
```

**Algorithm 2**: Algorithm for determining limit order prices of the \( M^* \) model
Maslov model | $M^*$ model | Real data
---|---|---
Limit order prices are computed with respect to the last traded price | Limit order prices are computed with respect to the contra side best price | Limit order prices may depend on the contra side properties (Parlour, 1998)
Last traded price cannot lie outside the spread | Last traded price can lie outside the spread | Last traded price can lie outside the spread
Market buy order can increase or re-generate the last traded price. Market sell order can decrease or re-generate the last traded price | Market buy order can increase, decrease, or re-generate the last traded price. Market sell order can increase, decrease, or re-generate the last traded price. | Market buy order can increase, decrease, or re-generate the last traded price.
Marketable limit orders are not allowed | Marketable limit orders are allowed | Marketable limit orders are allowed
Limit orders may decrease the bid-ask spread | Limit orders may decrease the bid-ask spread. The chance of decreasing the bid-ask spread is higher in comparison with the Maslov model | Limit orders may decrease the bid-ask spread
Market orders may increase the bid-ask spread | Market orders may increase the bid-ask spread | Market orders may increase the bid-ask spread
Market orders may increase or decrease the mid bid-ask spread | Market orders may increase or decrease the mid bid-ask spread | Market orders may increase or decrease the mid bid-ask spread
Limit orders may increase or decrease the mid bid-ask spread | Limit orders may increase or decrease the mid bid-ask spread | Limit orders may increase or decrease the mid bid-ask spread

Table 3.1: Comparison of the mechanics of Maslov and $M^*$ models

(2000) (i.e., referred to as “initial seeding period” in this thesis). After the initial seeding these models run for 10000 time steps. As a result, the data are recorded from $p(1) = price(1000)$ onwards. The random numbers in these simulations are generated using the Mersenne twister algorithm (Matsumoto and Nishimura, 1998). All experimental results were combined and averaged over 100 simulation runs.

Stylised market attributes and model properties are used to compare $M^*$ with Maslov.

### 3.4.1 Last traded price ($p(t)$)

The $M^*$ pricing method removes one major limitation in the Maslov model by allowing the last traded price to lie outside the bid-ask spread at any point in time (Figure 3.7, compare with Figure 3.5). In addition, the $M^*$ method can cater for marketable limit orders with the use of zero $\Delta$ values (Figure 3.8).

In both the Maslov and $M^*$ models, there is a possibility of placing limit orders inside the bid-ask spread, reducing the effect of generating cone-shaped patterns in the but we wanted to make as few changes as possible in the interests of comparability and parsimony.
Figure 3.7: Last traded price can lie outside the bid-ask spread in the $M^*$ model

price signal. However, the chance of filling the bid-ask spread gap by a limit order is higher in the $M^*$ model compared with the Maslov model (Figure 3.8). This is because the $M^*$ model computes the limit price with respect to the contra side best price. As a result, the $M^*$ model does not produce the magnitude of cone-shaped patterns that can be observed with the original the Maslov model (Figure 3.9).

### 3.4.2 Bid-ask spread

Bid-ask spread is reduced in the $M^*$ model (Figure 3.10) compared with Maslov. This is because the chance of filling the bid-ask spread gap via limit orders is higher in the $M^*$ model as compared with the Maslov model (Figure 3.8).

### 3.4.3 Price net change

The price net change is defined as the difference between the closing price (i.e., $p(10000)$) and the starting price (i.e., $p(1)$). This is analysed for both Maslov and $M^*$ models. It is observed that the standard deviation of these price net changes for 100 $M^*$ model runs is lower than the same for the 100 Maslov runs (Figure 3.11). However, both on average have a net change of zero. The greater chance of filling the bid-ask spread gap results in smaller price fluctuations in the $M^*$ model and therefore
Figure 3.8: A graphical illustration of limit order placements in both Maslov and $M^*$ models

Figure 3.9: Typical example price graph of the $M^*$ model

Figure 3.10: Bid-ask spread box plots of both Maslov and $M^*$ models (combined over 100 simulation runs). ☒ indicates the mean values

... low standard deviation in price net changes. This also implies that the $M^*$ prices are less volatile than the Maslov prices. This indicates that the $M^*$ model prices show a more anti-persistent behaviour than the Maslov last traded price signal (later we
confirm this anti-persistent behaviour using the behaviour of the Hurst exponent). As a result, the roughness (Gneiting and Schlather, 2004; Mandelbrot and Hudson, 2006) of the $M^*$ price signal is higher than the Maslov last traded price signal.

### 3.4.4 Autocorrelation of price increments

Autocorrelation of price and absolute price increments were analysed for both Maslov and $M^*$ models. Price increments refer here to first differences of the last traded price signal. Figure 3.12 illustrates the autocorrelation coefficient box plots of price increments, computed and combined over 100 simulation runs of the Maslov model. Figure 3.13 illustrates the corresponding graph for the $M^*$ model. These graphs indicate that the autocorrelation of price increments are negative in both Maslov and $M^*$ models. The negative autocorrelation decreases in magnitude when the lag is increased. In general, autocorrelation of price increments are negative due to the order book mechanism of the price fluctuating between best bid and ask prices (i.e., bid-ask spread). The first order negative autocorrelation coefficients of the $M^*$ price increments are significantly smaller\(^5\) (i.e., p-value < 0.05) than the Maslov model negative autocorrelation coefficients. This means that, the higher chance of filling the bid-ask

\(^5\)Here, a T-test is used to measure the significance.
spread gap by limit orders in the $M^*$ pricing mechanism reduces the negative first order correlation of price increments. However, the other autocorrelation coefficients of price increments are not significantly different between both models. As shown in Figures 3.14 and 3.15, the autocorrelation of absolute price increments is positive for both Maslov and $M^*$ models. Moreover, the first order autocorrelation of absolute increments is comparatively low in the $M^*$ model. This is also attributed to the increased chance of filling the bid-ask spread gap in the $M^*$ model. These means that the $M^*$ pricing mechanism adds an anti-persistent behaviour to the absolute price increments and persistent behaviour to the price increments. These results show that, in the $M^*$ model, the correlation behaviour in prices is low compared to the Maslov model.

![Figure 3.12: Autocorrelation box plots of price increments (first 14 lags) for the Maslov model (combined over 100 simulation runs)](image1)

![Figure 3.13: Autocorrelation box plots of price increments (first 14 lags) for the $M^*$ model (combined over 100 simulation runs)](image2)

### 3.4.5 Hurst exponent ($H$)

The Hurst exponent value of the price signal is estimated using the re-scaled range method (Qian and Rasheed, 2004). A graphical summary of the behaviour of the Hurst exponent is given in Appendix C. The estimated Hurst exponent value averaged over 100 Maslov simulation runs is 0.3 (in Maslov (2000), this value has been reported as 0.25). The estimated Hurst exponent value using the re-scaled range method in the $M^*$ model is 0.28. The estimated Hurst exponent values using the Fourier transform
of the autocorrelation function of the price signal (i.e., power spectral density \( S(f) \)) averaged over 100 runs for the Maslov and \( M^* \) models (Maslov (2000) used this method) were 0.275 and 0.215, respectively. Figures 3.16 and 3.17 illustrate the log-log plots of \( S(f) \) combined and averaged over 100 realisations for the Maslov and \( M^* \) prices. The relationship of the slope \( S \) of these plots to the value of the Hurst exponent \( H \) is of the form \( S = 1 + 2H \). The lower Hurst exponent for \( M^* \) is attributed to the low correlations of prices observed with \( M^* \) compared with the original Maslov model. This is also consistent with the rougher price signal observed with the \( M^* \) model.

### 3.4.6 Volatility clustering

Large stock price increments tend to be followed by large increments, of either sign, and small changes tend to be followed by small changes. This is referred to as volatility clustering in stock markets (Bollerslev et al., 1992; Rydberg, 2000; Maslov, 2000; Maslov and Mills, 2001). The power-law decay of the autocorrelation function of absolute values of price returns or increments is regarded as a typical manifestation of volatility clustering (Bollerslev et al., 1992; Ding et al., 1993; Cont et al., 1997; Guillaume et al., 1997). In real stock markets, this autocorrelation function of absolute
price returns decays according to a power law with a very small exponent in the range 0.3 - 0.4 and with no apparent cut-off.

It is observed that both the Maslov and $M^*$ models show a clustering behaviour in their price increments (Figures 3.18 and 3.19). However price fluctuations are low in magnitude (i.e., less volatility) in $M^*$ compared with the Maslov model. This is because the bid-ask spread is comparatively low in the $M^*$ model (Figure 3.10). The cone-shaped patterns that are observed in the original Maslov prices can also be visible in the price increments plot (Figure 3.18). Moreover, the power law decay exponent of the Fourier transform of price increments autocorrelation function averaged over 100 simulation runs is estimated as 0.36 in the Maslov model. The corresponding values for the $M^*$ model is 0.45.

3.4.7 Fat tailed property of price returns

The price returns (Equation 3.2) distributions of both Maslov and $M^*$ models show a sharp peak and broad tails and deviate from Gaussian distribution. Figures 3.20 and 3.21 show the histograms of price returns for combined data of 100 runs of Maslov and $M^*$ models. The sharp peak and fat tail characteristics in these graphs can be
commonly observed in financial data (Mandelbrot, 1963a,b; Mantegna and Stanley, 1995; Krause, 2006). This is confirmed by the positive excess kurtosis values observed in both price return distributions. This behaviour indicates that the probability of observing extremely large or extremely small price fluctuations is high compared with having moderate fluctuations (i.e., higher proportion of probability is in the tails of the distribution compared to normal distribution) in both Maslov and $M^*$ models.

\[
\text{Price return} = \frac{p(t) - p(t - 1)}{p(t - 1)}, \text{ where } p(t) \text{ is the price at time } t
\]

(3.2)

### 3.4.8 Aggregational Gaussianity

An “aggregational Gaussianity” effect is observed in the price increment histograms of both Maslov and $M^*$ models. This aggregational Gaussianity effect indicates that the probability of observing extremely small price fluctuations or returns decreases when the lag is increased. As illustrated in Figures 3.22 and 3.23, when the lag increases (i.e., 1, 10, and 100), the peak of the price increments histogram gradually reduces and approaches a Gaussian distribution in both Maslov and $M^*$.  

Figure 3.20: Fat tailed property of price returns in the Maslov model. Note that price returns are combined over 100 simulation runs.

Figure 3.21: Fat tailed property of price returns in the $M^*$ model. Note that price returns are combined over 100 simulation runs.

Figure 3.22: “aggregational Gaussianity” effect shown by the Maslov model. Note that price returns are combined over 100 simulation runs.

Figure 3.23: “aggregational Gaussianity” effect shown by the $M^*$ model. Note that price returns are combined over 100 simulation runs.
3.4.9 Buy/sell order percentages

Here the Maslov and $M^*$ models are analysed with different trader buy probabilities. It is found that more buy/sell orders can drive the price up/down, complying with common supply and demand properties. Figures 3.24 and 3.25 illustrate the net change (i.e., $p(10000) - p(1)$) behaviour when the probability of buying ($q_b$) is increased. The average price net change increases from negative to positive when $q_b$ increases. It is zero when $q_b$ is 0.5. In relation to this, it is observed that when there is an imbalance between buy and sell orders (i.e., $q_b \neq 0.5$) the Hurst exponent value is higher than the case where $q_b = 0.5$. Figures 3.26 and 3.27 illustrate the Hurst exponent behaviour with probability $q_b$ for the Maslov and $M^*$ models respectively. This means that more buying or selling (i.e., $q_b$ is close to 0 or 1) can increase the persistent behaviour of the prices. When all the trading actions are buying or selling the Hurst exponent value shows the highest value.

This probability of buying is used to simulate price increases/decreases (i.e., pushing up/down) in manipulative conditions in Chapters 5 and 7.
3.4.10 Limit/market order percentages

The Maslov and $M^*$ models are analysed with different market or limit order probabilities. The probability of submitting a limit or market order can affect the volatility and roughness of the price signal (Figures 3.28 and 3.29). This is because more market orders can produce more new last traded prices in both Maslov and $M^*$ models. Price net change box plots shown in Figures 3.30, and 3.31 confirm this price volatility increase with more market orders. The roughness of the price signal also decreases with more market orders. This behaviour is also reflected in the estimated Hurst exponent of the price signal. Figure 3.32 and 3.33 illustrate the behaviour of the Hurst exponent when the probability of submitting a market order (i.e., $q_{mo}=1-q_{lo}$) is increased. The Hurst exponent is low when there are more limit orders than market orders. Moreover, the Hurst exponent is significant greater when $q_{mo} = 0.8$. However, it is also observed that a higher market order percentage can result in frequent empty order book states and hence more market to limit order conversions. These results indicate that, when there are more limit orders in the market, the persistent behaviour of the price signal

---

6In both Maslov and $M^*$ model, when the contra side order book is empty, traders can only submit limit orders.
is low.

Figure 3.28: Price behaviour for different market order probabilities in the Maslov model (Note that the data were plotted with sampling only at every 50th point for clarity)

Figure 3.29: Price behaviour for different market order probabilities in the $M^*$ model (Note that the data were plotted with sampling only at every 50th point for clarity)

3.4.11 Order expiry or order cancellations

A maximum life time (“time to live” attribute ($ttl$)) for limit orders is introduced, whereby limit orders are removed from the order book immediately after their life time expires. The Maslov and $M^*$ models are simulated for different limit order life times and it is observed that the volatility of both price signals increases when the limit order life time is decreased (Figures 3.34 and 3.35). This is because removal of old orders can cause large price gaps between stale orders in the order book and hence higher price fluctuations. Greater bid-ask spreads due to the limit order cancellations can also cause larger price fluctuations. It is also observed that the Maslov model with order expiry does not produce the magnitude of cone-shaped patterns that can be observed with the original Maslov model.

The Hurst exponent of the price signal approaches 0.5 when the limit order life time is decreased in both Maslov and $M^*$ models (Figures 3.36 and 3.37). The maximum Hurst exponent value is observed when the life time of a limit order is minimum (i.e.,
one time step). This property confirms that when the memory of the order book is less (i.e., \( ttl \) is low and hence there are no old orders at any given time), the Hurst exponent value approaches from below the random walk Hurst exponent value (i.e., 0.5). However, when \( ttl = 1 \), the Hurst exponent value is slightly greater than 0.5 is due to the market to limit conversions when there are no limit orders in the order book.

### 3.4.12 Limit order price offsets (\( \Delta \))

The Maslov model uses the limit order price offset \( \Delta \) as a uniform discrete random number from 1 to 4. Maslov states that the pricing behaviour remains similar even if a constant \( \Delta \) (i.e., \( \Delta = 1 \)) value is used. These experiments confirm that the Maslov model does not show any significant behaviour differences for various \( \Delta \) values, however importantly the \( M^* \) model behaves differently with different \( \Delta \) distributions. Moreover, these \( \Delta \) distributions are used to evaluate the averaging methods used in estimating limit order book attributes. Refer to Appendix A for empirical evidence on limit order price offsets (\( \Delta \)) in real markets.

The limit order price offset distributions (i.e., \( \Delta \) distributions) uniform, Gaussian, power law, and gamma are used to represent various investor reactions to market con-
Figure 3.32: Hurst exponent box plots for different market order probabilities in the Maslov model (combined over 100 simulation runs)

Figure 3.33: Hurst exponent box plots for different market order probabilities in the $M^*$ model (combined over 100 simulation runs)

ditions and are tested with the Maslov and $M^*$ models. In order to ensure consistency, the mean value of the drawn limit order price offsets is set to 2.5 in all the distributions (see Figure 3.38). All other properties including seeds of all random number generators used in the simulations are identical.

In order to analyse the limit order book shape, the average order book profile is computed. This is the average over 100 simulation runs of the number of orders that exist for all available distances from the best bid or ask at the end of each simulation. Commonly used stylized features of stock data such as fat tails property of stock return distributions, negative auto correlations of price and mid spread increments, clustering of volatility, behaviour of price net changes, and Hurst exponent of prices, are analysed. Volatility clustering is quantified using the decay exponent of the autocorrelation function of absolute price increments (though we also found significant and consistent GARCH effects that are not reported here). Attributes such as mean, standard deviation, skewness, and kurtosis values are computed and compared for analysing the statistical properties of these distributions.

In assessing whether our modifications affect the behaviour of the Maslov model significantly, a two-sample unequal variance t-test (i.e., a two-sample t-test with Welch
Figure 3.34: Price behaviour for different $ttl$ values in the Maslov model (Note that the data were plotted with sampling only at every 50th point for clarity)

Figure 3.35: Price behaviour for different $ttl$ values in the $M^*$ model (Note that the data were plotted with sampling only at every 50th point for clarity)

Figure 3.36: Hurst exponent box plots for different $ttl$ values in the Maslov model (combined over 100 simulation runs)

Figure 3.37: Hurst exponent box plots for different $ttl$ values in the $M^*$ model (combined over 100 simulation runs)
degrees of freedom adjustment) is performed to test whether the mean value of the estimated market properties vary in different market conditions.

Figures 3.39 and 3.40 illustrate the last traded price graphs of Maslov and $M^*$ models with the four limit order price offset ($\Delta$) distributions. These figures indicate that the shape of the price graphs are similar between the two models. Moreover, the price graphs are identical in shape irrespective of their scale within a model and with different $\Delta$ distributions. This scale difference is confirmed by the behaviour of net changes in last traded price (see Figures 3.41 and 3.42). Moreover, the net changes in the $M^*$ model are comparatively smaller than the net changes in the Maslov model.

There is greater variability with the order book profiles for a given $\Delta$ distribution in the $M^*$ model. Figure 3.43 shows several example distributions after 10000 steps, which do not show any regular pattern and are clearly not bell-shaped. There is, however, a striking regularity in bell-shaped average order book profile distributions in the Maslov and $M^*$ models (see Figures 3.44 and 3.45). The properties of these average order book profile distributions (combined over 100 simulation runs) presented in Table 3.2 also do not show any significant differences (i.e., the skewness and kurtosis values given in the table are similar).

In terms of comparing the Maslov and $M^*$ models, the numerical properties of stylised features of stock data such as the Hurst exponent of prices, negative auto
correlation of price and mid spread increments and volatility clustering (i.e., ACF decay of absolute price increments) are presented in Tables 3.3 and 3.4. Here the stylised features of stock data in the Maslov model are not significantly different with
Figure 3.43: Individual order book profile distributions (Histogram mids versus Histogram counts) in the $M^*$ model for power law $\Delta$ distribution.

Figure 3.44: Average order book profiles in the Maslov model for different $\Delta$ distributions (combined over 100 simulation runs).

Figure 3.45: Average order book profiles in the $M^*$ model for different $\Delta$ distributions (combined over 100 simulation runs).
different $\Delta$ distributions. However, the $M^*$ model showed different characteristics with different $\Delta$ distributions.

In order to test whether these modifications affect the behavior of the stylized properties, a two-sample unequal variance t-test is performed and the test results ($p$-values) are presented in Tables 3.5 and 3.6.

These test results indicate that the stylized features are not significantly different with any $\Delta$ distributions when the reference price is set as the last traded price (i.e., in the original Maslov model). Stylized features such as the Hurst exponent, negative auto-correlation in price increments, and volatility clustering show significantly different behaviour between $\Delta$ distributions when the reference price is contra side best price (i.e., the $M^*$ model). Stylized features such as negative auto-correlation in mid spreads do not show any significant change in both Maslov and $M^*$ models for any of the $\Delta$ distributions.

Table 3.7 shows that the kurtosis values of price returns distribution have a higher value (i.e., fatter tails) in the power law $\Delta$ distribution with both Maslov and $M^*$ models compared with the other $\Delta$ distributions.

Although not shown here, we also observe that when the mean of the $\Delta$ distribution
### Table 3.4: Mean and Standard Error values of stylized features for different ∆ distributions in the $M^*$ model

<table>
<thead>
<tr>
<th>Distribution of ∆</th>
<th>Hurst Exponent</th>
<th>First Order AC of Price Increments</th>
<th>Mid Spread Increments</th>
<th>ACF Decay of Absolute Price Increments</th>
</tr>
</thead>
<tbody>
<tr>
<td>uniform</td>
<td>0.28</td>
<td>-0.20</td>
<td>-0.12</td>
<td>0.43</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.0011)</td>
<td>(0.0013)</td>
<td>(0.0018)</td>
</tr>
<tr>
<td>Gaussian</td>
<td>0.22</td>
<td>-0.23</td>
<td>-0.12</td>
<td>0.34</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.0007)</td>
<td>(0.0012)</td>
<td>(0.0028)</td>
</tr>
<tr>
<td>power law</td>
<td>0.33</td>
<td>-0.17</td>
<td>-0.12</td>
<td>0.44</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.0015)</td>
<td>(0.0016)</td>
<td>(0.0021)</td>
</tr>
<tr>
<td>gamma</td>
<td>0.28</td>
<td>-0.21</td>
<td>-0.12</td>
<td>0.41</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.0010)</td>
<td>(0.0014)</td>
<td>(0.0019)</td>
</tr>
</tbody>
</table>

### Table 3.5: t-test results (p-values) of the stylized features for different ∆ distributions in the Maslov model

<table>
<thead>
<tr>
<th>Distribution of ∆</th>
<th>Hurst Exponent</th>
<th>First Order AC of Price Increments</th>
<th>Mid Spread Increments</th>
<th>ACF Decay of Absolute Price Increments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gaussian vs. uniform</td>
<td>0.78</td>
<td>0.69</td>
<td>0.61</td>
<td>0.79</td>
</tr>
<tr>
<td>power law vs. uniform</td>
<td>0.11</td>
<td>0.43</td>
<td>0.57</td>
<td>0.36</td>
</tr>
<tr>
<td>gamma vs. uniform</td>
<td>0.91</td>
<td>0.96</td>
<td>0.68</td>
<td>0.78</td>
</tr>
<tr>
<td>power law vs. Gaussian</td>
<td>0.06</td>
<td>0.24</td>
<td>0.94</td>
<td>0.23</td>
</tr>
<tr>
<td>gamma vs. Gaussian</td>
<td>0.70</td>
<td>0.65</td>
<td>0.93</td>
<td>0.99</td>
</tr>
<tr>
<td>gamma vs. power law</td>
<td>0.14</td>
<td>0.45</td>
<td>0.87</td>
<td>0.22</td>
</tr>
</tbody>
</table>

### Table 3.6: t-test results (p-values) of the stylized features for different ∆ distributions in the $M^*$ model

<table>
<thead>
<tr>
<th>Distribution of ∆</th>
<th>Hurst Exponent</th>
<th>First Order AC of Price Increments</th>
<th>Mid Spread Increments</th>
<th>ACF Decay of Absolute Price Increments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gaussian vs. uniform</td>
<td>0.00</td>
<td>0.00</td>
<td>0.98</td>
<td>0.00</td>
</tr>
<tr>
<td>power law vs. uniform</td>
<td>0.00</td>
<td>0.00</td>
<td>0.59</td>
<td>0.04</td>
</tr>
<tr>
<td>gamma vs. uniform</td>
<td>0.39</td>
<td>0.00</td>
<td>0.71</td>
<td>0.01</td>
</tr>
<tr>
<td>power law vs. Gaussian</td>
<td>0.00</td>
<td>0.00</td>
<td>0.58</td>
<td>0.00</td>
</tr>
<tr>
<td>gamma vs. Gaussian</td>
<td>0.00</td>
<td>0.00</td>
<td>0.72</td>
<td>0.00</td>
</tr>
<tr>
<td>gamma vs. power law</td>
<td>0.00</td>
<td>0.00</td>
<td>0.41</td>
<td>0.00</td>
</tr>
</tbody>
</table>

### Table 3.7: Properties of stock returns distributions for different ∆ distributions

<table>
<thead>
<tr>
<th>Distribution of ∆</th>
<th>Maslov Mean</th>
<th>Std</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>M* Mean</th>
<th>Std</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>uniform</td>
<td>0</td>
<td>4e-04</td>
<td>0.09</td>
<td>142.88</td>
<td>0</td>
<td>2e-04</td>
<td>0.01</td>
<td>50.10</td>
</tr>
<tr>
<td>Gaussian</td>
<td>0</td>
<td>4e-04</td>
<td>0.09</td>
<td>163.13</td>
<td>0</td>
<td>2e-04</td>
<td>0.00</td>
<td>9.42</td>
</tr>
<tr>
<td>power law</td>
<td>0</td>
<td>5e-04</td>
<td>0.13</td>
<td>181.96</td>
<td>0</td>
<td>3e-04</td>
<td>0.06</td>
<td>152.76</td>
</tr>
<tr>
<td>gamma</td>
<td>0</td>
<td>4e-04</td>
<td>0.09</td>
<td>143.10</td>
<td>0</td>
<td>2e-04</td>
<td>0.02</td>
<td>49.93</td>
</tr>
</tbody>
</table>
is increased, there is a corresponding increase in bid-ask spread, price volatility, and the variance of net changes. The price graphs also shift upward. However, in this case, no significant changes are observed in stylized features such as the Hurst exponent, auto-correlation of price/spread increments, and volatility clustering.

These results confirm the results of Maslov (2000) that using different $\Delta$ distributions makes little difference to the behaviour of the original model. However when the limit order prices are computed with respect to the contra side best price (i.e., $M^*$ model), use of different $\Delta$ distributions generates significantly different results. These results indicate that when there is a greater chance of filling the bid-ask spread gap by a limit order (i.e., in the $M^*$ model), the likelihood of observing different effects with different $\Delta$ distributions increases. The span of $\Delta$ did not make any significant difference to the properties of the price signal except its scale. The power law distribution was found to generate the highest Hurst exponent value, which is closest to the Hurst exponent observed with real stock prices (Alvarez-Ramirez et al., 2008).

Most importantly, the similar average order book profile distribution (irrespective of the pricing mechanism) implies that taking averages over several stocks/different days in a same stock used in the literature may produce misleading results. As a consequence, when analyzing real data, taking an average may cancel variabilities that can be observed with individual stocks and may produce regularities such as the bell-shaped distribution often presented in order book profiles. These results imply that the similar average order book profile used in Biails et al. (1995) to compute supply and demand curves, the averaging method used in Bouchaud, Mézard, and Potters (2002) to compute the order book shape, and the average order book profile used in Weber and Weber and Rosenow (2005) to find inferences in price impact can be misleading, because they cancel out significant variabilities in individual order book profiles.

These results also indicate that the $M^*$ model is more capable of producing variable results in characterising different trader behaviours and market conditions than the

<table>
<thead>
<tr>
<th>Distribution of $\Delta$</th>
<th>Maslov Mean</th>
<th>Std</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>$M^*$ Mean</th>
<th>Std</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>uniform</td>
<td>5.42</td>
<td>6.34</td>
<td>6.12</td>
<td>65.49</td>
<td>2.55</td>
<td>1.95</td>
<td>4.65</td>
<td>51.39</td>
</tr>
<tr>
<td>Gaussian</td>
<td>6.08</td>
<td>6.76</td>
<td>6.72</td>
<td>83.46</td>
<td>2.84</td>
<td>1.09</td>
<td>2.85</td>
<td>25.63</td>
</tr>
<tr>
<td>power law</td>
<td>5.60</td>
<td>7.98</td>
<td>6.26</td>
<td>67.92</td>
<td>2.66</td>
<td>3.68</td>
<td>6.92</td>
<td>89.53</td>
</tr>
<tr>
<td>gamma</td>
<td>5.42</td>
<td>6.13</td>
<td>6.27</td>
<td>68.64</td>
<td>2.55</td>
<td>1.52</td>
<td>5.81</td>
<td>85.89</td>
</tr>
</tbody>
</table>

Table 3.8: Distribution properties of bid-ask spreads for different $\Delta$ distributions
Maslov model. Moreover, the power law $\Delta$ distribution in combination with the $M^*$ model produces a behaviour that is the closest approximation to commonly observed stock market behaviour.

### 3.5 The $M^*$ Base Model

The $M^*$ model has been shown to generate realistic bid, ask, and last traded price behaviour, due to the fact that the last traded price can lie outside the spread. However, the Maslov model fails to produce this behaviour. If zero $\Delta$ values are used, submitting marketable limit orders is possible in the $M^*$ model. The introduction of a $ttl$ property can reduce the effect of generating the cone-shaped patterns in the Maslov model. However, even with no cancellations, the $M^*$ model does not show the magnitude of cone-shaped patterns observed with the original Maslov model. The $M^*$ model produces the expected variabilities when simulated with different $\Delta$ distributions. However, the Maslov model fails to characterise these different market conditions due to the nature of its pricing mechanism. As a result, the $M^*$ model is more suitable in simplifying different market states. The power law $\Delta$ distribution in the $M^*$ model showed the highest Hurst exponent value. In addition, the power law shape is considered the most common $\Delta$ distribution often observed with real stock data (Zovko and Farmer, 2002).

Based on these properties, the $M^*$ model with power law $\Delta$ distribution (mean 2.5 and standard deviation 2) and no order cancellations, will be used as the base model in building the market manipulation framework. A starting price and the distribution of $\Delta$ provide an arbitrary scale to the model. Moreover, when computing market attributes, in order to avoid microstructure noise, the resulting values are averaged over multiple runs of the model.

### 3.6 Summary

Maslov (2000) simplifies the concept of a limit order book by constructing a limit order market model manipulated by an infinite pool of random (liquidity) traders.

In this chapter, the Maslov (2000) limit order market model was extended to be used as the base model in building the stock manipulation framework. It is shown that the extended Maslov model behaves more realistically than the original Maslov model. The properties of the Maslov and the extended Maslov model (i.e., $M^*$) were
discussed. Based on these experiments, the base model in building the manipulation framework was presented.

In the next chapter, heterogeneous trading actions are considered in the $M^*$ model.
Chapter 4

Heterogeneous Traders and the $M^*$ Model

4.1 Overview

This chapter analyses heterogeneous trading in the $M^*$ model. A simple and effective method of characterising heterogeneous trading is considered. The $M^*$ (modified Maslov) model is considered as a null stock market model without any exogenous processes. Selected trading strategies (normal and abnormal) used by the various types of market participants are simplified as heterogeneous trader types to the $M^*$ model. This is also an approach of characterising stylised traders in stock markets. These heterogeneous traders are introduced to the $M^*$ trader pool and their impact on the stylised features of the $M^*$ model is analysed.

In the next chapter, the profitability of these heterogeneous traders is analysed and the behaviour of heterogeneous traders is used to model profitable manipulation scenarios.

Some parts of this chapter are extensions of Withanawasam, Whigham, Crack, and Premachandra (2011) and Withanawasam, Whigham, and Crack (2012).

4.2 Market Participants

People trade for many reasons, including to invest, to borrow, to exchange, to distribute risks, to speculate, or to deal (Harris, 2002). If transaction costs are not considered, trading is a zero sum game (i.e., total gains of the winners is equal to the total loss of the losers). Intermediaries, however, who are not themselves traders extract transaction
costs. Traders win or lose based on the information they possess, motivations they have, and the strategies they follow.

Market participants are categorised in terms of the information that they utilise in making a trading decision. Common trader categories are liquidity traders (uninformed), informed traders, technical traders (information seekers or chartists), and manipulators (Bagehot, 1971; Glosten and Milgrom, 1985; Kyle, 1985; Allen and Gale, 1992; Allen and Gorton, 1992; Aggarwal and Wu, 2006). Liquidity trader actions are exogenous to the market conditions. Informed traders have private information and they utilise that information to take advantage of others. Technical traders generate information using past trading data and are influenced by their perception of informed trading. Manipulators generate false information in order to mislead other market participants.

Based on motivations for trading, market participants can be alternatively classified into three main types: utilitarian traders, profit motivated traders, and futile traders (Harris, 2002). Utilitarian traders trade because they expect to obtain some benefits other than trading profits. Borrowers, asset exchangers, hedgers, bluffers, and gamblers are utilitarian traders. Profit motivated traders trade with the sole expectation of profits from their actions. Speculators and dealers are profit motivated traders. Futile traders believe that they are profit motivated traders. However, they have no information advantage nor capability to make profits. Utilitarian and futile traders lose on average to the profit motivated traders. Information oriented trader categories such as informed traders, technical traders, and manipulators are profit motivated traders. However, technical traders may become futile traders if manipulators are present. Liquidity traders are utilitarian traders.

In empirical literature, there are two types of traders: fundamental traders and chartists (Beja and Goldman, 1980; Day and Huang, 1990; Hommes, 2006; Zeeman, 2007). Fundamental traders use fundamental values of stocks (i.e., financial statements and forecasts of them) to take their trading decisions. These traders push the price to its actual or true value. This is because these type of traders buy under valued stocks and sell over valued stocks. As a result of these buy/sell actions, the stock price can be pushed up/down, respectively towards the true value. In this thesis, the term “technical traders” is used to refer to chartists (i.e., chartists use various data analysis methods to generate their trading signals using past trends (i.e., typically in prices and volumes)).
4.3 Modelling Heterogeneous Traders

Many empirical studies model heterogeneous traders in stock markets (Palmer *et al.*, 1994; Arthur, Holland, LeBaron, Palmer, and Tayler, 1996; Epstein, 1999; Lux and Marchesi, 1999, 2000; Farmer, 2002; Ghoulmie *et al.*, 2005; Hommes, 2006). In most of these empirical studies, agent-based simulations have been used as computational platforms for performing controlled experiments in a financial market setting. Agent-based research has been able to produce stylised results in analysing stock markets. However, it is often difficult to extract quantitative inferences due to the large statistical fluctuations within the simulations (Lye *et al.*, 2012). Moreover, it is difficult to distinguish the behaviour introduced by these agents from the behaviour generated by the market micro-structure.

Therefore agent-based interactions are not considered in our simulations. As such, a simple and effective method of characterising heterogeneous trading in a limit order market will be introduced by extending trader types in the $M^*$ model. These traders characterise the universal properties of heterogeneous trading actions and hence can be considered stylised trader types. Table 4.1 gives a summary of trader types that will be considered. These stylised traders are used to characterise stylised manipulators in the next chapter.

4.4 Implications of Heterogeneous Trading in the $M^*$ Model

The original $M^*$ (liquidity) traders are considered as utilitarian (liquidity) traders because their actions are exogenous to the market (i.e., random). Normal/abnormal or repeating/not repeating strategies performed by various types of market participants are considered. These trader actions are simplified as external processes (i.e., stylised traders) to the $M^*$ model. In order to analyse the effects of these actions separately, these processes are characterised as stylised heterogeneous trader types in the $M^*$ model. Note, however, that in real stock markets traders may use multiple trading strategies. These stylised trader types fall into either profit motivated or futile trader categories. Via a heterogeneous trader type, a notion of information and information asymmetry is introduced to the $M^*$ model. How manipulators can exploit these asymmetries to profit will be presented in the next chapter.

These traders are introduced to the pool of liquidity traders in the $M^*$ model. Each
<table>
<thead>
<tr>
<th>Heterogeneous trader</th>
<th>Category</th>
<th>Market impact</th>
</tr>
</thead>
<tbody>
<tr>
<td>Liquidity trader</td>
<td>Utilitarian trader.</td>
<td>Supply liquidity to the market. Adds noise to the prices and makes prices more random.</td>
</tr>
<tr>
<td>Technical trader</td>
<td>Profit motivated trader.</td>
<td>Adds persistence/momentum to the prices. Decreases the roughness of the price signal. Makes prices more informative. Increases the predictability of prices. Makes the market more vulnerable to manipulation. Information seekers. Introduces the notion of information and information asymmetry to the market.</td>
</tr>
<tr>
<td>Buyer</td>
<td>Profit motivated trader.</td>
<td>Pushes the price up. Adds persistence to the prices. A riskier strategy of inflating the price. This strategy is a part of the pump and dump manipulation strategy. Can be a price corner.</td>
</tr>
<tr>
<td>Seller</td>
<td>Profit motivated trader.</td>
<td>Pushes the price down. Adds persistence to the prices. A riskier strategy of deflating the price. This strategy is a part of the pump and dump manipulation strategy.</td>
</tr>
<tr>
<td>Impatient trader</td>
<td>Manipulator.</td>
<td>Submits more market orders. Increases the bid-ask spread. Produces illiquid markets.</td>
</tr>
<tr>
<td>Order cancelling trader</td>
<td>Manipulator.</td>
<td>Adds persistence to the prices. Decreases the roughness of the price signal. Reduces the long memory of prices.</td>
</tr>
<tr>
<td>Pattern trader</td>
<td>Manipulator.</td>
<td>Adds a regularity to the market attributes.</td>
</tr>
<tr>
<td>Cyclic trader</td>
<td>Profit motivated trader.</td>
<td>Used to simulate circular trader interactions in stock markets. This is considered as a pattern. Can push the price up or down. Do not require order accumulation or shorting in order to push the price up or down. Not an effective method as buying to push the price due to the higher standard deviations in net changes. Less riskier because this does not involve gaining or losing position. Can add a regularity to the market attributes.</td>
</tr>
<tr>
<td>Informed trader</td>
<td>Profit motivated trader.</td>
<td>Can see the market behaviour ahead of other market participants. Prefer to trade without conveying information to the market.</td>
</tr>
</tbody>
</table>

Table 4.1: Summary of the behaviour of heterogeneous traders

trader type in this pool is assigned a probability of being selected to interact with the limit order book. This probability represents the chance of the corresponding trader type (i.e., heterogeneous trading) appearing in the market.

The modified $M^*$ model mechanism is explained in Algorithm 3. Unlike in the original $M^*$ simulation, the trader pool now consists of one or more trader types and while trading, these traders are selected to interact with the limit order book based on their respective pool selection probabilities. Trader types in the pool are represented by a generic definition $Trader(Strategy(q_b, q_{lo}), t_E, t_L, t_{ttl})$, where $q_b$ is the probability.
of buying, \( q_{lo} \) is the probability of submitting a limit order, \( t_E \) and \( t_L \) are entering and leaving times of a trader respectively, and \( t_{ttl} \) specifies the maximum lifetime of a limit order (i.e., \( ttl \)). Algorithm 4 defines the method in which a trader interacts with the limit order book. The \( \text{Strategy}(q_b, q_{lo}) \) function is a default input parameter to the trader definition and defines how the \( M^* \) type traders (i.e., liquidity traders) behave in the market (Algorithm 5). The definition and parameters of this \( \text{Strategy} \) function can be different depending on the trader type. For example, a trader who performs a repeating pattern such as a market sell followed by a market buy has a trading strategy \( \text{PatternStrategy}([\text{market buy, market sell}]) \). This \( \text{PatternStrategy} \) function is explained in Algorithm 6.

Consider the \( M^* \) model initialised with starting last traded price \( \text{price}(0) = 10000 \) and run for 11000 time steps. A typical \( M^* \) type trader (liquidity) is defined with \( \text{Trader}(\text{Strategy}(0.5, 0.5), 1000, 11000, 10000) \) (here \( t_{ttl} = 10000 \) means no order cancellations are done by these traders). Simulations are carried out by introducing new trader types to the \( M^* \) trader pool and allowing them to interact with the original \( M^* \) (liquidity) traders. The \( \Delta \) values of all these traders are drawn from a power law distribution with mean 1.7 and standard deviation 0.8 (i.e., \( \Delta \) takes discrete values between 1 and 4 having the power law exponent 1.5). All runs commence with 1000 steps.
to seed the limit order book as per Maslov (2000). As a result, the data are recorded from $\text{price}(1000) = p(1)$ onwards. Experimental results were combined and averaged over 100 simulation runs. By varying the trader selection probabilities, the impact of these external processes on the original market behaviour is analysed. T-tests are used to assess when these processes can significantly affect the behaviour of the $M^*$ model (these T-test results (i.e., p-values) are given in Appendix D).

The models for heterogeneous trading actions are now presented.

### 4.4.1 Technical traders (Chartists)

$M^*$ traders are random uninformed traders (i.e., liquidity or utilitarian traders). When making decisions, they are not influenced by actions of other traders or the state of the market. A real market includes, however, profit motivated technical traders. These technical traders generate market information and use that information when making trading decisions. As a result, technical traders try to predict price changes or price direction from technical data, including historical prices and volumes, current prices and volumes, and other trader actions (Beja and Goldman, 1980; Day and Huang, 1990; Zeeman, 2007). Chartist is another name for this trader category. Technical traders differ by the type of information that they try to discover (Harris, 2002). Information-oriented technical traders can be informed and they generate trading signals by analysing whether the market price is different from the perceived fundamental value. Sentiment-oriented technical traders try to identify the behaviour of other traders and use that information in generating inferences about market direction. Positively correlated/persistent price behaviour often observed in real stock prices (i.e., Hurst exponent greater than 0.5) is a consequence of these trader reactions to market information (Alfarano and Lux, 2003; Alvarez-Ramirez et al., 2008). Technical trading may also contribute to the “diagonal effect” of observing order actions in stock markets (Biasi et al., 1995; Majois, 2010).

Technical trading is now introduced as a new stylised trader type in the $M^*$ model. This technical trader predicts the future price behaviour using information in the actions of other traders (i.e., sentiment-oriented technical traders). Using this trader type, technical trading is introduced to the $M^*$ model as an external process. These traders also introduce a notion of information to the $M^*$ model.

Technical traders are modelled using a Bayesian learning framework to generate information from past trading. Using this framework, each technical trader models the probability of future price going up at time $t$ as a common $\pi_t$ (starting $\pi_t$ is
Input : $q_b$, $q_{lo}$

Output: Trader interaction

/* Buy or sell? */

if Rnd(0,1) ≤ $q_b$ then
  /* Buy behaviour */
  if Sell side is Empty or Rnd(0,1) ≤ $q_{lo}$ then
    /* Insert limit order to buy */
    Limit order price = price(t) - $\Delta$;
    InsertLOBuy(Limit order price);
  end
  else
    /* Buy at lowest sell price */
    price(t) = Best ask price;
    RemoveAndUpdateBestAsk();
  end
end

else
  /* Sell behaviour */
  if Buy side is Empty or Rnd(0,1) ≤ $q_{lo}$ then
    /* Insert limit order to sell */
    Limit order price = price(t) + $\Delta$;
    InsertLOSell(Limit order price);
  end
  else
    /* Sell at highest buy price */
    price(t) = Best bid price;
    RemoveAndUpdateBestBid();
  end
end

Algorithm 5: Trading strategy of a $M^*$ (i.e., liquidity) trader (i.e., $Strategy(q_b, q_{lo})$)
Input : Trading-Pattern TP
Output: Trader interaction

/* Buy or sell? */
while TP.End do
  Trading-Action TA in TP;
  if TA is Limit Buy then
    /* Insert limit order to buy */
    Limit order price = price(t) - Δ;
    InsertLOBuy(Limit order price);
  end
  if TA is Limit Sell then
    /* Insert limit order to sell */
    Limit order price = price(t) + Δ;
    InsertLOSell(Limit order price);
  end
  if TA is Market Buy then
    /* Buy at lowest sell price */
    price(t) = Best ask price;
    RemoveAndUpdateBestAsk();
  end
  if TA is Market Sell then
    /* Sell at highest buy price */
    price(t) = Best bid price;
    RemoveAndUpdateBestBid();
  end
end

Algorithm 6: Trading strategy of a pattern trader (i.e., PatternStrategy(Trading-Pattern TP))
The observed trading actions (i.e., orders and trades) are used when revising $\pi_t$. In other words, the posterior probability of $\pi_t$ given the observed trading action at time $t$ becomes the probability of future price going up at time $t+1$. A Bayesian probability tree based on the traders’ beliefs (Figure 4.1) is used to determine the posterior probabilities.

When forming this Bayesian belief model, a technical trader takes the following conditions into consideration: whether the trader involved in the observed order or trade is likely to be an informed trader or a liquidity trader, whether this trader is acting as a buyer or a seller, and whether he is placing a limit order or a market order. All these conditions are characterised by conditional probabilities as shown in Figure 4.1. Note that there are no informed traders in these simulations. However, technical traders believe that there may be informed traders in the market (and that therefore certain trades carry information) and adjust their trading patterns accordingly to follow these perceived informed traders.

Based on this Bayesian learning process, the prior probability of future price going up at any time $t$ can be stated as:

**Figure 4.1: Bayesian diagram to compute posterior probabilities**
\[
\pi_t = \frac{\pi_0(A + E)^w(B + F)^x(C + G)^y(D + H)^z}{\pi_0(A + E)^w(B + F)^x(C + G)^y(D + H)^z + (1 - \pi_0)(I + M)^w(J + N)^x(K + O)^y(L + P)^z}
\] (4.1)

where \(A, B, C, D, E, F, G, H, I, J, K, L, M, N, O,\) and \(P\) are probability multiples of each branch in the Bayesian probability tree given in Figure 4.1, and \(w, x, y,\) and \(z\) denote the number of observed limit buy, market buy, limit sell, and market sell trader actions respectively.

When using the generated information, the technical trader considers the probability of future price going up as his probability of buying (i.e., \(q_T^b = \pi_t\)) (i.e., the technical trader assumes that the signal of future price going up is favourable for buying). As a result, buy and sell actions in the market influence the \(q_T^b\) to go up and go down, respectively. This model allows technical traders to carry forward information in past trading in order to generate information when making their decisions to buy or sell.

Using the general notation, a technical trader is defined as \(\text{Trader}(\text{TechnicalStrategy}(\pi_0, q_{lo})), 1000, 11000, 10000)\). Algorithm 7 defines the \(\text{TechnicalStrategy}(\pi_0, q_{lo})\) function, where \(\pi_0\) is the starting prior probability of a technical trader.

Technical traders (i.e., \(\text{Trader}(\text{TechnicalStrategy}(0.5, 0.5), 1000, 11000, 10000)\)) are introduced to the trader pool and are selected to interact with the order book with a probability \(p_{ST}\). The selection probability for original \(M^*\) (liquidity) traders (i.e., \(\text{Trader}(\text{Strategy}(0.5, 0.5), 1000, 11000, 10000)\)) is \(p_{LT}\), where \(p_{ST} + p_{LT} = 1\). In their Bayesian belief model, technical traders assume a \(\lambda\) probability of informed traders and \(\mu_2\) probability of liquidity buying. Technical traders’ initial probability of future price going up is \(\pi_0\). It is also assumed that when the price is to go up, informed traders are definitely buying (\(\mu_1 = 1\)), and they definitely sell (\(\mu_3 = 0\)) when the price is to go down. The model also assumes that the probabilities of submitting limit and market orders are equal (\(\theta_1 = \theta_2 = \theta_3 = \theta_4 = \theta_5 = \theta_6 = \theta_7 = \theta_8 = 0.5\)). By changing the technical trader pool selection probability \(p_{ST}\), the impact of these technical traders on the stylised features of the \(M^*\) model are analysed.

Figure 4.2 illustrates the last traded price behaviour for a single run with pool selection probabilities for technical traders of 0, 0.2, 0.5, and 0.8. The inset in this figure illustrates the price net change box plots with technical trader selection probability \(p_{ST}\). The behaviour of net changes indicates that technical trading increases the price volatility.

The Hurst exponent value increases when the technical trader selection probability \(p_{ST}\) increases (Figure 4.3). Increasing Hurst exponent behaviour indicates that the
Input : $\pi_t$, $q_{lo}$
Output: Trader interaction

/* Take $\pi_t$ as the buying probability */
1 $q^T_b = \pi_t$;
/* Buy or sell? */
2 if $\text{Rnd}(0,1) \leq q^T_b$ then
   /* Buy behaviour */
   3 if $\text{Sell side is Empty or Rnd}(0,1) \leq q_{lo}$ then
      /* Insert limit order to buy */
      4 $\text{Limit order price} = \text{price}(t) - \Delta$;
      5 $\text{InsertLOBuy}(\text{Limit order price})$;
   end
   else /* Buy at lowest sell price */
      $\text{price}(t) = \text{Best ask price}$;
      7 $\text{RemoveAndUpdateBestAsk}()$;
   end
3 else /* Sell behaviour */
   8 if $\text{Buy side is Empty or Rnd}(0,1) \leq q_{lo}$ then
      /* Insert limit order to sell */
      9 $\text{Limit order price} = \text{price}(t) + \Delta$;
      10 $\text{InsertLOSell}(\text{Limit order price})$;
   end
   else /* Sell at highest buy price */
      $\text{price}(t) = \text{Best bid price}$;
      13 $\text{RemoveAndUpdateBestBid}()$;
   end
2 end

Algorithm 7: Trading strategy of a technical trader (i.e.,
$\text{TechnicalStrategy}(\pi_t, q_{lo})$)
roughness of last traded price signal decreases with technical traders (Gneiting and Schlather, 2004; Mandelbrot and Hudson, 2006). The standard deviation or error of estimating the Hurst exponent also increases with $p_{ST}$. The Hurst exponent is significantly higher (i.e., $p$-value $\leq 0.05$) than the original $M^*$ estimated value when $p_{ST} \geq 0.1$. The maximum Hurst exponent value ($\approx 0.7$) is observed when only technical traders are selected for trading (i.e., $p_{ST} = 1$). The Hurst exponent $> 0.5$ behaviour implies that technical trading adds persistent and long memory to the $M^*$ prices. In other words, with technical traders, it is more likely to observe an order in the same side after observing an order in the order book (i.e., order side and hence the price direction is positively autocorrelated). This can result in a less rough price signal. Moreover, due to the positive correlation of orders, predictability of price returns also increases and hence the vulnerability to manipulation can be increased (Aggarwal and Wu, 2006) (Refer to Appendix C for a graphical explanation on the vulnerability to manipulation using the Hurst exponent).

Figure 4.2: $M^*$ prices with technical traders (Note that the data were plotted with sampling only at every 50th point for clarity). The inset shows the net change box plots with technical traders ($\boxdot$ indicates the mean values)
Persistent behaviour of the price signal can also be partly explained with the behaviour of price net changes \( (p(10000) - p(1)) \) (see the inset of Figure 4.2). This is because persistence introduced by these technical traders causes the standard deviation of price net changes (i.e., price volatility) to go up. However, the mean net change value remains constant, indicating the unbiased nature of the \( M^* \) simulations even with technical traders.

Autocorrelation behaviour of price increments with \( p_{ST} \) (i.e., technical trader selection probability) is shown in Figure 4.4. Negative autocorrelation of price increments up to lag 2 decreases in magnitude with technical trading. With \( p_{ST} \), the behaviour of first order autocorrelation of price increments is shown in Figure 4.5. Moreover, first order autocorrelation of price increments becomes significantly lower (i.e., p-value ≤ 0.05) when \( p_{ST} \geq 0.3 \). This autocorrelation behaviour also indicates an increase of positive correlation of price increments with technical trading. In general, autocorrelation of price increments are negative due to the order book mechanism of price fluctuating between best bid and ask prices (i.e., bid-ask bounce). The strength of this negative autocorrelation decreases due to the positive correlation of same side orders introduced by the technical traders. However, the very small change in autocorrelation with the introduction of technical traders indicates that the negative autocorrelation of price increments occurs mainly as a result of the market micro-structure effect.
The power law decay exponent of the autocorrelation function of absolute price increments shows a decline with $p_{ST}$ (Figure 4.6). This indicates reduced volatility clustering with the presence of technical traders. Volatility clustering occurs when the price jumps between best bid and ask prices are positively correlated (i.e., larger price jumps are followed by large price jumps and small price jumps are followed by small price jumps). Technical trading adds a persistence to the order flow, causing fewer price jumps between the bid-ask spread and hence a lower volatility clustering effect. The autocorrelation function decay exponent is significantly lower (i.e., $p$-value $\leq 0.05$) when $p_{ST} \geq 0.3$. Moreover, with technical traders, this power law decay exponent value changes towards to 0.3, which is the value often estimated with real stock data (Maslov, 2000).

Distribution properties (mean, standard deviation, skewness, and kurtosis) of price returns and bid-ask spreads with technical trading are shown in Figures 4.7 and 4.8. The standard deviation of price returns shows a decay with $p_{ST}$. This standard deviation decrease is due to the decrease of large price returns caused by the more persistent prices and small price increments due to same side order matching with technical trading. However, other properties such as the mean, skewness and kurtosis of the returns distribution do not show any increasing or decreasing pattern with technical trading.
The mean and standard deviation of the bid-ask spreads distribution decay with $p_{ST}$. This mean and standard deviation decrease (i.e., narrower and more stable bid-ask spreads) is a consequence of positive correlation in same side orders causing a reduced bid-ask spread widening effect (i.e., market orders in both sides can increase the bid-ask spread widening effect). Behaviour of the bid-ask spreads distribution implies that technical trading adds informativeness to the prices (the bid-ask spread represents uncertainty of the market participants (Glosten and Milgrom, 1985; Glosten, 1987)), causing narrow bid-ask spreads. Narrow bid-ask spreads can also cause the standard deviation of price returns to go down.

Technical traders use trader beliefs and market information for trading. As a result, they introduce the notion of information or intelligence to the zero-intelligence $M^*$ model. This allows information asymmetry to be simulated. The notion of information introduced by the technical traders can be used to produce skewed price return distributions in stock markets. These skewed price return distributions occur due to asymmetric trader reactions to positive and negative information (Diamond and Verrecchia, 1987; Skinner, 1994; Rydberg, 2000; Soffer et al., 2000; Hutton et al., 2003;
Figure 4.7: Distribution properties of price returns in the $M^*$ model with technical traders (averaged over 100 simulation runs)

Figure 4.8: Distribution properties of bid-ask spreads in the $M^*$ model with technical traders (averaged over 100 simulation runs)

Anilowski et al., 2007; Kothari et al., 2008) (refer to Appendix B for more information on information asymmetries in stock markets). Technical trading is used to simulate an asymmetry in trader reactions. When technical traders believe there is information asymmetry (i.e., buyers are more informed than sellers and there can be more liquidity sellers than buyers, $\mu_2 < 0.5$), they respond more aggressively to buy transactions than sell transactions causing positively skewed price return distributions. Moreover, in crisis situations, traders can react more aggressively to negative information than positive information causing negatively skewed price return distributions (Rydberg, 2000). These scenarios can be simulated using technical traders. Figure 4.9 illustrates how the skewness of price returns distribution varies from positive to negative with information asymmetry introduced with $\mu_2$.

In the next chapter, technical traders are used to simulate information seekers in manipulation simulations. These technical traders are only influenced by the buy and sell actions (i.e., pushing the price up or down) of the other market participants. In addition, in real markets, manipulators may use strategies such as altering the bid-ask spreads. Modelling of a technical trader who is influenced by these other manipulator strategies is not considered in this thesis.

$\mu_2$ in the technical trader belief model represents the liquidity buying percentage assumed by the technical traders.
4.4.2 Buyers

Traders can consecutively buy stocks in order to push the price up in stock markets. These buyers are profit motivated traders. More specifically, they can be informed traders or manipulators. Informed traders and/or fundamental traders buy if they know the stock is under-valued. Consecutive buying can also be a part of manipulation attempt such as “pump and dump” and “price corner”.

A new stylised trader who buys with a higher probability ($q_b = 0.6$) is introduced (i.e., Trader(Strategy($q_b$, 0.5), 1000, 11000, 10000), where $q_b = 0.6$). This trader is selected for trading with a probability $p_{ST}$. All the other traders in this simulation are original $M^*$ (liquidity) traders (i.e., Trader(Strategy(0.5, 0.5), 1000, 11000, 10000)) and they are selected for trading with a probability $p_{LT}$ ($p_{ST} + p_{LT} = 1$). By varying $p_{ST}$, impact of these buyers to the behaviour of the $M^*$ model is analysed. This approach is different from increasing the buying probability of all the liquidity traders in Chapter 3. This is because this stylised trader (i.e., buyer) introduces the effect of buying as an external process to the $M^*$ model and allows the impact of buying as a proportion of liquidity traders to be analysed.
When $p_{ST}$ (i.e., selection probability of buyers) is increased, the price graph shows a clear upward trend (Figure 4.10). This is because, with buyers, the market buy order percentage goes up and as a result the ask side gets matched more often than the bid side. This causes an upward trend in the last traded price, as would be expected when demand exceeds supply. The price net change behaviour shown in the inset of Figure 4.10 confirms this upward trend. In price net change, the mean shows a clear upward trend while the standard deviation is unchanged. This means the price volatility is not affected by the buyers. The mean price net change becomes significantly higher (i.e., $p$-value $\leq 0.05$) when $p_{ST} \geq 0.1$. This indicates that under these experimental circumstances, buyers must be trading at least 10% of the time in order to introduce an actual impact on price behaviour.

The Hurst exponent also shows a clear increase with $p_{ST}$ (Figure 4.11). These Hurst exponent values are significantly higher (i.e., $p$-value $\leq 0.05$) when $p_{ST} \geq 0.1$. When there are more buyers, the persistent behaviour of the price signal goes up (i.e., the roughness goes down) causing the Hurst exponent to go up. Unlike with technical trading, this persistent price behaviour occurs due to consecutive buy trades which result in positively correlated buy orders. However, it is observed that the Hurst exponent increase due to technical traders is higher than the Hurst exponent increase due to buyers.

Autocorrelation behaviour of price increments with $p_{ST}$ is shown in Figure 4.12. Negative first order autocorrelation of price increments decreases in magnitude with buyers (Figure 4.13). This autocorrelation decrease proves the positive correlation introduced by buying (i.e., same side orders) to the price increments. The first order autocorrelation of these price increments are significantly different (i.e., $p$-value $\leq 0.05$) when $p_{ST} \geq 0.1$.

The power law decay exponent of the autocorrelation function of absolute price increments shows a decline with $p_{ST}$ (Figure 4.14). This power law decay exponent behaviour indicates a reduced volatility clustering effect. These decay exponents are significantly lower (i.e., $p$-value $\leq 0.05$) when $p_{ST} \geq 0.2$. Consecutive buying adds a persistence to the order flow, causing fewer price jumps between the bid-ask spread and hence a lower volatility clustering effect.

Distribution properties (mean, standard deviation, skewness, and kurtosis) of price returns and bid-ask spreads with buyers are shown in Figures 4.15 and 4.16. The mean and skewness of the price returns distribution increase while the standard deviation and kurtosis decrease with $p_{ST}$. The mean increases due to the higher percentage
Figure 4.10: Price graphs of the $M^*$ model with buyers (Note that the data were plotted with sampling only at every 50th point for clarity). The inset shows the net change box plots with buyers of positive returns generated by consecutive buying. The skewness of price returns is always positive with buyers because the percentage of positive returns is higher than the percentage of negative returns. The decrease in the standard deviation of returns is a consequence of smaller price jumps (i.e., same side order matching) with the increasing percentage of buying. The mean, standard deviation, skewness, and kurtosis of bid-ask spread distributions show a decay with $p_{ST}$. This bid-ask spreads distribution behaviour indicates that the bid-ask spread narrows with buyers. This can be attributed to the limit order pricing mechanism used in the $M^*$ model (i.e., buyers use the best ask as the reference price to submit their limit buy orders).

The behaviour of these buyers is used to characterise manipulation scenarios such as “pump and dump” and cornering in the next chapter.
4.4.3 Sellers

Consecutive sellers are profit motivated traders (i.e., informed traders or manipulators). Informed traders and/or fundamental traders sell if they know that the stock is over-
Figure 4.13: First order autocorrelation box plots of price increments in the $M^*$ model with buyers (combined over 100 simulation runs)

Figure 4.14: Autocorrelation decay exponent box plots of absolute price increments in the $M^*$ model with buyers (combined over 100 simulation runs)

Figure 4.15: Distribution properties of price returns in the $M^*$ model with buyers (averaged over 100 simulation runs)

Figure 4.16: Distribution properties of bid-ask spreads in the $M^*$ model with buyers (averaged over 100 simulation runs)
valued. In order to complete their strategy, “pump and dump” manipulators may require repeated selling of stocks.

A trader who sells with a probability $> 0.5$ (i.e., $q_b = 0.4$) is introduced (i.e., $\text{Trader(Strategy}(0.4, 0.5), 1000, 11000, 10000)$, where $q_b = 0.4$). This trader is selected for trading with a probability $p_{ST}$. This approach is different from increasing the selling probability of all the liquidity traders in Chapter 3. This is because, this stylised trader (i.e., seller) introduces the effect of selling as an external process to the $M^*$ model and allows the impact of selling related to the background of liquidity traders.

When $p_{ST}$ is increased, the downward trend of the price graph increases (Figure 4.17). This is because, when a trader sells more often, the market sell order percentage goes up and as a result the bid side gets matched more frequently than the ask side, causing a downward trend in the last traded price. Price net change box plots shown in the inset of Figure 4.17 confirm this downward trend, because the mean net change decays with $p_{ST}$. However, the standard deviation of net changes does not change with $p_{ST}$ (i.e., price volatility is not affected by these sellers). This constant standard deviation of net changes confirms the unbiased nature of the simulation with sellers. Price net changes become significantly lower (i.e., $p$-value $\leq 0.05$) when $p_{ST} \geq 0.1$.

The Hurst exponent also increases with $p_{ST}$ (Figure 4.18). This is similar to the Hurst exponent increase with buyers. Significantly higher (i.e., $p$-value $\leq 0.05$) Hurst exponents are observed when $p_{ST} \geq 0.2$. This Hurst exponent increase is due to the same side matching caused by the consecutive selling and hence adding a positive correlation or persistence to the prices. The behaviour of the standard deviation of price net changes also partly confirms this persistent price behaviour.

Autocorrelation behaviour of price increments with $p_{ST}$ is shown in Figure 4.19. The negative first order autocorrelation of price increments decreases in magnitude with $p_{ST}$ (Figure 4.20). These first order autocorrelations are significantly lower (i.e., $p$-value $\leq 0.05$) when $p_{ST} \geq 0.2$. This autocorrelation decrease proves the positive correlation introduced by selling (i.e., same side orders) to the price increments. The autocorrelation behaviour of price increments with sellers is also similar to the autocorrelation behaviour of price increments with buyers.

The power law decay exponent of the autocorrelation function of absolute price increments shows an irregular decay with $p_{ST}$ (Figure 4.21). Consecutive selling adds a persistence to the order flow, causing fewer price jumps between the bid-ask spread and hence causes a lower volatility clustering effect. The behaviour of this power law
Figure 4.17: Price graphs of the $M^*$ model with sellers (Note that the data were plotted with sampling only at every 50$^{th}$ point for clarity). The inset shows the net change box plots with sellers.

decay exponent is also consistent with the autocorrelation behaviour of price increments and indicates a decrease in correlation in price increments or volatility clustering. The power law decay exponent is significantly lower (i.e., p-value $\leq 0.05$) when $p_{ST} \geq 0.3$.

Distribution properties (mean, standard deviation, skewness, and kurtosis) of price returns and bid-ask spreads with sellers are shown in Figures 4.22 and 4.23. The mean, standard deviation, skewness, and kurtosis of the price returns distribution decrease with sellers. The mean values of the returns distribution is decreased (i.e., negatively increased) due to this higher percentage of negative returns generated by the sellers. Returns skewness is always negative with sellers. This is also because, with sellers, the percentage of negative returns are higher than the positive returns. The standard deviation of returns is decreased due to the smaller price jumps caused by the higher percentage of same side trades. The standard deviation and kurtosis of returns with sellers show a similar behaviour to the standard deviation and kurtosis behaviour with buyers. However, mean and skewness show opposite behaviour between buyers and sellers.
Figure 4.18: Hurst exponent box plots of the $M^*$ model with sellers (combined over 100 simulation runs)

Figure 4.19: Mean autocorrelation values of price increments for first 14 lags in the $M^*$ model with sellers (averaged over 100 simulation runs)

The mean, standard deviation, skewness, and kurtosis of bid-ask spread distributions also show a decay with sellers. This is similar to the spreads behaviour with
buyers. This bid-ask spreads distribution behaviour indicates that the bid-ask spread narrows with sellers. This can be attributed to the limit order pricing mechanism used in the $M^*$ model (i.e., sellers use the best bid as the reference price to submit their limit sell orders).

Here, buyers and sellers, positively and negatively increase the mean of the returns distribution, respectively while both buyers and sellers decrease the standard deviation of returns. Bid-ask spreads behaviour with sellers is also similar to the bid-ask spreads behaviour with buyers (i.e., both buyers and sellers narrow the bid-ask spread in the $M^*$ model).

The behaviour of these sellers is also used to characterise manipulation scenarios such as “pump and dump” in the next chapter.

### 4.4.4 Patient and impatient traders

There can be patient or impatient traders among market participants (Glosten, 1994; Maslov, 2000). The limit order book allows patient traders to submit limit orders and wait for their desired price; it may never come. Market orders are submitted to buy or sell at the best ask or best bid, respectively by impatient market participants. As a
result, the patience of a market participant can be characterised using the probability $q_{lo}$ of a market order being submitted. Patient and impatient trading can also be simulated using the limit order price offset $\Delta$ (Maslov, 2000). Refer to Appendix A for more information on the role of patience in determining limit order price offsets ($\Delta$).

In order to analyse the impact of these patient/impatient market participants on the limit order book properties, a trader who submits on average a lower/higher percentage of market orders ($q_{lo} = 0.75/0.25$) is introduced (i.e., $\text{Trader(Strategy}(0.5, q_{lo}), 1000, 11000, 10000)$, where $q_{lo} = 0.75/0.25$). This trader is selected for trading with a probability $p_{ST}$. All the other traders in the pool are original $M^*$ (liquidity) traders (i.e., $\text{Trader(Strategy}(0.5, 0.5), 1000, 11000, 10000)$), and selected for trading with a probability $p_{LT}$ ($p_{ST} + p_{LT} = 1$). By varying the trader selection probability $p_{ST}$, the impact of these patient and impatient traders on the behaviour of the original model is analysed.

This approach is different from increasing the limit or market probability of all the liquidity traders in Chapter 3 because these stylised traders (i.e., patient and impatient) introduce the effect of patient and impatient trading as external processes to the $M^*$ model.
Patient traders

Figure 4.24 illustrates the price behaviour with patient traders ($p_{lo} = 0.75$) in the $M^*$ model. These price graphs indicate that the price volatility is reduced with patient traders. The standard deviation of price net changes decreases confirming the reduced volatility with these patient traders (see the inset of Figure 4.24). Reduced volatility (i.e., low net change) is attributed to a reduced number of trades as a consequence of a higher percentage of limit orders. That is, there is increased depth in the limit order book. The Hurst exponent also decreases with patient traders (Figure 4.25). The Hurst exponent is significantly lower (i.e., $p$-value $\leq 0.05$) than the original $M^*$ estimated value (i.e., $p_{ST} = 0$) when $p_{ST} \geq 0.1$. These results indicate that the persistent behaviour of prices is decreased with patient traders.

![Figure 4.24: Price graphs of the $M^*$ model with patient traders (Note that the data were plotted with sampling only at every 50th point for clarity). The inset shows the net change box plots with patient traders.](image)

Autocorrelation of price increments show some variations with patient traders (Figure 4.26). Here, with patient traders, the first order autocorrelation of price increments shows a decrease in magnitude. However, the other order autocorrelations (from lag 3
Figure 4.25: Hurst exponent box plots of the $M^*$ model with patient traders (combined over 100 simulation runs)

to lag 8) show an increase. Moreover, first order autocorrelation of price increments becomes significantly lower (i.e., p-value $\leq 0.05$) when $p_{ST} \geq 0.1$ (Figure 4.26). Volatility clustering decreases when the value of $p_{ST}$ is increased (Figure 4.27). The autocorrelation function decay exponent is significantly lower (i.e., p-value $\leq 0.05$) when $p_{ST} \geq 0.1$. Volatility clustering is reduced due to there being fewer price fluctuations with patient trading.

Distribution properties (mean, standard deviation, skewness, and kurtosis) of price returns and bid-ask spreads with patient traders are shown in Figures 4.29 and 4.30. The mean, standard deviation, kurtosis, and skewness of the price returns distribution decrease with $p_{ST}$. This is attributed to the low number of returns caused by the reduced number of price fluctuations (i.e., trades). This also confirms that there is reduced price volatility with patient traders. With patient trading, the mean and standard deviation of bid-ask spread distribution also decrease because more limit orders submitted by these patient traders may narrow the bid-ask spread. This also results in higher book depths. With patient trading, narrow bid-ask spreads may also cause low price returns. However, skewness and kurtosis values of bid-ask spread distributions show an increase with patient trading. Moreover, skewness and kurtosis values with patient trading are very high.
Figure 4.26: Mean autocorrelation values of price increments for first 14 lags in the $M^*$ model with patient traders (averaged over 100 simulation runs)

Figure 4.27: First order autocorrelation box plots of price increments in the $M^*$ model with patient traders (combined over 100 simulation runs)

Figure 4.28: Autocorrelation decay exponent box plots of absolute price increments in the $M^*$ model with patient traders (combined over 100 simulation runs)
Figure 4.29: Distribution properties of price returns in the $M^*$ model with patient traders (averaged over 100 simulation runs)

Figure 4.30: Distribution properties of bid-ask spreads in the $M^*$ model with patient traders (averaged over 100 simulation runs)

Impatient traders

Figure 4.31 illustrates the price behaviour with impatient trading (i.e., $p_{lo} = 0.25$) in the $M^*$ model. The standard deviation of price net changes (i.e., volatility) increases with impatient traders due to the increased number of trades (i.e., more market orders) performed by the impatient traders (see the inset of Figure 4.31). However, impatient traders increase both buy and sell market order percentages simultaneously and as a result the mean values of these price net changes are not affected.

The Hurst exponent shows a small increase with impatient traders (Figure 4.32). Moreover, the standard error in estimating the Hurst exponent also increases. The Hurst exponent is significantly higher (i.e., $p$-value $\leq 0.05$) than the original $M^*$ estimated value when $p_{ST} \geq 0.6$. The Hurst exponent increase indicates a persistence increase in $M^*$ prices due to impatient traders.

The autocorrelation of price increments shows small variations with these impatient traders (Figure 4.33). The negative first order autocorrelation shows an increase in magnitude while the other order negative autocorrelations show a decrease or no change in magnitude. Moreover, the first order autocorrelation of price increments becomes significantly higher (i.e., $p$-value $\leq 0.05$) when $p_{ST} \geq 0.5$ (Figure 4.34). The volatility clustering also decreases with impatient traders (Figure 4.35). The autocorrelation
Figure 4.31: Price graphs of the $M^*$ model with impatient traders (Note that the data were plotted with sampling only at every $50^{th}$ point for clarity). The inset shows the net change box plots with impatient traders.

function decay exponent is significantly lower (i.e., p-value ≤ 0.05) when $p_{ST} ≥ 0.1$. This behaviour is also similar to the patient traders (i.e., more or less trades can reduce the volatility clustering effect).

The Hurst exponent and autocorrelation behaviour of price increments with impatient traders show an opposite behaviour to the behaviour with patient traders. Moreover, when there are more impatient traders, the $M^*$ order book often empties and as a result, the number of trades may be comparatively fewer than defined by the parameters of the model. This emptying of the limit order book is a result of too many market orders. Once the limit order book is empty, market orders are converted to limit orders.

Distribution properties (mean, standard deviation, skewness, and kurtosis) of price returns and bid-ask spreads with impatient trading are shown in Figures 4.36 and 4.37. The standard deviation of price returns shows an increase and then a decrease with $p_{ST}$. The mean and standard deviation of bid-ask spread distributions also show an
Figure 4.32: Hurst exponent box plots of the $M^*$ model with impatient traders (combined over 100 simulation runs)

Figure 4.33: Mean autocorrelation values of price increments for first 14 lags in the $M^*$ model with impatient traders (averaged over 100 simulation runs)

increase and then decrease with $p_{ST}$. In addition, the skewness and kurtosis of the bid-ask spreads distribution show a decrease with $p_{ST}$. This is because a higher percentage
of market order traders can remove the top of the book orders at a rapid rate increasing the bid-ask spread. Moreover, when there are more impatient traders, the limit order book may often empty and therefore traders can only submit limit orders. This effect may again reduce the bid-ask spread and hence price returns in the $M^*$ model. Note, however that the limit order book emptying effect does not affect patient traders.

In the next chapter, the behaviour of these patient and impatient traders is used to present manipulation models such as “painting the tape.” These patient and impatient traders are also used to simulate liquid/illiquid stocks in Chapter 7.

4.4.5 Order cancelling traders

Consider a trader behaviour where orders are submitted at the top of the book and cancelled before execution. This strategy is used to show activity in the market and to attract market participants. There is the temporary appearance of additional depth and therefore liquidity. These traders can be bluffers or manipulators. Manipulators who perform strategies such as “marking the close” and “painting the tape” use order cancellations at the end of the day as a part of their strategy (SEC, 2012b). In this
context, the artificial activity generated due to these order cancellations can attract other market participants to push the price up.

In the previous chapter, a maximum life time (“time to live” attribute or \(\text{ttl}\)) for limit orders was introduced, whereby limit orders are removed from the order book immediately after their life time expires. An order cancellation strategy is simulated in the \(M^*\) model by introducing a trader who submits orders with a very small \(\text{ttl}\) value (i.e., \(\text{Trader(Strategy(0.5, 0.5), 1000, 11000, t_{\text{ttl}})}\), where \(t_{\text{ttl}} = 10\)). Note however that some percentage of these limit orders may get executed before expiry. These traders buy and submit market orders with a probability 0.5. They are selected for trading with a probability \(p_{ST}\) and the probability of selecting a \(M^*\) trader (i.e., \(\text{Trader(Strategy(0.5, 0.5), 1000, 11000, 10000)}\)) is \(p_{LT}\).

This approach is different from specifying a common \(\text{ttl}\) value for all the liquidity traders in Chapter 3. This is because these stylised traders (i.e., order cancelling) introduce the effect of order cancelling as an external process to the \(M^*\) model.

When the pool selection probability of these order cancelling traders is increased, behaviours of the market properties such as the Hurst exponent, first order autocorrelation of price increments, and autocorrelation decay of absolute price increments deviate from the original behaviour.
Figure 4.38 shows the price behaviour with $p_{ST}$. It is observed that the price volatility is increased with order cancelling traders. This is confirmed by the standard deviation of price net changes increasing when $p_{ST}$ is increased (see the inset of Figure 4.38). This volatility increase occurs due to fewer old orders remaining in the book. Fewer old orders can cause large price gaps between stale orders in the order book and increase larger price fluctuations due to the trades. Moreover, cancelling limit orders may cause reduced book depths.

The Hurst exponent also increases when the percentage of order cancelling traders is increased (Figure 4.39). The Hurst exponent is significantly higher (i.e., p-value $\leq 0.05$) than the original $M^*$ estimated value when $p_{ST} \geq 0.1$. It is also noted that the increase in the Hurst exponent indicates the increase in persistent of the price signal. The maximum Hurst exponent value observed is around 0.5, indicating that the persistence introduced by the order cancelling traders is lower than that introduced by the technical traders. The Hurst exponent of 0.5 also indicates that when almost all the orders have a very small life time (i.e., 10), the price shows a random walk behaviour. This random walk behaviour is attributed to the frequent zero depth states in the limit order book.

Figure 4.40 presents the autocorrelation of price increments for the first 14 lags. Figure 4.41 shows first order autocorrelation behaviour of price increments. First order autocorrelation of price increments decreases in magnitude with $p_{ST}$ and is significantly lower (i.e., p-value $\leq 0.05$) when $p_{ST} \geq 0.4$. These results indicate an increase of positive correlation in price increments due to order cancelling traders.

Autocorrelation decay of absolute price increments decreases with $p_{ST}$ (Figure 4.42). This indicates that these order cancelling traders can remove the long memory of the prices causing reduced volatility clustering. These decay exponents are significantly lower (i.e., p-value $\leq 0.05$) when $p_{ST} \geq 0.1$.

Distribution properties (mean, standard deviation, skewness, and kurtosis) of price returns and bid-ask spreads with order cancelling traders are shown in Figures 4.43 and 4.44. The standard deviation and kurtosis of price returns distribution first increases and then decreases while the other properties do not show any increasing or decreasing pattern with $p_{ST}$. The mean, standard deviation, skewness, and kurtosis of bid-ask spread distributions first increases and then decreases with $p_{ST}$. The decreasing pattern in bid-ask spreads and returns is observed due to the limit order book emptying effect with frequent limit order removals in the $M^*$ model. The standard deviation of price returns shows a consistent behaviour (i.e., higher bid-ask spreads
cause higher returns and vice versa) with mean and standard deviation behaviour of bid-ask spreads.

The behaviour of these order cancelling traders is used to characterise the “orders without execution” manipulation scenarios in the next chapter.

### 4.4.6 Pattern traders

Some market regularities can occur due to abnormal trading patterns. For example, manipulation strategies such as “painting the tape” and “marking the close” can introduce behaviour regularities to stock market attributes. Market participants such as bluffers and gamblers (Harris, 2002) can also introduce these regularities to the market.

An order patterns is introduced via a stylised trader who performs a pre-defined repeating pattern (i.e., \([\text{market buy, market sell}]\)) in the \(M^*\) model. This pattern trader is denoted as \(\text{Trader(PatternStrategy(\[market buy, market sell\]), 1000, 11000, 10000)}\).
Figure 4.39: Hurst exponent box plots of the $M^*$ model with order cancelling traders (combined over 100 simulation runs)

Figure 4.40: Mean autocorrelation values of price increments for first 14 lags in the $M^*$ model with order cancelling traders (averaged over 100 simulation runs)

This trader is selected for trading with a probability $p_{ST}$. All the other traders in the pool are original $M^*$ (liquidity) traders (i.e., $Trader(Strategy(0.5, 0.5), 1000, 11000,$
Figure 4.41: First order autocorrelation box plots of price increments in the M* model with order cancelling traders (combined over 100 simulation runs).

Figure 4.42: Autocorrelation decay exponent box plots of absolute price increments in the M* model with order cancelling traders (combined over 100 simulation runs).

and they are selected for trading with a probability \( p_{LT} \) \( (p_{ST} + p_{LT} = 1) \). By varying \( p_{ST} \), the impact of this pattern trader to the market properties is analysed.

This pattern trader (i.e., \([\text{market buy, market sell}]\)) does not affect the buy and sell order proportions of the simulation. However, these traders can increase the market order percentage.

Figure 4.45 shows the behaviour of the price signal when the percentage of these pattern traders is increased. The behaviour of price net changes with \( p_{ST} \) is shown in the inset of Figure 4.45. The mean and standard deviation of price net changes increases with pattern trading. The mean increase indicates that performing a repeating market order pattern is not exactly the same as increasing the probability of submitting market orders (i.e., impatient trading). Price net changes become significantly higher (i.e., p-value \( \leq 0.05 \)) when \( p_{ST} \geq 0.2 \). The Hurst exponent shows an increase with \( p_{ST} \) (Figure 4.46). The Hurst exponent is significantly higher (i.e., p-value \( \leq 0.05 \)) than the original M* estimated value when \( p_{ST} \geq 0.2 \). Moreover, the standard deviation or error of estimating these Hurst exponents also significantly increases with \( p_{ST} \). This standard deviation increase is because with more market orders there can also be more
trades and as a result the roughness of the price signal can also be high (Gneiting and Schlather, 2004; Mandelbrot and Hudson, 2006).

Autocorrelation behaviour of price increments with pattern traders is shown in Figure 4.47. First order negative autocorrelation of price increments increases in magnitude with $p_{ST}$ (Figure 4.48). The standard error in estimating the first order autocorrelations also increases with $p_{ST}$. These negative first order autocorrelation values are significantly high (i.e., $p$-value $\leq 0.05$) when $p_{ST} \geq 0.1$. However, the second order autocorrelation values change from negative to positive with pattern traders. In addition, second order autocorrelations shows the maximum deviation with $p_{ST}$. Moreover, when $p_{ST} = 0.8$, an interesting pattern in autocorrelation is observed (see Figure 4.47). The autocorrelation behaviour of price increments proves that these patterns traders can introduce behaviour regularities to the market attributes.

The power law decay exponent of the autocorrelation of absolute price increments decreases while the standard deviation increases with $p_{ST}$ (Figure 4.49). The power law decay exponent is significantly different (i.e., $p$-value $\leq 0.05$) when $p_{ST} \geq 0.1$. This power law decay exponent decrease indicates a decrease in volatility clustering effect and it can be attributed to the regularity introduced by the [market buy, market sell] pattern. This behaviour is also different from the behaviour observed with impatient
Figure 4.45: Price graphs of the $M^*$ model with pattern traders (i.e., [market buy, market sell] pattern). (Note that the data were plotted with sampling only at every 50th point for clarity). The inset shows the net change box plots with pattern traders.

Distribution properties (mean, standard deviation, skewness, and kurtosis) of price returns and bid-ask spreads with pattern traders are shown in Figures 4.50 and 4.51. The mean and skewness of price returns distribution increase with $p_{ST}$ while the standard deviation shows a decrease. The mean and standard deviation of bid-ask spread distributions increase with $p_{ST}$ while the skewness and kurtosis show a decrease. This is because the [market buy, market sell] pattern removes best prices of both bid and ask sides causing wide bid-ask spreads. Wide bid-ask spreads can cause higher returns. Moreover, when there are more pattern traders, the limit order book may often empty and therefore traders can only submit limit orders.

These results indicate that performing a repeating market order pattern is not exactly the same as increasing the probability of submitting market orders (i.e., impatient trading). The behaviour of these pattern traders is used to characterise manipulation scenarios such as cyclic trading and wash sales in the next chapter.
Figure 4.46: Hurst exponent box plots (combined over 100 simulation runs) of the $M^*$ model with pattern traders (i.e., [market buy, market sell] pattern)

Figure 4.47: Mean autocorrelation values of price increments (averaged over 100 simulation runs) for first 14 lags in the $M^*$ model with pattern traders (i.e., [market buy, market sell] pattern)
4.4.7 Cyclic traders

A cyclic trading scenario takes place when a group of traders buys and sells shares frequently among themselves to push the stock price up or down or to generate artificial activity or volumes. These trades are related and do not represent a real change in the beneficial ownership of the stock. Cyclic traders are profit motivated traders.

Cyclic trading can be performed by two market participants. For example, two traders $A$ and $B$, who are trying to raise the price, could use a strategy as follows: $B$ submits a market order to buy immediately after a high priced (i.e., $\Delta = 4$) limit order to sell from $A$. The next step would be $B$ submits a sell limit order with $\Delta = 4$ (i.e., highest possible price in the $M^*$ model) followed by a market order to buy from $A$. They repeat the whole strategy several times to show an activity and raise the price. $A$ and $B$ traders work as a group to perform this strategy to make an artificial impact on the price. In modelling these cyclic traders, the order pattern generated by these cyclic trader interactions is considered. Cyclic traders that are pushing the price up can introduce $[\text{limit sell, market buy}]$ pattern to the market, however, if both buy and

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Figure 4.48: First order autocorrelation box plots (combined over 100 simulation runs) of price increments in the $M^*$ model with pattern traders (i.e., $[\text{market buy, market sell}]$ pattern)

Figure 4.49: Autocorrelation decay exponent box plots (combined over 100 simulation runs) of absolute price increments in the $M^*$ model with pattern traders (i.e., $[\text{market buy, market sell}]$ pattern)
sell parties use patterns such as \([\text{market sell, market buy}], \ [\text{limit buy, market sell}], \ \text{or} \ [\text{limit buy, limit sell}]\) the possibility of price increase is minimal. This is due to buy and sell market orders causing the price to fluctuate between the bid-ask spread rather than pushing it up. As a result, cyclic trading groups use buy market orders with sell limit orders in order to pass shares among themselves and raise the price. Alternatively, they can use patterns such as \([\text{limit buy, market sell}]\) to push the price down.

This can be considered a smooth way of pushing the price up or down, and also is a less noticeable strategy than the strategy of just buying to raise the price. Order accumulation is a noticeable strategy because it may appear as imbalances in market data.

In order to introduce the cyclic trading effect to the \(M^*\) model, a new trader who performs a repeating \([\text{limit sell, market buy}]\) pattern is introduced (\(\text{Trader(Strategy([\text{limit sell, market buy}]), 1000, 11000, 10000})\)). One trader is used here because, when repeating this cyclic trading strategy, the order pattern that one party may generate to perform a cyclic trading can still be \([\text{limit sell, market buy}]\). In order to increase the price, this trader submits limit sell orders at the highest possible limit sell price (i.e., \(\Delta = 4\)) in the \(M^*\) model. This cyclic trader is selected for trading
with a probability \( p_{ST} \) and the liquidity traders (i.e., \( M^* \)) are selected with a probability \( p_{LT} \) \( (p_{ST} + p_{LT} = 1) \). \( p_{ST} \) is varied to analyse the impact of cyclic trading to the market properties. This method does not consider agent interactions to simulate cyclic trading and is very simple.

A cyclic trading strategy will not alter either limit/market order percentage or buy/sell order percentage, however the number of limit buy and market sell orders percentages can be reduced. As a result, one can argue that the strategy of cyclic trading is similar to the strategy of buyers. However, the cyclic trading method can be more effective in the sense that it does not require order accumulation or shorting to push the price up or down.

Figure 4.52 shows the behaviour of the price signal when the percentage of cyclic trading \( (p_{ST}) \) is increased. This price behaviour indicates that cyclic trading pushes the price up. The mean of price net changes increases and then slightly decreases with \( p_{ST} \) (see the inset of Figure 4.52). The upward trend in the mean net changes confirms that cyclic trading can be used as a strategy to push the price up. Price net changes becomes significantly higher (i.e., p-value ≤ 0.05) when \( p_{ST} ≥ 0.1 \). However, cyclic trading is not as effective as buying to push the price up (i.e., the price increase is less).

The Hurst exponent increases with cyclic traders (Figure 4.53). The Hurst exponent is significantly higher (i.e., p-value ≤ 0.05) than the original \( M^* \) estimated value when \( p_{ST} ≥ 0.1 \).

First order autocorrelation of price increments becomes significantly lower (i.e., p-value ≤ 0.05) when \( p_{ST} ≥ 0.1 \) (Figure 4.54 and 4.55). Negative second order autocorrelation of price increments show an opposite behaviour to the behaviour of first order autocorrelation (Figure 4.54). Moreover, with cyclic traders, some negative second order autocorrelation values are greater in magnitude than the negative first order autocorrelations. However, unlike with pattern traders, autocorrelation of price increments are negative with cyclic traders. The volatility clustering effect (i.e., autocorrelation decay of absolute price increments) experiences a decrease with cyclic trading (Figure 4.56). Volatility clustering is significantly lower (i.e., p-value ≤ 0.05) when \( p_{ST} ≥ 0.4 \). This decrease is also different to the volatility clustering decrease observed with pattern traders.

Distribution properties (mean, standard deviation, skewness, and kurtosis) of price returns and bid-ask spreads with cyclic traders are shown in Figures 4.57 and 4.58. The mean and standard deviation of the price returns distributions first increases and then decreases with \( p_{ST} \). The skewness and kurtosis of price returns increases with
Figure 4.52: Price graphs of the $M^*$ model with cyclic traders (Note that the data were plotted with sampling only at every $50^{th}$ point for clarity). The inset shows the net change box plots with cyclic traders $p_{ST}$. The mean of bid-ask spread distributions increases with $p_{ST}$ while the standard deviation first increases and then slightly decreases with cyclic trading. The skewness and kurtosis of bid-ask spreads first increase and then decrease with cyclic trading.

The behaviour of these cyclic traders is used to characterise a cyclic trading manipulation scenario in the next chapter. It is also noted that pattern strategies can introduce different characteristics to the autocorrelation of price increments compared with the behaviour of other types of heterogeneous traders.

4.4.8 Informed traders

Informed traders have private information about the stock and as a result they can have information about the future price direction. This private information can be utilised by the informed traders to profit (Kyle, 1985; Glosten and Milgrom, 1985; Allen and Gale, 1992; Goettler et al., 2009). The “continuous auction framework” developed by Kyle (1985) presented an adverse selection problem faced by an informed trader when
Figure 4.53: Hurst exponent box plots of the $M^*$ model with cyclic traders (combined over 100 simulation runs)

Figure 4.54: Mean autocorrelation values of price increments (averaged over 100 simulation runs) for first 14 lags in the $M^*$ model with cyclic traders using his private information. In this context, an informed trader should trade in a way that his trades will not convey any information to the market Kyle (1985). Glosten and
Figure 4.55: First order autocorrelation box plots of price increments in the $M^*$ model with cyclic traders (combined over 100 simulation runs)

Figure 4.56: Autocorrelation decay exponent box plots of absolute price increments in the $M^*$ model with cyclic traders (combined over 100 simulation runs)

Figure 4.57: Distribution properties of price returns in the $M^*$ model with cyclic traders (averaged over 100 simulation runs)

Figure 4.58: Distribution properties of bid-ask spreads in the $M^*$ model with cyclic traders (averaged over 100 simulation runs)
Milgrom (1985) modelled an adverse selection problem of a market maker in a pure dealership market when they deal with informed traders. These market makers use a strategy of covering up the losses incurred due to informed trading from the traders with liquidity traders. Chakravarty and Holden (1995) considered characterising informed limit orders in their model.

Informed trading is modelled using a trader who can see the possible future worlds of trading and adjusts his buying/selling strategy accordingly. Before commencing the informed trading simulation, the $M^*$ model is run only with liquidity traders for 10000 steps and all the actions of traders and the last traded prices are recorded (i.e., prior simulation). In the (next) “informed trading simulation”, a new stylised trader who can see $t_F$ steps of future prices (prices of the prior simulation used here as the future prices) is introduced (i.e., $\text{Trader}(\text{InformedStrategy}(q_b, 0.5), 1000, 11000, 10000)$). This trader is selected for trading with a probability $p_{ST}$. Algorithm 8 defines the $\text{InformedStrategy}(\text{Future Price Series PS}, t_F)$ function, where PS is the future price series and the manipulator can see $t_F$ steps of future prices. All the other traders in this informed trading simulation are original $M^*$ (liquidity) traders. These liquidity traders are selected for trading as per in the prior simulation and they use the same set of actions that they used in the prior simulation. Using the available future prices and a simple linear regression method, informed trader computes the future price direction. This allows the informed trader to know the price direction ahead of the liquidity traders and decide his strategy based on what he knows about the future. This informed trader buys/sells with a higher probability (i.e., $q_b = 0.55/0.45$) if the price is to go up/down (i.e., upward/downward trend) in the future.

In these simulations, it is assumed that informed trader does not significantly affect the future price direction. Here, the informed trading is simulated only to analyse the utility of having private information in a limit order market. As a result, in these simulations, the informed trader probability $p_{ST}$ is not varied to analyse the impact of informed trading on the $M^*$ model. This is because when the behaviour of informed traders is significantly changing the behaviour of the original $M^*$ model it is hard to extract the utility of informed trading strategy. Moreover, very small buy/sell probability changes (i.e., 0.05) are used here to minimise the effect of this insider trader to the previously measured “future price direction”.

Figures 4.59, 4.60 illustrate the price behaviour of simulations with or without informed trading. In the simulation with informed trading, the informed trader is selected for trading with a probability $p_{ST} = 0.1$ and this trader can see 1000 steps
Input : Future Price Series PS, \( t_F \)

Output: Trader interaction

/* Compute the future price direction */

\[
\text{Price direction} = \text{ComputeFuturePriceDirection(Future Price Series PS, } \ t_F) \]

if Price direction is Upwards then
  \( q_b = 0.55; \)
else
  \( q_b = 0.45; \)
end

/* Buy or sell? */

if Rnd(0,1) \leq q_b then
  /* Buy behaviour */
  if Sell side is Empty or Rnd(0,1) \leq q_{lo} then
    /* Insert limit order to buy */
  end
  else
    /* Buy at lowest sell price */
  end
end
else
  /* Sell behaviour */
  if Buy side is Empty or Rnd(0,1) \leq q_{lo} then
    /* Insert limit order to sell */
  end
  else
    /* Sell at highest buy price */
  end
end

Algorithm 8: Trading strategy of an informed trader (i.e., \( \text{InformedStrategy(Future Price Series PS, } \ t_F) \))
Figure 4.59: Price graph without informed trader (i.e., prior simulation)

Figure 4.60: Price graph with informed trader (i.e., informed trading simulation). Here the informed trader is selected for trading with a probability $p_{ST} = 0.1$ and he could see $t_F = 1000$ steps ahead.

ahead (i.e., $t_F = 1000$). These two price graphs indicate that informed trading does not change the behaviour of the price direction significantly (i.e., this trader does not push the price up/down as per with buyers/sellers).

This informed trader is considered for profitability and to characterise “insider trading” manipulation in the next chapter.

4.5 Summary

Incorporating heterogeneous trading to the $M^*$ model has been described. Heterogeneous traders were characterised as stylised traders (i.e., simple external processes) and introduced to the $M^*$ model. The impact of these simple processes on the $M^*$ model was analysed (Table 4.1). It was shown how/when these processes can significantly affect the properties of the $M^*$ null model. The price effects due to different trading strategies are shown to be different. In the next chapter, these price effects are used to discuss the effectiveness of the underline trading/manipulation strategy.
The notion of information was introduced to the $M^*$ model via technical traders. In this analysis, a belief structure of a technical limit order trader is characterised. This belief model allows an analysis of trader beliefs in order to characterise their learning processes and effects on the limit order book. This belief model also allows a notion of information asymmetry to be introduced. Properties of these models are then used to explain normal and abnormal market behaviour.

These stylised heterogeneous traders can be used to generate different forms of normal and abnormal trader behaviour in stock markets. Heterogeneous trading actions will be used to model manipulation scenarios in the next chapter.
Chapter 5

Stock Manipulation Models

5.1 Overview

In this chapter, trade-based stock manipulation strategies are introduced to the $M^*$ model. Using manipulation models, formal explanations for manipulation scenarios are presented. Normal and abnormal heterogeneous trading actions introduced in Chapter 4 are used to characterise profitable manipulation scenarios. These manipulation scenarios are defined as stylised manipulator types and introduced to the $M^*$ model to build manipulation models. These manipulation models can be used by the researchers to test hypotheses on stock manipulation. Moreover, these manipulation models can be used by the market regulators to generate different forms of manipulation in different stock market conditions in order to design, develop, and evaluate detection mechanisms. In this chapter, manipulation models are used to identify what makes manipulations possible in stock markets. Supportive market conditions and trader behaviour that make manipulation profitable are also discussed. This study is the first to characterise manipulation in a single realistic model of a limit order market.

Some parts of this chapter are extensions of Withanawasam et al. (2011) and Withanawasam et al. (2012).

5.2 Stock Manipulation

Some market participants use trading and other supportive strategies to generate false information and alter market properties in order to gain advantage over other market participants. This scenario is considered illegal by market regulatory organisations and is termed ‘market manipulation.’ Manipulation affects fair and orderly markets and
may result in market participants losing confidence in stock trading.

Hart (1977) and Hart and Kreps (1986) showed that speculation can destabilise prices and increase volatility. Allen and Gale (1992) separate stock manipulation into three main categories: action based, information based and trade based manipulation. In action based manipulation, the manipulator takes publicly observable actions to mislead the market. For example, closing down a branch/plant or not bidding in an auction could be considered as action based manipulation. These actions could influence the price of a stock and therefore may be considered illegal attempts to give a false impression to market participants. In information based manipulation, manipulators spread rumours and false information to influence the price of a stock. Sometimes trading with an informational advantage is also considered illegal and this scenario is termed “insider trading.” In trade based manipulation, manipulators engage in a series of transactions in order to convey a false impression to other market participants. For example, the manipulators may work in groups and trade among themselves (i.e., trader pools) to create a perception of market activity that is not representative of the market. Information based manipulation and trade based manipulation are the most common types of manipulation (Allen and Gale, 1992; Öğüt et al., 2009). However, all these manipulation categories involve altering market information. As a result, manipulation can be generally defined as the illegal use of private information or generating false information in order to mislead market participants.

5.3 Importance of Manipulation Models

Stock markets compete with each other by attracting market participants into their trading venues. Moreover, market participants expect fair and orderly markets. Stock manipulation is a major reason market participant’s lose faith in a stock market. If market participants lose confidence in the integrity of a trading venue due to manipulation, it is highly likely that they will switch to another market or step back from any stock trading/investment at all. In contrast, manipulators prefer a market place where the chance of profitable manipulation is high. However, stock market authorities enforce rules and regulations to ensure market integrity in order to facilitate the expectations of the majority of their clients.

Before 1934, stock manipulation had been a major problem in stock markets. As a preventive measure, the Securities and Exchanges Act of 1934 implemented rules and regulations in order to enforce strict control on market manipulation in the US.
As a result of this act, since 1934, there has been a considerable decrease in market manipulation. However, manipulations are still observed in current day stock markets (Aggarwal and Wu, 2006).

In maintaining market integrity, stock markets employ surveillance systems that analyse the market both in real-time and off-line in order to detect suspicious trading activities. Regulators use these systems to take action in preventing manipulation. Detection of manipulation leads to legal actions against involved parties. Manipulation detection or stock surveillance does not directly generate profits for stock exchanges but they indirectly help increase their profits by ensuring market integrity and hence attracting and/or keeping more market participants. Apart from self regulatory organisations (SRO) (i.e., specialised surveillance departments in stock markets), there are government bodies such as the Securities and Exchange Commission (SEC) who enforce these manipulation prevention measures. These government organisations mainly consider cross market surveillance (i.e., manipulations that involve several exchanges (Cumming and Johan, 2008)) and also employ surveillance systems for detecting and/or preventing abnormal trading practices.

In general, the distinction between legal and illegal manipulative actions is not clear. From a market regulator’s perspective, it is important to observe suspicious behaviour in market attributes in order to prevent and/or detect manipulative attempts. Judgement for legitimacy of these suspicious actions is mainly based on the policies of the exchange and how and to what extent market authorities need to enforce the market integrity in their organisation. Surveillance systems may generate warnings in order to keep the market fair and orderly. However, the legal actions taken against these manipulators depend on the exchange policies and on the jurisdictions of the country.

Existing manipulation detection methods use pattern matching and classification of datasets. Although some academic solutions for manipulation detection exist (Pirrong, 2004; Reddy and Sebastin, 2006; Palshikar and Apte, 2008; Öğüt et al., 2009), surveillance software providers require simplified manipulation scenarios to design, develop, and evaluate their software patterns to detect manipulation. These simplified scenarios would also help researchers to understand subtle variations of manipulation behaviour and to test their hypotheses on profitability and detectability of manipulation.

Stock markets involve complex and dynamic interactions between market participants. It is not possible to perform controlled experiments on stock markets to study and test hypotheses about stock markets and manipulations. Moreover, real stock mar-
kets cannot be used to generate manipulated data samples in order to test detection systems.

In this thesis, modelling manipulation strategies is developed as a prime method to study stock manipulations. Manipulation models can be used to simplify and explain manipulation scenarios. These manipulation models can also be used to recreate manipulation scenarios and generate different forms of manipulations in different real stock market conditions. These recreated manipulation scenarios can be used by manipulation detectors to design, develop, and evaluate their manipulation detection mechanisms. Moreover, manipulation models can be used to test stock manipulation related hypotheses. For example, researchers can use these models to test possibility, profitability, and detectability of manipulation in stock markets. In this context, different stock market conditions can be produced and the implications of manipulation in those different market conditions can be tested.

Manipulation models are a novel and important contribution to industry level manipulation detection. In this chapter, trade-based manipulation for a limit order book for a single stock is considered.

5.3.1 Past literature on manipulation models

Many studies have considered trade-based manipulation in both empirical and theoretical (i.e., analytical) models.

Using the Kyle (1985) model, Van Bommel (2003) analysed the way in which traders can spread rumours in the market about their trades. He showed that a potentially informed party can pretend to be informed and mislead. Van Bommel (2003) also showed that the potentially informed party would prefer to commit not to trade against their own information (i.e., buying when the true value is low).

Jarrow (1992) constructed a model that showed large traders can manipulate stock markets due to price momentum (i.e., price increase due to a trade can affect the price in the future). Large traders can affect the price with their trades and profitable speculation is possible if there is price momentum.

Using a simple theoretical model, Allen and Gale (1992) showed that profitable manipulation is possible even when there exists no price momentum or a price corner. They show that a manipulation is possible when it is unclear that an action of a trader is due to private information or due to a manipulative attempt. As a result, normal traders have problems distinguishing informed traders from manipulators. Manipulators use this confusion in order to pretend to be informed and mislead the market.
Allen and Gale (1992) model is based on simply buying and selling (i.e., only trade based), and not based on using public actions to mislead or spread false information. According to Allen and Gale (1992), “the model is not intended to be a realistic description of an actual stock market.” This is because, “extreme assumptions are used to make the argument more transparent” (Allen and Gale, 1992, p.508).

By extending the Glosten and Milgrom (1985) model, Allen and Gorton (1992) showed that manipulation is possible due to the natural information asymmetry between liquidity purchases and liquidity sales. It is highly likely that buying is performed after doing a market analysis and selling can be due to many exogenous reasons. As a result, market participants believe that a purchase contains more information than a sale. This means price movement with respect to a buy transaction is higher than the price movement with respect to a sell transaction. This asymmetry in price responses can make profitable manipulation possible because, due to this information asymmetry, “a manipulator can repeatedly buy stocks, causing a relatively large effect on prices, and then sell with relatively little effect” (Aggarwal and Wu, 2006, p.1919).

Aggarwal and Wu (2006) also presented a mathematical model for manipulation. Aggarwal and Wu (2006) extended the framework of Allen and Gale (1992) and examined how a manipulator can trade in the presence of traders who seek information from the market. These information seekers increase market efficiency when the manipulators are absent, but when manipulators are present the information seekers reduce market efficiency because they are being manipulated. Information seekers increase the manipulator returns. According to Aggarwal and Wu (2006) illiquid stocks are more likely to be manipulated. In general, stock prices rise through the manipulation period and then fall in the post manipulation period. Prices and liquidity are higher when the manipulator sells than when the manipulator buys. Manipulation increases volatility (Aggarwal and Wu, 2006; Stoll and Whaley, 1987, 1991).


Most of these existing manipulation models consider the theoretical aspects of manipulation and are far from reality. As a result, these theoretical manipulation models cannot be used by the market regulators to generate different forms of manipulation scenarios in order to validate manipulation detection methods. Moreover, in the literature, agent-based simulations have been used to characterise manipulation scenarios.
such as circular trading. However, these agent-based simulations were designed to analyse the behaviour produced by trader interactions and fail to produce quantitative inferences due to manipulation. Moreover, all these manipulation models were built on different platforms and characterise different manipulation scenarios in different types of stock markets. As a result, these manipulation models cannot be integrated and used to analyse the market behaviour due to a combination of manipulation scenarios. This raises for requirement of a universal model that can be used to simulate a range of manipulation scenarios in a single environment.

Fulfilling this requirement, a framework to characterise trade-based manipulation scenarios in a single computational model is presented. In this framework, trade-based manipulations are considered for simulation separately in order to provide simplified formal explanations for individual manipulation scenarios.

5.4 Modelling Trade-Based Stock Manipulation

In this chapter, the $M^*$ model is extended to include manipulation scenarios. The heterogeneous trading actions that are discussed in Chapter 4 are considered in terms of their profitability and their involvement with profitable manipulation scenarios. Characterisable manipulation scenarios are identified. These identified manipulation scenarios are characterised using one or more heterogeneous trading actions and are simplified as external processes to the $M^*$ model. In order to analyse the profitability of these scenarios separately, these processes are characterised as stylised trader types (i.e., manipulators) in the $M^*$ model. These traders characterise the universal properties of manipulation scenarios and hence can be considered stylised manipulator types. These manipulators are introduced to the pool of liquidity traders, and where appropriate technical traders in the $M^*$ model. Each trader type in this pool is assigned a probability of being selected to interact with the limit order book. In order to analyse the profitability of these manipulation scenarios, at the end of each simulation, average profit of each trader type is computed.

Profit of market participants is defined as the difference between starting and ending wealth. All these traders are assumed to have initial stocks and money. The final profit of a trader is computed as the difference between initial and final wealth. In computing wealth, the stocks at hand are liquidated with respect to the last traded price at the designated time when wealth is calculated. In nullifying the effect of market parameters such as price, profits of other traders are computed with respect to the average liquidity
trader profit.

5.5 Profitability of Heterogeneous Trading

In Chapter 4, heterogeneous trading actions were characterised as external processes and introduced to the $M^*$ model using different stylised trader types. To commence our study on manipulation, simulations will be carried out by introducing these new trader types to the $M^*$ trader pool and allowing them to interact with the original $M^*$ liquidity traders. The profits of these heterogeneous traders with their arrival probability in the market (i.e., $p_{ST}$) will be analysed.

The $M^*$ model is initialised with $price(0) = 10000$ and is run for 11000 time steps. All runs commence with 1000 steps to seed the limit order book as per Maslov (2000). As a result, the data are recorded from $price(1000) = p(1)$ onwards. At the end of each simulation, the profit of each heterogeneous trader type with respect to the profit of liquidity traders is computed. Average profit is determined over 100 independent runs.

Technical trading is profitable compared with liquidity trading (Figure 5.1). Technical trader profit increases with technical trader arrival probability $p_{ST}$. This means that the strategy of following the market trend with the help of other trader actions (i.e., technical trading) is more profitable compared with randomly trading (i.e., liquidity trading) in stock markets. However, when almost all the transactions are done by the technical traders (i.e., $p_{ST} \approx 1$), technical traders’ profit decreases. These results show that technical trading is a profit motivated trader type.

Figure 5.2 illustrates the profit behaviour of buyers when their probability of buying (denoted here by $q_{Pb}^{PD}$), probability of submitting market orders (denoted here by $q_{mo}^{PD}$), and their arrival probability in the market ($p_{ST}$) are changed (these parameters can be used to represent manipulator aggressiveness). With arrival probability in the market, the trader profit first increases and then decreases. This means that these buyers can only be aggressive up to a certain level to perform a successful buying strategy. When the buyer is too aggressive (i.e., the arrival probability is very high), he does not allow other traders to enter the market and as a result his profit decreases. A higher probability of buying increases buyer profits, but increasing the probability of submitting market orders decreases the buyer profit. This is because, when the buyer is submitting more market orders, after some time he starts to empty the order book and as a result may fail to submit market orders to buy stocks. These results indicate that impatient buyers (i.e., more market orders) make less profits.
Figure 5.1: Profit box plots of technical trading (combined over 100 simulation runs) when technical trader arrival probability in the market ($p_{ST}$) is changed. $\bigcirc$ indicates the mean values

Figure 5.3 illustrates the profitability of sellers when their probability of selling, probability of submitting market orders, and their arrival probability in the market are changed. These graphs also show that sellers can only be aggressive up to a certain level. When the seller is too aggressive (i.e., the arrival probability is very high), he does not allow other traders to enter and as a result his selling is not successful. Similar to buyers, a higher probability of selling increases seller profits, but higher the probability of submitting market orders decreases the manipulator’s profit. These results also indicate that impatient sellers (i.e., more market orders) make less profits.

Buyer and seller strategies are observed to be returning positive profits. However, these profits may be temporary because buying/selling causes the price to go up/down and this profit is computed with respect to that inflated/deflated price and the accumulated/shorted stock. In real markets, after someone artificially inflates the price (by buying), the market (i.e., the other participants) takes some time to realise that the stock is over-valued (i.e., the true value of the stock is lower than stated by the market). As a result of this overvalued signal, traders push price down. If the person who inflated the price failed to sell out above his buying price, then a loss is incurred. This is also true for sellers, because with this type of selling, the stock becomes under-valued. These results show that buyers and sellers are profit motivated traders and
Figure 5.2: Average profits of buyers (averaged over 100 simulation runs) when their arrival probability in the market ($p_{ST}$) is changed. These traders buy with a probability $q_{b}^{PD}$ and submit market orders with a probability $q_{mo}^{PD}$. Note that the standard deviations of these trader profits are consistently low and hence are not shown in the figure for clarity.

also they can be manipulators.

Profit behaviour of patient and impatient traders with their arrival probability in the market is illustrated in Figures 5.4 and 5.5. Impatient trading is not profitable. This was also confirmed with impatient buying and selling. This is because impatient traders use more market orders to buy or sell immediately and when the bid-ask spread is positive (i.e., with transaction costs). Market orders can only ensure that buy high and sell low. However, if traders can wait (i.e., be patient traders), they can use limit orders to buy low and sell high. As a result, patient trading is a more profitable strategy than impatient trading. When the order book is empty, however, traders must convert their market orders to limit orders in the $M^*$ model. As a result, a most aggressive impatient trader can also make a profit in the $M^*$ model.

These results indicate that patient trading is a profit motivated trading strategy. Impatient trading is not a profit motivated trading strategy. However, impatient traders can be manipulators.

Order cancelling traders use a strategy of cancelling their limit orders. These traders
These traders buy with a probability $q_{b}^{PD}$ and submit market orders with a probability $q_{mo}^{PD}$. Note that the standard deviations of these trader profits are consistently low and hence are not shown in the figure for clarity.

do not make profits by this strategy (Figure 5.6). This is because when they cancel more limit orders, their market order percentage comparatively increases and hence they become unprofitable impatient traders. This is also not a profit motivated strategy and as a result this can be a manipulative strategy.

Pattern traders in this simulation (i.e., [market buy, market sell] pattern) also do not make a significant profit (Figure 5.7). However, it is observed that the cyclic trading strategy (this is also a pattern strategy) does make a profit (Figure 5.8). This is because the [limit sell, market buy] pattern allows these traders to buy low and sell high. Also due to the market buy orders, the rate of buying may be comparatively higher than the rate of selling (i.e., limit sell orders). As a result, at the end of the manipulation, the trader may have accumulated a small amount of stock and hence the inflated price can give him a temporary profit as explained with buyers (it was shown that this cyclic trading pushes the price up).

Pattern trading is also not a profit motivated strategy. However, cyclic trading is profitable. In addition, both these strategies can be manipulative.
5.6 Manipulation Models

Heterogeneous trading actions are used to characterise manipulation scenarios as stylised manipulator types. These stylised manipulators are introduced to the pool of liquidity traders in the $M^*$ model. Technical traders are also introduced to this trader pool where applicable. Trader types in the pool are selected for trading with their selection probabilities. These probabilities do not represent the number of these types of traders in the market. Rather, they represent the chance of observing a particular type of trader in the market. As a result, these probabilities allow control over the effect of these traders (i.e., external processes or manipulations) on the behaviour of the $M^*$ model.

5.6.1 Pump and dump

In a “pump and dump” strategy, manipulators buy at successively higher prices, giving the appearance of activity at a higher price than the actual market value (i.e., they pretend to be informed and mislead the market), and then sell or dump shares at an inflated price. Figure 5.9 illustrates the price behaviour of a pump and dump
Figure 5.5: Profit box plots of impatient traders (combined over 100 simulation runs) when their arrival probability in the market ($p_{ST}$) is changed. These traders buy with 0.5 probability and submit market orders with 0.75 probability.


Pump and dump manipulators can also use strategies such as spreading rumours and they may take some observable actions to push the price up. However, only pure trade-based pump and dump manipulation is considered in this thesis. Some of the other manipulation strategies that can be related to a pump and dump scheme are “cyclic trading,” “marking the close,” “wash sales,” “painting the tape,” and “orders without execution.” These can be used as supportive strategies by the pump and dump manipulators to mislead other market participants in pushing the price up/down or minimise the risk.

Allen and Gale (1992), Allen and Gorton (1992), and Mei et al. (2004) considered models of pump and dump manipulation scenario. Allen and Gorton (1992) modelled the possibility of trade-based pump and dump manipulation due to information asymmetry. They showed that a pump and dump is possible due to information asymmetry between buys and sells. Allen and Gale (1992) showed that normal traders always have a problem of distinguishing informed traders from manipulators. This asymmetry leads
Figure 5.6: Profit box plots of order cancelling traders (combined over 100 simulation runs) when their arrival probability in the market ($p_{ST}$) is changed. These traders buy with 0.5 probability and submit market orders with 0.5 probability to a manipulator being able to pretend to be informed and mislead the market. Using a model for pump and dump, Mei et al. (2004) showed that trade-based manipulation is possible due to the traders’ behavioural biases. All these manipulation models represent theoretical implications of pump and dump.

The $M^*$ model is extended to characterise pump and dump manipulation. Heterogeneous traders such as buyers, sellers, and technical traders are used. It is shown that pump and dump manipulation is not possible if the only other traders are traditional Maslov (liquidity) traders. The presence of technical traders, however, makes profitable pump and dump manipulation possible. When exploiting the behaviour of technical traders, manipulators can wait some time after their buying phase before selling, in order to profit. Moreover, if technical traders believe that there is an information asymmetry between buy and sell actions, the manipulator effort required to perform a pump and dump is comparatively low, and a manipulator can generate profits even by selling immediately after raising the price.
The pump and dump model

The pump and dump manipulation scenario is modelled using manipulators who mislead technical traders. The $M^*$ model is extended by adding technical traders and manipulators. Throughout the simulation, liquidity traders, technical traders, and manipulators are considered to be in a pool and are selected for trading with probabilities $p_L$, $p_T$, and $p_M$, respectively.

The simulation (i.e., $t_T$ time steps) is divided into two periods: a non-manipulation period and a manipulation period. In the manipulation period, manipulators use the pump and dump strategy to introduce the manipulation. In the non-manipulation period the manipulator’s strategy is similar to the strategy of liquidity traders. The manipulation period starts after $t_S$ time steps (see Figure 5.10).

Technical trader behaviour here is similar to that of technical traders introduced in Chapter 4. They use a Bayesian learning framework to generate information from past informed trading actions. This Bayesian framework is useful because it allows a belief structure of a trader type to be represented and to control and tune these beliefs explicitly in order to analyse learning processes and their effects on the order book.
Figure 5.8: Profit box plots of cyclic trading (combined over 100 simulation runs) when their arrival probability in the market ($p_{ST}$) is changed. These traders perform a \([\text{limit sell, market buy}]\) strategy.

Figure 5.9: The price graph of the pump and dump manipulation recorded in Universal stock (ticker symbol UVV) in the US market between April 1999 and July 1999.
Using the generated information, each technical trader models the probability of future price going up at any time $t$. This probability is used in making their buy and sell decisions. This framework allows technical traders to carry forward information in past trading in order to generate information when making their decisions to buy or sell. However, there are no informed traders in these simulations. Manipulators pretend to be informed and thereby mislead the technical traders. Moreover, the technical trader expectations are not rational, and as a result they don’t consider manipulators in their belief model. However, it is believed that in real markets, there is a continued existence of technical traders due to constant new trader arrivals (De Long, Shleifer, Summers, and Waldmann, 1991).

When attempting to inflate or deflate the price and mislead the market, a manipulator uses the price behaviour in response to supply and demand, along with the behaviour of technical traders. The manipulation period is divided into three periods, and these periods are termed “ignition period,” “momentum period” and “call-off period.” In the ignition period (of $t_I$ time steps), the manipulator buys with a probability $q_{ib}^I$ and submits market orders with a probability $q_{mo}^I$. This strategy is similar to the strategy of buyers discussed in Chapter 4. The momentum period (of $t_M$ time steps) is used by the manipulators to allow the technical traders to raise the price further. Finally, in the call-off period, the manipulator sells his stocks for $t_C$ time steps with probability $q_{is}^C$ and then exits from the market. The manipulator submits market orders with a probability $q_{mo}^C$ in this call-off period. The call-off period strategy of the manipulator is similar to the strategy of the sellers discussed in Chapter 4. The pump and dump manipulation time-line is depicted in Figure 5.10 as a stylised version of Figure 5.9. The parameters used in this pump and dump simulation are summarised in Table 5.1.

The $M^*$ model is initialised with $price(0) = 10000$ and simulated for $t_T$ (i.e., $t_S + t_I + t_M + t_C$) time steps. All runs commence with 1000 steps to seed the limit order book as per Maslov (2000). As a result, the data are recorded from $price(1000) = p(1)$ onwards.

Liquidity traders buy/sell and submit market/limit orders with equal probabilities (i.e., $q_b = q_{lo} = 0.5$).

At the beginning of the simulation, technical traders believe that the future price movement can be up or down with equal probability (i.e., $\pi_0 = 0.5$). In their Bayesian belief model, technical traders assume a $\lambda$ probability of informed traders and $\mu_2$ probability of liquidity buying. Technical traders’ initial probability of future price
All the traders are started performing buy/sell actions with equal probability. Manipulators buy at a higher rate, so the price starts to go up. Technical traders' learned demand increases the price further. The manipulator sells and profits from the market. Price collapses.

Figure 5.10: A graphical representation of the behaviour of the pump and dump model

<table>
<thead>
<tr>
<th>Trader</th>
<th>Parameter</th>
<th>Ignition period $t_I$</th>
<th>Momentum period $t_M$</th>
<th>Call-off period $t_C$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Liquidity trader</strong> (arrival probability $p_L$)</td>
<td>Probability of buying</td>
<td>$q_b$</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Probability of submitting market orders</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Technical trader</strong> (arrival probability $p_T$)</td>
<td>Probability of buying</td>
<td>$\pi_t$</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Probability of submitting market orders</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Manipulator</strong> (arrival probability $p_M$)</td>
<td>Probability of buying</td>
<td>$q_b^i$</td>
<td>0.5</td>
<td>$q_b^C$</td>
</tr>
<tr>
<td></td>
<td>Probability of submitting market orders</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 5.1: A summary of parameters used in pump and dump simulation

going up is $\pi_0$. Technical traders also assume that when the price is to go up, informed traders are definitely buying ($\mu_1 = 1$), and these technical traders are definitely selling ($\mu_3 = 0$) when the price is to go down. It is also assumed that the probabilities of submitting limit or market orders by the liquidity and informed traders are equal ($\theta_1 = \theta_2 = \theta_3 = \theta_4 = \theta_5 = \theta_6 = \theta_7 = \theta_8 = 0.5$). The information content possessed by a technical trader depends on the past records that he or she observes when computing.
π_t. For simplicity, it is assumed that all traders arrived in the market at the same time, and therefore they have the same set of information (i.e., common π_t).

In simulating the pump and dump manipulation, the manipulator parameters are set as: \( t_S = 0, t_I = t_C = 5000, t_M = 2500, q_b^I = 0.75, q_{mo}^I = 0.75, q_b^C = 0.25, \) and \( q_{mo}^C = 0.75 \). This means that the manipulator buys with 0.75 probability for 5000 steps, waits 2500 steps, and then sells with 0.75 probability for 5000 steps. The market order probability of the manipulator in both ignition and call-off periods is 0.75.

Limit order price offset (i.e., \( \Delta \)) values of all these traders are drawn from a power law distribution with mean 1.7 and standard deviation 0.8 (i.e., \( \Delta \) takes discrete values between 1 and 4, having the power law exponent 1.5).

The selection probabilities of each trader type for trading (i.e., \( p_L, p_T, \) and \( p_M \)) are used to control their aggressiveness for trading in the market. Profits of the technical traders and manipulator are computed with respect to the average liquidity trader profit and are averaged over 100 simulations.

The information asymmetry (between buying and selling) is introduced to the market through the probability of liquidity buying (i.e., \( \mu_2 \)) parameter in the technical trader belief model. This parameter is used because people sell for various exogenous reasons. However, they may buy for some specific reasons. As a result, in a market, there can be more liquidity sellers than buyers and also a buy transaction may contain more information than a sell transaction. When technical traders consider this asymmetry, they extract more information from buy transactions than sell transactions. As a result, their revision of beliefs with respect to a buy transaction is higher than the revision of beliefs with respect to a sell transaction. This technical trader behaviour can introduce an asymmetry to the market prices.

The role of supply and demand in determining price direction, how technical traders extract information from trading, how technical trader behaviour can introduce an information asymmetry, and how manipulators use these principles to alter market information are presented through the model properties.

**Profitability of pump and dump**

Figure 5.11 shows the price behaviour of the \( M^* \) model with technical traders. Here, in the technical trader belief model, technical traders expect 10% of informed trading and equal percentage of liquidity buying and selling (i.e., \( \mu_2 = 0.5 \)). The percentage of technical trading increases the positive autocorrelation in the price signal (i.e., the Hurst exponent increases with technical trading). This observation indicates that technical
trading adds a persistence behaviour (i.e., momentum) to the \( M^* \) prices. Persistence price behaviour is often observed in real stock prices (i.e., Hurst exponent is greater than 0.5) as a consequence of trader reactions to market information (Alfarano and Lux, 2003; Alvarez-Ramirez et al., 2008).

Figure 5.11: A comparison of typical single run price behaviour when technical traders are introduced to the \( M^* \) model (Note that the data were plotted with sampling only at every 50\(^{th}\) point for clarity)

In Figure 5.12, between the time steps 10000 and 20000, a manipulator performs buy/sell actions with a higher probability (manipulator buy/sell probability is 0.75 and market order probability is 0.75) to introduce a supply and demand imbalance to drive the price up/down. Figure 5.12 also shows that the momentum of technical trading amplifies the effect of this price change. Due to this momentum effect, the price continues to go up/down even after the manipulator stops his manipulation (i.e., aggressive buying/selling) at the 20000 time step. This momentum can be exploited by a manipulator in his pump and dump strategy.

Table 5.2 summarises the pump and dump manipulation profits with only liquidity traders and with both liquidity and technical traders. The manipulator profits with the presence of both liquidity and technical traders in simulations with/without the momentum period and with/without considering information asymmetry are also summarised.
<table>
<thead>
<tr>
<th>Profitability of technical trading</th>
<th>Simulation parameters</th>
<th>Technical trader profit</th>
<th>Manipulator profit</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$p_L$  $p_T$  $p_M$  $t_M$  $\mu_2$</td>
<td>Mean  Std  Std error</td>
<td>Mean  Std  Std error</td>
</tr>
<tr>
<td>With liquidity traders</td>
<td>0.5  0.5  0  NA  0.5</td>
<td>NA  NA  NA</td>
<td>NA  NA  NA</td>
</tr>
<tr>
<td>With technical traders (no momentum, no information asymmetry)</td>
<td>0.3  0.2  0.3  0  0.5</td>
<td>4087  4808  480</td>
<td>11817  6977  697</td>
</tr>
<tr>
<td></td>
<td>0.4  0.3  0.3  0  0.5</td>
<td>5014  4513  451</td>
<td>18594  7498  749</td>
</tr>
<tr>
<td></td>
<td>0.3  0.4  0.3  0  0.5</td>
<td>3528  4991  499</td>
<td>24936  6497  649</td>
</tr>
<tr>
<td>With technical traders (with momentum, no information asymmetry)</td>
<td>0.5  0.2  0.3  2500  0.5</td>
<td>7669  9899  989</td>
<td>19269  11545  1154</td>
</tr>
<tr>
<td></td>
<td>0.4  0.3  0.3  2500  0.5</td>
<td>5886  11151  1115</td>
<td>27580  15885  1588</td>
</tr>
<tr>
<td></td>
<td>0.3  0.4  0.3  2500  0.5</td>
<td>4433  12606  1260</td>
<td>34724  19825  1982</td>
</tr>
<tr>
<td></td>
<td>0.3  0.4  0.3  5000  0.5</td>
<td>11393  18119  1811</td>
<td>33795  29965  2996</td>
</tr>
<tr>
<td></td>
<td>0.3  0.4  0.3  7500  0.5</td>
<td>13546  20384  2038</td>
<td>28961  31289  3128</td>
</tr>
</tbody>
</table>

Table 5.2: Mean, standard deviation, and standard error values of technical trader and manipulator profits with respect to the liquidity trader profit averaged over 100 simulation runs. $p_L$, $p_T$, $p_M$ denote the liquidity, technical, and manipulator trader arrival probabilities respectively. $t_M$ denotes the length of the momentum period and $\mu_2$ represents the assumed percentage of liquidity buying in the Bayesian belief model. These results are averaged over 100 simulation runs. Note that low standard error values can be obtained by using higher number of simulation runs (Lindley, 1957)
Technical trader profits are analysed in a simulation with only liquidity and technical traders. These liquidity and technical traders arrive with probability $p_L = p_T = 0.5$ in the market. In their belief model, technical traders assume a probability of informed trading $\lambda = 0.1$ and a probability of liquidity buying $\mu_2 = 0.5$. The simulation is run for $t_T = 12500$ steps.

It is observed that technical traders make higher profits than liquidity traders (Table 5.2). This means that technical traders can successfully predict the future price direction using past information and use this ability to generate profits.

Manipulator profit with only liquidity traders is low (i.e., -3351). Moreover, if there is no momentum period and the overall manipulation behaviour is symmetric (i.e., ignition period is almost identical to the call-off period (i.e., $t_I = t_C$, $q^I_b = q^C_s$, and $q^I_{mo} = q^C_{mo}$) and there is no asymmetry considered between buying and selling (i.e., $\mu_2 = 0.5$)), the manipulator profit with both liquidity and technical trading is also low. These results indicate that manipulators are not able to make any significant profits by selling immediately after raising the price either in the presence of liquidity traders or technical traders.

However, when there are technical traders, the manipulator can exploit technical trader behaviour (i.e., momentum) by waiting some time between the ignition period
and call-off period (i.e., momentum period, $t_M = 2500$) in order to increase their profit. In this momentum period, technical traders buy stocks and their demand further raises the price (i.e., price momentum). Due to this price increase, manipulators can sell their stocks in the call-off period at a higher price than the buying price in the ignition period. These results confirm the findings of Jarrow (1992) that profitable manipulation is possible due to price momentum. Here, the technical trader arrival probability increases the manipulator profit.

However, when the manipulator waits a longer time in his momentum period (i.e., $t_M$ increases), the standard deviation of manipulator profit increases. This is because the perception the manipulator generated among technical traders may die out and the advantage he has produced can be lost.

Moreover, if technical traders believe in an information asymmetry between buy and sell transactions (i.e., if they believe a buy order contains more information than a sell order), manipulation is possible and profitable even without this momentum period. In addition, the percentage of technical trading increases manipulator profit. This information asymmetry is introduced to the model by varying the percentage of liquidity buying in the Bayesian belief model (i.e., $\mu_2 < 0.5$). Allen and Gorton (1992) also used the percentage of liquidity buying/selling in order to introduce information asymmetry and to demonstrate the possibility of manipulation in the Glosten and Milgrom (1985) model. In this approach, technical traders assume that there can be more liquidity sellers than buyers (i.e., $\mu_2 < 0.5$) and hence a buy order may contain more information than a sell order. Due to this information asymmetry, technical traders respond more to buy transactions than sell transactions. As a result, the price change in the manipulator’s ignition period becomes higher than the price change in the call-off period. Price graphs in Figure 5.13 illustrate how a manipulator uses this information asymmetry to buy with a higher effect on prices and sell with little effect. Figure 5.13 (i.e., simulated pump and dump prices) has the same characteristics as Figure 5.9 (i.e., real pump and dump prices).

Moreover, Figure 5.14 illustrates how the manipulator profit in comparison with the liquidity trader profit decreases with the assumed percentage of liquidity buying ($\mu_2$) in the technical trader belief model. When $\mu_2 < 0.5$ (i.e., when technical traders believe a buy transactions contain more information), the manipulator profits are high. However, when $\mu_2 > 0.5$ (i.e., when technical traders believe a sell transaction contains more information), manipulator profits are comparatively low. This means that pump and dump manipulation can be possible due to this natural information asymmetry in
stock markets. Based on these results, the Allen and Gorton (1992) findings about the role of information asymmetry in manipulation are confirmed for a limit order market.

When the manipulator increases his buying/selling probabilities in the ignition/call-off periods (i.e., $q_{Ib}^b/(1-q_{Cb}^b)$), the manipulator profit increases (Figure 5.15). However, the manipulator profit decreases when his market order probability (i.e., $q_{Imo}^b$ and $q_{Cmo}^b$) is increased (Figure 5.16). This happens because, when the manipulator is very aggressive (i.e., submits more market orders), the limit order book can be empty and as a result, his strategy of buying or selling to move the price is not successful. This will be further analysed in Chapter 7.

Figure 5.17 illustrates how manipulator profit behaviour varies with the arrival probability $p_M$ in the market. Here the liquidity trader arrival probability $p_T$ is 0.3. It is observed that when manipulator arrival probability is 0.7 (i.e., technical trader arrival probability is 0) the manipulator is not successful. However, with technical traders, manipulation is successful even with a very low manipulator arrival probability (i.e., $p_M = 0.1$).

Figure 5.18 illustrates the profit behaviour of successful pump and dump manipulation with the arrival probability of technical traders. When computing these manipu-
Figure 5.14: Manipulator profit box plots (combined over 100 simulation runs) for different liquidity buying percentages ($\mu_2$) in the Bayesian belief model. The assumed informed trader percentage is $\lambda = 0.1$.
Figure 5.15: Manipulator profit box plots (combined over 100 simulation runs) with varying probability of buying/selling in the ignition/call-off periods (i.e., $q_b/(1-q_b)$).

Figure 5.16: Manipulator profit box plots (combined over 100 simulation runs) with varying probability of submitting market orders in the ignition and call-off periods (i.e., $q_{mo}^I$ and $q_{mo}^C$).
Figure 5.17: Average manipulator profits (averaged over 100 simulation runs) with manipulator arrival probability $p_M$ ($p_L = 0.3$ and $p_L + p_T + p_M = 1$). Note that the standard deviations of these manipulator profits are consistently low and hence are not shown in the figure for clarity.

Detectability of pump and dump

Detecting the pump and dump manipulation scenario using limit order market attributes is difficult. This is because a pump and dump manipulation involves three different strategies (i.e., buying, waiting, and selling). However, individual strategies such as buying and selling can be detected using market attributes. In Chapter 4, it was shown that buying and selling strategies can alter market attributes such as the Hurst exponent, autocorrelation of price increments, volatility clustering, and distribution properties of bid-ask spreads and price returns. Buying and selling add persistence to the order flow. Moreover, when buyers or sellers are present, technical traders amplify
Aggarwal and Wu (2006) presented the common characteristics of manipulated stocks. Price normally rises in the manipulation period and then falls in the post manipulation period (after the true value is revealed). In general, prices are high when the manipulator sells than when he buys. These characteristics can be observed in our pump and dump model. According to Aggarwal and Wu (2006), in the manipulation period, liquidity, volume, and return are higher when compared with the non-manipulation period. Moreover, liquidity and volatility can be higher when the manipulator sells than when he buys. In this pump and dump simulation, higher liquidity (i.e., order book depth) and volume (i.e., number of trades) can be observed in the manipulation period. Moreover, greater buy and sell order book depths are observed when the manipulator sells (i.e., call-off period) than when he buys (i.e., ignition period). This is because, in the ignition period, an aggregated demand of both manipulator and technical trader increases the buy pressure and as a result greater buy
depth can be observed. However, when the manipulator sells, the technical traders’ learned demand produces greater buy depths and also the manipulators’ sell pressure causes greater sell depths. Moreover, as shown in Chapter 4, with buyers/sellers, higher returns can be observed when the manipulator is buying/selling (i.e., ignition/call-off periods). This also confirms the findings of Aggarwal and Wu (2006) for higher returns in the manipulation period.

5.6.2 Cyclic trading

A “cyclic trading” scenario takes place when a group of traders buy and sell shares frequently among themselves to push the stock price up/down or to generate artificial activity/volumes. These trades are related and do not represent a real change in the beneficial ownership of the stock. Cyclic trading strategy is used to introduce an artificial activity and attract other market participants. The artificial activity introduced by cyclic trading can generate an appearance of reduced risk of a liquidity premium\(^1\) for other investors and influence them to enter the market. By analogy, people are reluctant to enter a restaurant that is empty because people generally prefer to have their opinion validated by the behaviour of other people. Cyclic trading is considered as a manipulation strategy.

D’Hulst and Rodgers (1999) developed an agent-based model for cyclic trading of goods. In this chapter, a simple model is presented to characterise the profitability of cyclic trading in limit order markets. This model is used to analyse how manipulators can use this cyclic trading to generate profits.

It has been shown that the cyclic trading strategy itself is profitable (Figure 5.8). In Chapter 4, it was shown that cyclic trading can be used as a price driving strategy. In this chapter, the \(M^*\) model is extended to characterise a pump and dump manipulator who uses this cyclic trading strategy to generate profits. This pump and dump manipulator uses a cyclic trading strategy in order to push the price up in the momentum period. Using a data set from the stock market in Pakistan, Khwaja and Mian (2005) found evidence that brokerages can use strategies such as trading with each other (i.e., cyclic trading) to inflate price and perform a pump and dump. The properties of this cyclic trading model are considered in terms of profitability and detectability of cyclic trading in limit order markets.

This study is the first research to characterise cyclic trading in a model of a limit

\(^1\)An appearance of increased liquidity (Eleswarapu and Reinganum, 1993).
order market and the first to analyse profitability with cyclic trading.

**Pump and dump with cyclic trading**

The pump and dump manipulation scenario is modelled using a manipulator who performs a cyclic trading strategy to increase their profit. The $M^*$ model is extended by adding manipulators. Throughout the simulation, liquidity traders and manipulators are considered to be in a pool and are selected for trading with probabilities $p_L$ and $p_M$, respectively.

In modelling these cyclic traders, the order pattern generated by cyclic trader interactions is considered. In cyclic trading, one trader can submit a limit order to sell and the other trader can submit a market order to buy the same amount of stock at the same time. These actions can be repeated (i.e., the buyer can sell back his stocks in the same manner to the related party) to introduce an impact to the stock price. In cyclic trading, the buyer may not get the demanded stocks at the same price that the seller was offering and as a result these traders together may incur some temporary loss. However, this strategy has less risk than accumulating and shorting stocks in order to generate some price behaviour.²

A manipulator who performs a repeating $[\text{limit sell, market buy}]$ pattern is introduced. This cyclic trading manipulator submits limit sell orders at the highest possible price (i.e., $\Delta = 4$) in the $M^*$ model. This is because the intention of cyclic trading here is to increase the price.

The pump and dump simulation (i.e., $t_T$ time steps) is divided into two periods: a non-manipulation period and a manipulation period. In the manipulation period, manipulators use the pump and dump strategy to introduce the manipulation. In the non-manipulation period, the manipulator’s strategy is similar to the strategy of liquidity traders. The manipulation period starts after $t_S$ time steps.

In the ignition period (i.e., $t_I$ time steps), the manipulator buys with a probability $q_{ib}^I$ and submits market orders with a probability $q_{mo}^I$. This strategy is similar to the strategy of buyers discussed in Chapter 4. The momentum period (i.e., $t_M$ time steps) is used by the manipulators to perform cyclic trading strategy (i.e., the strategy $[\text{limit sell, market buy}]$) to push the price further. Finally, in the call-off period, the manipulator sells his stocks for a $t_C$ period of time with probability $q_{s}^C$ (the manipulator submits market orders with a probability $q_{mo}^C$) and exits from the market. The call-off period

²Inventory risk is a risk that you expose yourself to if you accumulate a large long or short position in stock. The risk is that price moves and you lose a lot of money.
strategy of the manipulator is similar to the strategy of sellers discussed in Chapter 4.

In simulating pump and dump with cyclic trading, the same manipulator who does pump and dump introduces the order pattern generated in cyclic trading. In real stock markets, this manipulator must associate with some other related party to perform the cyclic trading (i.e., perform \([\text{limit sell, market buy}]\) strategy). This is because in most real stock markets traders are not allowed to submit contra side orders (i.e., market/limit) when they have a limit order in the order book. However, when repeating this cyclic trading strategy, the order pattern that one party may generate to perform cyclic trading can still be \([\text{limit sell, market buy}]\).

The \(M^*\) model is initialised with \(\text{price}(0) = 10000, q_b = q_o = 0.5\) and is simulated for \(t_T = 31000\) time steps. All runs commence with 1000 steps to seed the limit order book as per Maslov (2000). As a result, the data are recorded from \(\text{price}(1000) = p(1)\) onwards. \(\Delta\) values of all these traders are drawn from a power law distribution with mean 1.7 and standard deviation 0.8 (i.e., \(\Delta\) takes discrete values between 1 and 4 having the power law exponent 1.5). The selection probabilities of each trader type for trading are set as \(p_L = 0.5\) and \(p_M = 0.5\). In simulating the pump and dump manipulation, the manipulator parameters are set as follows: \(t_S = 0, t_I = t_C = 10000, t_M = 10000, q^I_b = 0.75, q^I_m = 0.75, q^C_b = 0.25,\) and \(q^C_m = 0.75\). This means that the manipulator buys with 0.75 probability for 10000 steps, performs the cyclic trading strategy for 10000 steps, and then sells with 0.75 probability for 10000 steps. In both the ignition and call-off periods, the probability of submitting market orders by this manipulator is 0.75. The profit of the manipulator is computed with respect to the liquidity trader profit and is averaged over 100 simulations.

Cyclic trading makes a pump and dump manipulation possible even without technical traders. This is because, with cyclic trading, a manipulator does not require price momentum or information asymmetry in order to perform a pump and dump. However, a manipulator can perform this cyclic trading strategy only by collaborating with some other party.

We showed previously that when there is no price momentum or no information asymmetry (i.e., no technical traders), a pump and dump manipulation is not possible.

Figure 5.19 illustrates the price behaviour of a pump and dump manipulation without technical traders (i.e., only with liquidity traders) and without using cyclic trading. When a manipulator performs a cyclic trading strategy in the momentum period, however, his profit increases (Figure 5.20). This is because, as shown in Figure 5.21, cyclic trading helps the manipulator to push the price up in the momentum period and
therefore obtain a higher profit margin. Note that cyclic trading is also profitable.

![Graph showing price behaviour](image)

Figure 5.19: Last traded price behaviour of pump and dump manipulation without cyclic trading in the momentum period (Note that the data were plotted with sampling only at every 50\textsuperscript{th} point for clarity)

Although the chance of detection can be high due to the frequent related trader interactions, cyclic trading can be considered a less risky price driving strategy than buying/selling because cyclic trading does not require order accumulation/shorting in order to push the price up/down. A pump and dump manipulator who uses cyclic trading requires some stock at hand to perform this strategy in his momentum period. Moreover, cyclic trading can be more profitable to use in the momentum period rather than waiting for the technical traders to raise the price.

Cyclic trading can also be used to push the price down. Note that the price direction (i.e., up/down) depends mainly on the order pattern used in this strategy (i.e., \[\text{limit sell, market buy}/\text{limit buy, market sell}\] patterns can be used to push the price up/down). Manipulators can use \[\text{limit buy, market sell}\] strategy to push the price down after shorting stocks.

In Chapter 4, it was shown that cyclic trading may alter market attributes such as the Hurst exponent, autocorrelation of price increments, volatility clustering, and distribution properties of bid-ask spreads and price returns. Cyclic trading can add a persistent behaviour to the price signal. Moreover, with cyclic trading, regularities are observed in the autocorrelation of price increments.
5.6.3 Wash sales

A “wash sale” is a sale and a purchase of the same stock or substantially identical stocks at substantially the same time by the same person (SEC, 2012c). A wash sale occurs when a trader sells stocks at a loss within a short period of time before or after buying substantially identical stocks. A wash sale involves no change to the beneficial ownership of the stock. Wash sales can be used by a manipulator to create false activity and generate artificial volumes in order to attract more market participants. Grinblatt and Keloharju (2004) found empirical evidence for using wash sales to avoid taxes by Finnish investors towards end of December. Moreover, wash sales are used to introduce an artificial activity and attract other market participants. The artificial activities generated by manipulators can generate an appearance of a reduced risk of liquidity premium for other investors and influence them to enter the market.
Figure 5.21: Last traded price behaviour of pump and dump manipulation with cyclic trading in the momentum period (Note that the data were plotted with sampling only at every 50\textsuperscript{th} point for clarity)

Wash sales model

A wash sale is implemented via a trader who submits a market buy/sell order immediately after a market sell/buy order more than once and repeats the same steps to create the perception of activity. Here a wash sale involving a single stock is modelled. This is also similar to traders who use a \textit{market buy, market sell} pattern discussed in Chapter 4. As shown in Chapter 4, this strategy alone may not be able to increase or decrease the price; however it can be used to increase the bid-ask spread, number of trades, and volume to show an activity. This is also not a profitable strategy. This may be a short-term strategy only, because repeating this pattern may lead to detection.

Aggarwal and Wu (2006) suggested that a manipulator can engage in a wash sale strategy in order to increase the stock price. The wash sale strategy is similar to the cyclic trading strategy. However, manipulators who are unable to form trading relationships may prefer to use wash sales to show activity. They cannot use a strategy or pattern similar to cyclic trading (i.e., \textit{limit sell, market buy}) by themselves because the chance of being detected is high and also most stock exchanges do not allow traders to submit contra side orders if they have a limit order in the order book. This makes it impossible for the same person to buy or sell his own stock. As a result, a manipulator
has to perform this wash sale strategy with two market orders (or wait some time for the limit order to get executed) and hence the possibility of pushing the price with wash sales strategy alone is low compared with cyclic trading. However, with wash sales, manipulators expect to show some artificially created activity and hence influence other market participants in order to increase the price. Moreover, wash sales manipulators expect to increase the appearance of uncertainty of the market by increasing the bid-ask spread.

The wash sale strategy is not profitable (i.e., average profit of the pattern manipulator who uses \([\text{market buy, market sell}]\) pattern is close to zero (Figure 5.7)). This is because market buy and sell orders cannot assure a buy high and sell low policy due to the bid-ask spread.

5.6.4 Creating a floor and creating a cap

“Creating a floor and creating a cap” involves controlling the share price falling below or rising above a certain level and are considered as suspicious activities in stock markets. Market regulators can also impose this strategy to reduce possible manipulation attempts (Kim and Park, 2010). The first day of trade in Facebook stock in 2012 the underwriter propped up the stock is an example for this scenario. Chen (1993) analysed the effect of using this strategy on price volatility on the Taiwan Stock Exchange. Phylaktis et al. (2002) performed a similar analysis for the Athens Stock Exchange. These strategies could also be extended by manipulators to mislead the chart pattern signals in technical analysis. In this scenario, a manipulator can generate an upper or lower breakout of the price envelope to mislead technical traders who observe trend breaks. In strategies such as pump and dump, creating a floor and creating a cap can be used to support price increase or decrease.

Creating a floor and creating a cap scenarios can be modelled via a trader who pushes the price up or down whenever it reaches a lower or an upper threshold. Figure 5.22 illustrates the price behaviour when a manipulator pushes the price up by buying with a higher probability (0.75) when the price goes below a floor level (i.e., \(p_{\text{floor}} = 10050\)). Manipulator and liquidity trader selection probabilities are 0.2 and 0.8 (respectively) in this simulation.

Creating a floor strategy can be used in a pump and dump simulation with technical trading. In this context, it was shown that a manipulator can use price momentum introduced by the technical traders to profit. The \(M^*\) model is used to simulate an application of creating a floor strategy in performing this pump and dump. Here, if
the price falls below some value \( (p_{\text{floor}}) \) in the momentum period, a pump and dump manipulator uses the floor strategy in order to push the price up to the desired level (i.e., \( p_{\text{floor}} \)). Here the value of \( p_{\text{floor}} \) is defined with respect to the ignition period closing (i.e., last) price. This allows the manipulator to stop the price falling below his desired level in order to avoid unexpected losses. The pump and dump manipulator can maintain the price floor by performing strategies such as buying. In this scenario, creating a floor strategy is used by the pump and dump manipulator to minimise the risk of the price falling in the momentum period.

Figure 5.23 illustrates the profit behaviour of the pump and dump manipulation with/without creating the floor to minimise the risk. In this scenario, if the price has fallen below some value \( (p_{\text{floor}}) \) in the momentum period, a pump and dump manipulator buys again with a higher probability to push the price up to \( p_{\text{floor}} \). Here the value of \( p_{\text{floor}} \) is defined as 50 price ticks from the ignition period closing price. Moreover, the technical trader selection probability \( p_T \) in these simulations is fixed at 0.3.

This profit graph shows that, by using this floor strategy, the manipulator can maintain a consistent price increase in the momentum period and as a result, achieve a greater profit.
Figure 5.23: Average profits of the pump and dump manipulation (averaged over 100 simulation runs) with and without a “creating a floor” to minimise risk. Note that the standard deviations of these manipulator profits are consistently low and hence are not shown in the figure for clarity.

5.6.5 Marking the close

Changes in closing price are considered to be a good performance indicator for a stock (Felixson and Pelli, 1999). “Marking the close” involves using trading strategies including buying and selling stocks at the close of trading with the intention of altering the closing price. The purpose of doing this is to mislead outsiders who are interested in summaries of market activity (Felixson and Pelli, 1999; Hillion and Suominen, 2004). Kucukkocaoglu (2008) analysed the behaviour of the closing day price manipulations in the Istanbul Stock Exchange. Marking the close may take place in an individual trading day (e.g., end of the month or quarter) or may be associated with a series of trading days. This is mainly a long-term strategy. Felixson and Pelli (1999) built a simple regression model to test closing price manipulation in the Finnish stock market. Carhart et al. (2002) and Bernhardt and Davies (2005) showed that this marking the close can be a “painting the tape” strategy. Marking the open is also similar to marking the close.
Marking the close model

The $M^*$ model is extended to include a marking the close scenario. This simple model is used to show the long-term implications of a marking the close strategy on stock prices. A parameter to set the time frame of a conceptual day is introduced to the $M^*$ model (neither the original Maslov nor $M^*$ models has a natural concept of a “day”). This strategy can be simulated without heterogeneous traders discussed in Chapter 4. Marking the close is introduced using 10 conceptual trading days. When simulating multiple days, the previous day closing price is used as the starting price of the current (next) day. At the end of each trading day (i.e., new simulation), the closing price of the simulation is shifted upward by $p_S$ to introduce a long-term price trend. Each trading day is simulated for 100 runs. Price net change (price change with respect to the starting price of the starting day) box plots of these 10 conceptual trading days in Figure 5.24 confirms the long-term trend introduced by this marking the close strategy. However, note the market properties during the day do not change with this strategy.

![Figure 5.24: Net change (i.e., price change of each day with respect to the starting price of the starting day) box plots (combined over 100 simulation runs) of the $M^*$ model when simulated for “marking the close” strategy]

This end of the day price shift can also be simulated using a manipulator who

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3 Of course, in the real world a stock price can “gap up” or “gap down” in the overnight period.
performs manipulative strategies to increase the price at the end of the day. This conceptual day also makes it possible to introduce day orders that expire at the end of the day to show some activity.

A marking the close strategy can be used to raise the price over a long period of time in order to make a profit. A pump and dump manipulator can use this strategy in his momentum period over a long period of time to push the price up and therefore produce a higher profit. This is a less noticeable (i.e., less risk of detection) strategy than cyclic trading. However, marking the close takes a comparatively longer period of time than cyclic trading to make an impact.

Data generated by these marking the close simulations can be used to test software patterns to detect this manipulation scenario.

5.6.6 Orders without execution

Placing a series of orders and cancelling them before execution is termed “orders without execution.” This scenario is also called “layering” or “spoofing” (SEC, 2012b). In this strategy, a manipulator places orders with no intention of having them executed. Later he cancels the order after influencing others into buying or selling at an artificial price driven by his order. This strategy gives a misleading impression that there is high demand or supply for the stock at a particular price point.

According to the SEC, “Traders placed a bona fide order that was intended to be executed on one side of the market (buy or sell). The traders then immediately entered numerous non-bona fide orders on the opposite side of the market for the purpose of attracting interest to the bona fide order and artificially improving or depressing the bid or ask price of the security. The nature of these non-bona fide orders was to induce other traders to execute against the initial, bona fide order. Immediately after the execution against the bona fide order, the overseas traders canceled the open non-bona fide orders, and repeated this strategy on the opposite side of the market to close out the position.” (SEC, 2012b, p.1).

This could be a part of marking the close or painting the tape attempts and could be modelled via a manipulator who performs order cancellations. Orders without execution is characterised using the order cancelling trader introduced in Chapter 4. The intention of modelling this strategy is to analyse how a manipulator can use this strategy to affect market attributes. This model can be used to find the implications of an order cancelling strategy on market properties.

This is not a profitable strategy (Figure 5.6). However, this strategy increases
market properties such as bid-ask spread and price momentum to give a misleading picture to other market participants. The artificial activities generated by this strategy can also generate an appearance of reduced risk of liquidity premium (i.e., increased liquidity). By analogy, people are reluctant to enter a market that is static because they generally prefer to have their opinion validated by the behaviour of other people.

5.6.7 Painting the tape

“Painting the tape” involves carrying out a series of transactions to give a false impression of market activity or price movement to outside parties (Bernhardt and Davies, 2005). Increasing the traded volume on a day and increasing the number of trades on a day are common ways of giving a false impression of activity. A painting the tape manipulator can also vary his order submission strategy (i.e., change the probabilities of submitting limit/market orders and hence change the number of trades) in a period of several days to show activity (i.e., “patient and impatient trading”). “Cyclic trading,” “orders without execution,” and “marking the close” can be considered as painting the tape manipulation attempts. Carhart et al. (2002) and Bernhardt and Davies (2005) showed that “marking the close” can be a painting the tape strategy. This is a long-term strategy.

Several methods of simulating painting the tape in the $M^*$ model are considered. The resulting models can be used to test the implications of a painting the tape manipulation in limit order markets.

Painting the tape manipulators can use their order aggressiveness (i.e., probability of market orders) in generating a series of activities. As a result, the strategies of patient/impatient and pattern traders introduced in Chapter 4 can be described as models of painting the tape.

Normally the painting the tape strategy (i.e., patient/impatient trading) may not be profitable. Patient trading is, however, more profitable than impatient trading (Figures 5.4 and 5.5). Due to waiting costs, however, patient trading (i.e., submitting more limit orders) may be more costly than impatient trading. Painting the tape strategies such as cyclic trading can be profitable (Figure 5.8). Moreover, cyclic trading can be used to push the price up/down (i.e., the price direction depends on the order pattern used in cyclic trading strategy).

A painting the tape manipulator can affect market properties such as the bid-ask spread (i.e., patient trading decreases the bid-ask spread and impatient trading increases the bid-ask spread). Patient trading can also make a market more liquid.
while impatient trading can make a market more illiquid. As a result, painting the tape can be used to provide misleading information to the market.

5.6.8 Insider trading

Insider trading is an information-based manipulation scheme, which involves buying or selling securities of a company by a trader who has access to private knowledge of a company and taking advantage of that private information. This is performed by a stakeholder of a company or a person related to a stakeholder, prior to publishing market sensitive information to the public. Kyle (1985), Benabou and Laroque (1992), and Maug (2002) analysed insider trading in stock markets.

Kyle (1985) modelled an adverse selection problem of an informed party. This informed party uses the best strategy to use his privileged information to maximise his profit. A realistic model of insider trading can be used to analyse how an informed party can profit in stock markets.

A simple model of insider trading is used here to show the profitability of insider trading in a limit order market. The informed trader introduced in Chapter 4 is used to characterise insider trading manipulation. In this context, insider trading is modelled using a trader who can see the possible future worlds of trading and adjusts his buying/selling strategy accordingly.

The prior and the informed trading simulations introduced in Chapter 4 are repeated for 100 time steps. After each informed trading simulation, the profits of this insider trader are compared with the profits of liquidity traders. It is observed that this insider can make a higher profit than liquidity traders. Also, the manipulator profit increases when the length of the time frame that this manipulator can see in the future is increased (Figure 5.25). Here the insider trader and liquidity trader selection probabilities are 0.1 and 0.9 respectively. The main assumption used here was that this insider trader does not affect the future price direction. The main difference between this insider trader and technical traders is that a technical trader uses past patterns to take his decision and this insider trader uses future private knowledge when making decisions. Insider trading is illegal while technical trading is legal. However, both these strategies are shown to be profitable in stock markets.
5.6.9 Cornering

“Cornering” is a technique used to purchase all or most of the purchasable supply of a stock or commodity. In other words, this is a market condition that is intentionally generated when a large percentage of the company stock is held by an individual or group, who could dictate the price when a settlement is called. Jarrow (1992) and Allen et al. (2006) analysed this manipulation scenario. Examples for famous cornering cases are Harlem Railway corner in 1863 and the silver market corner by the Hunt brothers of Texas in 1979-1980.

Cornering is modelled with the heterogeneous trader type “buyers” that are discussed in Chapter 4. Corners (i.e., buyers) make a temporary profit after buying. Moreover, these traders can extend their strategy to some profitable manipulation attempts such as pump and dump and cyclic trading.

5.7 Trade-Based Manipulations that Cannot be Characterised in the $M^*$ Model

Some trade-based manipulation schemes that may not directly impact stock market attributes are “churning” and “front running.” Churning occurs when a brokerage
house trades excessively for a customers portfolio to increase brokerage income despite the customers best interest. Front running is the practice of a stock broker or a related party trading on a security ahead of an order submitted by their client. Stock brokers front run their clients (i.e., take advantage of the knowledge about client orders), when they have information about a client order that is going to come to the market.

These two manipulation scenarios occur at the brokerage level, and their main intentions are not about altering market attributes in order to mislead the other market participants. As a result the chance of outside detection is very low. However, market regulatory organisations detect these manipulations by analysing patterns in data such as orders and trader-broker relationships.

5.8 Summary

In this chapter, stock manipulation was considered in a realistic model of a limit order market. Characterisable trade-based manipulation scenarios were identified and modelled as manipulator types (i.e., external processes) in the $M^*$ model. This is also an approach of characterising stylised manipulators in stock markets. Simple models of manipulation scenarios in the $M^*$ model were presented. The implications of these manipulation models are summarised in Table 5.3. This chapter has shown that the $M^*$ model can be used to represent a range of manipulation models and characterise their profitability. The results support and confirm previous theoretical work and demonstrate the utility of the approach.
### Manipulation Scenario Summary

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Summary</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Pump and dump</strong></td>
<td>Pump and dump manipulation is not possible/profitable if the only other traders are liquidity traders. Rather, manipulators require technical traders to profit. Increasing the percentage of technical trading makes manipulation more profitable. When exploiting the behaviour of technical traders, a manipulator can wait some time after the ignition phase to make a profit. However, if technical traders believe that there is an information asymmetry in the market, the manipulator effort required to perform pump and dump is low and they can even make profits by selling immediately after raising the price.</td>
</tr>
<tr>
<td><strong>Cyclic trading</strong></td>
<td>This itself can be a profitable strategy. A pump and dump manipulator can use cyclic trading to push the price up in the momentum period in order to profit. Cyclic trading involves less inventory risk than pump and dump because it does not require order accumulation. However, cyclic traders may have to put some extra effort to hide their manipulation from market regulators. Modelled as a supportive strategy to pump and dump.</td>
</tr>
<tr>
<td><strong>Wash sales</strong></td>
<td>This is similar to cyclic trading. However, there are limitations in the order types that can be used. Only difference is the pattern of orders used. Not a price driving strategy and not profitable.</td>
</tr>
<tr>
<td><strong>Marking the close</strong></td>
<td>Price driving strategy. A long-term strategy compared with the other strategies. Not profitable. Can be used in pump and dump to raise the price up in the momentum period. Modelled as a supportive strategy to pump and dump.</td>
</tr>
<tr>
<td><strong>Orders without execution</strong></td>
<td>Can be used to show activity and attract other market participants. Not profitable. This can be used in a painting the tape strategy. Can increase the bid-ask spread and mislead the other traders.</td>
</tr>
<tr>
<td><strong>Painting the tape</strong></td>
<td>Not a price driving strategy. Can be used to show activity. Not profitable.</td>
</tr>
<tr>
<td><strong>Creating a cap and Creating a floor.</strong></td>
<td>Price driving strategy. This is used by the manipulator to drive the price and maintain a high/low price level in order to avoid unexpected losses. Modelled as a risk reduction strategy for pump and dump.</td>
</tr>
<tr>
<td><strong>Insider trading</strong></td>
<td>This is a profitable strategy. The profit increases with the degree of private information.</td>
</tr>
<tr>
<td><strong>Cornering</strong></td>
<td>This is a profitable strategy. Can be extended to a profitable strategy such as pump and dump.</td>
</tr>
</tbody>
</table>

Table 5.3: Implications of manipulation models
Chapter 6

A Theoretical Model for Trade-Based Manipulation

6.1 Overview

This chapter considers a pump and dump manipulation using a theoretical model of a limit order market. This theoretical model characterises the price impacts of buy and sell transactions in a market with technical traders and fundamental traders. This model can be simulated analytically as well as computationally. Due to an asymmetry introduced in the technical trader’s behaviour by the behaviour of fundamental traders, it is shown that a trade-based manipulation can be possible and profitable even without price momentum and/or information asymmetry between buy and sell considered by Allen and Gorton (1992). This model isolates the asymmetry introduced by the fundamental trader behaviour and allows a simulation of trade-based manipulation.

6.2 Fundamental vs. Technical Trading

In empirical literature, two types of traders are considered: fundamental traders and technical traders (i.e., chartists) (Beja and Goldman, 1980; Day and Huang, 1990; Alfarano and Lux, 2003; Zeeman, 2007; Lye et al., 2012). Traders who use fundamental values of stocks (i.e., financial statements and forecasts of them) to make their trading decisions are fundamental traders. They buy when the price is low (i.e., when the stock is under valued) and sell when the price is high (i.e., when the stock is over valued). A fundamental traders’ strategy can be a long-term strategy. Fundamental traders aim to push the price to its actual or true value. This is because these type
of traders buy under valued stocks and sell over valued stocks. As a result of these buy and sell actions, the stock price can be pushed up and down respectively towards the true value. Technical traders use various data analysis methods to generate their trading signals using past trends (i.e., typically in prices and volumes). Technical trader strategies are mainly based on the short-term history of the market and can be relative to their current information associated with the current price and the recent trades. Technical traders tend to buy after observing buy transactions and sell after observing sell transactions. Due to this technical trader behaviour there is a higher chance of increasing/decreasing the price after a buy/sell. As a result, technical traders can add momentum to the order flow and therefore prices. Technical traders discussed in Chapter 4 involve a trader behaviour that can add momentum to the price signal.

### 6.3 Possibility of Trade-Based Manipulation with Information Asymmetry

Trading in a way that would give a misleading impression to the market is trade-based manipulation. Hart (1977) and Jarrow (1992) showed that trade-based manipulation is profitable if unstable market equilibriums or non-linear demand functions exist. Allen and Gale (1992) and Allen and Gorton (1992) showed that trade-based manipulation is possible due to information asymmetry in stock markets.

According to Allen and Gorton (1992), buyers are considered to be more informed than sellers. Therefore a buy transaction may contain more information than a sell, and as a result the price movement in response to a purchase is greater than in response to a sale.

Short selling constraints in stock markets make it easier to exploit good news rather than bad news (Diamond and Verrecchia, 1987; Skinner, 1994; Soffer et al., 2000; Hutton et al., 2003; Anilowski et al., 2007; Kothari et al., 2008). This means that driving the price down is more difficult than driving the price up. This asymmetry allows a manipulator to buy repeatedly, thus increasing the price and then sell with less overall effect on the market.

The asymmetry introduced by Allen and Gorton (1992) considered the fact that a buyer is more informed than a seller. However, in the Allen and Gorton (1992) model, the degree of information in buying when the price is high or low is not considered. This also makes for path-independent price behaviour (i.e., order sequence is not important or \([\text{buy, buy, sell, sell}] = [\text{buy, sell, buy, sell}]\)) in the Allen and Gorton (1992) model.
Allen and Gale (1992) discussed another form of asymmetry that can make pump and dump possible. Investors always have the problem of distinguishing informed traders from manipulators. This asymmetry leads to a manipulator being able to pretend to be informed and mislead the market.

In Chapter 5, via a realistic simulation, it was shown that pump and dump manipulation is possible due to the price momentum introduced by technical traders. Manipulators push the price up and wait some time (i.e., momentum period) to let the price go further up and then sell to profit. Moreover, if these technical traders believe in an information asymmetry (i.e., buy contains more information than a sell) profitable manipulation is possible even without the momentum period (i.e., manipulator can profit by selling stocks followed by buying). It was also shown that increasing the percentage of technical trading can increase the manipulator profit. In this context, the manipulator pretends to be informed and misleads the technical trader to profit.

The technical traders used to simulate manipulation in Chapter 5 used past information to predict the future price direction. As a result these traders introduce a momentum carrying technical trader behaviour. They are also capable of introducing information asymmetry between buy and sell using their Bayesian belief model. Fundamental trader behaviour is not considered for the manipulation simulation in Chapter 5. In this chapter, a theoretical model is presented to characterise a technical trader behaviour that is influenced due to an asymmetry in fundamental strategy. Using this model, the profitability of trade-based manipulation is analysed in a market with this asymmetry introduced by the combination of technical and fundamental traders. This model is a novel contribution since the possibility of trade-based manipulation has not been considered with this type of asymmetric behaviour.

6.3.1 Information asymmetries in financial markets

Not all market related information is known to every market participant and this is referred to as information asymmetry or uncertainty. Kyle (1985), Allen and Gale (1992), Allen and Gorton (1992), Chan and Lakonishok (1993), Keim and Madhavan (1995), and Keim and Madhavan (1997) considered the implications of asymmetric information in stock markets. Asymmetric information can occur in a financial market due to either adverse selection, moral hazard, or monitoring cost (Bebczuk, 2003). Refer to Appendix B for more information on information asymmetries in stock markets.
6.4 The Limit Order Market Model

In this model, the effects of buy and sell orders (limit and market) on a limit order book in the presence of both technical and fundamental traders is defined (i.e., price responses (impacts) on best bid and ask prices due to buy and sell transactions). It is assumed that due to the behaviour of technical traders, a buy/sell transaction increases/decreases both the bid and ask price of an order book. This is because technical traders react to the information in past trading. Here the price responses due to a buy/sell transaction can be considered as positive/negative. This is because the information in buy/sell transactions are inferred by the technical traders as the possibilities that the price will go up/down in the future and their reactions push the price up/down. In this model, it is assumed that the amount of information to be extracted (i.e., the size of the price response) by the technical traders may be influenced by the fundamental trader behaviour (i.e., fundamental traders buy when the price is low and sell when the price is high). This means that, due to the presence of fundamental traders, observing a buy transaction when the price is low may have less information than observing a buy transaction when the price is high. This is also true for selling. As a result of the behaviour of fundamental traders, the price responses by technical traders with respect to these buy and sell transactions may also depend on the stock price. Note that traders determine the price low or high based on their perceived true value of the stock.

In simulating trader behaviour, a dynamic order book (i.e., bid and ask prices) that responds to the incoming buy and sell orders is modelled. In this order book, the bid and ask prices are increased/decreased after a buy/sell order. The price increase/decrease after a buy/sell order is termed buy/sell price responses (defined by \( \delta_{B_t} \) and \( \delta_{S_t} \)).

These price responses are computed for real data on the NYSE for a period of three months.\(^1\) Figures 6.1, 6.2, 6.3, and 6.4 confirm that the buy price response (i.e., \( \delta_{B_t} = A_{t+1} - A_t \), where \( A_t \) denotes the ask price when the buy order is submitted) is more positive and the sell price response (i.e., \( \delta_{S_t} = A_{t+1} - A_t \), where \( A_t \) denotes the ask price when the sell order is submitted) is more negative for GE and BA (General Electric and Boeing Company). Zero price responses in these figures are not considered.

\(^1\)In this study, the TORQ database made available by the New York Stock Exchange (NYSE) is used. This dataset covers all the transaction information of 144 firms listed in NYSE for a three-month period during 1990-91. Lee and Radhakrishna (2000) and Jackson (2007) used the same dataset for their studies.
for clarity. It is also observed that the number of times that the price has changed due to buy transactions is higher than the number of times that the price has changed due to sell transactions (Note that the considered number of buy and sell transactions are similar in this context). This empirically confirms the information asymmetry between buy and sell transactions. In this context, although the buy/sell transactions may also result in negative/positive price responses, a first order approximation is used; a buy/sell transaction can only have a positive/negative price response. This first order approximation does not affect the overall behaviour of the model because this work is only interested in characterising an asymmetry in these buy and sell price responses. Glosten and Milgrom (1985), Kyle (1985), and Allen and Gorton (1992) also used this approximation in their models.

![Figure 6.1: Ask price changes with respect to buy orders ($\delta_{B_t} = A_{t+1} - A_t$) for GE (General Electric Company) traded on the NYSE, where $A_t$ denotes the ask price when the buy order is submitted](image)

Technical traders in this model believe that the starting price represents the true value of the stock. This true value is assumed to be a constant during a simulation run. For simplicity, it is considered that both limit and market orders have the same effect on prices. Moreover, the price responses due to buy and sell on both bid and ask prices are the same and hence the bid-ask spread ($S$) is constant.

The price responses by technical traders with respect to buy and sell transactions ($\delta_{B_t}$ and $\delta_{S_t}$) depend on the stock price. The base (and starting) buy and sell responses
Figure 6.2: Ask price changes with respect to sell orders ($\delta_{S_t} = A_{t+1} - A_t$) for GE (General Electric Company) traded on the NYSE, where $A_t$ denotes the ask prices when the sell order is submitted.

Figure 6.3: Ask price changes with respect to buy orders ($\delta_{B_t} = A_{t+1} - A_t$) for BA (The Boeing Company) traded on the NYSE, where $A_t$ denotes the ask price when the buy order is submitted.
Figure 6.4: Ask price changes with respect to sell orders \( \delta S_t = A_{t+1} - A_t \) for BA (The Boeing Company) traded on the NYSE, where \( A_t \) denotes the ask prices when the sell order is submitted

at \( t = 0 \) are defined with respect to the starting ask price (i.e., \( A_0 \)). Note that the price responses on both bid and ask prices are assumed to be the same. When the current price is equal to the starting price (i.e., true price perceived by technical traders), ask price change with respect to a buy transaction (i.e., the base buy response) is defined by \( \delta B_0 \). When the current price is equal to the starting price (i.e., true price perceived by technical traders), ask price change with respect to a sell transaction (i.e., the base sell response) is defined by \( \delta S_0 \). This means when the price is \( A_0 \), buy and sell responses are \( \delta B_0 \) and \( \delta S_0 \), respectively.

The values for \( \delta B_0 \), \( \delta S_0 \), and \( A_0 \) are initialised before commencing the simulation. It is assumed that the information content associated with buy and sell transactions depend on \( \delta B_0 \) and \( \delta S_0 \). As a result, \( \delta B_0 \) and \( \delta S_0 \) can be used to introduce an information asymmetry between buy and sell transactions. For example, if \( \delta B_0 > \delta S_0 \), the buy price responses are greater than the sell price responses. In Chapter 5, this information asymmetry was introduced using the parameter of assumed probability of liquidity buying (i.e., \( \mu_2 \)) in the technical trader belief model.

It is also assumed that although price responses due to buy and sell actions depend on the stock price, the proportional price changes of the price \( A_t \) with respect to these buy and sell actions (defined by \( \theta_B \) and \( \theta_S \), respectively) are constant. Under this con-
stant assumption, buy and sell proportional price changes are computed with respect to the base buy and sell response values using the starting ask price $A_0$ (Equations (6.1) and (6.2)).

\[ \theta_B = \frac{\delta_{B_0}}{A_0} \]  \hspace{1cm} (6.1)

\[ \theta_S = \delta_{S_0} * A_0 \]  \hspace{1cm} (6.2)

Assuming $\theta_B$ and $\theta_S$ as constants is also a first order approximation since the corresponding real data values computed for $\theta_{B_t}$ and $\theta_{S_t}$ (proportional changes for buy and sell orders, respectively) are not constants (Figures 6.5, and 6.6 show the $\theta_{B_t}$ and $\theta_{S_t}$ distributions of the stock BA computed for a 3 months period during 1990-91 on the NYSE). Although the corresponding real proportional price changes are not constants, an asymmetry can be observed between these positive and negative values. In this context, only the effect of this asymmetry is considered and hence the approximation of a constant value (i.e., $\theta_B$ and $\theta_S$).

Using the proportional price changes defined in Equations (6.1) and (6.2), the buy and sell responses at time $t$ (i.e., $\delta_{B_t}$ and $\delta_{S_t}$) are defined (Equations (6.3) and (6.4)). In these buy and sell responses, when the ask price is $A_0$ (i.e., the perceived true value by the technical traders) buy and sell responses are $\delta_{B_0}$ and $\delta_{S_0}$. In addition, when the price is high or low, a buy response is high or low, respectively. Similarly, a sell response is low or high (respectively).

\[ \delta_{B_t} = A_{t+1} - A_t = \theta_B * A_t \]  \hspace{1cm} (6.3)

\[ \delta_{S_t} = A_{t+1} - A_t = \frac{\theta_S}{A_t} \]  \hspace{1cm} (6.4)

Using the defined buy and sell proportional changes (Equations (6.1) and (6.2)), the new ask price after a buy and sell transaction can be derived as functions of the current ask price $A_t$. The formulas to compute the new ask price are given in Equations (6.5), and (6.6). Note that the buy and sell price responses are assumed to be positive and negative, respectively.
Figure 6.5: Proportional ask price changes with respect to buy orders \((\theta_B = \delta_B/A_t)\) for the stock BA (The Boeing Company) traded on the NYSE, where \(A_t\) denotes the ask price when the buy order is submitted

\[ A_{t+1} = A_t(1 + \theta_B) \]  \hspace{1cm} (6.5)

\[ A_{t+1} = A_t - \frac{\theta_S}{A_t} \] \hspace{1cm} (6.6)

Note, that the bid-ask spread \((S)\) is assumed to be a constant. So, the new bid is given by Equation (6.7).

\[ B_{t+1} = A_{t+1} - S \]  \hspace{1cm} (6.7)

When the price is high, the presented model characterises that a buy transaction contains more information than a sell transaction (i.e., pushes the price more and hence the price response is higher) and vice versa. When the price is low, however, a sell transaction contains more information (i.e., pushes the price more and hence the price
response is higher) and vice versa. This type of scenario can occur in stock markets due to the presence of technical trader and fundamental trader behaviour. Note that the price being high or low is defined here with respect to the starting price of the simulation. Moreover, information asymmetry between buy and sell can be introduced by setting base price responses $\delta_{B_0} > \delta_{S_0}$.

The last traded price of this order book is denoted as $p_t$. After a buy or sell transaction at time $t$, $A_t$ or $B_t$ becomes the last traded price at time $t$, respectively and the next ask (i.e., $A_{t+1}$) and the bid (i.e., $B_{t+1}$) prices are computed.

The model is initialised with parameter values $A_0 = 1000$, $B_0 = 998$, and $\delta_{B_0} = \delta_{S_0} = 1$. This means that the bid-ask spread is given by $S = 2$ and the information content of buy and sell transactions are equal (i.e., no information asymmetry). Using these initial values $\theta_B$ and $\theta_S$ are computed. After observing a buy or sell action at time $t$, Equation (6.5) or (6.6) is used (respectively) to compute the new ask price at time $t + 1$.

Various stock trading strategies are considered in this model to analyse price behaviour and profitability in a technical trader and fundamental trader environment.

### 6.5 Simulating Heterogeneous Trading Strategies

The model behaviour for the following trading strategies will now be considered: \{buy, sell, buy, sell, buy, sell\} and \{buy, buy, buy, sell, sell, sell\}.

Figures 6.7 and 6.8 illustrate the generated price behaviour ($p_t$) for these two trading strategies. The closing prices of these two strategies indicate that the \{buy, sell, buy, sell, buy, sell\} and \{buy, buy, buy, sell, sell, sell\} have two different impacts on the stock price. In the Glosten and Milgrom (1985) model, however, these two strategies result in the same closing prices. This means the price behaviour in the Glosten and Milgrom (1985) model is path independent. Moreover, the information asymmetry introduced by Allen and Gorton (1992)$^2$ considered the fact that a buyer is more informed than a seller. In the Allen and Gorton (1992) model the degree of information in buying when the price is high or low, however, is not considered. This also results in path independent price behaviour in the Allen and Gorton (1992) model. However, the trading strategies simulated in the presented model show path dependent (i.e., the order of buy and sell actions in the strategy is important or \{buy, buy, sell, sell\}

\footnote{Allen and Gorton (1992) extended the Glosten and Milgrom (1985) model and showed that manipulation is possible due to the natural asymmetry between liquidity purchases and liquidity sales.}
≠ \{buy, sell, buy, sell\}) characteristics and are therefore more realistic (i.e., in real markets, performing a series of sells followed by the same number of buys is different from performing a repeating pattern of buy and sell due to information asymmetry). Note that the price high or low here is defined with respect to the starting price (i.e., assumed true or actual value) of the simulation and this true value is assumed to be static during the simulation.

Figure 6.7: Price behaviour for the \{buy, sell, buy, sell, buy, sell\} strategy

Figure 6.8: Price behaviour for the \{buy, buy, buy, sell, sell, sell\} strategy

Price behaviour for a randomly generated trading strategy (i.e., randomly generated buy and sell actions) is illustrated in Figure 6.9. The Hurst exponent \(H\) of this price graph averaged over 100 simulation runs is 0.5. This indicates that a simulated price graph of this model shows random walk (i.e., efficient market) characteristics. In an “efficient market,” price is an unbiased estimate of the true or actual value (i.e., “price is right” hypothesis) and stock prices show random walk characteristics (i.e., \(H = 0.5\)). However, real markets are not efficient and show persistent characteristics with Hurst exponent \(H \approx 0.6 - 0.7\) (Maslov, 2000; Alvarez-Ramirez et al., 2008).

\[3\]In general, however, market efficiency need not imply random walk behaviour. The presence of taxes, transaction costs, and risk aversion mean that contrary to Samuelson (1965), price need not behave as random walks in efficient markets (Crack and Ledoit, 2010).
6.5.1 Profitability of heterogeneous trading

A number of heterogeneous trading strategies are presented in Table 6.1. Trader profits\(^4\) for short-term strategies are negative here due to the positive bid-ask spread. Trader profits for the long-term strategies such as \{buy\}\(^{100}\}\{sell\}^{100}\) (i.e., 100 buys followed by 100 sells) and \{buy, sell\}\(^{100}\) (i.e., repeating buy and sell actions 100 times) are given in Table 6.1. These results indicate that the most profitable strategy is to sell after buying all the stocks.

<table>
<thead>
<tr>
<th>Strategy</th>
<th>Profit</th>
</tr>
</thead>
<tbody>
<tr>
<td>buy, sell, buy, sell</td>
<td>-2</td>
</tr>
<tr>
<td>buy, buy, sell, sell</td>
<td>-1.99</td>
</tr>
<tr>
<td>buy, sell, buy, sell, buy, sell</td>
<td>-3</td>
</tr>
<tr>
<td>buy, buy, sell, sell, buy, sell</td>
<td>-2.99</td>
</tr>
<tr>
<td>buy, sell, sell, sell, sell  ( {buy}^{100}{sell}^{100} )</td>
<td>47.25</td>
</tr>
<tr>
<td>buy, sell  ( {buy, sell}^{100} )</td>
<td>-45.65</td>
</tr>
</tbody>
</table>

Table 6.1: Profitability of different trading strategies in the theoretical manipulation model

The average profit of a trader who uses a random buy and sell strategy (1000

\(^4\)Profit of market participants is defined as the difference between the starting and ending wealth. All these traders are assumed to have initial stocks and money. The final profit of a trader is computed as the difference between initial and final wealth. In computing wealth, the stocks at hand are liquidated with respect to the last traded price at the designated time when wealth is calculated.
buy/sell orders) in this model is -4602 and standard deviation is 31858.\textsuperscript{5} This means that a liquidity trader cannot make a profit by trading with traders who uses a technical trader strategy.

### 6.6 Manipulation Model

A pump and dump manipulation is considered in this theoretical model of a limit order book.

A pump and dump scenario is characterised with \( n_B \) transactions with more buy orders (i.e., buy orders with probability 0.75) followed by the same number of transactions with more sell orders (i.e., sell orders with probability 0.75). The momentum period is characterised with a price jump of \( p_M \) in between these buying (i.e., ignition) and selling (i.e., call-off) phases. The model behaviour in this pump and dump simulation is depicted in Figure 6.10. The trader profits of pump and dump simulations are averaged over 100 independent runs.

![Figure 6.10: A graphical illustration of a pump and dump manipulation in the theoretical model](image)

Table 6.2 summarises the average profits of this pump and dump manipulation for different parameter combinations of \( \delta_{B0} \), \( \delta_{S0} \), and \( p_M \) averaged over 100 independent runs. Here information asymmetry is considered using \( \delta_{B0} \) and \( \delta_{S0} \) (i.e., if a buy

\textsuperscript{5}The standard deviation of profits are very high due to the high starting price used in the simulations.
contains more information than a sale, $\delta_{B_0} > \delta_{S_0}$). The momentum period price jump is introduced using $p_M$. The manipulator performs 500 buy transactions followed by 500 sell transactions (i.e., $n_B = 500$).

<table>
<thead>
<tr>
<th>Simulation</th>
<th>Profit</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\delta_{B_0}$</td>
<td>$\delta_{S_0}$</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>0.9</td>
</tr>
<tr>
<td>1</td>
<td>0.75</td>
</tr>
</tbody>
</table>

Table 6.2: A summary of pump and dump manipulation profits (averaged over 100 independent runs) in the theoretical manipulation model. Note that the standard deviation of profits is very high due to the high starting price used in simulations

Table 6.2 summarises the pump and dump manipulation profits. It is observed that even without a momentum period (i.e., $p_M = 0$) and with no information asymmetry (i.e., $\delta_{B_0} = \delta_{S_0}$), the pump and dump manipulation is profitable. Moreover, with either a momentum period or if there is information asymmetry, pump and dump manipulation is even more profitable.

Figure 6.11 illustrates the price behaviour of this pump and dump simulation when the momentum period price jump (i.e., $p_M$) is zero and when no information asymmetry is considered between buy and sell. This price graph indicates that the price of the selling phase of the manipulation decreases at a slower rate than the price decrease in the buying phase. This is because, due to the role of fundamental traders and the technical trader beliefs (i.e., behaviour) of this model, selling when the price is high may have a lower impact on the price than selling when the price is low. Due to this lower price impact in the selling phase, a manipulator can buy low and sell high to perform a profitable trade-based manipulation. These results indicate that due to an asymmetry in the price reactions of the technical traders introduced by a fundamental trader strategy, a pump and dump manipulator can profitably manipulate the market even without price momentum and/or an information asymmetry between buy and sell considered by Allen and Gorton (1992). The asymmetry caused by this fundamental trader behaviour (i.e., information in buying or selling when the price is low or high is different) has not been considered in relation to stock manipulation in literature.

The price behaviour of this pump and dump simulation with a momentum period (i.e., $p_M = 100$) is shown in Figure 6.12. When $p_M > 0$, due to this momentum
period price jump, the manipulator is able to sell his stocks at a much higher price than his buying price and make an increased profit. The profit results in Table 6.2 show that this momentum period can increase the manipulator profit. Information asymmetry between buy and sell (i.e., $\delta_{B_0} > \delta_{S_0}$) also helps profitable manipulation due to the asymmetry in price responses. In this scenario, the price of the selling phase decreases at a slower rate in Figure 6.13 compared with the selling phase price decrease in Figure 6.11. As a result, information asymmetry between buy and sell allows the manipulator to maximise his profits (Table 6.2). These results confirm the Chapter 5 results on the profitability of a pump and dump simulation.

![Figure 6.11: Pump and dump price behaviour without momentum period (i.e., $p_M = 0$)](image1)

![Figure 6.12: Pump and dump price behaviour with momentum period (i.e., $p_M = 100$)](image2)

### 6.7 Summary

This chapter presented a theoretical model of a limit order book. This model introduces an order book with a technical trader behaviour who believes there are fundamental traders. A simple simulation to characterise a “pump and dump” manipulation in this theoretical model was analysed. Based on the results it was shown that due to an information asymmetry introduced by the fundamental traders on technical trader behaviour (i.e., information in buying or selling when the price is low or high is different), a pump and dump manipulation is profitable even without price momentum or
information asymmetry between buy and sell considered by Allen and Gorton (1992). The asymmetry caused by this fundamental trader behaviour has not been previously considered in relation to stock manipulation in the literature. Moreover, using the properties of this pump and dump theoretical model, it was confirmed that a pump and dump manipulation is possible either due to price momentum or an information asymmetry between buy and sell. This study can be considered the first to present an asymmetry introduced by fundamental traders (i.e., information in buying or selling when the price is low or high is different) in relation to manipulation.
Chapter 7

Simulating Price Manipulation in Liquid/Illiquid Stocks

7.1 Overview

The manipulation framework presented in the previous chapter provides a means to test market manipulation theories and hypotheses. In this chapter, an application of the pump and dump manipulation model is used to test stock manipulation related hypotheses.

Models of stock manipulation are used to answer three questions: Can a liquid or illiquid stock be more easily manipulated? Is a manipulator strategy more profitable in a liquid or an illiquid stock? Can manipulation be more easily detected in liquid or illiquid stocks?

7.2 Manipulation in Liquid and Illiquid Markets

Liquidity refers to the ability of a trader to buy or sell an asset easily and immediately (O’Hara, 2004). The role of liquidity traders is to provide liquidity to a stock (Glosten and Milgrom, 1985; Allen and Gorton, 1992). An asset is liquid if there are ready sellers and buyers (i.e., liquidity traders) at all times. As a result, an order book in a liquid stock always contains positive buy and sell depths.

An order book of a very liquid stock is illustrated in Table 7.1 and an order book of a very illiquid stock is illustrated in Table 7.2. Both came from the New Zealand Stock Exchange. These order books indicate that a trader can buy and sell any amount of stocks immediately in Fisher & Paykel, however buying and selling of stocks in GFNZ
Group Limited is difficult.

<table>
<thead>
<tr>
<th>Buyers</th>
<th>Buy Quantity</th>
<th>Prices</th>
<th>Prices</th>
<th>Sell Quantity</th>
<th>Sellers</th>
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<td>103</td>
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</tbody>
</table>

Table 7.1: Order book of Fisher & Paykel Appliances Holdings Limited Ordinary Shares (FPA-NZX) as at 14:41:20, Wednesday 12 September, 2012 (NZT). (+u - Limit orders can be placed onto the market with an undisclosed quantity. The undisclosed quantity of the order must be value equal to or greater than $100,000.)

<table>
<thead>
<tr>
<th>Buyers</th>
<th>Buy Quantity</th>
<th>Prices</th>
<th>Prices</th>
<th>Sell Quantity</th>
<th>Sellers</th>
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<td></td>
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<td>324,870</td>
<td></td>
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<td></td>
<td>464,500</td>
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<td>2</td>
</tr>
</tbody>
</table>

Table 7.2: Order book of GFNZ Group Limited Ordinary Shares (GFL-NZX) as at 01:35:07, Friday 28 September, 2012 (NZT)

Illiquid markets are inefficient\(^1\) and have less regulatory requirements\(^2\) for traders (Aggarwal and Wu, 2006). “There are much lower disclosure requirements for firms listed on these markets, and they are subject to much less stringent securities regulations and rules” (Aggarwal and Wu, 2006, p.1917).

It has been suggested that a less liquid and less volatile (i.e., the variation of price over time is less) stock is more likely to be manipulated, largely because most of stock manipulation cases are recorded in illiquid stocks (Aggarwal and Wu, 2006). If this is

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\(^1\)In an “efficient market,” price is an unbiased estimate of the true or actual value (i.e., “price is right” hypothesis) (Timmermann, 1993; Malkiel, 2003).

\(^2\)In maintaining market integrity, surveillance departments in stock markets (i.e., self regulatory organisations) and Securities and Exchange Commission (i.e., SEC) in the U.S. impose trading rules and regulations for their market participants.
wrong, “one would have to argue that a manipulator who manipulates a more liquid or more volatile stock is more likely to be caught than one who manipulates less liquid and less volatile stocks” (Aggarwal and Wu, 2006, p.1917). According to Aggarwal and Wu (2006), this is implausible because market activity is higher in more liquid stocks and as a result, in a more liquid stock, a manipulator can easily hide his activities among the trades of other market participants.

Jiang et al. (2005) studied “stock pools” and concluded that “unlike the small and illiquid stocks studied by Aggarwal and Wu (2004), the average pool stock is of comparable size and is more liquid than other companies in its industry” (Jiang et al., 2005, p.168). Maug (2002) also showed that informed trading is more profitable in highly liquid stocks. Maug (2002) assumed this was because more liquid stocks provide more opportunities to camouflage informed trades.

Based on previous research, it is difficult to determine under what conditions a liquid/illiquid stock is easy to be manipulated. In this chapter, the following questions will be addressed: Can a liquid or illiquid stock be more easily manipulated? Is a manipulator strategy more profitable in a liquid or an illiquid stock? Can manipulators be more easily detected in liquid or illiquid stocks?

The supply of liquidity to the $M^*$ model is controlled in order to simulate liquid and illiquid stocks. Properties of these liquid and illiquid stocks including trader returns and the capacity for price driving are analysed. Then a pump and dump manipulation is simulated in these liquid and illiquid stocks. A pump and dump manipulation strategy is considered with attributes such as manipulator aggressiveness, profitability, and detectability in liquid and illiquid stocks.

7.3 Simulating Liquid and Illiquid Stocks

Liquid and illiquid stocks are simulated in the $M^*$ model. These liquid and illiquid stock simulations include liquidity and technical traders. Liquidity and technical traders are selected for trading with probabilities $p_L$ and $p_T$, respectively. In liquid stocks, the order book does not empty while trading. In illiquid stocks, however, the order book (or one side of it) may occasionally become empty during trading. Therefore, order book depth (i.e., limit orders in the order book) in the $M^*$ model is controlled in order to change the liquid or illiquid behaviour of the stock. A highly liquid stock is referred

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3Stock pools are manipulative attempts, “through which groups of investors actively traded in a specified stock” (Jiang et al., 2005, p.148).
to here as a liquid stock and a highly illiquid stock is referred as an illiquid stock. The liquidity of the stock is decreased from a liquid stock to an illiquid stock. The range of these simulated liquid and illiquid stocks are referred to as “liquid/illiquid stocks” hereafter.

The $M^*$ model is initialised with $\text{price}(0) = 10000$ and is run for 11000 time steps. All runs commence with 1000 steps to seed the limit order book as per Maslov (2000). As a result, the data are recorded from $\text{price}(1000) = p(1)$ onwards. Arrival probabilities for liquidity and technical traders are set as $p_L = p_T = 0.5$. Two methods are considered to simulate liquid/illiquid stocks. In liquid/illiquid stock simulations, the order book is seeded with 25000 steps prior to the simulation (i.e., initial seeding period).

In the first method, the book depth of the simulation is controlled by changing the probability of submitting market orders in the initial seeding period $q^{\text{Seed}}_{\text{mo}}$ (termed as “initial seeding method”) (Figure 7.1). As a result, the liquidity of the stock is controlled. In this method, a simulation with higher probability of submitting market orders in the seeding period (i.e., causing lower book depths) is an illiquid stock, and a simulation with lower probability of submitting market orders in the seeding period (i.e., causing higher book depths) is a liquid stock. Hence the liquidity behaviour of the stock decreases with an increase of this seeding period market order probability $q^{\text{Seed}}_{\text{mo}}$ from 0 to 1.

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{figure7.1}
\caption{The liquid/illiquid model in the initial seeding method}
\end{figure}

Figures 7.2 and 7.3 show the mean buy and sell side empty occurrences$^4$ averaged over 100 simulation runs for market order probabilities (i.e., $q^{\text{Seed}}_{\text{mo}}$) ranging from 0 to 1 in the initial seeding period. The order book in these liquid/illiquid stocks does not empty until the market order probability $\approx 0.45$. However, after the order book starts

\footnotesize
$^4$Buy and sell side empty occurrences refer to the number of times that buy and sell sides were empty during a simulation run.

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to empty, the mean buy and sell empty occurrence values show a similar behaviour irrespective of the market order probability $q_{m_{m_0}}^{Seed}$. This indicates that the simulation shows a highly liquid characteristic until the initially loaded limit orders are sufficient to be consumed during simulations. Moreover, when these initially loaded limit orders are not sufficient, liquidity and technical traders become the main source of liquidity. As a result, the liquidity of the stocks remain unchanged.

![Figure 7.2: Mean buy side empty occurrences (averaged over 100 simulations) of liquid/illiquid stocks in the initial seeding method (i.e., with $q_{m_0}^{Seed}$). Note that the standard deviations are consistently low and hence are not shown in the figure for clarity. Note that higher $q_{m_0}^{Seed}$ corresponds to lower liquidity.](image)

![Figure 7.3: Mean sell side empty occurrences (averaged over 100 simulations) of liquid/illiquid stocks in the initial seeding method (i.e., with $q_{m_0}^{Seed}$). Note that the standard deviations are consistently low and hence are not shown in the figure for clarity. Note that higher $q_{m_0}^{Seed}$ corresponds to lower liquidity.](image)

Based on these results, filling the order book initially in order to control the liquidity of the stock is not entirely successful. This is due to the nature of the $M^*$ model, since buy and sell order book depths cannot be controlled (i.e., from liquid to illiquid) over the range of probability $q_{m_0}^{Seed}$ from 0 to 1. This initial seeding method is, however, successful in simulating extremely liquid (i.e., $q_{m_0}^{Seed} < 0.45$) and comparatively illiquid (i.e., $q_{m_0}^{Seed} > 0.55$) stocks.
In the second method, the probability for submitting market orders by liquidity traders \( q_{mo} \) (i.e., aggressiveness of the liquidity traders) is used to control the order book depth and hence the liquidity of the stock. This method is termed the “liquidity trading” method (Figure 7.4). The liquidity trading method is used because liquidity traders are considered as the main liquidity suppliers in a market. These liquidity traders can change their supply of liquidity to change the order book depths. A simulation with a lower probability of submitting market orders by liquidity traders (i.e., a stock with less aggressive liquidity traders) is considered as a liquid stock (i.e., \( q_{mo} = 0 \) is the most liquid stock) and a simulation with higher probability of submitting market orders by liquidity traders (i.e., a stock with more aggressive liquidity traders) is considered as an illiquid stock (i.e., \( q_{mo} = 1 \) is the most illiquid stock). The liquidity of the stock decreases when \( q_{mo} \) is increased from 0 to 1.

![Market liquidity increases](image)

<table>
<thead>
<tr>
<th>Highly liquid market ( q_{mo} = 0 )</th>
<th>Highly illiquid market ( q_{mo} = 1 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Probability of submitting market orders by liquidity traders = ( q_{mo} )</td>
<td></td>
</tr>
</tbody>
</table>

Figure 7.4: The liquid/illiquid model in the liquidity trading method

Figures 7.5 and 7.6 illustrate the mean buy and sell order book empty occurrences averaged over 100 simulations for selected \( q_{mo} \) values ranging from 0 to 1. These two buy and sell book empty graphs indicate that in more liquid stocks, the order book does not empty, while in less liquid stocks, the order book may empty during trading. The liquid to illiquid transition with probability \( q_{mo} \) in simulated markets (in this liquidity trading method) is gradual and hence is more useful when compared with the same transition (with \( q_{Seed}^{Seed} \)) in the initial seeding method (i.e., Figures 7.2 and 7.3).

Based on these results when simulating a range of markets from liquid to illiquid, the liquidity trading method has a smooth transition of behaviour and therefore performs better compared with the initial seeding method.

Bid and ask order book depth behaviour (i.e., histogram mid values vs. counts) of these liquid/illiquid stocks (i.e., with the probability of submitting market orders by liquidity traders \( q_{mo} \)) is shown in Figures 7.7 and 7.8. Bid and ask order book depths are recorded during simulations and combined over 100 runs to draw these
histograms. These graphs show that the order book depths reduce with market order probability \( q_{mo} \). However, the standard deviation of price net changes increases and then decreases with \( q_{mo} \) (Figure 7.9). Here, the standard deviation is increased due to higher price fluctuations caused by the lower order book depths. Moreover, a decrease in the standard deviation is observed due to fewer number of trades in an illiquid market. Also, with a very high probability of submitting market orders (i.e., \( q_{mo} \approx 1 \)), the order book empties more often and the subsequent market orders may get converted to limit orders.\(^5\) This market to limit order conversion causes smaller price net changes than expected. This price net change graph also indicates that the \( M^* \) model is very sensitive to the probability of submitting market orders (\( q_{mo} \)). This means that, even

\(^5\)If the order book is empty, traders can only submit limit orders in the \( M^* \) model.
with very small change in probability (i.e., \( \Delta q_{mo} \approx 0.01 \)), there is an observable change in the behaviour of price net change. These net change and book depth graphs also indicate that the \( M^* \) model shows very strong liquid and illiquid characteristics when the probability of submitting market orders by liquidity traders \( q_{mo} \) is 0.45 and 0.55, respectively. Figure 7.10 shows single run price graphs for simulated liquid/illiquid stocks. The liquid stock shown in the Figure 7.10 is simulated for \( q_{mo} = 0.45 \) and the illiquid stock is simulated for \( q_{mo} = 0.55 \). The box plot distributions of relative bid-ask spread distributions in liquid/illiquid stocks (i.e., with probability of submitting market orders by liquidity traders \( q_{mo} \)) is illustrated in Figure 7.11. This graph indicates that the relative bid-ask spreads are greater in illiquid stocks than in liquid stocks.

Liquid stocks show higher bid and ask depths and consequently, a trader can immediately buy or sell stocks (i.e., submit market orders) in liquid stocks. Price behaviour in simulated liquid stocks is less volatile (i.e., standard deviation of price net changes are small) than the price behaviour in illiquid stocks. Price and price net change graphs
in liquid and illiquid stocks indicate that the price variation due to trading in liquid stocks is low compared with the price variation in illiquid stocks. This means that in liquid stocks, traders can buy and sell without having a large price impact. This is because, in liquid stocks, there are sufficient limit orders at the top of the order book to match the incoming orders without moving the prices. Moreover, in liquid stocks, liquidity providers constantly supply liquidity that supports the price to be bounced back to its original position. Liquid stocks also show tight relative bid-ask spreads compared with illiquid stocks.

7.4 Price Driving in Liquid and Illiquid Stocks

Moving the price by manipulative strategies in liquid and illiquid stocks is now considered. Price driving is simulated in liquid/illiquid stocks by introducing a manipulator who drives the price up by introducing more market and buy orders (i.e., buyers introduced in Chapter 4). Here, the manipulator buys with a probability $q^P_D$ and submits market orders with a probability $q^P_{mo}$. This manipulator is selected for trading with
Figure 7.10: Single run price graphs of liquid (i.e., probability of submitting market orders by liquidity traders $q_{mo} = 0.45$) and illiquid (i.e., $q_{mo} = 0.55$) stocks. $p_L = p_T = 0.5$ (Note that the data were plotted with sampling only at every 50th point for clarity). Note that higher $q_{mo}$ corresponds to lower liquidity.

a probability $p_M$. The trader pool also consists of liquidity (pool selection probability $p_L$) and technical traders (pool selection probability $p_T$). The liquidity of the stock is controlled using the probability of submitting market orders by liquidity traders (i.e., $q_{mo}$).

Price driving is considered in liquid/illiquid stocks for different manipulator aggressiveness parameters (i.e., manipulator buy probability $q^{PD}_b$ and market order probability $q^{PD}_{mo}$). A less aggressive manipulator drives the price with lower buy and market order probabilities and a more aggressive manipulator drives the price with higher buy and market order probabilities. In all these price driving simulations, the trader selection parameters are set as $p_M = 0.1$, $p_L = p_T = 0.45$. This means that the price driving manipulator appears in the market for trading with a probability 0.1 and a liquidity or technical trader appears in the market with probability 0.45.

Figures 7.12 and 7.13 illustrate the mean buy and sell empty occurrences for 100 simulations in liquid/illiquid stocks simulated with $q_{mo}$ ranging from 0 to 1. The behaviour of average buy and sell order book empty occurrences change with $q^{PD}_b$ and $q^{PD}_{mo}$ (i.e., manipulator aggressiveness). With more aggressive manipulators, the order
book empties more often than with less aggressive manipulators. This means that manipulator aggressiveness contributes significantly to the empty book states (i.e., liquidity) in simulations. These book empty statistics confirm that, other than in a very liquid stock, the liquidity can be a relative market attribute to the trader behaviour controlled by the patient or impatient attributes of the market participants. This is because, when traders are very aggressive (i.e., impatient), a liquid stock can even become an illiquid stock. Likewise, when traders are less aggressive (i.e., patient), illiquid stock can become liquid.

A summary of mean price net change behaviour in liquid/illiquid stocks (i.e., with $q_{mo}$) for different manipulator aggressiveness values (i.e., $q_{b}^{PD}$ and $q_{mo}^{PD}$) is illustrated in Figure 7.14. The price net change box plots for simulated least and most aggressive (i.e., ($q_{b}^{PD} = 0.55, q_{mo}^{PD} = 0.5$) and ($q_{b}^{PD} = 0.75, q_{mo}^{PD} = 0.9$)) manipulator price driving in liquid/illiquid stocks (i.e., with $q_{mo}$) are shown in Figures 7.15 and 7.16, respectively.

The manipulator is not successful in moving the price up in both highly liquid or highly illiquid stocks. This is because, when the stock is very liquid (i.e., $q_{mo} \approx 0$), the book depth is very high and hence trading strategies cannot move the price. When
Figure 7.12: Mean buy side empty occurrences (averaged over 100 simulations) of price driving simulation in liquid/illiquid stocks (i.e., with \( q_{mo} \)) for different manipulator aggressive levels (i.e., manipulator buy probability \( q_{b}^{PD} \) and market orders probability \( q_{mo}^{PD} \)). Here manipulator arrival probability \( p_{M} = 0.1 \) and liquidity and technical trader arrival probabilities \( p_{L} = p_{T} = 0.45 \). Note that the standard deviations are consistently low and hence are not shown in the figure for clarity. Note that higher \( q_{mo} \) corresponds to lower liquidity

the stock is very illiquid (i.e., \( q_{mo} \approx 1 \)), the manipulator is also unsuccessful in buying stocks because, there is no counter party to sell stocks .

When the manipulator uses low buy and market order probabilities (i.e., a less aggressive manipulator), the price increase in illiquid stocks is higher than the price increase in liquid stocks (Figures 7.14 and 7.15). This indicates that when the manipulator is less aggressive, his price driving is more successful in illiquid stocks than in liquid stocks. These results indicate that when using little efforts, a manipulator can drive the price up or down more in illiquid stocks than in liquid stocks. This makes sense because a less aggressive manipulator should have power in a less liquid stock but be unable to move a very liquid stock.

When the manipulator is more aggressive, however, (i.e., when the manipulator uses higher buy and market order probabilities), the price increase is higher in liquid stocks and hence the more aggressive manipulator is more successful in liquid stocks.
Figure 7.13: Mean sell side empty occurrences (averaged over 100 simulations) of price driving simulation in liquid/illiquid stocks (i.e., with $q_{mo}$) for different manipulator aggressive levels (i.e., manipulator buy probability $q_{P,D}^b$ and market orders probability $q_{P,D}^{mo}$). Here manipulator arrival probability $p_M = 0.1$ and liquidity and technical trader arrival probabilities $p_L = p_T = 0.45$. Note that the standard deviations are consistently low and hence are not shown in the figure for clarity. Note that higher $q_{mo}$ corresponds to lower liquidity than in illiquid stocks (Figures 7.14 and 7.16).

A more aggressive manipulator is not successful in illiquid stocks because, due to the nature of the $M^*$ model, when the manipulator uses more market orders in illiquid stocks, the sell side of the order book empties more often (Figures 7.13). As a result, subsequent market orders are converted to limit orders. These converted limit orders may resist a move in the price and hence the manipulator is not able to achieve his expected price increase in illiquid stocks. Moreover, this more aggressive manipulator is successful in liquid stocks because, due to the manipulator behaviour, the liquidity of the market can be reduced and as a result the manipulator can easily move the price.

Based on these results, price driving is successful only if there is an adequate supply of orders to cater for the manipulator’s demand. Moreover, with aggressive manipulation, a more liquid stock can also show illiquid characteristics and hence price driving becomes easier. These results show that a trader can move the price more easily in a
Figure 7.14: Mean price net change behaviour (averaged over 100 simulations) of price driving in liquid/illiquid stocks (i.e., with $q_{mo}$) for different manipulator aggressive levels (i.e., manipulator buy probability $q_{bP}$ and market orders probability $q_{mP}$). Here manipulator arrival probability $p_M = 0.1$ and liquidity and technical trader arrival probabilities $p_L = p_T = 0.45$. Note that the standard deviations are consistently low and hence are not shown in the figure for clarity. Note that higher $q_{mo}$ corresponds to lower liquidity.

less liquid stock than in a more liquid stock (which is not to say that profits are higher in less liquid stocks).

Manipulator price driving is also tested in a market that does not allow the traders to convert their market orders to limit orders (i.e., order type) when the order book is empty (referred to as “order type conversion disabled” market). In these simulations, when the order book is empty, the market order is cancelled.

The mean buy and sell book empty occurrences in order type conversion disabled simulations are illustrated in Figures 7.17 and 7.18. The behaviour of average buy and sell order book empty values change with $q_{bP}$ and $q_{mP}$ (i.e., manipulator aggressiveness). With more aggressive manipulators, the order book empties more often than with less aggressive manipulators. This also shows that manipulator aggressiveness contributes significantly to the empty book states (i.e., the liquidity) in simulations. These results also confirm that, other than in a very liquid stock, the liquidity of a
Figure 7.15: Price net change box plots (combined over 100 simulations) of less aggressive price driving (i.e., trader arrival probabilities, $p_M = 0.1$ and $p_L = p_T = 0.45$) in liquid/illiquid stocks (i.e., with $q_{mo}$). Manipulator buys with probability $q_{PD}^b = 0.55$ and submits market orders with probability $q_{PD}^{mo} = 0.5$. Note that higher $q_{mo}$ corresponds to lower liquidity.

Mean price net change behaviour in these order type conversion disabled liquid/illiquid stocks simulated with the liquidity trading method (i.e., with probability of submitting market orders by liquidity traders $q_{mo}$) for different manipulator aggressiveness levels (i.e., manipulator buy probability $q_{PD}^b$ and market orders probability $q_{PD}^{mo}$) is illustrated in Figure 7.19. When market to limit order type conversions are not allowed, the manipulator is not successful in moving the price in highly liquid stocks, but is successful in illiquid stocks. When the liquidity of the stock is reduced due to manipulator aggressiveness, however, the manipulator is able to move the price. In these manipulative conditions, a highly illiquid stock is observed when the market order probability of liquidity traders $q_{mo}$ (i.e., liquidity controlling parameter) is 0.6. When $q_{mo} > 0.6$ (i.e., when the stock is highly illiquid), a non-trivial price decrease/increase is observed with less/more aggressive price driving manipulators. The standard deviation of the price net change is also very high in this period.

When $0 < q_{mo} < 0.6$, manipulator buying dominates the price net change behaviour
Figure 7.16: Price net change box plots (combined over 100 simulations) of more aggressive price driving (i.e., trader arrival probabilities, $p_M = 0.1$ and $p_L = p_T = 0.45$) in liquid/illiquid stocks (i.e., with $q_{mo}$). Manipulator buys with probability $q_{PD}^b = 0.75$ and submits market orders with probability $q_{PD}^{mo} = 0.9$. Note that higher $q_{mo}$ corresponds to lower liquidity.

and the manipulator has sufficient liquidity in the market to perform his price driving strategy. However, when $q_{mo} > 0.6$, market orders submitted by liquidity traders dominate the price net change behaviour. In this case, when the manipulator is less aggressive (i.e., $q_{PD}^b$ is low and the manipulator submits more limit buy orders), aggressive liquidity traders can sell some stocks (i.e., submit only sell market orders) to the manipulators and due to these sell transactions the price goes down. When the manipulator is also aggressive, liquidity come only from the technical traders and due to the buying pressure from the manipulator, the price goes up. This means that when $q_{mo} > 0.6$, the liquid/illiquid behaviour of the stock is not clear.

These results also confirm that moving stock price by performing trading strategies in illiquid markets is easier than in liquid markets. However, when the market to limit conversions are not allowed, simulating price driving in liquid/illiquid stocks is not successful.
Figure 7.17: Mean buy side empty occurrences (averaged over 100 simulations) of price driving in liquid/illiquid stocks (with $q_{mo}$, when no market to limit conversions are allowed) for different manipulator aggressive levels (i.e., manipulator buy probability $q_{b}^{PD}$ and market orders probability $q_{mo}^{PD}$). Here manipulator arrival probability $p_{M} = 0.1$ and liquidity and technical trader arrival probabilities $p_{L} = p_{T} = 0.45$. Note that the standard deviations are consistently low and hence are not shown in the figure for clarity. Note that higher $q_{mo}$ corresponds to lower liquidity.

7.5 Profitability of Trading in Liquid and Illiquid Stocks

In testing the behaviour of trader returns in liquid/illiquid stocks, an isolated liquidity trader is introduced to the pool of liquidity and technical traders in both liquid/illiquid stocks. The probability of submitting market orders (i.e., $q_{mo}$) for all the other liquidity traders in the pool is used to control the liquidity of the stock. The selection probabilities of the isolated trader, liquidity trader, and technical trader are 0.1, 0.45, and 0.45, respectively. The average profit behaviour of this isolated liquidity trader in liquid/illiquid stocks (i.e., with $q_{mo}$) is analysed.

Figure 7.20 illustrates the profits of this isolated liquidity trader in liquid/illiquid stocks.
Figure 7.18: Mean sell side empty occurrences (averaged over 100 simulations) of price driving in liquid/illiquid stocks (with $q_{mo}$, when no market to limit conversions are allowed) for different manipulator aggressive levels (i.e., manipulator buy probability $q_{bPD}$ and market orders probability $q_{mPD}$). Here manipulator arrival probability $p_M = 0.1$ and liquidity and technical trader arrival probabilities $p_L = p_T = 0.45$. Note that the standard deviations are consistently low and hence are not shown in the figure for clarity. Note that higher $q_{mo}$ corresponds to lower liquidity stocks (i.e., with $q_{mo}$) for 100 simulations. Figure 7.20 indicates that the trader returns are less volatile (i.e., show low standard deviation) in liquid stocks than in illiquid stocks. This is because, due to lower bid-ask spreads (i.e., lower transactions costs), a trader may obtain less variable returns in liquid stocks than in illiquid stocks.

### 7.6 Pump and Dump Manipulation in Liquid and Illiquid Stocks

The pump and dump manipulation scenario is considered in simulated liquid/illiquid stocks.

In these simulations, the liquidity of the stock is controlled by the probability of
Figure 7.19: Mean net change behaviour (averaged over 100 simulations) of price driving in liquid/illiquid stocks (with \( q_{mo} \), when no market to limit conversions are allowed) for different manipulator aggressive levels (i.e., manipulator buy probability \( q_{b}^{PD} \) and market orders probability \( q_{mo}^{PD} \)). Here manipulator arrival probability \( p_{M} = 0.1 \) and liquidity and technical trader arrival probabilities \( p_{L} = p_{T} = 0.45 \). Note that the standard deviations are consistently low and hence are not shown in the figure for clarity. Note that higher \( q_{mo} \) corresponds to lower liquidity submitting market orders by liquidity traders (\( q_{mo} \)). Note that \( q_{mo} = 0 \) represents a highly liquid stock, \( q_{mo} = 1 \) represents a highly illiquid stock, and the liquidity behaviour of the stock decreases when \( q_{mo} \) is increased from 0 to 1.

These liquid/illiquid stocks consist of liquidity traders, technical traders, and manipulators. These three types of traders are selected for trading with probabilities \( p_{L} \), \( p_{T} \), and \( p_{M} \) respectively. Liquidity traders buy with probability \( q_{b} \) and submit market orders with probability \( q_{mo} \). In their Bayesian belief model, technical traders assume probability \( \lambda \) of informed traders and probability \( \mu_{2} \) of liquidity buying. The technical traders’ initial probability of future price going up is \( \pi_{0} \). The pump and dump manipulator enters after \( t_{S} \) steps and buys with a probability \( q_{I}^{I} \) for period of time \( t_{I} \) (i.e., the ignition period). After this ignition period, the manipulator waits for \( t_{M} \) time steps (i.e., the momentum period) to allow technical traders to raise the price and then
Figure 7.20: Profitability of trading in liquid/illiquid stocks (i.e., with $q_{mo}$) without manipulation (combined over 100 simulations). Note that higher $q_{mo}$ corresponds to lower liquidity.

sells with a probability $q_b^C$ for period of time $t_C$ to profit. Market order probabilities of this manipulator in his ignition and call-off periods are $q_{mo}^I$ and $q_{mo}^C$, respectively. This manipulator behaves similar to a liquidity trader in his non-manipulation (i.e., $t_S$) and momentum (i.e., $t_M$) periods (i.e., the buy and market order probabilities are 0.5). Parameters used in this pump and dump simulation are summarised in Table 7.3.

The $M^*$ model is initialised with $\text{price}(0) = 10000$, $q_b = 0.5$, $\pi_0 = 0.5$ and are simulated for $t_T = 12500$ time steps. All runs commence with 1000 steps to seed the limit order book as per Maslov (2000). As a result, the data are recorded from $\text{price}(1000) = p(1)$ onwards. The price offset $\Delta$ values of all these traders are drawn from a power law distribution with mean 1.7 and standard deviation 0.8 (i.e., $\Delta$ takes discrete values between 1 and 4, having the power law exponent 1.5). The profits of each trader type are averaged over 100 simulations. In the Bayesian belief model, technical traders assume that informed traders can be present in the market with probability $\lambda = 0.1$ and a liquidity buying probability $\mu_2 = 0.45$ (i.e., information asymmetry). In simulating the pump and dump manipulation, the manipulator parameters are set as: $t_I = t_C = 5000$ and $t_M = 2500$. This means that the manipulator submits buy/market orders with $q_b^I/q_{mo}^I$ probability for 5000 steps, waits 2500 steps, and then submits sell/market orders with $1-q_b^C/q_{mo}^C$ probability for 5000 steps. The pump and
dump manipulation is considered in liquid/illiquid stocks for different manipulator aggressiveness parameters (i.e., manipulator arrival probability $p_M$, buy probability $q^b_{PD}$, and market order probability $q^m_{PD}$).

The profit of the manipulator, when the manipulator arrival probability $p_M = 0.1$ ($p_L = 0.45$ and $p_T = 0.45$) is illustrated in Figure 7.21. Here, in his ignition period, the manipulator buys with probability $0.75$ and submits market orders with probability $0.75$ (i.e., $q^I_b = 0.75$ and $q^I_m = 0.75$). In his call-off period, this manipulator buys with probability $0.25$ and submits market orders with probability $0.75$ (i.e., $q^C_b = 0.25$ and $q^C_m = 0.75$). Figure 7.21 indicates that neither the manipulator nor the technical trader can profit in highly liquid or highly illiquid stocks (i.e., $q^m_m \approx 0$ and 1). This is because, in highly liquid stocks, the manipulator is not successful in moving price using his trading strategies. Moreover, in highly illiquid stocks, there can be fewer trades because traders have difficulty finding a matching trader to buy/sell their stocks.

It is also observed that in Figure 7.21, this manipulator’s arrival probability ($p_M = 0.1$) is not aggressive enough to beat the technical traders. However, when this manipulator’s arrival probability in the market is increased to $0.3$ (i.e., the manipulator is more aggressively trading), the manipulator earns more profit than the technical traders (Figure 7.22). It is observed, however, that a very aggressive manipulator is more successful for making profits in liquid stocks than in illiquid stocks (Figure 7.23). This means that when the manipulator increases his buy/market order probability (i.e.,

<table>
<thead>
<tr>
<th>Trader</th>
<th>Parameter</th>
<th>Ignition period $t_I$</th>
<th>Momentum period $t_M$</th>
<th>Call-off period $t_C$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Liquidity trader</strong></td>
<td>Probability of buying $q_b$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(arrival probability $p_L$)</td>
<td>Probability of submitting market orders $q_m$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Technical trader</strong></td>
<td>Probability of buying $\pi_t$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(arrival probability $p_T$)</td>
<td>Probability of submitting market orders $0.5$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Manipulator</strong></td>
<td>Probability of buying $q^I_b$</td>
<td>0.5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(arrival probability $p_M$)</td>
<td>Probability of submitting market orders $q^I_m$</td>
<td>0.5</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Probability of buying $q^C_b$</td>
<td></td>
<td>$q^C_m$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Probability of submitting market orders $q^C_m$</td>
<td></td>
<td></td>
<td>$q^C_m$</td>
</tr>
</tbody>
</table>

Table 7.3: A summary of parameters used in pump and dump simulation
Figure 7.21: Average profits (averaged over 100 simulations) of a less aggressive pump and dump manipulator (i.e., manipulator arrival probability \( p_M = 0.1, p_L = 0.45 \), \( p_T = 0.45 \), \( q^L_B = 0.75 \), \( q^I_B = 0.75 \), \( q^C_B = 0.25 \), \( q^C_{mo} = 0.75 \) in liquid/illiquid stocks (i.e., \( q_{mo} \)). Note that the standard deviations of these trader profits are consistently low and hence are not shown in the figure for clarity. Note that higher \( q_{mo} \) corresponds to lower liquidity.

\( q^L_B = 0.9, q^I_{mo} = 1, q^C_B = 0.1, \) and \( q^C_{mo} = 1 \), the manipulator profit increases in highly liquid stocks. This is because, even in a very liquid stock, when the manipulator is more aggressive, the liquidity behaviour of the stock can be reduced, and as a result the manipulator can move the price easily and obtain a higher profit (Figure 7.23). This also confirms that the liquidity behaviour of a stock can be different under manipulative conditions and hence the liquidity of a stock can be driven by trader aggressiveness.

These results indicate that although the prices in illiquid stocks are easier to move and hence the manipulator profits are potentially higher, the pump and dump manipulator is more successful for making profits in liquid stocks. This is because illiquid stocks are not sufficiently liquid to manipulate. When the manipulator is less aggressive, the manipulator earns more money in illiquid stocks. His aggressiveness, however, is still not sufficient to perform a profitable manipulation. In illiquid stocks, a more aggressive manipulator cannot achieve his expected price increase and hence expected profits. However, when the manipulator is more aggressive, the manipulator behaviour
Figure 7.22: Average profits (averaged over 100 simulations) of more aggressive pump and dump manipulator (i.e., manipulator arrival probability $p_M = 0.3$, $p_L = 0.45$, $p_T = 0.25$, $q_b^I = 0.75$, $q_{mo}^I = 0.75$, $q_b^C = 0.25$, $q_{mo}^C = 0.75$) in liquid/illiquid stocks (i.e., $q_{mo}$). Note that the standard deviations of these trader profits are consistently low and hence are not shown in the figure for clarity. Note that higher $q_{mo}$ corresponds to lower liquidity.

...
Figure 7.23: Average profits (averaged over 100 simulations) of highly aggressive pump and dump manipulator (i.e., manipulator arrival probability $p_M = 0.3$, $p_L = 0.45$ $p_T = 0.25$, $q_{ib}^l = 0.9$ $q_{imo}^l = 1$, $q_b^C = 0.1$, $q_{imo}^C = 1$) in liquid/illiquid stocks (i.e., $q_{mo}$). Note that the standard deviations of these trader profits are consistently low and hence are not shown in the figure for clarity. Note that higher $q_{mo}$ corresponds to lower liquidity attribute to trader aggressiveness. This is because, when traders are very aggressive (i.e., impatient), a liquid stock can even become an illiquid stock. Likewise, when traders are less aggressive (i.e., patient), illiquid stock can become liquid.

### 7.7 Detectability of Manipulation in Liquid and Illiquid Stocks

Figure 7.24 illustrates that the estimated Hurst exponent values are low and more volatile in liquid stocks than in illiquid stocks. Real stock prices often show Hurst exponent values $> 0.5$. The estimated Hurst exponent values for simulated liquid/illiquid stocks indicate that a real stock market may be in the middle part of this liquid/illiquid scale.

Detectability of manipulation is tested by analysing the Hurst exponent of the
Figure 7.24: Hurst exponent box plots (combined over 100 simulations) of liquid/illiquid stocks (i.e., with probability of submitting market orders by liquidity traders $q_{mo}$). $p_L = p_T = 0.5$. Note that higher $q_{mo}$ corresponds to lower liquidity prices in the ignition period (i.e., price driving) of the pump and dump manipulation. Figure 7.25 illustrates the Hurst exponent estimates of price driving in liquid/illiquid stocks (i.e., with probability of submitting market orders by liquidity traders $q_{mo}$) for different manipulator aggressive levels (manipulator buy probability $q_{b}^{PD}$ and market orders probability $q_{mo}^{PD}$). With manipulator aggressiveness, the change in Hurst exponent in a liquid stock is high compared with the Hurst exponent change in an illiquid stock. In addition, with manipulator aggressiveness, the Hurst exponent is decreased in illiquid stocks and increased in liquid stocks. However, with manipulation, liquidity of the stock can be different than the liquidity defined by the parameters of the model.

7.8 Summary

This chapter presented evidence that manipulation models facilitate a means to test market manipulation theories and hypotheses. It was shown that price is less volatile and bid-ask spreads are tighter in liquid stocks than in illiquid stocks. Due to tighter bid-ask spreads, trader returns can be less volatile in liquid stocks than in illiquid stocks. It is difficult to move price in a highly liquid or highly illiquid stock. A manipulator
Figure 7.25: Mean Hurst exponent estimates (averaged over 100 simulations) of price driving in liquid/illiquid stocks (i.e., with probability of submitting market orders by liquidity traders $q_{mo}$) for different manipulator aggressive levels (i.e., manipulator buy probability $q_{bP}$ and market orders probability $q_{mo}^{P}$). $p_{M} = 0.1$ and $p_{L} = p_{T} = 0.45$. Note that the standard deviations are consistently low and hence are not shown in the figure for clarity. Note that higher $q_{mo}$ corresponds to lower liquidity.

requires more effort in manipulating a liquid stock than an illiquid stock. Consequently, manipulator profit in a liquid stock is less than the manipulator profit in an illiquid stock. However, the pump and dump manipulation is shown to be more profitable in liquid stocks. This is because, although a manipulator is more successful in driving the price in illiquid stocks and hence the manipulator profits are potentially higher, illiquid stocks are not sufficiently liquid enough to manipulate. When the manipulator is more aggressive, he can reduce the liquidity of the market. As a result, aggressive manipulators are more successful in driving the price in liquid stocks than in illiquid stocks and hence his profit becomes higher in liquid stocks. When the manipulator is less aggressive, his manipulation may not be successful.
Chapter 8

Discussion, Future Work, and Conclusion

8.1 Overview

This chapter provides a summary of previous research, a discussion of the overall implications of the work, and directions for future research. The contributions of the thesis are also highlighted.

8.2 Research Summary and Results

In this thesis, micro-economic modelling was developed as a method for understanding the behaviour of stock markets, and execution and detection of stock manipulation. Computational models to characterise manipulation (i.e., a stock manipulation framework) were presented. These models simplify and explain trade-based stock market manipulation scenarios.

The limit order market model presented by Maslov (2000) was extended in order to develop a more realistic representation of a limit order book. This extended model was then used to explain different dynamics of limit order trading. Based on these experiments, the base model in building the stock manipulation framework was presented (i.e., the $M^*$ model). A comparison of the original Maslov and $M^*$ models is given in Table 8.1.

The impact of normal and abnormal heterogeneous trading actions was considered in the $M^*$ model. These heterogeneous trading actions were characterised as stylised trader types and introduced to the $M^*$ model as external processes. A summary of
these heterogeneous trading impacts on the behaviour of the \( M^* \) model is given in Table 8.2.

Profitability of these heterogeneous trading actions was considered. These heterogeneous trading actions were then used to characterise profitable trade-based manipulation scenarios. These manipulation scenarios were characterised as stylised manipulators and introduced to the \( M^* \) model as external processes to build manipulation models.

Manipulation models were used to discuss what makes manipulation possible in limit order markets. For example, it was shown that a trade-based manipulation can be possible due to price momentum and the natural asymmetry between buying and selling as stated by Allen and Gorton (1992). Manipulation models were also used to examine profitability of manipulation scenarios in limit order markets. Implications of these manipulation models are summarised in Table 8.3.

A theoretical model was introduced to characterise buy and sell price impacts due to technical and fundamental traders. This theoretical model was used to show the possibility of trade-based manipulation due to an information asymmetry generated in technical trader beliefs by the behaviour of fundamental traders (i.e., information in buying or selling actions when the price is low or high is different). This theoretical model was also used to confirm the possibility of manipulation due to price momentum and the information asymmetry between buy and sell as stated by Allen and Gorton (1992).

An application of the pump and dump manipulation model was used to test stock manipulation related hypotheses. In this context, the possibility and profitability of trade-based manipulation in liquid and illiquid markets were analysed. Using simulation, it was shown that the liquidity of a market can be a relative attribute to trader behaviour such as aggressiveness of trading. The pump and dump manipulation was shown to be more profitable in liquid stocks. This is because, although a manipulator is more successful in driving the price in illiquid stocks and hence the manipulator profits are potentially higher, illiquid stocks may not have sufficient depths to be manipulated.

### 8.3 Discussion

Stock manipulation has been a major problem in stock markets and is difficult to detect because manipulators can use various appearances (in order to fool other traders) and can use variable strategies to avoid detection systems. As a result, manipulation
Limit order prices are computed with respect to the last traded price. Limit order prices are computed with respect to the contra side best price. Limit order prices may depend on the contra side properties (Parlour, 1998). Last traded price cannot lie outside the spread. Last traded price can lie outside the spread. Last traded price can lie outside the spread. Market buy order can increase or re-generate the last traded price. Market sell order can decrease or re-generate the last traded price. Market buy order can increase, decrease, or re-generate the last traded price. Market sell order can increase, decrease, or re-generate the last traded price. Market buy order can increase, decrease, or re-generate the last traded price. Market sell order can increase, decrease, or re-generate the last traded price. Market buy order can increase, decrease, or re-generate the last traded price. Market sell order can increase, decrease, or re-generate the last traded price. Market buy order can increase, decrease, or re-generate the last traded price. Market sell order can increase, decrease, or re-generate the last traded price.

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<table>
<thead>
<tr>
<th>Maslov model</th>
<th>$M^*$ model</th>
<th>Real data</th>
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<tbody>
<tr>
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<td>Limit order prices are computed with respect to the contra side best price</td>
<td>Limit order prices may depend on the contra side properties (Parlour, 1998)</td>
</tr>
<tr>
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<td>Last traded price can lie outside the spread</td>
<td>Last traded price can lie outside the spread</td>
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<tr>
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<td>Marketable limit orders are not allowed</td>
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<td>Limit orders may decrease the bid-ask spread</td>
</tr>
<tr>
<td>Market orders may increase the bid-ask spread</td>
<td>Market orders may increase the bid-ask spread</td>
<td>Market orders may increase the bid-ask spread</td>
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<td>Market orders may increase or decrease the mid bid-ask spread</td>
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<td>Limit orders may increase or decrease the mid bid-ask spread</td>
<td>Limit orders may increase or decrease the mid bid-ask spread</td>
<td>Limit orders may increase or decrease the mid bid-ask spread</td>
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</tbody>
</table>

Table 8.1: Comparison of the Maslov and $M^*$ models – Revisited

detection involves continuous evaluation and enhancement of detection mechanisms. Therefore, manipulation detection requires some mechanism to create different manipulation scenarios in order to design, develop, and evaluate detection measures.

Industry and researchers use real stock data of detected manipulation scenarios in order to develop and tune their detection mechanisms. However, real manipulation data relates only to past manipulators who were caught and only those caught via previously used detection measures. Hence, these data do not represent all possible manipulation scenarios. They are biased since they only represent the manipulations that were detected using current or previous detection methods. However, there are likely to be other manipulators who have avoided detection using sophisticated strategies. Moreover, manipulators can also learn from the past and plan for the future. As a result, real manipulation data fail to replicate all these possible variations of manipulation strategies. Therefore, designing a detection mechanism based on past detected manipulation cases may not be successful. In addition, stock manipulation data may also contain confidential information and there might be limitations on sharing these data among countries, exchanges, or research institutions for manipulation detection purposes.
<table>
<thead>
<tr>
<th>Heterogeneous trader</th>
<th>Category</th>
<th>Market impact</th>
</tr>
</thead>
<tbody>
<tr>
<td>Liquidity trader</td>
<td>Utilitarian trader.</td>
<td>Supply liquidity to the market. Adds noise to the prices and makes prices more random.</td>
</tr>
<tr>
<td>Technical trader</td>
<td>Profit motivated trader.</td>
<td>Adds persistence/momentum to the prices. Decreases the roughness of the price signal. Makes prices more informative. Increases the predictability of prices. Makes the market more vulnerable to manipulation. Information seekers. Introduces the notion of information and information asymmetry to the market.</td>
</tr>
<tr>
<td>Buyer</td>
<td>Profit motivated trader.</td>
<td>Pushes the price up. Adds persistence to the prices. A riskier strategy of inflating the price. This strategy is a part of the pump and dump manipulation strategy. Can be a price corner.</td>
</tr>
<tr>
<td>Seller</td>
<td>Profit motivated trader.</td>
<td>Pushes the price down. Adds persistence to the prices. A riskier strategy of deflating the price. This strategy is a part of the pump and dump manipulation strategy.</td>
</tr>
<tr>
<td>Impatient trader</td>
<td>Manipulator.</td>
<td>Submits more market orders. Increases the bid-ask spread. Produces illiquid markets.</td>
</tr>
<tr>
<td>Order cancelling trader</td>
<td>Manipulator.</td>
<td>Adds persistence to the prices. Decreases the roughness of the price signal. Reduces the long memory of prices.</td>
</tr>
<tr>
<td>Pattern trader</td>
<td>Manipulator.</td>
<td>Adds a regularity to the market attributes.</td>
</tr>
<tr>
<td>Cyclic trader</td>
<td>Profit motivated trader.</td>
<td>Used to simulate circular trader interactions in stock markets. This is considered as a pattern. Can push the price up or down. Do not require order accumulation or shorting in order to push the price up or down. Not an effective method as buying to push the price due to the higher standard deviations in net changes. Less riskier because this does not involve gaining or losing position. Can add a regularity to the market attributes.</td>
</tr>
<tr>
<td>Informed trader</td>
<td>Profit motivated trader.</td>
<td>Can see the market behaviour ahead of other market participants. Prefer to trade without conveying information to the market.</td>
</tr>
</tbody>
</table>

Table 8.2: Summary of the behaviour of heterogeneous traders – Revisited

Stock markets involve complex and dynamic interactions between market participants. It is not possible to perform controlled experiments on stock markets to study and test hypotheses about stock markets and manipulations. As a result, real stock markets cannot be used to generate manipulated data samples in order to test detection systems.

Manipulation models can be used to simplify and explain manipulation scenarios. These manipulation models can be used to recreate manipulation scenarios and gen-
<table>
<thead>
<tr>
<th>Manipulation Scenario</th>
<th>Summary</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pump and dump</td>
<td>Pump and dump manipulation is not possible/profitable if the only other traders are liquidity traders. Rather, manipulators require technical traders to profit. Increasing the percentage of technical trading makes manipulation more profitable. When exploiting the behaviour of technical traders, a manipulator can wait some time after the ignition phase to make a profit. However, if technical traders believe that there is an information asymmetry in the market, the manipulator effort required to perform a pump and dump is low and they can even make profits by selling immediately after raising the price. Pump and dump can be profitable due to an asymmetry introduced by the fundamental traders on technical trader behaviour (i.e., information in buying or selling when the price is low or high is different).</td>
</tr>
<tr>
<td>Cyclic trading</td>
<td>This itself can be a profitable strategy. A pump and dump manipulator can use cyclic trading to push the price up in the momentum period in order to profit. Cyclic trading involves less inventory risk than pump and dump because it does not require order accumulation. However, cyclic traders may have to put in some extra effort to hide their manipulation from market regulators. Modelled as a supportive strategy to pump and dump.</td>
</tr>
<tr>
<td>Wash sales</td>
<td>This is similar to cyclic trading. However, there are limitations in the order types that can be used. Only difference is the pattern of orders used. Not a price driving strategy and not profitable.</td>
</tr>
<tr>
<td>Marking the close</td>
<td>Price driving strategy. A long-term strategy compared with the other strategies. Not profitable. Can be used in pump and dump to raise the price up in the momentum period. Modelled as a supportive strategy to pump and dump.</td>
</tr>
<tr>
<td>Orders without execution</td>
<td>Can be used to show activity and attract other market participants. Not profitable. This can be used in a painting the tape strategy. Can increase the bid-ask spread and mislead the other traders.</td>
</tr>
<tr>
<td>Painting the tape</td>
<td>Not a price driving strategy. Can be used to show activity. Not profitable.</td>
</tr>
<tr>
<td>Creating a cap and Creating a floor.</td>
<td>Price driving strategy. This is used by the manipulator to drive the price and maintain a high/low price level in order to avoid unexpected losses. Modelled as a risk reduction strategy for pump and dump.</td>
</tr>
<tr>
<td>Insider trading</td>
<td>This is a profitable strategy. The profit increases with the degree of private information.</td>
</tr>
<tr>
<td>Cornering</td>
<td>This is a profitable strategy. Can be extended to a profitable strategy such as pump and dump.</td>
</tr>
</tbody>
</table>

Table 8.3: Implications of manipulation models – Revisited
erate different forms of manipulations in different real stock market conditions. These recreated manipulation scenarios can be used by researchers to design, develop, and evaluate their manipulation detection mechanisms. In addition, stylised heterogeneous traders can also be used to generate different forms of normal and abnormal trader behaviour in stock markets in order to help evaluate these manipulation detection systems. Moreover, manipulation models can be used to test stock manipulation related hypotheses. For example, researchers can use these models to test possibility, profitability, and detectability of manipulation in stock markets. In this context, different stock market conditions can be produced and the implications of manipulation in those different market conditions can be tested.

Jarrow (1992), Allen and Gale (1992), Allen and Gorton (1992), and Aggarwal and Wu (2006) have considered trade-based manipulation using micro-economic models. Using these manipulation models, they found evidence for the possibility of pump and dump type manipulation in stock markets. However, these models consider the theoretical aspects of manipulation and are far from reality. Agent-based models developed by D’hulst and Rodgers (1999) characterise manipulation scenarios such as circular trading in stock markets. However, these agent-based simulations are designed to analyse the behaviour produced by trader interactions and fail to produce quantitative inferences due to manipulation. Moreover, all these manipulation models were built on different platforms and characterise different manipulation scenarios in different types of stock markets. As a result, these manipulation models cannot be integrated and used to analyse market behaviour due to a combination of manipulation scenarios. This raised the requirement for a universal model that can be used to simulate a range of manipulation scenarios in a single environment.

This thesis has presented a framework to characterise manipulation scenarios in a single computational model. Manipulation modelling in a pure limit order driven market was considered. Due to advances in technology, pure limit order markets are the fastest growing market category in the world (Parlour and Seppi, 2008). Most of the small market places in developing countries are pure limit order driven markets and these markets are vulnerable to trade-based manipulation. Moreover, due to fewer manual human interactions for trading, these markets are easy to characterise computationally. In these manipulation models, for simplicity, only one order book of a stock was considered for manipulation. Manipulation models in this framework are intended to replicate realistic representations of real manipulation scenarios.

Trade-based manipulations were considered for modelling in the presented manip-
ulation framework. An extension of the Maslov model (i.e., the $M^*$ model) was used as the base model for characterising stock manipulation. Experiments were carried out to finalise the null model for building the market manipulation framework. This model considers the behaviour of stock traders when determining limit order prices. The modified model does not produce the magnitude of cone-shaped patterns that can be observed with the original Maslov model. A time to live ($ttl$) value (i.e., limit order life time) for the limit orders in the Maslov model was proposed. It was shown that the new model generates more realistic stylised features compared with the original Maslov model. Moreover, the extended Maslov model was used to study limit order pricing in stock markets. Based on these results, a more realistic method of modelling limit order price offsets in the Maslov model was introduced. In addition, the base model in building the manipulation framework was presented.

The Maslov and $M^*$ models were used to evaluate the existing averaging methods used in analysing limit order book shape and attributes in the literature. Using the $M^*$ model properties it was shown that when analysing real data, taking an average over several stocks and/or different days with the same stock may cancel variabilities that can be observed with individual stocks and may produce misleading regularities. This analysis was also used to show that the $M^*$ model is more capable of producing variable results in characterising different trader beliefs and market conditions than the original Maslov model.

Not all market related information is known to every market participant at the same time. This is referred to as information asymmetry or uncertainty. The role of information and information asymmetry in stock manipulation was considered. The $M^*$ model was extended to represent a tunable concept of trader information. This modification allowed an investigation of how manipulators can exploit information asymmetries in order to profit. The extended Maslov model presents a suitable platform for researchers to introduce and test the impact of external processes on a limit order book.

Trade-based manipulation scenarios that can be characterised in this framework were selected. These manipulation scenarios have been identified by market regulatory organisations. These scenarios were shown to affect fair and orderly markets and hence are illegal. These manipulation scenarios can be performed by a single manipulator or a group of manipulators. Note that not all manipulation scenarios are profitable. Some may be performed for a purpose other than profit (Harris (2002) categorised these types of traders), or they can be defined as a part of other profitable manipulation scenarios.
Some of these manipulation scenarios have not been considered for modelling in the past literature.

Manipulation models can help to simplify and explain these manipulation scenarios using a collection of trading strategies. These trading strategies can be characterised as heterogeneous trading actions. Heterogeneous trader actions such as technical traders, buyers, sellers, patient and impatient traders, order cancelling traders, pattern traders, cyclic traders, and informed traders can be used to characterise profitable manipulation scenarios. These trading strategies have not been considered for modelling in a single framework in the past literature. For example, the pump and dump manipulation scenario can be characterised using trading strategies such as liquidity traders, buyers, sellers, and technical traders. Taken in isolation, normal or abnormal behaviour may not be profitable. However, a combination of these heterogeneous trading actions can lead to profitable manipulation strategies. Therefore, regulators and/or researchers who study stock markets consider the normal behaviour of stock markets. In this context, any abusive practice that is carried out to distort the normal behaviour of stock markets is of interest.

Impacts of these heterogeneous trading actions on the base model for building the manipulation framework (i.e., $M^*$ model) were presented. This is an approach to allow the modelling of stylised traders to characterise trading strategies in stock markets. These stylised traders characterise universal properties of different trading actions and can be used to isolate individual trading behaviour and their impacts on stock markets and stock manipulations.

Heterogeneous trading can affect the behaviour of the $M^*$ model significantly. Moreover some of these trading actions (i.e., buyers, sellers, patient trading) are profitable (i.e., profit motivated strategies) and some of these actions are not profitable (i.e., not-profit motivated strategies). These non profit motivated actions such as impatient trading, order cancelling, and pattern trading can be classified as manipulative strategies.

These normal and abnormal heterogeneous trader actions were used to characterise and provide formal explanations for manipulation scenarios. Manipulation scenarios are simplified and characterised as stylised manipulator types (i.e., external processes to the $M^*$ model). Behaviour of these stylised manipulators with the $M^*$ model (i.e., manipulation models) was used to present the possibility and profitability of manipulation in limit order markets. Prior to this work, an approach to presenting stylised manipulators and manipulation models had not been considered in the literature.
In this framework, simple models to characterise and simulate manipulation scenarios such as “pump and dump,” “cyclic trading,” “wash sales,” “marking the close,” “orders without execution,” “painting the tape,” “creating a cap and creating a floor,” “insider trading,” and “cornering” were presented. All these manipulation scenarios can be computationally simulated. However, manipulation scenarios such as “churning” and “front running” were shown to be difficult to simulate in this framework because they are executed at the broker level.

Pump and dump manipulation is shown to be the primary method of profitable manipulation in stock markets. This thesis only considers trades of market participants that involve pushing the price (i.e., information based and action based methods were not considered in this thesis). Via simulation, it was shown that pump and dump manipulation is not possible if the only other traders are liquidity traders. Manipulators cannot profit by simply selling after raising the price. This is because selling pushes the price down, and as a result the manipulator may not be able to sell his stocks at a higher price than the purchase price.

However, it was shown that the presence of information seekers (i.e., technical traders) can make profitable manipulation possible. This is because these technical traders add a momentum to prices. As a result of this momentum introduced by the technical traders, a manipulator can wait some time after buying in order to let the technical traders raise the price and after that he can start selling. This can allow the manipulator to sell his stocks at a price higher than his buying price and hence profit. Moreover, if these technical traders believe an information asymmetry exists, a pump and dump manipulation was shown to be profitable even without this waiting period (i.e., the manipulator can profit by selling after buying). In this form of asymmetry, technical traders believe that buyers are more informed than sellers. This is because they believe that buying stocks may involve more analysis than selling for various exogenous reasons. This proves the possibility of manipulation due to information asymmetry as stated by Allen and Gorton (1992). In this context, information asymmetry was introduced to the simulation via the technical trader belief model. When technical traders believe that there is an information asymmetry, they respond more to buy transactions than sell transactions and as a result the price increase due to manipulator buying is greater than the price increase due to manipulator selling. As a result, this information asymmetry allows the manipulator to buy low and sell high thus achieving profits. According to Allen and Gale (1992), traders always have a problem distinguishing manipulators from informed traders and as a result manip-
ulators can pretend to be informed traders and mislead other traders. The technical traders in this thesis follow the manipulator actions by assuming they are informed and are mislead by the manipulators.

It was shown that pump and dump is difficult to detect, mainly because pump and dump consists of three different periods: buying period, waiting period, and selling period. A pump and dump manipulator behaves in three different ways in these three periods. However, these different periods can be separately identified using changes in market attributes. In this context, heterogeneous traders such as buyers and sellers were shown to be affecting market attributes such as the Hurst exponent, autocorrelation of price increments, volatility clustering, and distribution properties of bid-ask spreads and price returns. It was also shown that price returns are higher in the manipulation period than in the non-manipulation period. Moreover, greater buy and sell order book depths are observed when the manipulator sells (i.e., during the call-off period) than when he buys (i.e., during the ignition period). This is because, in the ignition period, the aggregated demand of the manipulator and technical trader increases the buying pressure and as a result a greater buy depth can be observed. However, when the manipulator sells, the technical traders’ learned demand produces a greater buy depth and also manipulators’ sell pressure causes a greater sell depth.

Manipulation scenarios such as “cyclic trading,” “marking the close,” and “creating a cap and creating a floor” can be considered as strategies supportive to the profitable trade-based pump and dump manipulation. These strategies were shown to be used by the manipulators to raise the price in order to achieve a profit. Cyclic trading was shown to be a less risky strategy than accumulating stocks (i.e., buying) because a build up of inventory is not involved. However, cyclic trading requires at least two related parties. Moreover, cyclic trading is only a price driving strategy, and as a result a manipulator requires an initial position to raise the price and sell his stocks. Marking the close was shown to be a possible strategy to raise the price. It is, however, a long-term strategy. Creating a cap and creating a floor strategies were simulated as risk minimisation strategies by the pump and dump manipulators. Using these strategies, a pump and dump manipulator can maintain a low price level in order to minimise the risk of a loss. Cyclic trading can also be used in this context as a risk minimisation strategy.

Other manipulation scenarios such as “wash sales,” “orders without execution,” “painting the tape,” “insider trading,” and “cornering” can be considered as separate strategies. These are shown, however, to be non-profitable. They can, however, be
used to alter market attributes in order to attract other market participants to generate artificial demand or supply.

There are limitations to the orders that can be used to perform wash sales strategies. In this context, the differences between order patterns used in cyclic trading and wash sales can be compared. Cyclic trading manipulators can use a pattern of \([\text{limit sell}, \text{market buy}]\) orders to push the price up. However, if both buy and sell parties use patterns such as \([\text{market sell}, \text{market buy}]\) or \([\text{limit buy}, \text{limit sell}]\) the possibility of a price increase is minimal. Moreover, cyclic traders can use patterns such as \([\text{limit buy}, \text{market sell}]\) to push the price down. A single manipulator cannot, however, perform \([\text{limit sell}, \text{market buy}]\), because some stock markets do not allow their traders to submit contra side orders when they have limit orders in the limit order book. As a result, a wash sales manipulator cannot use \([\text{limit sell}, \text{market buy}]\) strategy to raise the price. Moreover, it was shown that a manipulator is not able to push the price alone other than accumulating or shorting stocks. However, it was shown that a wash sales manipulator can use \([\text{market buy}, \text{market sell}]\) in order to increase the bid-ask spread and hence influence other market participants.

Manipulation scenarios such as orders without execution and painting the tape were shown to affect market attributes such as the bid-ask spread and therefore may mislead other market participants. A model of “insider trading” can be used to show that with a degree of private information an insider trader can achieve higher profits. In this context, the insider trader profit increases with the length of time that they can see into the future (i.e., the degree of information). “Cornering” was shown as a part of the pump and dump strategy (i.e., buying).

This thesis introduced a simple theoretical model of a limit order book to characterise price responses (i.e., impacts) of trading due to the behaviour of fundamental and technical traders. In this model, technical traders believe that, due to the behaviour of fundamental traders, information associated with buying stocks at a lower price is different from information associated with buying when the price is high. This is because fundamental traders buy when the price is low and sell when the price is high. This means the fundamental trader behaviour can introduce an asymmetry to the information extracted by the technical traders from buy and sell actions. Moreover, the information asymmetry introduced by Allen and Gorton (1992) considered the fact that a buyer is generally more informed than a seller. In the Allen and Gorton (1992) model information in buying when the price is high or low is not considered, making the price behaviour path independent (i.e., the order of buy and sell actions in the
strategy is not important or \([\text{buy, buy, sell, sell}] = [\text{buy, sell, buy, sell}]\). The model proposed in this thesis shows, however, a path dependent (i.e., \([\text{buy, buy, sell, sell}] \neq [\text{buy, sell, buy, sell}]\)) and therefore more realistic price behaviour.

Using this theoretical model, it was shown that trade-based manipulation is possible due to an information asymmetry in technical trader beliefs about the fundamental traders (i.e., information in buying or selling when the price is low or high is different). In this context, a pump and dump manipulator can profit even without price momentum and an information asymmetry between buy and sell introduced by Allen and Gorton (1992). This asymmetry also helps a manipulator to buy causing a higher effect on prices and selling with little effect.

It is believed that a more liquid market is easy to be manipulated. This is because a manipulator can easily hide trades among the trades of other market participants. However, most real manipulation cases have been recorded in illiquid markets. This could, however, be because manipulation detection is easier in illiquid markets. Based on previous research, it is difficult to determine under what conditions a liquid/illiquid stock is more open to manipulation.

Using a liquid/illiquid stock simulation, properties of liquid and illiquid stocks as well as trader returns and capabilities of price driving were presented. Pump and dump was considered in these liquid/illiquid stocks with attributes such as manipulator aggressiveness, profitability, and detectability. Manipulator aggressiveness was controlled using parameters such as manipulator arrival probability, and the probabilities of submitting buy/sell and limit/market orders.

It was shown that prices are less volatile and bid-ask spreads are tighter in liquid stocks than in illiquid stocks. Due to tighter bid-ask spreads, trader returns can be less volatile in liquid stocks. This indicates that trading in more liquid stocks is more profitable than trading in less liquid markets. The prices in highly liquid or highly illiquid stocks are difficult to move using trading strategies. A manipulator requires much effort to manipulate a liquid stock. Consequently, manipulator profit in liquid stocks is reduced. However, it was shown that the pump and dump manipulation is more profitable in liquid stocks. This is because, although a manipulator is more successful in driving the price in illiquid stocks and hence the potential manipulator profits are higher, illiquid stocks are not sufficiently liquid for manipulation to be easy. As a result, when the manipulator is more aggressive, he can be more successful in driving the price in liquid stocks than in illiquid stocks and hence his profit becomes higher in liquid stocks. When the manipulator is less aggressive, his manipulation may
not be successful. Based on these results, it was also shown that the liquidity of a stock is a relative market attribute to manipulator aggressiveness. This is because, when traders are very aggressive (i.e., impatient), a liquid stock can even become an illiquid stock. Likewise, when traders are less aggressive (i.e., patient), illiquid stock can become liquid. These results confirm the findings of Kyle (1985) that if the order book depth is higher (i.e., more liquid), an informed trader can trade more intensely and make greater profits using his information.

These manipulation models are easy to understand. For example, users can separate the dynamics of the base model dynamics (i.e., $M^*$ model) from the impacts of external processes (i.e., stylised heterogeneous traders or manipulators). This allows analysis of different trading strategies and manipulations. The dynamics of heterogeneous traders and manipulators are characterised as stylised trader types and as a result these traders can be used as tunable entities in different simulation environments.

Due to their tunable nature, the presented base model and manipulation models are scalable to suit different market and trader dynamics. In this context, flexible parametrisations allow users to adjust these models to generate different dynamics such as liquid/illiquid and efficient/inefficient markets under different assumptions.

Manipulation models presented in this thesis can be used by researchers and market regulation authorities. Researchers can use these models to test hypotheses on different aspects of stock trading and manipulation. Market regulatory organisations can use these models to produce different forms of manipulation in order to test their manipulation detection systems.

In summary, this thesis presented a limit order book model for characterising manipulation. Stylised traders were characterised to isolate and study heterogeneous trading actions. These heterogeneous traders were used to characterise stylised manipulators for trade-based manipulation scenarios. Stylised manipulators were introduced to the computational limit order market in order to present trade-based manipulation models.

8.3.1 Contributions

The main contribution of this thesis is the analysis of stock manipulation in relation to trading related information and the definition of a simple framework for manipulation. This framework is presented in the context of a realistic computational model of a limit order market. In this framework, models to characterise and simulate manipulation scenarios such as pump and dump, cyclic trading, wash sales, marking the close, orders without execution, painting the tape, creating a cap and creating a floor,
insider trading, and cornering were presented. This manipulation framework is a novel contribution to the stock manipulation literature.

The Maslov model was extended to be a more realistic representation of a limit order book. Stock trading beliefs were considered in this analysis. A more realistic representation of a limit order price computation method based on trader beliefs was introduced. The extended Maslov model was then used to show that the existing aggregation methods used in stock data analysis may be misleading. In this context, when analysing real data, taking an average may cancel variabilities that can be observed with individual stocks and may produce misleading regularities such as the bell-shaped distribution that can be observed in order book profiles. Based on these experiments, a base model for characterising stock manipulation scenarios was presented.

A novel approach to considering the impacts of heterogeneous trading on a microeconomic model was introduced. In this method stylised traders to characterise heterogeneous trading actions were presented. A belief structure of a limit order trader was presented. This belief model allows control over trader beliefs in order to analyse their learning processes and their effects on the order book. This belief structure was used to simulate information asymmetries in stock markets. Stylised heterogeneous traders can be used to generate different forms of normal and abnormal trader behaviour in stock markets in order to characterise market responses and to help design manipulation detection systems.

Using heterogeneous trading actions, stylised manipulators that characterise trade-based manipulation scenarios were presented. These stylised manipulators are a novel contribution to the literature.

Stylised manipulators were introduced to the extended Maslov model to present manipulation models. Until the work presented in this thesis, manipulation scenarios have not been considered in a single realistic stock market model. These stylised manipulators and manipulation models can be used to generate different forms of manipulation scenarios in stock markets in order to help design manipulation detection systems.

Using these manipulation models the possibility and profitability of manipulation scenarios were discussed. It was shown that pure trade-based pump and dump manipulation is not possible when performed in the presence of only liquidity traders.

A theoretical model to characterise the price impacts of buy and sell transactions was introduced. This model presents a novel and effective approach (i.e., path dependent) to modelling stock price changes with respect to market information. This
model was shown to be a more realistic representation than the existing models in the literature.

This theoretical model was used to show the possibility of trade-based manipulation in stock markets. Using this model, it was shown that trade-based manipulation can occur due to an information asymmetry generated in technical trader beliefs by the behaviour of fundamental traders (i.e., information in buying or selling when the price is low or high is different). This study is the first to present this information asymmetry in relation to stock manipulation.

These manipulation models were used to test hypotheses on stock manipulation. For example, using the pump and dump manipulation model, the profitability and detectability of manipulation in liquid/illiquid stocks was presented. In this analysis, models of stock manipulation were used to answer questions: Can a liquid or illiquid stock be easily manipulated? Is a manipulator strategy more profitable in a liquid or an illiquid stock? Can manipulation be more easily detected in liquid or illiquid stocks?

### 8.3.2 Limitations and future work

This thesis only models trade based manipulation scenarios. In the future, this manipulation framework can be developed as a more generic framework to be able to simulate other manipulation types such as information based and action based manipulations in other types of markets.

The detection of manipulation is discussed but not explored fully in this thesis. A clear direction for future research is to take the framework developed here and use it to find and test manipulation detection mechanisms.

Finding optimal strategies for manipulation is a natural extension for the framework developed in this thesis. For known manipulation scenarios, optimal parameters that maximize manipulator profits can be simulated. Future work will be developed to find these optimal manipulation scenarios. In this analysis, a manipulator who is not constrained by a known manipulation scenario can be evolved to find the most effective strategy to manipulate a market. Since this is a search problem, one possible approach is to use a heuristic search algorithm such as a Genetic Algorithm (Holland, 1975) to explore the space of possible manipulator behaviors. Profit maximizing, satisfying, or loss avoiding strategies of the manipulators will also be discussed as future work under optimal manipulation strategies.

The $M^*$ model characterises trading of a single stock in a limit order market. However, this can be extended to simulate manipulation of multiple stocks via multiple
instances of an $M^*$ stock run in parallel. In this context, manipulations involving multiple stocks such as wash sales can be characterised.

The $M^*$ model facilitates trading of a single unit of stock at a time. This can be extended to allow traders to trade multiple units of stocks at a time (i.e., block trades). In this aspect, different sized orders can be simulated first by choosing the order size from a probability distribution and second by changing the probability of buy/sell order arrivals (vary through time as a serially correlated process). Moreover, the $M^*$ model does not allow marketable limit orders. However, marketable limit orders to the $M^*$ model can be added by allowing zero limit price offsets ($\Delta$).

In this thesis, we considered only heterogeneous trading actions that are required to build manipulation models. However other heterogeneous trading actions such as large traders can be characterised. In this context, heterogeneous trading methods such as technical traders can also be implemented using different methods. For example, traders who use methods such as price trends, chart patterns, and technical analysis indicators can be implemented. This analysis will be useful in characterising various forms of manipulations in stock markets.

When extracting information from past trading actions, the technical trader belief model can be extended to consider other traders such as manipulators. This will allow technical traders to reduce the risk of being misled by manipulators. Moreover, this belief structure can be used to consider different market properties such as bid-ask spread and order book depth and also market conditions such as liquid/illiquid markets.

The probability of future price going up was used as a universal value for all technical traders in $M^*$ simulations. However, this could be different based on trader arrival times. In the future, these technical traders can be extended to consider their actual arrival time and hence compute these probabilities based on that time, thus capturing the context of entry into a market.

In the theoretical model for manipulation presented in Chapter 6, first-order approximations such as constant proportional price changes were used. In the future, this theoretical model can also be extended to use distributions to compute these proportional price changes. Moreover, this theoretical model can be used to characterise other manipulation scenarios such as cyclic trading, order cancelling traders, and marking the close.

In liquid/illiquid market simulation, the presented research has only considered the order book depth to control the liquidity of a stock. However, properties such as
speed of transactions can be used to control the liquidity of these stocks. This will allow a model that controls trading volume and the number of orders and/or trades to represent more/less liquid markets.

Stylised traders and stylised manipulators can be simulated together to analyse their interactions. This allows analysis of market behaviour due to a combination of trading actions/manipulation scenarios.

This framework is customisable to characterise some other markets such as dealer/auction markets.

The validation of the models presented in this thesis using real data is future work. However, it must also be acknowledged that there is a paucity of data for real manipulations, even though the theory of manipulation strategies and detection is well developed.

8.4 Conclusion

This thesis explains aspects of stock manipulation in relation to market related information. Moreover, stock manipulations were simplified and characterised using micro-economic models. These micro-economic models were used to test hypotheses regarding the possibility and profitability of manipulation in different stock market conditions such as liquid/illiquid stocks. It was shown that these models can be used to produce and study different forms of manipulation. The resulting models offer a framework for the design, development, and evaluation of manipulation detection methods and market properties.
Bibliography


Appendix A

Limit Order Pricing

In real markets, the amount of deviation of limit orders from a reference price is found to be distributed according to the power law (Zovko and Farmer, 2002; Bouchaud et al., 2002; Potters and Bouchaud, 2003; Lillo, 2007). Moreover, these distributions are found to be identical for both buy and sell sides of the order book (Bouchaud et al., 2002; Potters and Bouchaud, 2003). However, the value of the reported power law exponent differs rather widely (i.e., $\approx 1.5 - 2.5$) from one study to another (Slanina, 2008).

Zovko and Farmer (2002) studied the choice of reference prices to analyse these limit order price offsets (i.e., $\Delta$) in real stock markets. They used the same side best price as the reference price in their analysis and also considered other possible alternatives such as contra side best price, and last traded price. However, according to their findings, the choice of these three types of reference prices do not make any large difference in the tail of the observed limit order price offset distribution in real stocks.

There exist several findings about the origin of this power law distribution.

Bouchaud et al. (2002) found that the volatility patterns used by the traders to model price dynamics decides the power law shape of the limit order price offset distribution. According to them, a power law tail is formed because when the volatility is high, price fluctuates more and traders tend to place limit orders with larger limit order price offsets, still expecting to get an execution. Zovko and Farmer (2002) also showed that the levels of limit order price offset are positively correlated with and are led by price volatility. They concluded that this correlation may potentially contribute to the volatility clustering effect in stock markets.

Submitting an order close to the best market price enables fast execution, while deviation from that price leads to a better profit (Zovko and Farmer, 2002; Bouchaud et al., 2002; Potters and Bouchaud, 2003; Lillo, 2007). As such, choosing a limit order
price offset ($\Delta$) is a strategic decision that involves a trade-off between patience and profit (Chakravarty and Holden, 1995; Harris and Hasbrouck, 1996; Zovko and Farmer, 2002; Peterson and Sirri, 2002; Goettler et al., 2004). As a result, determining the price when submitting a limit order can be described as an “adverse selection” problem. Lillo (2007) investigated the origins of the power law distribution in $\Delta$ and concluded that the adverse selection problem determines the shape of the power law distribution.

Moreover, the decision of selecting $\Delta$ involves picking-off risk in limit order trading. Picking-off risk occurs when a trader gets an execution after the true value of the stock has deviated from the expected value. As a result, if the chance of the future price going up is high, a trader may not want to sell the stock at the current price, as it would give him a lower profit (Hollifield, Miller, Sandás, and Slive, 2006).

Maslov (2000) also noted that the value of $\Delta$ can be use to characterise the patient/impatient behaviour of limit order traders.
Appendix B

Information Asymmetries in Financial Markets

Asymmetric information can occur in a financial market due to either adverse selection, moral hazard, or monitoring cost (Bebczuk, 2003).

“Adverse selection”: When allocating credits, a lender faces adverse selection when he is not capable of distinguishing between projects with different credit risks. For example, an insurance company faces this problem because they want to sell insurance policies to people with low risk, however people with high risk are often more likely to buy insurance policies.

“Moral hazard”: The ability of borrowers to apply the funds for different uses other than those agreed upon with the lender. For example, people who are with insurance covers tend to do riskier activities than people who do not have an insurance cover.

“Monitoring cost”: Monitoring costs are associated with hidden actions of the borrower. Borrowers can take advantage of their better information to declare lower values than the actual earnings. For example, people who buy insurance policies can hide their actual problems or risks.

Kyle (1985) models adverse selection problems faced by a specialist and an informed trader. The specialist in this model faces information asymmetry when dealing with informed traders. As a result, the market maker is facing an adverse selection problem in selecting a party to trade with. Informed traders also have the problem of selecting the optimal strategy (i.e., trading intensity with time) to be used with their superior information in order to get the maximum expected profit. Informed traders face this adverse selection problem because, trades of informed traders may convey information to the other market participants, reducing their expected profit.
Glosten and Milgrom (1985) model also addresses an adverse selection problem of a market maker. This market maker’s task is to provide liquidity to the market and the other investors must trade with this market maker. Some traders can be more informed than the market maker and as a result the market maker is facing an adverse selection problem in selecting a party to trade with.

According to Allen and Gorton (1992), buy transactions are more informative than sell transactions (i.e., buys are perceived asymmetrically from sells by market participants). People do more analysis before buying than selling. As a result, the price response with respect to a buy transaction is greater than the price response with respect to a sell transaction (i.e., a market reacts differently to buy and sell orders) in stock markets. Note that here buy and sell transactions refer to the buyer and seller initiated (i.e., aggressive party) transactions.

Allen and Gale (1992) showed that another type of asymmetry can occur when a normal trader cannot figure out whether a large investor is an informed trader or a manipulator.

Allen and Gale (1992) and Allen and Gorton (1992) used these asymmetries to show that profitable manipulation is possible due to information asymmetry in stock markets.

Chan and Lakonishok (1993) pointed out that out of the many alternatives available, there are more liquidity-motivated reasons to sell a stock than the choice to buy a stock. As a result, buy transactions may convey positive private information. Because of this asymmetry, a buy transaction can increase the price followed by a small drop or another increase, and a sell transaction can push the price down to the original position followed by the price recovery.

Keim and Madhavan (1995) noted that buys can take longer to execute than the equivalently sized sells. As a result, buyer-initiated trades are more informative and are needed to be broken up to reduce their price impacts.

Keim and Madhavan (1997) studied the price impacts and execution costs of US stocks traded by institutional investors. They found that buys are more expensive to trade than sells, causing an information asymmetry.

Kraus and Stoll (1972), Holthausen, Leftwich, and Mayers (1987), and Keim and Madhavan (1996) studied the effect of large block transactions and suggested that there is asymmetry in the price response to buyer-initiated and seller-initiated block trades. The price increases for buyer-initiated block trades are generally permanent, while the price drops for seller-initiated block trade are predominantly temporary.
Block dealers are normally willing to buy from large sellers, but they are reluctant to sell short to satisfy large buyers (Kraus and Stoll, 1972; Chan and Lakonishok, 1993; Berkman, Avital, Breuer, Bardach, Springer, and Godfrey, 2005). As a result, it is easier to sell large amounts than to buy large amounts (Chan and Lakonishok, 1993). Therefore, it is less or more likely that the block price for buyer-initiated or seller-initiated trades includes a fee to block dealers in the form of a price change respectively.

An information asymmetry can occur because the seller of a good often knows more about its quality than the prospective buyer (Lofgren, Persson, and Weibull, 2002). For example, a job applicant knows more about his ability than his potential employer, and the buyers of an insurance policy usually know more about their individual risks than the insurance company.

Wagner and Edwards (1993), Keim (2003), and Chiyachantana, Jain, Jiang, and Wood (2004) suggested that the price impact of buy and sell transactions is determined mainly by the underlying market condition. In bullish markets, sell interest can be absorbed by buyers and therefore buys have a bigger price impact than sells. However, similarly, in the bearish markets, sells can have a higher price impact.

Analysing the total price impact as a measure of trading cost, Keim (2003) and Chiyachantana et al. (2004) found empirical evidence supporting the hypothesis that buys are more expensive to execute than sells on bullish markets and sells are more expensive to execute than buys in bearish markets.

Several studies have showed that there is a significantly larger price impact due to bad news relative to a good news (Diamond and Verrecchia, 1987; Skinner, 1994; Soffer et al., 2000; Hutton et al., 2003; Anilowski et al., 2007; Kothari et al., 2008). An asymmetry can occur when short selling restrictions make it easier to exploit good news rather than bad news (Diamond and Verrecchia, 1987). An information asymmetry can also occur because managers withhold bad news and accelerate the disclosure of good news (Kothari et al., 2008).
Appendix C

Hurst Exponent

Figure C.1: A graphical summary of the Hurst exponent behaviour in relation to stock markets
## Appendix D

### T-test Results (p-values) of the Impact of Heterogeneous Trading

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Table D.1: T-test results (p-values) of the impact of heterogeneous trading on the $M^*$ model. These p-values are obtained by the pairwise comparison of datasets corresponding to each $p_{ST}$ value and the $M^*$ model.