Closing price manipulation and the integrity of stock exchanges

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A thesis submitted in partial fulfilment of the requirements for the degree of

Doctor of Philosophy

Discipline of Finance
Faculty of Economics & Business
University of Sydney
November 2009

Statement of originality

This is to certify that to the best of my knowledge, the content of this thesis is my own work. This thesis has not been submitted previously for a higher degree or qualification at any other university or institute of higher learning. I certify that the intellectual content of this thesis is the product of my own work and that all the assistance received in preparing this thesis, and sources used have been acknowledged.

Tālis J. Putniņš

To my parents

Acknowledgements

First and foremost, I thank my academic supervisor, Associate Professor Carole Comerton-Forde, for her consistently strong support and guidance throughout the preparation of this thesis. It has been a pleasure to work with Carole and learn from her expertise.

This research has also benefited greatly from the thoughtful insights and feedback provided by Robert Bartels, Jonathan Batten, Henk Berkman, Utpal Bhattacharya, Bidisha Chakrabarty, Ryan Davies, Marina Druz, Jonathan Feinstein, Michael Fleming, Doug Foster, Richard Gerlach, Robin Hanson, Doug Harris, Joel Hasbrouck, David Johnstone, Petko Kalev, Si Li, Pamela Moulton, Terrence Odean, Ryan Oprea, Michael Pagano, Charles Plott, Mike Prior, Maxwell Stevenson, Angelo Ranaldo, James Rydge, Tom Smith, Terry Walter, and Tracy Yue Wang.

I gratefully acknowledge research funding provided by: the Australian Government Department of Innovation, Industry, Science and Research; the Australian Research Council (ARC Linkage Project LP0455536); the Australian Stock Exchange; the Faculty of Economics and Business; and the Securities Industry Research Centre of Asia-Pacific (SIRCA). I also thank SIRCA and Reuters for providing data used in this thesis, and Kevin Cheng and Ian Friedman for their support in working with these data.

A special thank you goes to my family, friends and fellow research students. I am especially grateful to Vēsma for her wholehearted support and for enduring my neglect throughout my work on this thesis. Finally, I have dedicated this thesis to my parents. Besides being a source of constant encouragement, they are an inspiration to me.

Preface

Some of the work in this thesis has been presented as joint work. A version of Chapter 3 was presented as a working paper co-authored with Assoc. Prof. Carole Comerton-Forde at various academic conferences and seminar series, including the Financial Management Association Annual Meeting, the European Financial Management Association Annual Conference, the University of Sydney 2nd Annual Microstructure Meeting, the Financial Integrity Research Network (FIRN) Doctoral Workshop, the University of Technology Sydney, Macquarie University and the Stockholm School Of Economics (Riga) / Baltic International Centre for Economic Policy Studies.

A version of Chapter 4, with parts of Chapter 6, is forthcoming in the *Journal of Financial Intermediation*, as an article co-authored with Assoc. Prof. Carole Comerton-Forde. This paper has also been presented at various academic conferences and seminar series, including the Financial Management Association Annual Conference, the European Financial Management Association Annual Conference, the Australasian Banking and Finance Conference, the Australian National University, the Ontario Securities Commission, Regulation Services/DeGroote Business School Lecture Series, the University of New South Wales, the University of Western Australia and Villanova University

A version of Chapter 5 was presented as a working paper co-authored with Assoc. Prof. Carole Comerton-Forde at various academic conferences and seminar series, including the Financial Management Association Annual Conference, the Asian Finance Association Annual Conference, the Australasian Banking and Finance Conference, the FINRISK 8th Swiss Doctoral Workshop in Finance, the University of New South Wales, the University of Tasmania and the University of Western Australia.

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Abbreviations

AMEX	American Stock Exchange
AMEX DRC	AMEX Division of Regulation and Compliance
ASX	Australian Stock Exchange (now the Australian Securities Exchange)
AUROC	Area under Receiver Operating Characteristics curve
DCE	Detection controlled estimation
ECU	Experimental currency unit
ETF	Exchange traded fund
EU	European Union
IDA	Investment Dealers Association (Canada)
IIROC	Investment Industry Regulatory Organization of Canada (Canada)
LOC	Limit on close
MFDA	Mutual Funds Dealers Association (Canada)
MOC	Market on close
NYSE	New York Stock Exchange
NYSE Reg	NYSE Regulation Inc.
OSC	Ontario Securities Commission (Canada)
ROC	Receiver Operating Characteristics
RS	Market Regulation Services Inc. (Canada)
SEC	Securities and Exchange Commission
SIRCA	Securities Industry Research Centre of Asia-Pacific
TSX	Toronto Stock Exchange
TSX-V	TSX Venture Exchange
US	United States of America

Abstract

Allegations of market manipulation abound in the popular press, particularly during the recent financial turmoil. However, many aspects of manipulation are poorly understood. The purpose of this thesis is to enhance our understanding of market manipulation by providing empirical evidence on the prevalence, effects and determinants of closing price manipulation.

The first issue examined in this thesis is the *prevalence* of closing price manipulation. This thesis uses a hand collected sample of prosecuted closing price manipulation cases from US and Canadian stock exchanges, and methods that explicitly model the incomplete and non-random detection of manipulation. The results suggest that approximately 1.1% of closing prices are manipulated. For every prosecuted closing price manipulation there are approximately 300 instances of manipulation that remain undetected or not prosecuted. Closing price manipulation is more prevalent on larger exchanges than smaller ones, but is detected at a higher rate on small exchanges.

Second, this thesis examines the *effects* of closing price manipulation. Using a sample of prosecution cases, this thesis finds that closing price manipulation is associated with large day-end returns, subsequent return reversals, increases in day-end spreads and increases in day-end trading activity. At the broader level of market quality, this thesis provides evidence from a laboratory experiment that closing price manipulation decreases both price accuracy and liquidity. Even the mere possibility of manipulation decreases liquidity and increases trading costs.

The third issue analysed in this thesis is the *determinants* of closing price manipulation and its detection. Estimating an empirical model of manipulation and detection, this thesis finds that the likelihood of closing price manipulation is increased by smaller regulatory budgets, greater information asymmetry, mid to low

levels of liquidity, month-end days and lower volatility. Manipulation is more likely to be detected when regulatory budgets are larger and when the manipulation causes abnormal trading characteristics. Further evidence from laboratory experiments suggests that regulation helps restore price accuracy by deterring some manipulation and making remaining manipulation less aggressive. These experiments also show that regulation has an insignificant effect on liquidity because participants in regulated markets still face relatively high uncertainty about the presence of manipulators.

This thesis also examines how closing price manipulation is conducted and how other market participants respond. It develops an index of closing price manipulation that can be used to study manipulation in markets or time periods in which prosecution data are not available. It also provides a tool for the detection of manipulation, which can be used by regulators in automated surveillance systems.

Finally, this thesis has implications for economic efficiency and policy. Closing price manipulation is significantly more prevalent than the number of prosecution cases suggests. Further, it harms both pricing accuracy and liquidity and therefore undermines economic efficiency. The prevalence of closing price manipulation can be reduced by increasing regulatory budgets, improving the accuracy of market surveillance systems by using the detection tools developed in this thesis, structuring markets such that participants are better able to identify manipulation, and implementing closing mechanisms that are difficult to manipulate. These actions would enhance market integrity and economic efficiency.

Chapter 1

Introduction

Among the plays which men perform in taking different parts in this magnificent world theatre, the greatest comedy is played at the Exchange. There, … the speculators excel in tricks, they do business and find excuses wherein hiding places, concealment of facts, quarrels, provocations, mockery, idle talk, violent desires, collusion, artful deception, betrayals, cheatings, and even tragic end are to be found

- Joseph de la Vega (1688), describing the Amsterdam Stock Exchange.

1.1 Background and motivation

Since the beginning of trading on organised exchanges, speculators have manipulated markets to profit at others' expense. This is illustrated by Joseph de la Vega's eloquent description of one of the earliest organised exchanges, in which he lists a variety of strategies used by speculators, many of which would today be labelled 'market manipulation'. Numerous cases of manipulation exist in history, such as when the influential Rothschilds sold large amounts of stock to create the false impression that Napoleon had defeated Wellington, causing prices to crash and allowing them to repurchase the stock at depressed prices (Griffin, 1980). The magnitude of manipulation's effects can be extraordinary; for example, the price of nearly bankrupt NEI Webworld Inc. shot up by 11,400% within a day in response to rumour mongering on the internet.[1] Manipulation is not confined to small and illiquid

[1] See "Stock pump-n-dump fraudsters settle suit, earn jail time", by Brian Krebs, Newsbytes, 24 January 2001.

companies; for example, multibillion dollar Lucent Technologies was successfully manipulated (Leinweber and Madhavan, 2001). The amount of funds used in manipulation and scale of profits can be immense; for example, in 2004 Citigroup netted €18.2 million profit from manipulation that involved placing €12.9 billion worth of sell orders in 200 different government bonds within 18 seconds and later repurchasing them.[2] Manipulation is not confined to sophisticated market participants; for example, Jonathan Lebed, a teenager from New Jersey successfully manipulated stocks 11 times by posting messages on Yahoo Finance message boards and made profits of $800,000 (Lewis, 2001). Nor is manipulation confined to individual securities; for example, in 1996 Nomura Int. Plc. manipulated an entire market index (Australian All Ordinaries) by selling a $600 million basket of stocks (more than the average daily market turnover) within minutes of the close of trading.[3]

Allegations of manipulation abound in the popular press. During bull markets, media attention tends to be focussed on manipulation that inflates stock prices. However, during the recent market turmoil manipulation has been widely blamed for contributing to sharp price declines and collapses of companies. Regulators such as the US Securities and Exchange Commission (SEC) have introduced a number of new rules and implemented temporary short selling bans, citing combating manipulation as an underlying reason.

Despite the significant interest in manipulation, many aspects of manipulation are not well understood. This thesis enhances our understanding of manipulation by providing evidence on the prevalence, effects and determinants of a particular type of manipulation, closing price manipulation.

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[2] See "The day Dr Evil wounded a financial giant", by Avinash Persaud and John Plender, Financial Times, 23 August 2006.

[3] See "The financial monster that tried to eat Australia", by Ben Hill, Sydney Morning Herald, 11 December 1998.

1.1.1 Closing price manipulation

Closing price manipulation is the illegal act of intentionally forcing a closing price to an artificial level. It is usually conducted by aggressively buying or selling stock at the end of a trading day. Figure 1.1 illustrates a typical example of closing price manipulation obtained from a prosecution case. At the beginning of the day the stock is trading below $20 and the manipulator instructs his broker, "do your buying today, at the end of the day … up into the twenties" (recorded telephone conversation, see Case 3 in Appendix B for further details). Later that day, the broker requests from the manipulator, "give me some more sugar to buy", and shortly before the close he executes a series of trades in quick succession raising the price and setting an inflated closing price.

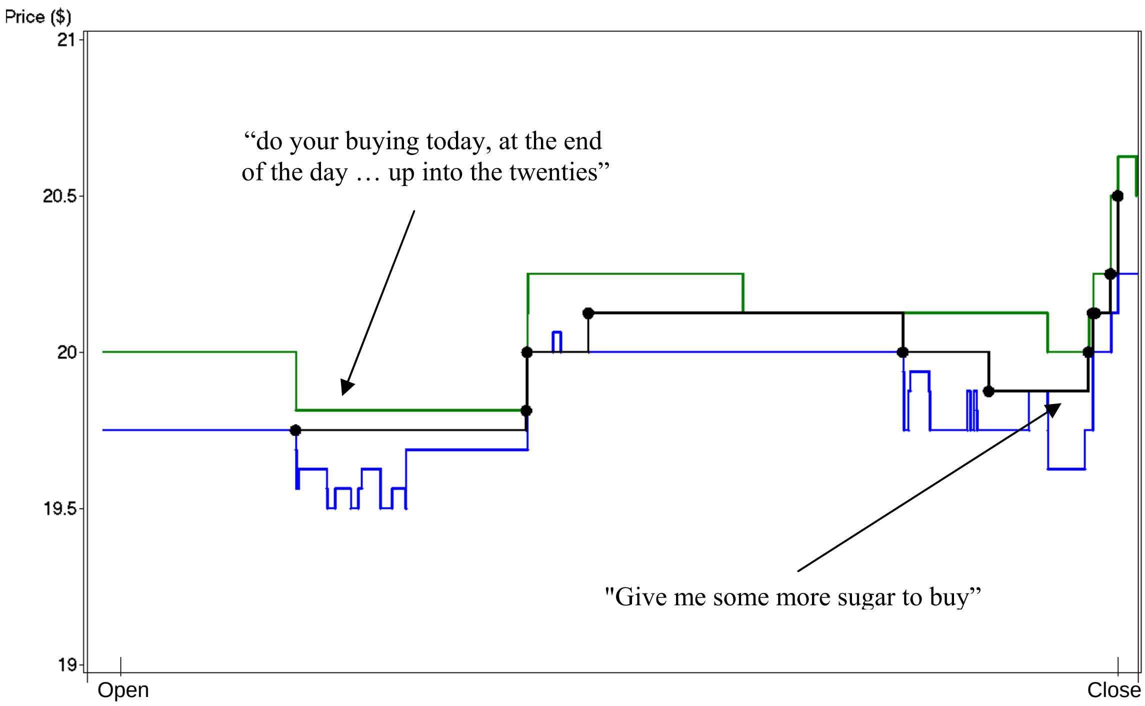

Figure 1.1 An example of closing price manipulation
This figure plots the best bid (bottom line), best ask (top line), last trade price (middle line), and trades (dots) for Southern Union Company (SUG) on the New York Stock Exchange during 25 October 1999. The quoted text is from telephone conversations between the manipulator and his broker recorded by the US Securities and Exchange Commission (SEC).

This thesis's focus on closing price manipulation is driven by the importance of closing prices. A large number of contracts are based specifically on closing prices, creating incentives for many different parties to manipulate them. For example, mutual fund net asset values (NAV) and fund performance are often calculated using closing prices. The performance of a fund determines its ranking relative to competitors and is also commonly used to determine fund manager remuneration. Given these incentives, it comes as little surprise that some fund managers manipulate closing prices.[4] Closing prices have also been manipulated in order to profit from positions in derivatives on the underlying stock[5] and by brokers attempting to alter their customers' inference of their execution ability.[6] Closing prices have been manipulated during pricing periods for seasoned equity issues and takeovers, to maintain a stock's listing on an exchange with minimum price requirements, to avoid margin calls, and on stock index rebalancing days for a stock to gain inclusion in an index.

Recognising the problems closing price manipulation can create, numerous stock exchanges have introduced closing call auctions to make manipulation more difficult. Several contracts have been redesigned to be more robust to manipulation, for example, by using volume weighted average prices (VWAP) in place of closing prices. Despite these measures, closing price manipulation remains a significant issue because many exchanges still utilise simple closing mechanisms, cases of closing price manipulation are still found in markets with closing call auctions, and many contracts today still provide incentives to manipulate closing prices.

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[4] This type of manipulation is commonly conducted on the last day of a reporting period such as a month-end or quarter-end. See Carhart et al. (2002) and Bernhardt and Davies (2005). This practice is also known as 'marking the close', 'painting the tape', 'high closing', 'marking up' or 'portfolio pumping'.

[5] See, for example, Kumar and Seppi (1992) and Ni et al. (2005).

[6] See, for example, Hillion and Suominen (2004).

1.1.2 Why manipulation matters

Most market manipulation is detrimental to stock markets and their participants. Manipulation can discourage participation and cause investors to trade in alternative markets, thereby decreasing liquidity and increasing trading costs. Consequently, manipulation can lead to an increase in the cost of capital, making firms reluctant to list their shares in markets known for manipulation. Manipulation impairs price discovery through reduced order flow and distorts prices from their natural levels. This reduces market efficiency and causes deadweight economic losses due to distorted resource allocation and wealth redistribution (Pirrong, 1995). The price distortions caused by closing price manipulation are particularly harmful because of the widespread use of closing prices (Kahan, 1992). For these reasons, understanding closing price manipulation is of great importance to academics, exchanges and regulators.

1.2 Purpose and contributions

The purpose of this thesis is to enhance our understanding of market manipulation. Thel (1994, p. 287) points out "[w]e do not know how often prices are manipulated, how much harm manipulation does or how existing manipulation rules influence behavior." The main contribution of this thesis is providing evidence on precisely these issues - the prevalence, effects and determinants - in the specific context of closing price manipulation.

The first issue is the prevalence of closing price manipulation. This thesis estimates the frequency of closing price manipulation on US and Canadian stock exchanges. The estimates are obtained using a hand collected sample of prosecuted closing price manipulation cases and methods that explicitly model the incomplete and non-random detection of manipulation. The results suggest that approximately 1.1% of closing prices are manipulated. For every prosecuted closing price manipulation there are approximately 300 instances of manipulation that remain undetected or not prosecuted. Closing price manipulation is more prevalent on larger exchanges than smaller ones, but is detected at a higher rate on small exchanges.

The second issue is the effects of closing price manipulation. Using a sample of prosecution cases, this thesis finds that closing price manipulation is associated with large day-end returns, subsequent return reversals, increases in day-end spreads and increases in day-end trading activity. At the broader level of market quality, this thesis provides evidence from a laboratory experiment that closing price manipulation decreases both price accuracy and liquidity. Even the mere possibility of manipulation decreases liquidity and increases trading costs. Following the arguments of Kyle and Viswanathan (2008), closing price manipulation therefore undermines economic efficiency and should be prohibited.

The third issue is the determinants of closing price manipulation and its detection. Using a sample of prosecuted manipulation cases, this thesis finds that the likelihood of closing price manipulation is increased by smaller regulatory budgets, greater information asymmetry, mid to low levels of liquidity, month-end days and lower volatility. Manipulation is more likely to be detected when regulatory budgets are larger and when the manipulation causes abnormal trading characteristics. Further evidence from a laboratory experiment suggests that regulation helps restore price accuracy by deterring some manipulation and making remaining manipulation less aggressive. These experiments also show that regulation has an insignificant effect on liquidity because participants in regulated markets still face relatively high uncertainty about the presence of manipulators.

This thesis makes some further contributions. It examines how closing price manipulation is conducted and how other market participants respond. It develops an index of closing price manipulation that can be used to study manipulation in markets or time periods in which prosecution data are not available. It also provides a tool for the detection of manipulation, which can be used by regulators in automated surveillance systems.

1.3 Structure of this thesis

The next chapter discusses what constitutes market manipulation and reviews the relevant literature. Chapter 3 analyses the determinants of closing price manipulation and its detection, and estimates its prevalence. It describes the hand collected sample of prosecution cases that is also used in Chapters 4 and 6. Chapter 4 examines the trading characteristics (returns, return reversals, trading frequency, spreads and trade size) around cases of closing price manipulation. Chapter 5 analyses the effects of closing price manipulation on market quality, using a laboratory experiment. Chapter 6 constructs an index of closing price manipulation and a closely related tool for the detection of manipulation, drawing on the findings of earlier chapters. Chapter 7 concludes.

Chapter 2

Literature review

This chapter reviews the literature on market manipulation. It begins by summarising the debate on what constitutes market manipulation. The intent is to provide context to the trading strategies studied in the literature and illustrate how closing price manipulation, the focus of this thesis, fits among the diverse range of manipulation strategies. Next, this chapter reviews the theoretical work on market manipulation, followed by the less numerous and more recent empirical and experimental studies. This chapter finishes with a summary of the conclusions that can be drawn from the literature.

2.1 Definition and forms of market manipulation

There is no generally accepted definition of market manipulation. This may seem surprising given the long history of manipulation in world financial markets[7] and the fact that more than three quarters of a century has passed since the inception of US federal securities regulation against market manipulation.[8] Legal definitions

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[7] For example, one of the most famous of the early manipulation prosecutions during the Napoleonic wars involved a group of manipulators spreading false rumours about the death of Napoleon and that the allies had entered Paris. The Court of King's Bench in England ruled that it was an offence to conspire to raise the price of Government securities by false rumours with the intent of injuring purchasers (Rex v De Berenger in Maule and Selwyn's reports 67 (1814), see Baxt et al. (1996)).

[8] A common view is that regulation against market manipulation in the US began in the 1930s with the Securities Act of 1933, the Securities Exchange Act of 1934, and the creation of the Securities and Exchange Commission (SEC) in 1934, largely in response to the massive losses suffered by the public in the Great Depression. However, Berle (1938) points out that while the reforms of the 1930s contributed significantly to bringing legal action against market manipulators, the forms of

are often intentionally not explicit, and much of the finance and economics literature uses the term market manipulation in an imprecise manner. This situation has led to a longstanding debate and controversy over the definition of market manipulation. This section reviews the legal interpretation of market manipulation, the definitions used in academic studies and the range of practices commonly regarded as market manipulation.

2.1.1 Legal interpretation of market manipulation

Legal definitions vary across jurisdictions and in many cases are not explicit about what constitutes market manipulation. For example, the Corporations Law in Australia, the Securities Exchange Act 1934 in the US and the Market Abuse Directive in the European Union (EU) prohibit market manipulation and contain various provisions to achieve this purpose, but none of these laws attempt to precisely define manipulation (Goldwasser, 1999). The task of defining manipulation is largely left to the courts on a case-by-case basis. According to US statutory law it is unlawful "to use or employ, in connection with the purchase or sale of any security … any manipulative or deceptive device or contrivance".[9] In Australia, statutory law prohibits "transactions that have or are likely to have; the effect of … creating an artificial price".[10] The EU has recently adopted a principles-based approach to describing prohibited practices. EU statutory law stipulates, "market manipulation shall mean transactions or orders to trade which give, or are likely to give, false or misleading signals as to the supply of, demand for or price of financial instruments, or which secure … the price of one or several financial instruments at an abnormal or

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manipulation banned by the Acts of 1933-1934 were already effectively outlawed by the courts through common law.

[9] Section 10(b), Securities Exchange Act 1934. For a detailed discussion see Thel (1990) and Goldwasser (1999).

[10] Section 1041A, Corporations Act 2001.

artificial level".[11] A definition that captures the essence of the relevant statutory law in several jurisdictions, but by itself is neither precise nor objective, is provided by the Australian Stock Exchange (ASX):

> "*Market manipulation describes a deliberate attempt to interfere with the free and fair operation of the market and create artificial, false or misleading appearances with respect to the price of, or market for, a stock.*"[12]

Given that statutory law does not provide a precise definition of manipulation, one must turn to case law to understand what is viewed as manipulation by courts. US case law has established a four part test for manipulation involving ability, intent to deceive, causation and artificiality (Johnson, 1981). Across a number of jurisdictions, arguably the two most important elements, and often the most difficult to prove, are artificiality and intent. Artificiality can be with respect to trading activity (e.g., creating the appearance of more trading than what would naturally take place), or price (e.g., altering the price by raising or depressing it). Intent distinguishes manipulative from non-manipulative trading. Because intent can rarely be determined with certainty, this element causes significant difficulties in identifying manipulation. Proper, non-manipulative market participation can cause an increase in market activity or alteration of the market price. Manipulative trading can have exactly the same effects on the market, but is distinguished by the fact that it is undertaken for an impermissible purpose (Goldwasser, 1999). Broadly speaking, case law establishes that market manipulation involves actions or trades undertaken with the intent of forcing a price to an artificial level, inducing other people to trade, or deceiving others.

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[11] Section 1(2)(a) Market Abuse Directive 2003.

[12] See http://www.asx.com.au/supervision/participants/market_manipulation.htm.

2.1.2 Law and economics literature definitions

The law and economics literature contains considerable debate about how to define manipulation. In a sharp departure from mainstream legal thought, Fischel and Ross (1991) argue that market manipulation is too vague a concept to form the basis for criminal charges. They point out that there is no objective definition of manipulation and suggest that manipulation could only be defined as dishonest intent to move stock prices. Fischel and Ross argue that irrespective of intent, trades should not be prohibited as manipulative; but fictitious trades (e.g., trades in which the buyer and seller is the same person) and spreading false information should be classified as fraud. Their reasoning is that: (i) purely trade based manipulation is unlikely to be successful; and (ii) rules that prohibit manipulation deter some legitimate trading.

Thel (1994) delivers a strong rebuttal. Based on evidence in the economics literature Thel states that manipulation is easier to accomplish than Fischel and Ross claim. Thel argues that manipulators can sometimes control prices with trades and in doing so profit either from pre-existing contracts that are contingent on prices, or by inducing other market participants to trade at manipulated prices.

Thel uses the term manipulation to mean trading undertaken with the intent of increasing or decreasing the reported price of a security. Jarrow (1992) uses the term market manipulation in the context of large uninformed traders to mean a trading strategy that generates positive real wealth with zero risk. Cherian and Jarrow (1995) define manipulation as trading by an individual (or group of individuals) in a manner such that the share price is influenced to his advantage. More recently, Kyle and Viswanathan (2008) propose that trading strategies should only be classified as illegal price manipulation if they undermine economic efficiency both by decreasing price accuracy and reducing liquidity. Unless both of these conditions are satisfied, the trading strategy is not unambiguously socially harmful and therefore, according to Kyle and Viswanathan, should not be prohibited.

2.1.3 Forms of market manipulation

The generic term ‘market manipulation’ encompasses many distinct and widely varied strategies. To illustrate some of the relations between strategies, this overview constructs a simple taxonomy of the most common types of market manipulation (Figure 2.1). At the broadest level, manipulation can be divided into runs, contract-based manipulations and market power techniques. Within these groups, manipulation can be further broken down into trade-based, information-based and action-based forms. This overview first describes the two levels on which manipulation can be grouped and then defines the individual techniques.

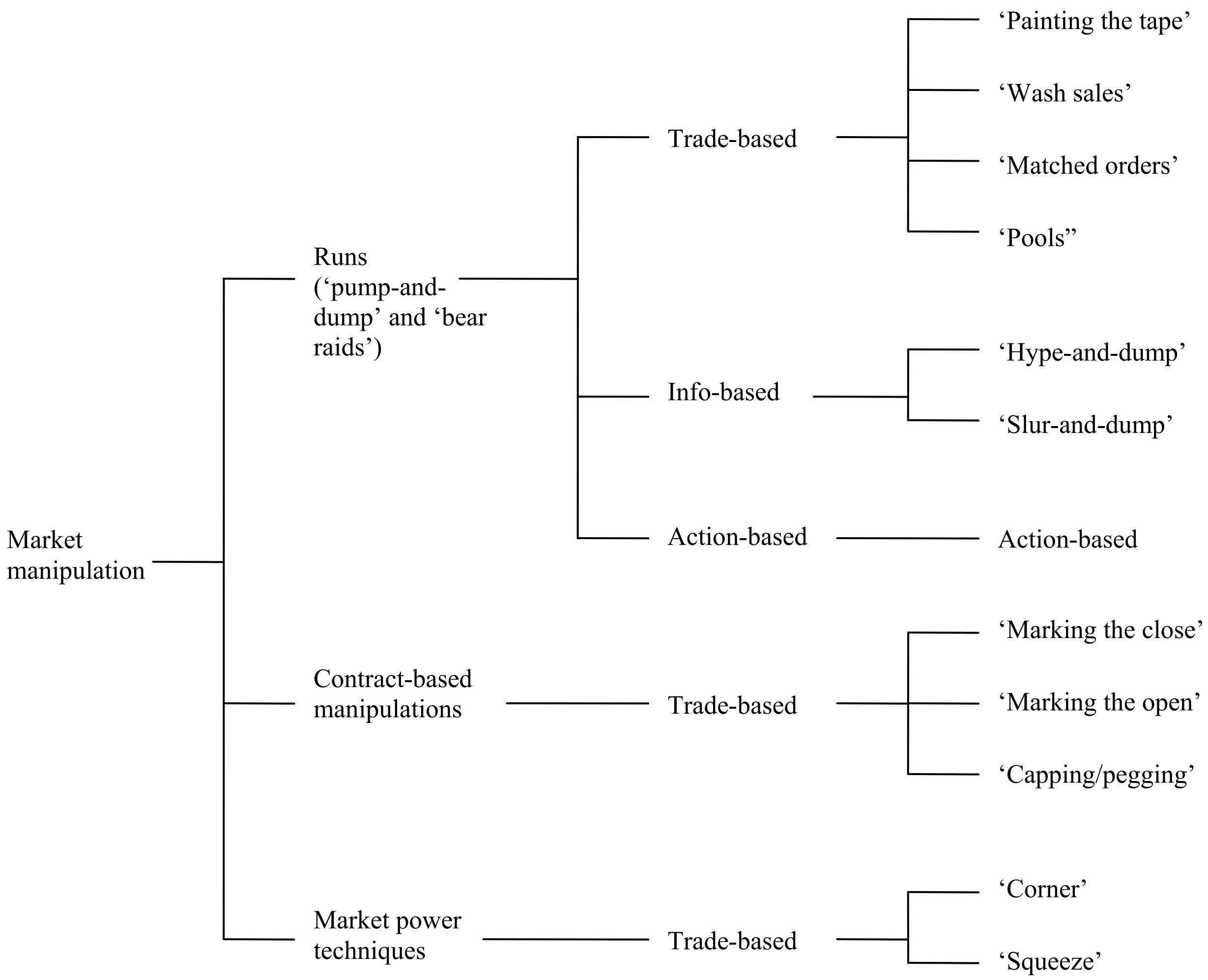

Figure 2.1 Taxonomy of manipulation techniques

In a run the manipulator takes either a long or a short position in a stock, inflates or deflates the stock's price while attracting liquidity to the stock, and finally reverses his position at the inflated or deflated price. Runs that inflate a stock's price are often referred to as 'pump-and-dump' manipulation. The stock 'pumping' can take anywhere from a matter of hours to several years and make use of techniques such as rumour spreading, wash sales and pooling by several manipulators. 'Bear raids' are a form of run in which the manipulator short sells a stock, manipulates its price downwards by inducing others to sell, and covers his position at a depressed price. A common feature of runs is that the manipulator profits directly from the manipulated market by exploiting investors that buy at inflated prices or sell at depressed prices.

In contract-based manipulation, on the other hand, the manipulator profits from a contract or market that is external to the manipulated market. For example, a manipulator might take a position in a derivatives contract then manipulate the underlying stock price to profit on the derivatives position. An important difference is that such manipulation does not require the manipulator to induce others to trade at manipulated prices and therefore tends to be more mechanical by nature.

The third broad group of manipulation techniques involves the manipulator exploiting market power by, for example, taking a controlling position in the supply of a security. Like contract-based manipulation, market power techniques are more mechanical in nature than runs. However, they are similar to runs in that the manipulator profits by exploiting participants of the manipulated market.

Within the three broad types, manipulation techniques can be further broken down using Allen and Gale's (1992) definitions of trade-based, information-based and action-based manipulation. Trade-based manipulation involves influencing the price of a stock through trading. In information-based manipulation a manipulator releases false information or rumours about a company in order to inflate or depress its price. Action-based manipulation involves taking actions to affect the value or perceived value of a firm. For example, a company director may shut down a factory to depress the share price.

Each of the three forms of manipulation consists of a wide variety of techniques, particularly trade based manipulation (see Cumming and Johan (2008) for a list of the techniques targeted by market surveillance authorities). Engaging in a series of transactions that are reported on a public display facility which give the impression of trading activity or price movements is known as 'painting the tape'. This technique often involves 'wash sales', i.e., improper transactions in which the buyer and seller is the same person such that there is no genuine change in ownership, or 'matched orders', i.e., pairs of buy and sell orders placed by different but colluding parties at the same time for the same price and volume. 'Pools' are when a group of manipulators trade shares back and forth among themselves to influence prices and create the appearance of trading volume. Dissemination of false information or rumours via the media, internet or other means is commonly known as 'hype-and-dump' when the intent is to inflate a stock price, and 'slur-and-dump' when the intent is to depress the stock price.

'Marking the close' (also known as closing price manipulation and 'high closing') involves buying or selling securities at or shortly before the close in an effort to alter the closing price. 'Marking the open' is similar, but involves influencing the opening price rather than closing price. Closing and opening price manipulation are common techniques for contractual manipulation because often contacts are based on closing prices (and less often opening prices), but are also used in conjunction with other techniques to facilitate runs. 'Pegging' and 'capping' refer to placing orders that effectively prevent a price from moving up or down. This is often done to ensure a derivatives contract expires in or out of the money. 'Corners' and 'squeezes' are techniques in which the manipulator secures a controlling position in the supply of an asset and/or a derivative contract. The manipulator then uses this position to manipulate the price by exploiting investors that need the underlying asset to close out short positions.

To summarise this section, a definition of market manipulation that captures the key elements of statutory and case law, as well as the main arguments in the economics and law literature, is interference with the free and fair operation of a market, conducted with the intent to create a misleading price or a misleading trading activity. Broadly speaking, market manipulation can be divided into runs, contract based manipulations and manipulation using market power, each of which can be conducted with a range of action-, information- and trade-based techniques. Closing price manipulation is typically a trade-based form of contractual manipulation, although it is also sometimes used in conjunction with other techniques to facilitate a run.

2.2 Theoretical literature

The theoretical market manipulation literature provides insights about the conditions under which manipulation is possible and profitable. The literature, which spans the past 20 years, is fairly extensive, particularly regarding trade-based manipulation, and to a lesser extent information-based techniques. Although action-based manipulation is not explicitly studied in the literature, it can often be viewed as a type of information-based strategy because the manipulator's actions create a false signal similar to false information. Consequently, many of the findings about information-based manipulation are relevant for action-based manipulation.

2.2.1 Information-based manipulation

Vila (1989) uses game theory to model a simple scenario in which a manipulator short sells a stock, releases false and damaging information about the stock and then covers his position at the depressed price. Bagnoli and Lipman (1996) analyse a model in which a manipulator announces a false takeover bid to drive up the price of a stock. The profitability of both strategies hinges on the credibility of the information released by the manipulator. In repetitions of such games, if market participants are able to deduce that false information originated from a manipulator, the manipulator will quickly be discredited and the manipulation strategy will cease to be profitable.

To overcome the problem of credibility in repeated games, Benabou and Laroque (1992) and Van Bommel (2003) model the use of imprecise information to influence stock prices. In Benabou and Laroque (1992), noise in private information restricts the ability of traders to verify the truthfulness of a piece of information. Consequently traders, such as company insiders, journalists or stock analysts, can manipulate stock prices over a long period of time without losing credibility by mixing truth and lies in the information they release. Van Bommel (2003) uses a Kyle (1985) framework to model informed investors that manipulate prices by spreading imprecise rumours. In equilibrium, rumours are informative and therefore rational profit maximising agents trade on them. Because the rumours are imprecise, prices occasionally overshoot. This allows the informed rumourmonger to profit not only from trading on their information, but also from trading against overshot prices. Eren and Ozsoylev (2006) use a similar model to Van Bommel (2003) and find that 'hype-and-dump' manipulation increases market depth and trading volume, but decreases market efficiency.

2.2.2 Trade-based manipulation

Early theoretical trade-based manipulation literature establishes very general conditions under which pure trade-based manipulation in a single market (e.g., a series of buys followed by a series of sells) is and is not profitable. Fischel and Ross (1992), among others, argue that trade based manipulation is not possible in an efficient market. Jarrow (1992), Cherian and Kuriyan (1995) and Cherian and Jarrow (1995) build on the model of Hart (1977) and derive conditions under which trade-based manipulation is not possible. In Cherian and Kuriyan's model manipulation is not possible with rational agents when price responses are symmetric. Jarrow demonstrates that a sufficient condition to exclude market manipulation strategies is that the price response function depends only on a trader's aggregate stock holdings and not on his past sequence of trades, in other words, when prices do not exhibit 'momentum'. Huberman and Stanzl (2004) demonstrate that uninformed trading strategies that generate infinite expected profits are ruled out when price update functions, i.e., the permanent effect of trade size on future prices, are time independent and linear.

Many theoretical studies seek to prove that trade-based manipulation is possible in variations of the seminal models of Kyle (1985) and Glosten and Milgrom (1985). Allen and Gorton (1992) argue that the natural asymmetry between liquidity purchases and liquidity sales gives rise to profitable trade-based manipulation. If liquidity motivated sales are more likely than liquidity motivated purchases, buy orders are more informed on average and therefore have a larger effect on prices. In a Glosten and Milgrom (1985) model, this asymmetry allows an uninformed manipulator to generate a profit by executing a series of buys to bid the price up and then sell the stock causing a relatively smaller decrease in price. Allen and Gale (1992) similarly use a Glosten and Milgrom (1985) framework, but in their model an uninformed manipulator mimics an informed trader with positive information about the stock. The uninformed trader's manipulation is profitable under certain restrictions on the strategy of the informed trader. Of critical importance to the success of such a strategy is information asymmetry. Investors are uncertain whether a large trader who buys the stock does so because he knows it is undervalued or because he intends to manipulate the price. Aggarwal and Wu (2006) extend this model and provide the insight that although information seekers (or arbitrageurs) generally make markets more efficient, when manipulation is possible more information seekers imply greater competition for shares, making it easier for an uninformed manipulator to enter the market and harm market efficiency.

Unlike the previous studies that examine *uninformed* manipulators, Chakraborty and Yilmaz (2004a, 2004b) demonstrate that in Glosten and Milgrom (1985) and Kyle (1985) models, *informed* traders also benefit from manipulating the market. When the existence of an informed trader is uncertain and there is a large number of trading periods before all private information is revealed, long-lived informed traders will manipulate the market in every equilibrium by initially trading in the opposite direction to their information. This strategy results in short-term losses for the informed traders, however, the increased noise in the trading process allows them to retain their informational advantage for longer and extract more profit from their information. When there are many competitive rational traders who hold coarser information than the insider but finer information than the market maker, the manipulator has added incentive to manipulate because the competitive rational traders follow the insiders trades in equilibrium (Chakraborty and Yilmaz, 2008).

A number of studies model how specific securities (e.g., derivatives), events (e.g., seasoned equity offerings), or market design features (e.g., trade reporting requirements) give rise to profitable trade-based manipulation. Jarrow (1994) provides evidence of manipulation strategies that arise from derivative securities. In Gerard and Nanda (1993) strategic informed traders short sell a stock just prior to a seasoned equity offering to place downward pressure on the price. The manipulators then more than cover their position by purchasing stocks in the offering at a discount price and finally liquidate their positions at a profit when the stock price is eventually restored to its fair value. In Fishman and Hagerty (1995) a manipulator takes advantage of the Securities Exchange Act (1934) mandatory disclosure rule for large trades. The manipulator declares large buys, thereby forcing prices up, and then sells the position anonymously in a series of small trades. John and Narayanan (1997) and Huddart et al. (2001) also examine the effect of mandatory disclosure laws on the insider's incentive to manipulate. Kyle (1984), Vila (1987) and Allen et al. (2006) model corners and squeezes in which manipulators control prices by obtaining a large fraction of the supply. Pirrong (1993) shows that squeezes hinder price discovery and create deadweight losses. In Vila (1989) and Bagnoli and Lipman (1996) a manipulator trades to give the impression of a takeover bid, misleading the market and allowing the manipulator to profit by selling at an inflated price.

Theory suggests that another mechanism manipulators can exploit to their advantage is the feedback effect from financial markets to the real value of a firm. This occurs when directors use their company's stock price as a signal in making decisions about the company's investment. In Goldstein and Geumbel's (2008) model manipulators aggressively short sell shares to depress share prices, thereby negatively influencing companies' investment decisions, harming fundamentals and allowing the short sellers to cover their positions at depressed prices. Khanna and Sonti (2004) demonstrate that feedback effects from stock prices to fundamental values can also be exploited in the other direction. In their model long-term shareholders manipulate prices upwards to encourage value creating investment. These studies illustrate that manipulation can reduce economic efficiency by distorting resource allocation.

In contrast to much of the theoretical literature, Hanson and Oprea (2009) do not seek to demonstrate the possibility or profitability of manipulation, but rather they examine the effects of manipulators on price accuracy. They find that in a Kyle (1985) model adapted to the case of a thin prediction market a manipulator with an exogenous preference for manipulation has the somewhat counter-intuitive ex-ante effect of *increasing* price accuracy. This effect arises because in the presence of a manipulator, the profitability of informed trading is higher and consequently more traders exert costly effort to become informed.

A few studies specifically analyse closing price manipulation. Kumar and Seppi (1992) use a Kyle (1985) framework to model a manipulator that takes a substantial long position in the futures market and then aggressively bids up the spot price before the close to profit from a more favourable futures settlement price. In Hillion and Suominen (2004) brokers manipulate closing prices to alter customers' perceptions of their execution quality. Their model demonstrates that closing call auctions reduce manipulation and enhance price efficiency. A recent model of a mutual fund manager's investment decision (Bernhardt and Davies, 2009) suggests that fund managers have incentives to use short-term price impacts to manipulate closing prices at the ends of reporting periods.

2.3 Empirical literature

The theoretical literature is valuable, particularly in: (i) providing insights about the conditions under which manipulation is possible; and (ii) identifying circumstances in which profitable manipulation opportunities may exist even if no such cases have yet been reported. However, many manipulation strategies are too complicated to be modelled theoretically and the assumptions and simplifications made in order for theoretical models to be tractable lead to questions about the validity of their results in real markets. For these reasons empirical research is crucial to understanding market manipulation. Compared to the theoretical literature, empirical studies are fewer and more recent. This is largely due to the difficulties in obtaining data. This section reviews studies that provide circumstantial or indirect evidence on manipulation, followed by studies of known manipulation cases and finally, the small number of experimental studies.

2.3.1 Indirect empirical evidence

Early empirical asset pricing and market microstructure literature identifies various abnormalities in closing prices, but does not link the abnormalities to market manipulation.[13] More recently, however, several studies attribute seasonal patterns and anomalies in day-end trading to closing price manipulation. Felixson and Pelli (1999) examine whether closing prices are manipulated in the Finnish stock market using regression analysis. Although their results are consistent with the hypothesis that closing prices are manipulated, they concede that further research is required to be conclusive. Carhart et al. (2002) find more conclusively that in US equities

[13] See Keim (1983), Ariel (1987) and Ritter (1988) on seasonal patterns and Wood et al. (1985) and Harris (1989) on intraday anomalies.

markets price inflation is localised in the last half hour before the close and that it is more intense on quarter-end days. They report that 80% of funds beat the S&P 500 Index on the last trading day of the year, but only 37% do so on the first trading day of a new year. They attribute this phenomenon to manipulation by fund managers. Similarly, Hillion and Suominen (2004) find on the Paris Bourse that significant rises in volatility, volume and bid-ask spreads occurs mainly in the last minute of trading and they attribute this to manipulation. Akyol and Michayluk (2009) make use of the Istanbul Stock Exchange's design involving two trading sessions per day to isolate end of period effects from end of day effects. They report evidence of closing price manipulation.

Empirical studies that analyse underlying stock prices around options expiration generally find that effects of manipulation can be found in the last hour before options expire and that the price effect is reversed in the first half hour of trading after expiration (Stoll and Whaley, 1987; Chamberlain et al., 1989; Stoll and Whaley, 1991). Ni et al. (2005) find evidence that on option expiration dates the closing prices of stocks with listed options cluster at option strike prices. They attribute this finding to closing price manipulation. McDonald and Michayluk (2003) examine whether manipulators exploit the trading halt mechanism on the Paris Bourse, where trading is halted in a stock when an order is submitted outside the daily price limits. They document suspicious trading characteristics around some trading halts, consistent with manipulators submitting trade-ending orders to secure the most recent trade price as the closing price. Onayev and Zdorovtsov (2008) find patterns of abnormal returns around the reconstitution of the Russell 3000 index. They suggest the patterns of returns are caused by closing price manipulation that is intended to influence the index reconstitution.

Two recent studies find evidence of manipulation by examining the trading records of likely manipulators, rather than market prices. Khwaja and Mian (2005) find evidence of 'pump-and-dump' market manipulation by brokers in Pakistan's main stock exchange. Brokers earn at least 8% higher returns on their own trades and neither market timing nor liquidity provision offer sufficient explanations for this result. They conclude that traders in developing markets resist stronger regulation to maintain high rents, suggesting poor regulatory systems hinder market development. Gallagher et al. (2009) support the earlier findings of Carhart et al. (2002) that some fund managers manipulate closing prices to influence their fund's reported performance. Gallagher et al. find that on the last day of the quarter, fund managers tend to purchase illiquid stocks in which they already hold overweight positions. Unlike in Carhart et al. (2002), however, Gallagher et al. (2009) find that poor performing managers are more likely to manipulate prices.

A limitation of studies that are based on indirect evidence is that usually there are alternative explanations for their results and it is virtually impossible to eliminate all alternative explanations. Despite this limitation, they provide some indication of the magnitude of price distortions caused by manipulation (in the order of 0.5% to 2% in Carhart et al. (2002)) and the scale of profits earned by a manipulator (in an emerging market, 50% to 90% higher annual returns than the average investor (Khwaja and Mian, 2005)). These studies support theoretical models (e.g., stock price manipulation related to derivatives) and identify motivations for manipulation not studied in the theoretical literature (e.g., around index reconstitutions).

2.3.2 Empirical studies of known manipulation cases

Studies of known manipulation cases are relatively few and in several instances resemble case studies due to the unavailability of larger and more representative datasets. A recent and significant study in this area due to its relatively large sample of cases is Aggarwal and Wu (2006). Aggarwal and Wu analyse 'pump-and-dump' manipulation cases obtained from The US Securities and Exchange Commission (SEC) litigation releases. They identify 142 cases of manipulation, of which they are able to obtain data on 51 manipulated stocks during the period 1990-2001. The minimum length of a manipulation periods is two days, the median is 202 days and the maximum is 1,373 days, highlighting the variation in the nature of pump-and-dump manipulation. They find that in their sample of prosecution cases stocks generally experience a price increase during the manipulation period, a subsequent decrease during the post-manipulation period, and increased volatility. Their sample of cases is more concentrated in illiquid stocks and most of the manipulation is conducted by informed insiders such as management, substantial shareholders, market-makers or brokers. Aggarwal and Wu (2006), however, do not address the sample selection bias arising from incomplete detection. This is discussed further in Chapter 3.

A widely stated reason for the introduction of closing call auctions on stock exchanges is to minimise the ability for the closing price to be manipulated. Despite this, Comerton-Forde and Rydge (2006) identify several cases of closing price manipulation in exchanges with closing call auctions. In their sample of 25 closing auction manipulations from six developed markets, manipulators exhibit similar behaviour across markets in that they tend to submit large, unrepresentative orders in the final seconds of the auction. Their analysis indicates that the design of the closing auction algorithm influences how easily the closing price can be manipulated. Some algorithm designs are more effective than others in reducing the impact of manipulation.

A small number of studies examine corners, squeezes, the stock pools of the 1920s. Although the widespread manipulation through stock pools before the crash of 1929 is vividly documented in Galbraith (1972) and one of the main reasons for the introduction of the US federal securities legislation in the 1930s, Mahoney (1999) and Jiang et al. (2005) find little evidence of manipulation in the alleged stock pools of the 1920s. They conclude that these pools did not harm investors. Their sample consists of 55 stock pools identified from a US Senate report. Allen et al. (2006) examine several well-known stock and commodity market corners which occurred between 1863 and 1980. They find that manipulation by large investors and corporate insiders using market power increases market volatility and has an adverse price impact on other assets. They also find that the presence of large investors makes it risky for would-be short sellers to trade against the mispricings, which in some cases are severe. Merrick et al. (2005) examine a case of manipulation involving a delivery squeeze on a bond futures contract traded in London, while Jegadeesh (1993) and Jordan and Jordan (1996) examine the Salomon brothers' market corner of a Treasury note auction in 1991.

Besides the somewhat obvious limitation of small sample sizes, a less obvious limitation of these studies is non-randomness of their samples that arises as a result of incomplete detection (and prosecution) of manipulation. The biases in inference that can arise when this problem is ignored are well documented by Feinstein (1990). Despite this limitation, studies of known manipulation cases provide rich insights about manipulation that can not be gained using other approaches.

2.3.3 Experimental studies

In an unusual field experiment, Camerer (1998) attempts to manipulate horse racing odds by making bets and then cancelling them shortly before the race. Although making and then cancelling bets is costless, this is not widely known by bettors at the time. Camerer finds that that the bets placed by the experimenter do not distort prices.

Hanson et al. (2006) conduct the first laboratory work on price manipulation. In their study, 12 participants trade stock and cash in an electronic limit order book market. In their manipulation treatment, half of the participants are given monetary incentives to manipulate the stock price. Their main result is that manipulators are unable to distort price accuracy because other traders counteract the actions of the manipulator.

Experimental studies are able to overcome many of the limitations of other empirical methods because the experimenter is able to observe and control information, incentives and fundamental asset values, as well as being able to overcome the problems caused by incomplete detection of manipulation. The main limitation in this type of research is in the ability to construct the experimental setting in a sufficiently realistic manner so that results have external validity and offer meaningful insights for real markets. Despite this limitation, experimental studies are a promising and underutilised method for enhancing our understanding of market manipulation.

2.4 Conclusions

The generic term 'market manipulation' refers to a very large number of highly varied strategies generally involving the intent to create a misleading appearance regarding the price or trading activity of a security. Closing price manipulation is typically a trade-based form of contractual manipulation, although it is also sometimes used in conjunction with other techniques to facilitate a run on a stock.

The large body of theoretical market manipulation literature provides insights about the conditions under which manipulation is profitable. A limitation of this literature is that the assumptions and simplifications made in order for theoretical models to be tractable lead to questions about the validity of their results in real markets. The empirical literature by comparison is scarce, largely due to the difficulties in obtaining data, but provides some rich insights. The greatest difficulty for studies based on circumstantial or indirect evidence is ruling out alternative explanations. Studies of known manipulation cases use small non-random samples, which brings into question the ability to generalise their results. Controlled experiments can overcome many of the difficulties faced by empirical studies, however, there is almost no work in this area yet. Many aspects of market manipulation are not yet well understood, such as its prevalence, determinants and effects. Further empirical evidence on these issues would be valuable. Future empirical studies might seek to obtain more comprehensive datasets of manipulation cases, addressing the incomplete detection problems in existing datasets, or using controlled experiments.

There is only a small amount of work specifically on closing price manipulation, despite the many uses of closing prices and the perceived pervasiveness of this form of manipulation.[14] Theoretical studies demonstrate that derivative traders, brokers and fund managers have incentives to manipulate closing prices and empirical studies find evidence that these market participants engage in closing price manipulation. There is scope for research that furthers our understanding of closing price manipulation, particularly its prevalence, determinants and effects.

This thesis contributes to the empirical literature using the approaches suggested by this review: collection of a comprehensive dataset of closing price manipulation cases, application of econometric methods that address the incomplete detection problem, and a controlled experiment. This thesis adds to the small number of studies specifically focussed on closing price manipulation. Unlike many existing studies, this research is not limited to specific motivations for closing price manipulation or specific groups of market participants, and examines closing price manipulation more broadly. Rather than providing evidence of the possibility or profitability of closing price manipulation, this thesis focuses on the prevalence, determinants and effects of manipulation.

[14] For example, an article in news magazine Maclean's (10 July 2000, Vol. 113 No. 28, page 39) comments "nearly everyone seems to agree that high closing is common".

Chapter 3

Prevalence and determinants of closing price manipulation

3.1 Introduction

Our understanding of the pervasiveness and underpinnings of closing price manipulation is limited by the fact that only some non-random fraction of manipulation is detected and prosecuted by market regulators. Thel (1994, p. 223) remarks "manipulation is theoretically possible and probably occurs fairly often". Closing price manipulation in particular is perceived by market participants to be common, but how common is common? Similarly, the underpinnings of manipulation are not well understood. For example, fund managers have been prosecuted for manipulating closing prices on quarter-ends but is closing price manipulation more likely on quarter-ends than on other days?

This chapter makes two main contributions. First, it quantifies the extent to which various factors drive closing price manipulation and its detection, and second, it estimates the prevalence of closing price manipulation in stock markets. The analysis uses a hand collected sample of actual manipulation cases and detection controlled estimation (DCE) methods, which explicitly take into consideration that only a non-random subset of manipulation is detected. The sample of prosecuted manipulation cases is from four US and Canadian stock exchanges: the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), the Toronto Stock Exchange (TSX) and the TSX Venture Exchange (TSX-V).

The results indicate that stocks with high levels of information asymmetry and mid to low levels of liquidity are most likely to be manipulated. A significant proportion of manipulation occurs on month-end and quarter-end days suggesting fund managers are responsible for a considerable fraction of manipulation. Stock price volatility deters manipulation by drawing the attention of regulators. The DCE models estimate that approximately 1.1% of closing prices are manipulated. For each prosecuted instance of closing price manipulation approximately 280 to 310 instances of manipulation remain undetected or not prosecuted. The rates of manipulation and detection differ substantially across exchanges. Larger government regulatory budgets increase the rate of prosecution and deter manipulation. Therefore, increased government regulatory budgets are likely to enhance market integrity.

The estimates of the fraction of manipulation that remains undetected are crucial in evaluating the effectiveness of regulation and deciding whether or not current regulatory effort is sufficient. The insights into what drives manipulation have implications for improving the efficiency with which scarce regulatory resources are utilised in detecting and deterring manipulation. The estimates of the frequency of closing price manipulation and where it is most likely to occur help quantify the harm caused by manipulators to market efficiency and social welfare.

3.2 Empirical model of manipulation and detection

Many violations of laws and regulations, such as manipulation and insider trading, are not detected and not prosecuted. Analysing only the detected and prosecuted fraction can lead to substantial biases in inference about the characteristics or frequency of violations. This problem is overlooked or inadequately addressed in much of the empirical literature.

Biases in inference about the characteristics of market misconduct arise when the set of detected cases systematically differ from all violations because of non-random detection. Due to their limited resources, regulators such as the US Securities and Exchange commission (SEC) are unable to pursue all violations and are likely to focus enforcement effort on egregious violations and high-profile cases that will have the most deterrence effect (Agrawal and Chadha, 2005).

The biases caused by non-random detection become particularly problematic when some aspect of the detection process is related to the effects being examined. For example, Aggarwal and Wu (2006) analyse a sample of 'pump-and-dump' manipulation cases prosecuted by the US Securities and Exchange Commission (SEC). In a pump-and-dump scheme a manipulator takes a long position in a stock, inflates the price through aggressive trading or by releasing false information and then profits from selling the stock at the inflated price. If cases of manipulation that cause large price changes are more likely to be detected and prosecuted by the SEC, then the inferences of Aggarwal and Wu about the effect of manipulation on prices, or what types of stocks are more likely to be manipulated, are potentially significantly biased. The difficulty in estimating the underlying rate of violations (consisting of detected *and* undetected violations) is more obvious – if undetected violations cannot be observed, how can one infer what fraction goes undetected?

The econometric problems caused by incomplete detection are well documented by Feinstein (1990, 1991). To overcome these problems, Feinstein (1990) develops detection controlled estimation (DCE) methods that allow inference about undetected violations, which are not directly observable. DCE models have been applied to the regulation of nuclear power plants (Feinstein, 1989), income tax evasion (Feinstein, 1990, 1991), compliance with environmental protection legislation (Brehm and Hamilton, 1996; Helland, 1998) and false positives in mammograms (Kleit and Ruiz, 2003). The idea behind DCE is simple: jointly estimating models of the detection and violation processes explicitly allows for incomplete detection. In its simplest form, a DCE model is a system of two equations: one modelling violation and the other modelling detection conditional on violation having occurred.

3.2.1 The model setup

This chapter modifies the basic DCE model in Feinstein (1990) to represent the detection of closing price manipulation as a two stage process. Therefore, the model used in this analysis consists of three stages. The first stage models the probability that the closing price of a particular stock on a particular date is manipulated and the second two stages model the probability that a particular manipulation is detected.

The reason for modelling detection as a two stage process is as follows. Closing price manipulation can be detected by a regulator when price and volume movements trigger 'alerts' in automated market surveillance systems. This is more likely when a pattern emerges of several alerts generated from trades made by a particular broker, in a particular stock or on a particular day (Cumming and Johan, 2008). I refer to this as *direct* detection. Once a trader has been detected for manipulating prices, further investigation of their trading records often reveals other instances of manipulation, attempted manipulation or conspiring manipulators that were not detected by automated surveillance system alerts. Also, some instances of manipulation that do not trigger alerts in surveillance systems are brought to the attention of the regulator by complaints from market participants. I refer to detection of manipulation that does not trigger alerts in surveillance systems as *indirect* detection.

The manipulation sample contains examples of indirect detection: instances in which day-end returns are zero or even negative despite the manipulator's intent to inflate the closing price. These instances represent unsuccessful attempts at manipulation or cases in which the manipulator reduced a day-end price decrease, for example, by keeping prices flat when they would have fallen without the manipulative buying. This chapter models direct and indirect detection separately because their empirical characteristics are quite different. For example, directly detected manipulation is likely to have a large abnormal return on the day of manipulation, whereas indirectly detected manipulation may not.

Prosecution is implicit in the model of detection. Although the two processes could be modelled separately, such a model is likely to suffer from identification problems due to the lack of observable variables that affect one process but not the other. To separately identify detection and prosecution requires variables that are generally not available, such as whether incriminating telephone conversations are recorded or whether incentives and gain to the manipulator can be convincingly demonstrated in court. Therefore, this chapter models detection and prosecution as a single process and simply refers to this as detection, consistent with other DCE models in the literature. The limitations of constructing the model this way are discussed together with the results.

The propensity for closing price *i* (the closing price of a particular stock on a particular day) to be manipulated is modelled as a continuous latent variable, Y_{1i}^*, that is a function of market-, stock- and time-specific attributes, X_{1i}.

$$Y_{1i}^* = X_{1i}\beta_1 + \varepsilon_{1i} \tag{3.1}$$

$$Y_{1i} = \begin{Bmatrix} 1 & \text{(manipulated)} \\ 0 & \text{(not)} \end{Bmatrix} \text{ if } \begin{Bmatrix} Y_{1i}^* > 0 \\ Y_{1i}^* \leq 0 \end{Bmatrix} \tag{3.2}$$

Y_{1i} is the binary variable for whether closing price *i* has been manipulated. Y_{1i} cannot be directly observed if detection is incomplete. Manipulation is only directly observable if the closing price is manipulated and the manipulation is detected.

Conditional on manipulation having occurred, the propensity for closing price *i* to be directly detected by a regulator is modelled as a continuous latent variable, Y_{2i}^*, that is a function of market-, stock- and time-specific attributes, X_{2i}.

$$Y_{2i}^* = X_{2i}\beta_2 + \varepsilon_{2i} \tag{3.3}$$

$$Y_{2i} = \begin{Bmatrix} 1 & \text{(directly detected)} \\ 0 & \text{(not)} \end{Bmatrix} \text{ if } \begin{Bmatrix} Y_{2i}^* > 0 \\ Y_{2i}^* \leq 0 \end{Bmatrix} \tag{3.4}$$

Similarly, Y_{2i} is the binary variable for whether manipulated closing price *i* is directly detected.

Conditional on manipulation having occurred and not having been directly detected, the propensity for closing price *i* to be indirectly detected is modelled as a continuous latent variable, Y^*_{3i}, that is a function of market-, stock- and time-specific attributes, X_{3i}.

$$Y^*_{3i} = X_{3i}\beta_3 + \varepsilon_{3i} \tag{3.5}$$

$$Y_{3i} = \begin{cases} 1 \text{ (indirectly detected)} \\ 0 \text{ (not)} \end{cases} \text{if} \begin{cases} Y^*_{3i} > 0 \\ Y^*_{3i} \leq 0 \end{cases} \tag{3.6}$$

Y_{3i} is the binary variable for whether the manipulated closing price *i* is indirectly detected.

Figure 3.1 provides a graphical illustration of the three-equation DCE model. A sample of closing prices falls into two disjoint sets, A and A^c. Set A consists of closing prices that have been manipulated and either directly or indirectly detected. Set A^c consists of closing prices that have either not been manipulated or have been manipulated but have evaded both direct and indirect detection. It is important to recognise that Y_{1i}, Y_{2i} and Y_{3i} cannot be separately observed. The data identify sets A and A^c. This information is used to estimate the model's parameters by maximising the likelihood of the sample given the model. This procedure takes into consideration the incomplete detection of manipulation.

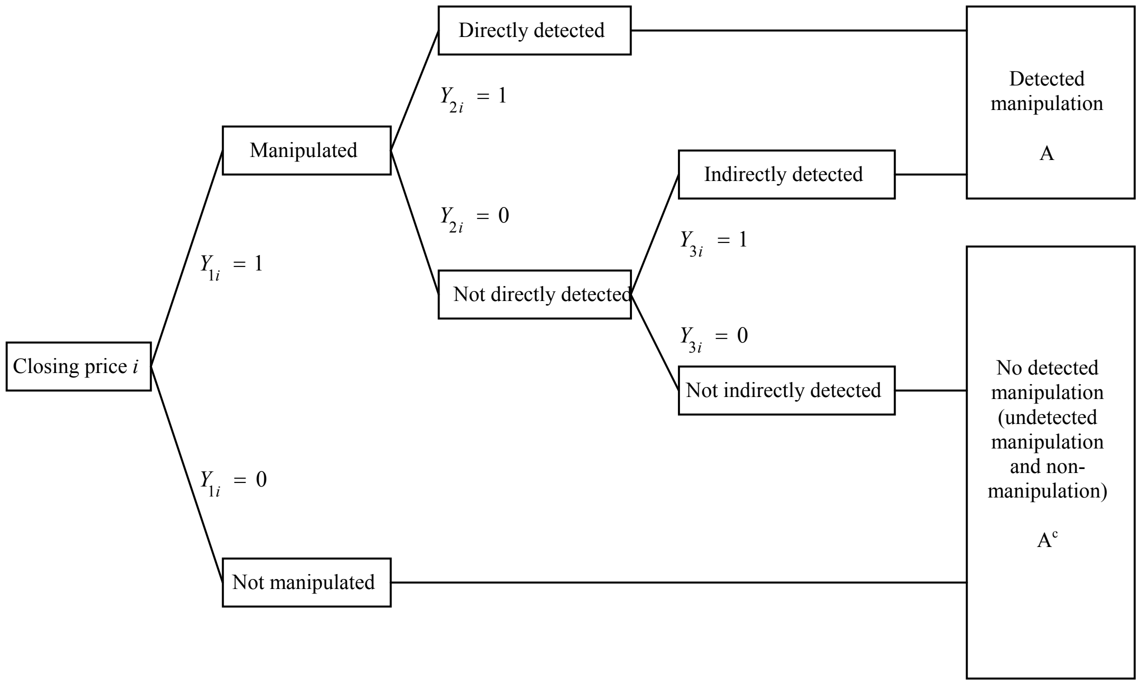

Figure 3.1 Modified detection controlled estimation model

This DCE model is similar to Heckman-style selection bias correcting models in that both explicitly model the process that causes the sample to be a non-random subset of the population. However, Heckman-style models are not suited to incomplete detection problems. The reason is that one of the outcomes of the selection process, undetected or not prosecuted manipulation, cannot be directly observed as it would be in a Heckman-style application (non-respondents in survey data, for example).

3.2.2 Estimation

I use the maximum likelihood method proposed by Poirier (1980) and Feinstein (1990) to estimate this model. I define $M(\ )$, $D(\ )$ and $I(\ )$ to be monotonic link functions that link $X_{1i}\beta_1$, $X_{2i}\beta_2$ and $X_{3i}\beta_3$, to latent probabilities for manipulation, direct detection and indirect detection respectively.[15] That is,

$$M\left(X_{1i}\beta_1\right) = \Pr\left(Y_{1i}=1\right) \tag{3.7}$$

$$D\left(X_{2i}\beta_2\right) = \Pr\left(Y_{2i}=1|Y_{1i}=1\right) \tag{3.8}$$

$$I\left(X_{3i}\beta_3\right) = \Pr\left(Y_{3i}=1|Y_{1i}=1,Y_{2i}=0\right) \tag{3.9}$$

In order to observe a detected manipulated closing price, that closing price must have been manipulated and either directly or indirectly detected.[16] Therefore, the likelihood that closing price i is from set A (the set of detected manipulation) is:

$$L_{A\ i} = M\left(X_{1i}\beta_1\right)D\left(X_{2i}\beta_2\right) + M\left(X_{1i}\beta_1\right)\left[1-D(X_{2i}\beta_2)\right]I\left(X_{3i}\beta_3\right) \tag{3.10}$$

The log-likelihood of the entire set of detected manipulated closing prices (set A), is therefore:

$$\log L_A = \sum_{i\in A}\log\{M(X_{1i}\beta_1)D(X_{2i}\beta_2)+M(X_{1i}\beta_1)[1-D(X_{2i}\beta_2)]I(X_{3i}\beta_3)\} \tag{3.11}$$

Similarly, for a closing price in which manipulation has not been detected, either: (i) manipulation has not occurred; or (ii) manipulation has occurred and evaded both direct and indirect detection. Therefore, the likelihood that closing price i has no detected manipulation (falls into set A^c) is:

$$L_{A^c i} = \left[1-M(X_{1i}\beta_1)\right] + M\left(X_{1i}\beta_1\right)\left[1-D(X_{2i}\beta_2)\right]\left[1-I(X_{3i}\beta_3)\right] \tag{3.12}$$

---

[15] In this implementation of this model the link functions are cumulative logistic distribution functions, that is, $M\left(X_{1i}\beta_1\right) = \frac{1}{1+e^{-X_{1i}\beta_1}}$, $D\left(X_{2i}\beta_2\right) = \frac{1}{1+e^{-X_{2i}\beta_2}}$ and $I\left(X_{3i}\beta_3\right) = \frac{1}{1+e^{-X_{3i}\beta_3}}$. The disturbance terms, ε_{1i}, ε_{2i} and ε_{3i}, are from independent logistic distributions with mean zero and variance $\frac{\pi^2}{3}$ (scale parameter of one). In robustness tests I examine alternative distributions for the disturbance term.

[16] I make the simplifying assumption of no false detection, that is, the probability of detecting and prosecuting manipulation given that manipulation has not occurred is zero. This seems reasonable considering the strength of evidence required to prosecute closing price manipulators.

The log-likelihood of the entire set of observations in which manipulation is not detected (set A^c) is therefore:

$$\log L_{A^c} = \sum_{i \in A^c} \log\{[1-M(X_{1i}\beta_1)]+M(X_{1i}\beta_1)[1-D(X_{2i}\beta_2)][1-I(X_{3i}\beta_3)]\} \quad (3.13)$$

The log-likelihood of the full sample is the sum of the log-likelihoods of each of the two sets of observations. To estimate this model with data collected from endogenous stratified sampling (choice-based sampling) I add weights to the observations and the resulting weighted maximum-likelihood estimator (due to Manski and Lerman (1977)) becomes:

$$\log L = w_A \sum_{i \in A} \log\{M(X_{1i}\beta_1)D(X_{2i}\beta_2)+M(X_{1i}\beta_1)[1-D(X_{2i}\beta_2)]I(X_{3i}\beta_3)\}$$

$$+ w_{A^c} \sum_{i \in A^c} \log\{[1-M(X_{1i}\beta_1)]+M(X_{1i}\beta_1)[1-D(X_{2i}\beta_2)][1-I(X_{3i}\beta_3)]\} \quad (3.14)$$

where $w_A = \tau / s$, $w_{A^c} = (1-\tau)/(1-s)$ and τ and s are the fractions of stock-days with prosecuted manipulation in the population and sample respectively.

Maximum likelihood estimation maximises the likelihood of the sample (Equation 3.14) through an iterative process, allowing consistent estimation of the coefficients for the factors that affect manipulation and detection, β_1, β_2 and β_3.

3.2.3 Alternative models

Identification is a potential problem in all DCE models. The model decomposes a single datum, detected manipulation, into three components, manipulation, direct detection and indirect detection. The identification issue arises because initially it is unknown if this decomposition can be uniquely performed. Intuitively, the model needs to ascertain whether a sample of cases for which the rate of detected manipulation is low is characterised by a low rate of manipulation or a low rate of detection. The model also needs to ascertain for cases of detected manipulation whether they were directly or indirectly detected.[17]

Identification requires predictor variables uniquely associated with each stage. That is, the model needs at least one variable that predicts manipulation but not direct or indirect detection, at least one variable that predicts direct detection but not manipulation or indirect detection and at least one variable that predicts indirect detection but not manipulation or direct detection. While this condition is theoretically satisfied by the three-equation DCE model, the estimates must be treated with caution because identification can, in practice, still be a problem. Identification also depends on the amount of variation in the explanatory variables and the strength of their relations with the dependent variables.

I estimate an alternative two-equation model, similar to the original DCE model used in Feinstein (1989, 1990), because such a model is expected to have fewer problems with identification. This model allows detection to result from direct or indirect detection but, in contrast to the three-equation model, it makes no effort to distinguish between the two. Appendix A contains the equations and likelihood function for this model.

Another model specification issue is that the model used in this analysis, like the rest of the DCE literature, assumes errors are independently distributed. In practice, the errors of one process (e.g., manipulation) may be correlated with the errors of another (e.g., detection), or errors from the one process may be correlated in cross-section or time. I address these two distinct forms of correlation separately.

Brehm and Hamilton (1996) demonstrate with Monte Carlo simulations that using an uncorrelated error DCE model when errors are correlated between processes may lead to modest underestimation of the most significant coefficients and increased error around those estimates. Expectations simultaneity, if not incorporated into the model, can cause error correlation between processes. Two examples of expectations

[17] For a more formal discussion of the identification issue see Feinstein (1990).

simultaneity are: (i) a regulator that is more likely to investigate stock-days that have a higher probability of being manipulated; and (ii) manipulators that choose to manipulate stocks with a lower probability of investigation.

To overcome the potential correlation of errors between processes and allow for more sophisticated behaviour I estimate a third model with expectations simultaneity. Based on the three-equation modified DCE model I replace the equations of the propensities for direct and indirect detection with the following:

$$Y_{2i}^{*} = X_{2i}\beta_2 + M(X_{1i}\beta_1)\delta_2 + \varepsilon_{2i} \tag{3.15}$$

$$Y_{3i}^{*} = X_{3i}\beta_3 + M(X_{1i}\beta_1)\delta_3 + \varepsilon_{3i} \tag{3.16}$$

In this model the probability that a regulator investigates a closing price for manipulation, and therefore the propensity for manipulation to be detected, depends on the regulator's assessment of the probability of manipulation, $M(X_{1i}\beta_1)$. Appendix A contains the full set of equations and likelihood function.

Correlation of errors in cross-section or time does not bias the parameter estimates (as it would be in some other models), but may lead to under- or over-estimation of standard errors depending on the nature of the correlation (Robinson, 1982). To minimise the potential bias in standard error estimates, I include dummy variables to absorb the effects of the most plausible scenarios causing error correlation. For example, cross-sectional error correlation may arise if, for example, a fund manager decides to manipulate several stocks in his portfolio on the same day or several derivatives traders manipulate stock prices on an option expiry day. To absorb these effects I also include month-end and options expiry day dummy variables. I include dummy variables for the different exchanges to absorb error clustering by exchange.

3.3 Variables and model specifications

Most variables primarily influence either manipulation or detection, but may also have indirect effects on the other process due to interaction between manipulators and regulators. Regulators, to some extent, anticipate the behaviour of manipulators and manipulators anticipate the behaviour of regulators. For example, if fund managers manipulate closing prices at quarter-ends then a primary determinant of the probability of manipulation is whether or not a day is a quarter-end. A regulator that is aware of this association is more likely to investigate suspicious trading on quarter-end days and therefore whether or not a day is a quarter-end is a secondary determinant of the probability of detecting manipulation. Another example is that if regulatory budget affects the detection rate, the probability of manipulation will depend on regulatory jurisdiction because manipulators are likely to take into consideration the probability of being caught.

Table 3.1 defines the variables. The following paragraphs discuss variables according to their primary association - first those associated with manipulation, then detection and, finally, both manipulation and detection.

An order can move prices for at least two reasons: (i) it mechanically moves price from the bid quote to the ask quote (or vice versa), or beyond the prevailing best quotes by executing the volume at the best quotes; and (ii) it conveys information and subsequently causes the market to revise its belief about the value of the stock. A manipulator can exploit one or both of these mechanisms to influence prices. While the first mechanism is possible in all stocks to differing degrees depending on the depth, spread and trading volume, the second mechanism only arises if information is distributed asymmetrically between market participants. The following discussion refers to the two mechanisms as liquidity and information asymmetry, respectively.

Table 3.1
Definitions of variables

This table defines the variables used in the models of manipulation and detection. The third column reports the transformation that is applied to the raw data to normalise and scale the variables. Where required by the transformation, negative values are multiplied by negative one before and after applying the transformation.

Variable	Definition	Transform
	Panel A: Variables associated with both manipulation and detection	
Detected manipulation	Indicator variable for the 184 instances of detected and prosecuted closing price manipulation.	
Exchange	Four indicator variables for the exchanges: American Stock Exchange (AMEX), New York Stock Exchange (NYSE), Toronto Stock Exchange (TSX), TSX Venture Exchange (TSX-V).	
Industry	Ten indicator variables based on the Industry Classification Benchmark (ICB) to represent the industry of a stock. The industries are (1) oil and gas, (2) basic materials, (3) industrials, (4) consumer goods, (5) health care, (6) consumer services, (7) telecommunications, (8) utilities, (9) financials and (10) technology.	
	Panel B: Variables associated primarily with manipulation	
Market capitalisation	Share price multiplied by the number of ordinary shares on issue. The number of shares on issue is updated whenever new tranches of stock are issued or after a capital change. Calculated on the first day of each month in millions of US dollars.	$\log(\cdot)$
Turnover	Median number of trades per day in the stock during the previous month. Alternative definitions used for robustness tests:	$\ln(\cdot)$
	Turnover (2) - median daily traded US dollar volume in previous month.	$\log(\cdot)$
	Turnover (3) - median daily US dollar volume traded in previous month divided by market capitalisation.	$\log(\cdot)$
Spread	The median of the past month's daily mean proportional spreads for that stock. Daily mean proportional spreads are calculated as the equal weighted mean of the difference between the best bid and ask divided by the bid-ask midpoint price at every quote update and trade.	$\sqrt{\cdot}$
Closing price	The price of the last trade before the market closes at 4:00pm. The closing time is adjusted on days when the close is delayed.	$\sqrt[3]{\cdot}$
Institutional	Institutional following defined as the total number of IBES analyst forecasts of that financial year's earnings per share (EPS). Calculated on the first day of each month.	$\sqrt{\cdot}$
Index stock	Indicator variable for whether a stock is a constituent of the Standard and Poor's (S&P) 500 Index or the S&P/TSX Composite Index (TSE 300 Index prior to May 2002). Calculated on the first day of each month.	
Optionable	Indicator variable for whether the stock has options trading on it that expire within a month.	
Option expiry	Indicator variable for whether an optionable stock is in its last day of trade before options on that stock expire.	
Trend	Close to close return over previous calendar month.	$\sqrt[3]{\cdot}$
Month-end	Indicator variable for the last trading day of a month.	
Quarter-end	Indicator variable for the last trading day of a quarter, that is, the last trading days in the months of March, June, September and December.	
Volatility	Standard deviation of daily returns calculated from closing prices over the previous month.	$\sqrt{\cdot}$

Table 3.1 (continued)

Variable	Definition	Transform
	Panel C: Variables associated primarily with detection	
Prosecutions	Number of closing price manipulation prosecutions filed by the market regulators in that country in the previous year (rolling one year window) based on the date of filling the statement of allegations.	
Regulator budget	Budget of the principal government regulator divided by the number of common stocks for which the regulator is responsible. The principal regulator for AMEX and NYSE is the US Securities and Exchange Commission (SEC) and for TSX and TSX-V it is the Ontario Securities Commission (OSC). Budgets are taken from the annual reports of the regulators for each regulator's financial year, deflated by the OECD published CPI of the corresponding country and converted to US dollars. The units of this variable are '00,000s of US dollars in real (August 1998) terms per common stock.	
Abnormal return (AR)	Abnormal day-end return calculated as the return from the bid-ask midpoint 30 minutes before the close to the closing price (or in the absence of trades in the last 30 minutes then the return from the midpoint at time of the last trade to closing price), less that stock's previous month's median day-end return. Alternative definitions used for robustness tests:	$\sqrt{\cdot}$
	AR2 - as per AR1 but using last 60 minutes of trading in place of 30.	$\sqrt{\cdot}$
	AR3 - abnormal daily return calculated as close to close return less that stock's previous month's median close-to-close return.	$\sqrt{\cdot}$
Reversal (RV)	Overnight return reversal calculated as the return from the closing price to the next morning's 11am bid-ask midpoint price.	$\sqrt{\cdot}$
Abnormal volume (AV)	Abnormal day-end dollar volume, V, relative to benchmark daily traded dollar volume. Calculated as ((V/Turnover2)*100), where V is the traded US dollar volume in the last 30 minutes before the close less that stock's previous month's median day-end volume. Turnover2 is the median daily traded US dollar volume in that stock in the previous month. Alternative definitions used for robustness tests:	$\sqrt[4]{\cdot}$
	AV2 - as per AV but using the last 60 minutes of trading in place of 30.	$\sqrt[4]{\cdot}$
	AV3 - abnormal daily volume calculated as per AV but using daily traded dollar volume in place of the last 30 minute traded dollar volume.	$\sqrt[4]{\cdot}$
AR time-series	Abnormal day-end return aggregated over a period of time for a particular stock. Calculated as the median value of AR for that stock in a two-week period starting seven days back in time and ending seven days forward in time. Alternative definitions used for robustness tests:	$\sqrt{\cdot}$
	AR2 time-series – as per AR time-series but using AR2 in place of AR.	$\sqrt{\cdot}$
	AR3 time-series – as per AR time-series but using AR3 in place of AR.	$\sqrt{\cdot}$
RV time-series	Reversal aggregated over a period of time for a particular stock. Calculated as the median value of RV for that stock in a two-week period starting seven days back in time and ending seven days forward in time.	$\sqrt{\cdot}$
AV time-series	Abnormal day-end volume aggregated over a period of time for a particular stock. Calculated as the median value of AV for that stock in a two-week period starting seven days back in time and ending seven days forward in time. Alternative definitions used for robustness tests:	$\sqrt[4]{\cdot}$
	AV2 time-series – as per AV time-series but using AV2 in place of AV.	$\sqrt[4]{\cdot}$
	AV3 time-series – as per AV time-series but using AV3 in place of AV.	$\sqrt[4]{\cdot}$
AR cross-section	Abnormal day-end return aggregated in stock cross-section. Calculated as the median value of AR for all stocks on the corresponding exchange on that day. Alternative definitions used for robustness tests:	
	AR2 cross-section – as per AR cross-section but using AR2 in place of AR.	
	AR3 cross-section – as per AR cross-section but using AR3 in place of AR.	
RV cross-section	Reversal aggregated in stock cross-section. Calculated as the median value of RV for all stocks on the corresponding exchange on that day.	
AV cross-section	Abnormal day-end volume aggregated in stock cross-section. Calculated as the median value of AV for all stocks on the corresponding exchange on that day. Alternative definitions used for robustness tests:	$\sqrt{\cdot}$
	AV2 cross-section – as per AV cross-section but using AV2 in place of AV.	$\sqrt{\cdot}$
	AV3 cross-section – as per AV cross-section but using AV3 in place of AV.	$\sqrt{\cdot}$

I use market capitalisation, turnover, bid-ask spread and closing price as measures of liquidity, although at no stage are all four variables included in a model at the same time. Trades in relatively illiquid stocks, with little depth and wide spreads, generally have more substantial price impact than similar trades in relatively liquid stocks. Further, the manipulator of a low-turnover stock has to compete with fewer trades to control the price and is more likely to be successful in making the last trade of the day and setting the closing price. This intuition is consistent with Hillion and Suominen's (2004) model of closing price manipulation, in which illiquid stocks are more frequently manipulated.

I include two variables to measure the degree of information asymmetry in a stock. The first is the number of analysts' forecasts of a stock's earnings and the second is whether or not the stock is included in a broad market index.[18] Allen and Gale (1992) demonstrate the theoretical possibility of profitable stock price manipulation under a rational expectations framework. The basis of their argument is information asymmetry. Investors are uncertain whether a large trader who buys the stock does so because he knows it is undervalued or because he intends to manipulate the price. The models of manipulation in Kumar and Seppi (1992) and Aggarwal and Wu (2006) are constructed on the same basis. The implication of this is that manipulation is more likely in stocks with higher levels of information asymmetry.

I also include variables that capture various motivations for manipulation. Both theoretical and empirical evidence suggests that stock prices are manipulated to profit from options on the underlying stock or from futures contracts on indices, particularly in the period immediately prior to expiry.[19] Therefore, I include an

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[18] Whether or not a stock is a constituent of an index may also be associated with effects other than those that occur through information asymmetry. Kumar and Seppi (1992) show that cash settled options (such as futures on stock indices) provide a profitable manipulation strategy. An Australian prosecution case (Australian Securities Commission v Nomura International Plc. – 29 ACSR 473) provides evidence that such a manipulation strategy is possible.

[19] Jarrow (1994) demonstrates by example that a derivative security creates market manipulation trading strategies that would otherwise not exist. Kumar and Seppi (1992) develop a model in which

indicator variable for whether or not a stock has listed options and a second indicator variable indicating, for stocks with listed options, whether it is the last trading day prior to expiry of the options.

Fund managers are known to manipulate closing prices at the end of reporting periods such as the last day of a month or a quarter (Carhart et al., 2002).[20] Therefore, I include indicator variables for the last trading day in each month and quarter. Closing prices are also known to have been manipulated to avoid margin calls and to maintain a stock's listing on an exchange with a minimum price requirement. These incentives for manipulation are triggered when a stock's price falls to a critical level and therefore are more likely to occur following declines in a stock's price. I include a price trend variable (a stock's rolling one-month return) to examine these two and other similar motivations related to price movements.

Volatility is likely to have more than one effect on manipulation. Hillion and Suominen (2004) model the behaviour of brokers that manipulate closing prices to alter their customers' inference about their execution ability. Their model implies that stock price volatility increases the likelihood of manipulation because broker ability is more valuable when volatility is higher. However, it is also possible that volatility attracts the attention of regulators and therefore deters manipulation. I measure volatility using the standard deviation of daily returns.

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the manipulator takes a position in the futures market and then manipulates stock prices at expiry to profit from the futures position. Empirical studies on the effect of expiry days on the underlying stock prices generally find that effects of manipulation can be found in the last hour before expiry and that the price effect is reversed in the first half hour of trading after expiry (Stoll and Whaley, 1987; Chamberlain et al., 1989; Stoll and Whaley, 1991). Ni et al. (2005) find evidence that on option expiry dates the closing prices of stocks with listed options cluster at option strike prices. They attribute this finding to closing price manipulation.

[20] Bernhardt and Davies (2009) develop a theoretical model of a mutual fund manager's investment decision and prove that fund managers have incentives to use short-term price impacts to manipulate closing prices at reporting period ends.

The variables associated primarily with detection and prosecution include government regulatory budget, number of closing price manipulation prosecutions and various indicators of abnormal trading activity that is likely to draw the attention of a regulator. Government regulatory budgets, in this case the budgets of the US SEC and the Ontario Securities Commission, determine the amount of resources available to conduct investigations and prepare cases for prosecution. Therefore, larger regulatory budgets are likely to be associated with greater capacity to prosecute manipulation. Stock exchanges also have responsibility for manipulation surveillance, so government regulatory budget only measures part of the total amount spent on regulation.[21] The number of closing price manipulation prosecutions measures the effectiveness and experience of the regulator in detecting and prosecuting closing price manipulation.

Closing price manipulation is often detected by a regulator when abnormal trading triggers 'alerts' in automated market surveillance systems – described earlier as *direct* detection. The measures of abnormal trading characteristics that I use are abnormal return, abnormal volume, and price reversal (the return from the closing price to the following morning's price). These trading characteristics are influenced by manipulation for the following reasons. First, the aim of a manipulator is to cause changes in the price of a stock. Second, to affect the closing price, the manipulator trades or releases information which is likely to induce additional trading by speculators or arbitrageurs. Finally, an examination of actual closing price manipulation cases documented in litigation records suggests that manipulation is often carried out by aggressive trading in the last minutes before the close creating liquidity imbalances. Given overnight for new orders to enter the market and resolve

[21] A potential problem with this measure of regulator budget is that it is endogenous, i.e., government regulatory budgets are increased in times or countries in which manipulation is more widespread. The consequence of this potential endogeneity is to underestimate regulation's deterrence effect on manipulation.

the liquidity imbalance, prices often revert towards their original levels the following morning, as demonstrated by Carhart et al. (2002).

Many instances of manipulation, however, do not create the abnormal trading characteristics that trigger alerts, but may be detected through investigations of other instances of manipulation or investor complaints – discussed earlier as *indirect* detection. Indirect detection is more likely if other closing prices in near proximity (nearby days in the same stock, or other stocks on the same day) are also manipulated because the probability of an alert and subsequent investigation is higher. Therefore, as factors that affect the probability of indirect detection, I include measures of abnormal trading aggregated through time in a particular stock, and measures of abnormal trading on a particular day aggregated across all stocks on the corresponding exchange. In the two-equation model the direct and indirect detection variables are combined into a single detection equation, thereby reducing the potential problem of weak identification of direct and indirect detection.

Table 3.2 specifies the variables that are used in each of the equations. I use two approaches to address the fact that many variables influence both manipulation and detection. In models without expectations simultaneity (Model 1 and Model 2) I include some variables in both equations, for example, regulatory budget and number of manipulation prosecutions. These variables measure the capacity and effectiveness of the regulator and, at the same time, affect the manipulator's perceived probability of being caught. On the other hand, I do not include the abnormal trading variables as determinants of manipulation because manipulation influences these variables and therefore their values can only be observed ex-post the manipulation, not ex-ante.

Table 3.2
Specification of models

This table specifies which variables are used in each of the equations for the three models. Model 1 is a three-equation modified detection controlled estimation (DCE) model, Model 2 is a standard two-equation DCE model and Model 3 is a modified three-equation DCE model with expectations simultaneity. *M( )* is the probability of manipulation, *D( )* is the conditional probability of direct detection (conditional probability of detection in the standard two-equation DCE model) and *I( )* is the conditional probability of indirect detection. Variables are defined in Table 3.1. The symbol + indicates a variable is included as a factor in the corresponding probability equation.

Variable	Model 1			Model 2		Model 3		
	M( )	D( )	I( )	M( )	D( )	M( )	D( )	I( )
Exchange	+	+	+	+	+	+	+	+
Industry	+	+	+	+	+	+	+	+
Market capitalisation	+			+		+		
Turnover	+			+		+		
Spread	+			+		+		
Closing price	+			+		+		
Volatility	+			+		+		
Institutional	+			+		+		
Index stock	+			+		+		
Optionable	+			+		+		
Option expiry	+			+		+		
Trend	+			+		+		
Month-end	+			+		+		
Quarter-end	+			+		+		
Prosecutions	+	+	+	+	+	+	+	+
Regulator budget	+	+	+	+	+	+	+	+
Abnormal return (AR)		+			+		+	
Reversal (RV)		+			+		+	
Abnormal volume (AV)		+			+		+	
AR time-series			+		+			+
RV time-series			+		+			+
AV time-series			+		+			+
AR cross-section			+		+			+
RV cross-section			+		+			+
AV cross-section			+		+			+
M( )							+	+

The primary determinants of manipulation are not included in the detection equation. In this regard, the regulators in the first two models are somewhat naïve in that they do not take advantage of all the information available about the determinants of manipulation. In these models the regulator treats all alerts equally rather than devoting more resources to investigating particular alerts, such as those on quarter-end days or in illiquid stocks.

The third model addresses the secondary associations of variables by incorporating the probability of manipulation as a determinant of the probability of detection. Regulators are modelled as being sophisticated, i.e., they are aware of the probability of manipulation and use this information in their detection processes. The manipulators, as in the first two models, also take into consideration the regulator's budget and previous manipulation prosecutions when deciding whether or not to manipulate.

Conceptually, identification in these models can be thought of in the following simplified way. Suppose that for a manipulated closing price the larger the day-end price increase the greater the probability of detection and prosecution. The subset of observations with very large day-end price increases have a high probability that manipulation, if present, gets detected and therefore this subset is used to identify the determinants of manipulation. Having identified the determinants of manipulation, the subset of observations that are likely to have been manipulated is used to identify the other factors that influence detection. Of course, this process is not sequential as in this simplified description, but rather, simultaneous.

3.4 Data

I construct samples of prosecuted closing price manipulation cases (events) and stock-days in which no manipulation is detected or prosecuted (non-events) using endogenous stratified sampling. Due to the rare nature of events, I collect all available events and only a fraction of non-events.

I manually collect all of the closing price manipulation cases detected and prosecuted by market regulators in the US and Canada in the period 1 January 1997 to 1 January 2009. I systematically identify the cases from searches of the litigation releases and filings of the market regulators SEC, OSC, RS, IDA, MFDA, IIROC, NYSE Reg and AMEX DRC[22] and searches of the legal databases *Lexis*, *Quicklaw* and *Westlaw*. From the appendices of SEC annual reports I obtain lists of the case names and filing dates of all the instances of market manipulation against which the SEC took legal action. I manually examine the litigation releases of each case in these lists to identify instances of closing price manipulation. For cases in which insufficient details are provided by the market regulators I obtain court records and filings through the Administrative Office of the US Courts using the PACER service.

I eliminate cases from the sample if: (i) insufficient information is available to determine which stocks were manipulated on which days; (ii) the manipulation occurred in an over-the-counter market; (iii) the manipulated securities were not common stock; (iv) the manipulation did not involve trade-based techniques; (v) trade and quote data are not available; or (vi) the manipulated stocks do not have at least three months of trading prior to the start of manipulation.[23]

The final sample of detected and prosecuted closing price manipulation is comprised of 184 instances of manipulation with complete data. These 184 instances of a stock manipulated on a particular day are obtained from eight independent legal cases, each containing multiple instances of closing price manipulation. These instances of closing price manipulation involve 31 stocks from four exchanges: NYSE, AMEX, TSX and TSX-V. The case names, alleged misconduct and legal outcomes are described in Appendix B.

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[22] The full names of these regulators are US Securities and Exchange Commission (USA), Ontario Securities Commission (Canada), Market Regulation Services Inc. (Canada), Investment Dealers Association (Canada), Mutual Funds Dealers Association (Canada), Investment Industry Regulatory Organization of Canada (Canada), NYSE Regulation Inc. (USA) and AMEX Division of Regulation and Compliance (USA), respectively.

[23] Although cases in which insufficient information is available to determine the manipulated stock and date cannot be included in the manipulation sample, they are included in the population count of prosecuted manipulation. Consequently, these cases affect the model estimates via their influence on the weights in Equation 3.14.

To obtain the sample in which manipulation is not detected and not prosecuted, for each manipulated stock-day I take all other stock-days on the corresponding exchange in a period of one month up to and including the manipulation date. After eliminating stock-days with missing or erroneous data the sample includes 1,249,748 observations. I obtain intra-day trade and quote data, expiry dates for listed options, and index composition data from a *Reuters* database maintained by the *Securities Industry Research Centre of Asia-Pacific* (*SIRCA*). The remaining data are from *Thomson's Datastream* and the websites of the regulators. I apply normalising transformations to the data as documented in Table 3.1.

Table 3.3 reports the means, standard deviations and medians of the variables for the sample of detected and prosecuted closing price manipulation and the sample in which manipulation is not detected and not prosecuted. The summary statistics provide an indication of the magnitude and dispersion of these variables to allow a quantitative interpretation of the coefficient estimates reported in the following section. Due to incomplete detection, a simple comparison of the means between the two samples may lead to biases in inference about the effects of these variables on manipulation and detection.

Ignoring the potential biases for now, the difference in means and medians between the two samples is consistent with prior literature and anecdotal evidence. The sample of detected and prosecuted manipulation involves less liquid stocks (lower market capitalisation, turnover, closing prices and larger spreads), lower levels of institutional following (less analyst forecasts and index constituency), higher volatility, and is more concentrated in month-end and quarter-end days. The detected manipulation sample is also associated with lower government regulatory budgets, higher abnormal returns, greater return reversals and higher abnormal volume, as well as higher aggregate levels of the abnormal trading on other days in the same stock.

Table 3.3
Summary statistics

This table reports summary statistics for variables used in the model of manipulation and detection. The variables are defined in Table 3.1. *Raw data* are actual observed values. *Normalised and scaled* are values after applying normalising transformations to the variables. *Detected manipulation* refers to the sample of stock-days in which manipulation has been detected and prosecuted by a regulator (*Yes*) and the sample of stock-days without detected and prosecuted manipulation (*No*). Medians and standard deviations (*Std dev*) are not reported for dichotomous variables.

Variable	Detected manipulation	Raw data			Normalised and scaled		
		Mean	Std dev	Median	Mean	Std dev	Median
Panel A: Variables associated with both manipulation and detection							
Exchange (AMEX)	Yes	0.17			0.17		
	No	0.13			0.13		
Exchange (TSX)	Yes	0.46			0.46		
	No	0.25			0.25		
Exchange (TSX-V)	Yes	0.20			0.20		
	No	0.05			0.05		
Exchange (NYSE)	Yes	0.18			0.18		
	No	0.56			0.56		
Panel B: Variables associated primarily with manipulation							
Market capitalisation	Yes	442	1,579	67	2.01	0.58	1.83
	No	2,963	12,737	236	2.39	1.01	2.37
Turnover (2)	Yes	973,184	4,980,952	77,306	4.96	0.61	4.89
	No	8,066,446	31,288,453	205,415	5.43	1.29	5.31
Spread	Yes	2.71	1.44	2.56	1.57	0.49	1.60
	No	2.32	3.68	0.88	1.22	0.91	0.94
Closing price	Yes	9.06	8.68	5.75	1.90	0.62	1.79
	No	17.4	20.4	12.69	2.26	0.93	2.33
Institutional	Yes	1.63	4.42	0.00	0.62	1.12	0.00
	No	3.93	5.94	1.00	1.32	1.48	1.00
Trend	Yes	2.81	22.1	1.59	0.21	2.35	1.17
	No	-0.14	17.5	0.00	0.01	2.06	0.00
Volatility	Yes	4.01	2.13	3.80	1.93	0.52	1.95
	No	3.53	3.71	2.40	1.72	0.77	1.55
Index stock	Yes	0.11			0.11		
	No	0.18			0.18		
Optionable	Yes	0.09			0.09		
	No	0.28			0.28		
Option expiry	Yes	0.00			0.00		
	No	0.01			0.01		
Month-end	Yes	0.31			0.31		
	No	0.05			0.05		
Quarter-end	Yes	0.20			0.20		
	No	0.02			0.02		

Table 3.3 (continued)

Variable	Detected manipulation	Raw data			Normalised and scaled		
		Mean	Std dev	Median	Mean	Std dev	Median
Panel C: Variables associated primarily with detection							
Prosecutions	Yes	0.47	0.66	0.00	0.47	0.66	0.00
	No	0.73	0.99	0.00	0.73	0.99	0.00
Regulator budget	Yes	58.1	75.5	9.80	0.58	0.76	0.10
	No	130	90.9	165	1.30	0.91	1.65
Abnormal return (AR)	Yes	1.24	2.39	0.86	0.72	1.17	0.93
	No	0.04	2.54	0.00	0.01	1.06	0.00
Reversal (RV)	Yes	1.55	3.72	1.71	0.93	1.40	1.31
	No	-0.19	3.66	0.00	-0.05	1.39	0.00
Abnormal volume (AV)	Yes	64.7	143	9.99	1.51	1.84	1.78
	No	12.5	102	0.00	0.34	1.52	0.00
AR time series	Yes	0.20	0.77	0.14	0.20	0.72	0.37
	No	0.01	1.17	0.00	0.00	0.67	0.00
RV time series	Yes	1.15	1.28	1.12	0.81	0.85	1.06
	No	-0.17	1.78	0.00	-0.06	0.91	0.00
AV time series	Yes	16.1	60.2	0.00	0.33	1.56	0.00
	No	1.32	10.7	0.00	0.14	1.09	0.00
AR cross-section	Yes	-0.01	0.09	0.00	-0.01	0.09	0.00
	No	0.00	0.07	0.00	0.00	0.07	0.00
RV cross-section	Yes	-0.29	0.54	-0.18	-0.29	0.54	-0.18
	No	-0.06	0.49	0.00	-0.06	0.49	0.00
AV cross-section	Yes	0.86	2.63	0.00	0.34	0.89	0.00
	No	0.20	1.66	0.00	0.15	0.68	0.00
Observations	Yes	184					
	No	1,249,748					

3.5 Results

First, this section presents the estimated model coefficients and discusses the determinants of manipulation and detection. This is followed by the analysis of the frequency of manipulation and detection. Finally, this section reports results of robustness tests.

3.5.1 The determinants of manipulation and detection

I use maximum likelihood estimation to obtain the model coefficients. To select variables for the final models from the large number of potential variables and alternative measures (e.g., the several proxies for liquidity), I use two approaches. In the first approach I include all of the variables suggested by theory (as specified in

Table 3.2), then remove insignificant variables and re-estimate the models. The second approach is a forward stepwise variable selection procedure.[24] Both approaches give similar sets of variables so I only report the results from the first procedure. For robustness I also estimate models with alternative sets of variables including those not deemed to be significant by the stepwise procedure. I use various starting values to ensure convergence to a consistent set of estimates.

Table 3.4 reports the coefficient estimates. Because probabilistic model coefficients are difficult to interpret, Table 3.4 also reports (in parentheses) the marginal effect of each variable on the dependant variable (probability of manipulation, direct detection and indirect detection).[25] For continuous variables, the marginal effects measure the percentage change in the probability of either manipulation, direct or indirect detection for a one percent change in the value of the independent variable.

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[24] Starting with just the constant terms, in each iteration I add variables that result in the largest increase in log-likelihood and re-estimate the model. This is repeated until additional variables do not yield a significant improvement in the log-likelihood.

[25] Marginal effects are calculated as $\frac{\partial \Pr}{\partial X} = \frac{\beta^* e^{\beta^* X}}{(1+e^{\beta^* X})^2}$, where: Pr is the estimated probability of manipulation, direct detection and indirect detection; β^*, are the coefficient estimates; and X are the observed variable values. They are reported as a percentage of Pr. Marginal effects are calculated for each observation and then averaged over the entire sample.

Table 3.4
Model estimates

This table reports estimated model coefficients. Model 1 is a three-equation modified DCE model, Model 2 is a standard two-equation DCE model and Model 3 is a modified three-equation DCE model with expectations simultaneity. *M( )* is the probability of manipulation, *D( )* is the conditional probability of direct detection (detection in the standard two-equation DCE model) and *I( )* is the conditional probability of indirect detection. Variables are defined in Table 3.1. Numbers not in parentheses are the coefficient estimates. Numbers in parentheses are the marginal effects (partial derivatives of the dependent probability with respect to the explanatory variables, reported as a percentage of the estimated dependent probability). Significance at the 10%, 5% and 1% levels is indicated by *, ** and ***, respectively.

	Model 1			Model 2		Model 3		
Variable	M( )	D( )	I( )	M( )	D( )	M( )	D( )	I( )
Constant	-0.78	-12.0***	-333***	2.01*	-14.2***	-2.73**	-9.88***	-330***
Regulator budget	-2.87***	1.85***	71.1***	-3.95***	3.13***	-3.34***	1.87***	72.5***
	(-2.81)	(1.82)	(69.0)	(-3.87)	(2.95)	(-3.32)	(1.83)	(70.4)
Institutional	-0.37***			-0.39***		-0.37***		
	(-0.37)			(-0.38)		(-0.37)		
Index stock	-0.80***			-0.77***		-0.93***		
	(-0.79)			(-0.75)		(-0.93)		
Market capital.	0.78***			0.57***		0.80***		
	(0.77)			(0.56)		(0.80)		
Turnover (2)	0.24**			0.10*		0.31**		
	(0.24)			(0.10)		(0.31)		
Month-end	1.58***			1.54***		1.56***		
	(1.55)			(1.51)		(1.55)		
Quarter-end	2.11***			2.18***		2.38***		
	(2.07)			(2.14)		(2.37)		
Volatility	-0.85***			-0.65***		-0.85***		
	(-0.83)			(-0.64)		(-0.84)		
Abnormal return (AR)		0.80***			0.54***		0.82***	
		(0.79)			(0.51)		(0.80)	
Reversal (RV)		0.23***			0.16**		0.21***	
		(0.23)			(0.15)		(0.21)	
Abnormal volume (AV)		0.93***			0.81***		1.05***	
		(0.91)			(0.76)		(1.03)	
AR time series			2.81***		0.07			1.69**
			(2.73)		(0.06)			(1.64)
RV time series			59.4***		1.45***			54.3***
			(57.6)		(1.37)			(52.7)
AV time series			-8.27***		0.15**			-7.26***
			(-8.03)		(0.14)			(-7.05)
Exchange (AMEX)	-5.05***	5.31***	178***	-5.66***	6.25***	-2.78***	2.61***	178***
	(-4.94)	(5.23)	(172)	(-5.55)	(5.88)	(-2.77)	(2.55)	(172)
Exchange (TSX)	-7.30***	6.82***	243***	-10.2***	11.2***	-5.76***	4.55***	247***
	(-7.15)	(6.71)	(236)	(-10.0)	(10.59)	(-5.74)	(4.44)	(240)
Exchange (TSX-V)	-6.87***	-0.02	262***	-8.65***	10.1***	-5.13***	-2.25	261***
	(-6.73)	(-0.02)	(255)	(-8.47)	(9.54)	(-5.11)	(-2.19)	(254)
M( )							-9.36**	-5.35
Observations		1,249,932		1,249,932			1,249,932	
Log likelihood		-2,542		-2,586			-2,530	

The results indicate that government regulator budget has a strong effect on both manipulation and detection. Across all three models larger government regulator budgets increase the probability of detecting and prosecuting manipulation and also decrease the probability of manipulation. The latter effect is likely to be because increased regulator capacity has a deterrence effect on manipulation. This is consistent with the conclusions made by Pirrong (1995) based on a historical overview of manipulation under various regulatory regimes. The results suggest that a 1% increase in a government regulator's real budget per stock results in a 3.3% decrease in the amount of closing price manipulation and a 2.9% increase in the rate of prosecution.[26] Because the models include dummy variables for each of the markets, the effect of budget on manipulation and detection is identified primarily through its time series variation.

The coefficients of the number of analyst forecasts and the index constituency indicator suggest that stocks with greater information asymmetry are more likely to be manipulated. The results indicate that a 10% reduction in the number of analysts' forecasts increases the probability of manipulation by approximately 4%. This finding holds across all three models and the two information asymmetry variables make the largest contribution to maximising the model likelihood. The estimates suggest that information asymmetry is among the most important determinants of manipulation. This result is consistent with the key assumption and underlying intuition of the theoretical models in Allen and Gale (1992), Kumar and Seppi (1992) and Aggarwal and Wu (2006).

[26] The former estimate is the average marginal effect across the three models and the later is from Model 2. Because Model 2 aggregates direct and indirect detection, it provides a single estimate for the effect of budget on the total amount of detection (direct and indirect). Models 1 and 3 provide separate estimates for the effect of budget on direct and indirect detection.

The coefficients of the two liquidity variables, market capitalisation and turnover, are positive.[27] The interpretation of this result is not straightforward. The liquidity variables are correlated with the asymmetric information proxies. Therefore, highly liquid stocks, which also tend to have low information asymmetry, are given a low probability of manipulation by the information asymmetry variables. The positive coefficients of the liquidity variables therefore suggest that manipulators do not favour the most illiquid stocks. Taken together, the information asymmetry and liquidity coefficients suggest that manipulators generally prefer stocks that are at neither end of the liquidity spectrum. To confirm this interpretation I re-estimate the models replacing the continuous market capitalisation and turnover variables with quintile dummy variables. The results indicate that the probability of manipulation is highest for stocks in the third and fourth quintiles where the first quintile is defined as having the highest liquidity. I conclude that manipulators favour stocks with mid to low levels of liquidity.

An explanation of the previous result is that highly liquid stocks are difficult to manipulate because of the high levels of trading activity, substantial order book depth and low information asymmetry. Very illiquid stocks are not favoured by manipulators because they generally lack the incentives or magnitude of potential profits that middle-range and highly liquid stocks have. For example, fund managers, in general, hold relatively liquid stocks and any illiquid stocks they may hold only represent a small proportion of their portfolios. Therefore, manipulating the closing prices of very illiquid stocks is unlikely to give fund managers much benefit in overstating their portfolio's performance. Similarly, derivatives are less frequently available on very illiquid stocks and such stocks are typically not constituents of major indices. Finally, brokers are more likely to manipulate stocks for the purpose of altering their clients' inference of their execution ability when the clients and orders are large. This seldom occurs in very illiquid stocks.

[27] Using spread as an alternative measure of liquidity produces similar results. However, the model fit (measure by the log-likelihood) is better for market capitalisation and turnover.

The results in Table 3.4 also indicate that stocks are significantly more likely to be manipulated on month-end and quarter-end days. Carhart et al. (2002) present evidence that stock price manipulation on month-end and quarter-end days is largely attributable to fund managers. Therefore, the results suggest that fund managers are responsible for a significant proportion of all manipulation. On the other hand, the listed options indicator variables are not statistically significant in the model. Because options tend to be listed on relatively liquid stocks, the results do not rule out the possibility that options do affect manipulation but that this effect is overshadowed by the liquidity variables. Whether a stock's price has been increasing or decreasing over a period of one month (trend) does not have a significant effect on manipulation.

Stock price volatility reduces the likelihood of manipulation. The estimates suggest that a 10% increase in the standard deviation of daily returns decreases the probability of manipulation by 8%. This finding is consistent with the explanation that volatility attracts the attention of regulators and therefore deters manipulation. Hillion and Suominen's (2004) model of brokers that manipulate closing prices predicts that volatility increases the likelihood of manipulation. My finding is not necessarily inconsistent with Hillion and Suominen because there are many other reasons why people manipulate closing prices and it could be that these dominate the effects of brokers attempting to alter perceptions of their execution ability.

Turning to the variables that affect detection, in all three models the abnormal trading characteristics (abnormal returns, reversals and abnormal volume) increase the probability of direct detection. Indirect detection of manipulation in a particular stock-day is more likely when there is abnormal trading in that stock during a period of a few days either side of that day. In particular, manipulation of stocks that have a number of overnight return reversals in a period of two weeks has an increased probability of being indirectly detected. The regulator notices the abnormal pattern of return reversals and upon investigation reveals instances of manipulation that did not trigger alerts in surveillance systems.

On the other hand, abnormal trading in stock cross-section on a particular day does not increase the likelihood of indirect detection. This may be because on any particular day, at most, a small proportion of stocks are manipulated and the effect of the manipulation is negligible in cross-section. When both direct and indirect detection processes are combined into a single detection process, as in the two-equation model, similar results are obtained regarding the effect of the abnormal trading characteristics on the probability of detection.

The effect of the probability of manipulation, $M(\ )$, on the probability of detection (in Model 3) is somewhat surprising. The results suggest that *ceteris paribus*, i.e., after controlling for things such as the effect of abnormal trading characteristics on detection, the probability of detection decreases as the probability of manipulation increases, although this result has low statistical significance. Viewing the interaction between manipulators and regulators as a strategic game, one way to interpret this result is that manipulators are the more strategic party and that regulators do not take advantage of all available information. This interpretation is supported by the previous finding that manipulators react strategically in response to changes in regulatory budget and volatility. However, alternative explanations exist such as the implicit role of prosecution in the model of detection. It may be that where manipulation is most likely to occur it is more difficult to prosecute and consequently the probability of detection *and* prosecution in such circumstances decreases. For example, the probability of manipulation is higher on month-end days but prosecution of manipulation on such days may be more difficult due to the legitimate reasons to trade at the close on month-end days.

I include the exchange indicator variables in all equations to allow for different levels of manipulation and detection in each of the two countries (US and Canada) or in different exchanges within a country.[28] On the other hand, I do not

[28] Although the exchange indicator coefficients are highly statistically significant they cannot, in isolation, be used to infer differences in the overall levels of manipulation and detection between the exchanges because there are significant systematic differences in the other explanatory variables across

include industry indicator variables in the final models as they are generally not statistically significant.

3.5.2 The frequency of manipulation and detection

The three models of manipulation and detection allow estimation of the underlying rate of manipulation (detected and not detected) and the fraction of manipulation that remains undetected. Denoting the parameter estimates by β_1^*, β_2^* and β_3^*, applying Bayes's law for the three-equation models gives the probability of an undetected manipulated closing price in the sample with no detected or prosecuted manipulation (set A^c) as:

$$\Pr\left(Y_{1i}=1 \mid Y_{2i}=0, Y_{3i}=0\right) = \frac{M\left(X_{1i}\beta_1^*\right)\left[1-D\left(X_{2i}\beta_2^*\right)-D\left(X_{2i}\beta_2^*\right)I\left(X_{3i}\beta_3^*\right)\right]}{1-M\left(X_{1i}\beta_1^*\right)D\left(X_{2i}\beta_2^*\right)-M\left(X_{1i}\beta_1^*\right)\left[1-D\left(X_{2i}\beta_2^*\right)\right]I\left(X_{3i}\beta_3^*\right)} \tag{3.17}$$

For the two-equation model this probability is:

$$\Pr\left(Y_{1i}=1 \mid Y_{2i}=0\right) = \frac{M\left(X_{1i}\beta_1^*\right)\left[1-D\left(X_{2i}\beta_2^*\right)\right]}{1-M\left(X_{1i}\beta_1^*\right)D\left(X_{2i}\beta_2^*\right)} \tag{3.18}$$

The estimates of the probability of manipulation (given that manipulation has not been prosecuted) are useful in efficiently allocating regulators' resources. The probability estimates can also be used to study the characteristics of undetected or not prosecuted closing price manipulation. I use Equations 3.17 and 3.18 in Chapter 6 as part of a manipulation detection tool designed for use in automated market surveillance systems.

Using a similar approach to Feinstein (1990), the fraction of undetected manipulation in the population can be consistently estimated as:

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the exchanges. For this reason the levels of manipulation and detection by market are examined separately in the following subsection.

$$\left(\frac{N}{Tn}\right)\sum_{i\in A^c}\Pr\left(Y_{1i}=1|Y_{2i}=0,Y_{3i}=0\right) \tag{3.19}$$

where T is the total number of observations in the population (the sum of the number of observations in sets A and A^c), N is the population number of observations in set A^c and n is the sample number of observations in set A^c.

Models 1 and 2 estimate the fraction of undetected closing price manipulation in the population as 1.17% and 1.06% of all stock-days, respectively. The rate of detected and prosecuted manipulation in the population (number of observations in set A divided by T) is 0.004%. This suggests that there are many more instances of manipulation that are not prosecuted than there are prosecuted manipulations. In fact, the estimates suggest that only about 0.4% of all manipulation is prosecuted. For every prosecuted closing price manipulation approximately 280 to 310 instances of manipulation remain either undetected or not prosecuted. Here the limitation of modelling detection and prosecution together becomes clear – one cannot infer what fraction of the not prosecuted manipulation was detected. Adding the rates of prosecuted and not prosecuted manipulation, the underlying rate of manipulation in the population is estimated at 1.17% to 1.06% of stock-days – not significantly different from the rate of manipulation that is not prosecuted, because such a small fraction of manipulation is prosecuted.

Table 3.5 reports estimates of the frequency of manipulation and detection by exchange and reveals some interesting differences between exchanges and countries. The two smaller exchanges in each country by market capitalisation, AMEX and TSX-V, have equal or lower rates of closing price manipulation than the corresponding larger exchanges. This finding differs from Aggarwal and Wu (2006) who conclude that manipulation occurs more frequently in small and illiquid markets. While Aggarwal and Wu (2006) also use a sample of prosecuted manipulation cases, they do not address the bias introduced by incomplete detection. This is likely to be the reason why our findings differ, and the difference in findings highlights the importance of controlling for incomplete detection.

Table 3.5
Estimated frequency of manipulation and detection by exchange

This table reports estimates of the frequency of manipulation and detection from Model 1 (three-equation modified DCE model). *NYSE* is the New York Stock Exchange, *AMEX* is the American Stock Exchange, *TSX* is the Toronto Stock Exchange and *TSX-V* is the TSX Venture Exchange. *Fraction detected* and *Fraction undetected* are the fraction of detected closing price manipulation and the estimated fraction of undetected or not prosecuted manipulation in the population, respectively. *Multiplier* estimates the number of manipulations that remain undetected or not prosecuted for every prosecuted manipulation (calculated as *Fraction undetected* divided by *Fraction detected*). *Manipulation rate* is the sum of *Fraction detected* and *Fraction undetected.*

Exchange	Fraction detected	Fraction undetected	Multiplier	Manipulation rate
NYSE	0.0032%	2.06%	635	2.06%
AMEX	0.0048%	0.051%	11	0.055%
TSX	0.0041%	0.068%	17	0.072%
TSX-V	0.0050%	0.031%	6	0.036%

Aggarwal and Wu's finding can be reconciled with the results presented in this chapter by considering the difference in *detection* rates for large and small exchanges. The multiplier reported in Table 3.5 (the number of manipulation instances that remain undetected or not prosecuted for every prosecuted instance) is considerably smaller for AMEX and TSX-V relative to the corresponding larger exchanges. It ranges from six for the TSX-V to 635 for the NYSE. So, while it may be true that there are more prosecuted manipulation cases in the smaller exchanges (the basis for Aggarwal and Wu's conclusion that manipulation occurs more frequently on illiquid exchanges), the results from this chapter suggest that this is because the proportion of manipulation detected on small exchanges is considerably higher. The underlying rate of manipulation is in fact, on average, greater on the larger exchanges.

Further, the results in Table 3.5 suggest a difference in the detection rates across the two countries. Detection rates for the Canadian exchanges are several times greater than for the US exchanges. Considering that the budget per stock of the SEC is considerably larger than that of the OSC, this result suggests that either the OSC is more efficient in detecting and prosecuting closing price manipulation, or the

OSC's enforcement effort, in comparison to the SEC, is more focussed at closing price manipulation relative to other misconduct.[29]

The results indicate that manipulation is much more pervasive on the NYSE than any of the other exchanges. Further analysis validates the robustness of this result. Throughout the sample period trading on the Canadian exchanges took place with decimal pricing, whereas the US exchanges switched from fractional to decimal pricing within the sample.[30] The change to decimal pricing affected spreads and liquidity, which in turn affect manipulation and detection. To ensure that the differences in manipulation rates are not caused by effects from the pre-decimalisation period I re-estimate the models and rates using only the post-decimalisation portion of data. In doing so, I remove 32 instances of closing price manipulation from the NYSE and AMEX. The results suggest that the previous finding, that the NYSE has the highest rate of manipulation, continues to hold. However, the frequency of closing price manipulation on the NYSE and AMEX in the post-decimalisation period is lower than in the pre-decimalisation period. More precisely, the estimated rates of manipulation on the NYSE and AMEX in the post-decimalisation period are 1.52% and 0.023% respectively, compared to 2.06% and 0.051% for the full sample. There is no significant change for the Canadian exchanges in the later time period.

To further test the robustness of this result I add country interactions with key explanatory variables, add dummy variables for the pre-decimalisation period, and examine estimates of the manipulation rate through time. The results suggest that the rate of manipulation on the NYSE has declined through time and on average during the sample period is higher than the manipulation rates of the other exchanges.

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[29] The same does not apply for other types of violation. Bhattacharya (2006) reports that the SEC prosecutes 10 times more cases per firm for all securities laws violations than the OSC prosecutes.

[30] All Canadian stock exchanges switched from fractional to decimal trading systems on 15 April 1996, whereas the NYSE and AMEX began phasing in decimal trading systems from 28 August 2000 and completely switched to decimal trading on 29 January 2001.

As a final note, variable coefficients and estimates of the underlying rates of manipulation and detection should be interpreted cautiously. The estimates are obtained from statistical techniques that rely on certain statistical assumptions. The most important assumptions, as discussed in Feinstein (1989, 1990, 1991), are those required to identify manipulation from detection.

3.5.3 Robustness tests

This subsection examines the robustness of the results to several factors, among the most important of which is the assumed distribution of the disturbance term. In the initial implementation, the disturbance terms, ε_{1i}, ε_{2i} and ε_{3i}, are assumed to be drawn from independent standard logistic distributions with probability density function $f(\varepsilon) = \frac{e^{-\varepsilon}}{(1+e^{-\varepsilon})^2}$. To test the sensitivity of the results to this assumption I re-estimate the models using four alternative disturbance term distributions. The alternative distributions are modifications of the standard logistic distribution with fatter tails, thinner tails, a right skew and a left skew.[31]

Table 3.6 reports the model estimates under the alternative disturbance term distributions. The marginal effects of the independent variables are very similar under the different disturbance term distributions. Overall this suggests that the results are not overly sensitive to the assumed disturbance term distribution.

[31] The fat and thin tailed distributions are equal mixtures of a standard logistic distribution and a logistic distribution with larger or smaller scale parameter respectively. Their probability density functions are given by $f(\varepsilon) = \frac{e^{-\varepsilon}}{2(1+e^{-\varepsilon})^2} + \frac{e^{-\varepsilon/s}}{2s(1+e^{-\varepsilon/s})^2}$ with s=2 for the fat tailed distribution and s=0.5 for the thin tailed distribution. The right and left skew distributions are generalised logistic distributions with probability density $f(\varepsilon) = \frac{be^{-\varepsilon}}{(1+e^{-\varepsilon})^{(b+1)}}$ and b=3 for the right skew distribution and b=0.5 for the left skew distribution.

Table 3.6
Robustness tests

This table reports the coefficients of Model 1 (the three-equation modified DCE model) estimated under alternative disturbance term distributions. *Fat tails* and *Thin tails* are equal mixtures of a standard logistic distribution and a logistic distribution with larger or smaller scale parameter, respectively. *Right skew* and *Left skew* are generalised logistic distributions with the skew parameter chosen to produce right and left skew distributions, respectively. *M( )* is the probability of manipulation, *D( )* is the conditional probability of direct detection and *I( )* is the conditional probability of indirect detection. Variables are defined in Table 3.1. Numbers not in parentheses are the coefficient estimates. Numbers in parentheses are the marginal effects (partial derivatives of the dependent probability with respect to the explanatory variables, reported as a percentage of the estimated dependent probability). Significance at the 10%, 5% and 1% levels is indicated by *, ** and ***, respectively.

	Fat tails			Thin tails		
Variable	M( )	D( )	I( )	M( )	D( )	I( )
Constant	-1.41	-21.7***	-333***	-0.66	-11.1***	-151
Regulator budget	-4.64***	2.73***	71.8***	-2.43***	1.43***	33.1
	(-2.32)	(1.36)	(34.9)	(-2.42)	(1.42)	(32.0)
Institutional	-0.65***			-0.33***		
	(-0.32)			(-0.33)		
Index stock	-1.61***			-0.82***		
	(-0.80)			(-0.82)		
Market capital	1.50***			0.76***		
	(0.75)			(0.76)		
Turnover (2)	0.53**			0.29***		
	(0.27)			(0.29)		
Month-end	2.98***			1.50***		
	(1.49)			(1.50)		
Quarter-end	4.32***			2.20***		
	(2.16)			(2.20)		
Volatility	-1.73***			-0.77***		
	(-0.86)			(-0.76)		
Abnormal return (AR)		1.60***			0.82***	
		(0.80)			(0.82)	
Reversal (RV)		0.50***			0.26***	
		(0.25)			(0.26)	
Abnormal volume (AV)		1.69***			0.85***	
		(0.84)			(0.85)	
AR time series			0.66			-0.39
			(0.32)			(-0.38)
RV time series			57.7***			21.1***
			(28.1)			(20.4)
AV time series			-6.79***			-0.78
			(-3.31)			(-0.75)
Exchange dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	No	No	No	No	No
Observations		1,249,932			1,249,932	
Log likelihood		-2,537			-2,538	

Table 3.6 (continued)

	Right skew			Left skew		
Variable	M( )	D( )	I( )	M( )	D( )	I( )
Constant	-0.69***	-3.80***	-70.6***	-4.18*	-22.3***	-335**
Regulator budget	-0.89*** (-2.34)	0.61*** (1.47)	16.7*** (45.2)	-4.05*** (-2.01)	2.36*** (1.18)	72.1* (35.1)
Institutional	-0.16*** (-0.42)			-0.68*** (-0.34)		
Index stock	-0.31*** (-0.83)			-1.66*** (-0.82)		
Market capital	0.30*** (0.80)			1.57*** (0.78)		
Turnover (2)	0.06 (0.15)			0.53** (0.26)		
Month-end	0.61*** (1.61)			3.10*** (1.54)		
Quarter-end	0.75*** (1.98)			4.16*** (2.06)		
Volatility	-0.16*** (-0.43)			-1.79*** (-0.89)		
Abnormal return (AR)		0.34*** (0.81)			1.62*** (0.80)	
Reversal (RV)		0.09*** (0.22)			0.49*** (0.25)	
Abnormal volume (AV)		0.50*** (1.19)			1.72*** (0.86)	
AR time series			0.80 (2.17)			0.30 (0.15)
RV time series			13.5*** (36.6)			57.8** (28.1)
AV time series			-1.30*** (-3.52)			-6.85*** (-3.33)
Exchange dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	No	No	No	No	No
Observations		1,249,932			1,249,932	
Log likelihood		-2,606			-2,542	

I also examine the robustness of the results to changes in the sample composition, the time period from which the sample is drawn, different model specifications and alternative variable definitions. To test the sensitivity to the particular sample and time period I split the data into two sub-samples, first by time (earliest half of the data and latest half of the data) and then randomly, and estimate the model separately on each sub-sample. I also re-estimate the model using only post-decimalisation data. I test alternative model specifications by including the variables from Table 3.1 that are left out of the reported models. I examine the sensitivity of the results to the way the variables are measured by replacing variables with their alternative definitions given in Table 3.1. The main results hold in each of these robustness tests and therefore I do not report these results.

3.6 Conclusions

Using methods that explicitly take into consideration that detected and prosecuted market manipulation is a non-random subset of all manipulation, this chapter examines the determinants of manipulation and its detection. Stocks with high levels of information asymmetry and mid to low levels of liquidity are most likely to be manipulated. The probability of manipulation is higher on month-end and quarter-end days suggesting fund managers account for a significant proportion of manipulation. Stock price volatility deters manipulation by attracting the attention of regulators. Larger government regulatory budgets increase the rate of prosecution and significantly deter manipulation. These insights help understand the underpinnings of closing price manipulation and have important implications for efficiently utilising scarce regulatory resources.

The results indicate that only a small fraction of manipulation is detected and prosecuted. For each instance of prosecuted closing price manipulation there are approximately 280 to 310 instances of manipulation that remain undetected or not prosecuted and this rate differs substantially across exchanges. Overall, manipulation is more common on larger exchanges but is detected at a significantly higher rate on small exchanges. The Canadian regulator is more efficient at prosecuting closing price manipulation than the US regulator.

The findings of this chapter highlight the pervasiveness of manipulation relative to the number of prosecuted cases suggesting manipulation is a serious issue for exchanges and regulators. The amount of manipulation can be reduced by allocating additional resources to regulation. The results suggest that a 1% increase in government regulatory budgets would decrease the amount of closing price manipulation by 3.3% and increase in the rate of prosecution by 2.9%.

The pervasiveness of closing price manipulation suggests increased surveillance and enforcement effort may be warranted. However, the regulatory response needs to also consider the amount of harm or benefits manipulation causes to market quality, particularly liquidity and price accuracy (Kyle and Viswanathan, 2008). These issues are examined in the following two chapters.

Chapter 4

Trading characteristics around closing price manipulation cases

4.1 Introduction

This chapter analyses the effect of closing price manipulation on prices and various trading characteristics. This is important for two reasons. First, understanding the effects of manipulation on markets is necessary to evaluate the benefits or harm caused by manipulators. The pervasiveness of undetected manipulation documented in the previous chapter is concerning from the perspective of economic efficiency if manipulation is detrimental to markets. Second, identifying manipulation requires an understanding of how it affects prices and trading characteristics. Therefore, the findings of this chapter are used in constructing a manipulation index in Chapter 6.

This chapter analyses a manually constructed sample of 184 instances of closing price manipulation from US and Canadian stock exchanges.[32] The analysis controls for selection bias that could result from the non-random occurrence of manipulation and detection.

This chapter finds strong evidence of large increases in day-end returns, return reversals, trading activity and bid-ask spreads in the presence of manipulation. Manipulation causes abnormal day-end returns of between 1.4% and 1.9% - approximately six times larger than their usual levels. Most of these abnormal returns

[32] New York Stock Exchange (NYSE), American Stock Exchange (AMEX), Toronto Stock Exchange (TSX) and TSX Venture Exchange (TSX-V).

are reversed by the following morning. Trading frequencies more than triple and spreads increase by between 0.11% and 0.63% in the presence of manipulation.

As pointed out in Chapter 2, there is a longstanding and unresolved debate about what constitutes market manipulation and how it should be defined (see, for example, Fischel and Ross, (1991) and Kyle and Viswanathan (2008)). In examining prosecuted manipulation cases, this chapter simply adopts the US and Canadian regulators' definition. A similar approach is taken by Aggarwal and Wu (2006). The main advantage of this approach is that it provides the most direct evidence of the effects of a sample of manipulation. A downside of this approach is that the sample reflects the characteristics of detection and prosecution as well as manipulation. The analysis is mindful of this and takes measures to minimise the influence of the detection characteristics.

Three caveats are worth noting about the results. First, the sample of prosecuted manipulation cases is not a random sample of manipulation and consequently the empirical results should be viewed as the characteristics of prosecuted manipulation. Second, despite the systematic method used in identifying prosecuted manipulation cases the sample is small due to the fact that few cases of manipulation are prosecuted. Third, this chapter only examines manipulation that is intended to increase prices because the sample of prosecutions does not contain any cases in which prices are manipulated down.

4.2 Related literature

While early empirical studies do not link manipulation with various closing price abnormalities,[33] a small number of later studies attribute seasonal closing price patterns and day-end anomalies, at least in part, to manipulation. Carhart et al. (2002) find that in US equities markets price inflation is localised in the last half hour before

[33] See Keim (1983), Ariel (1987) and Ritter (1988) on seasonal patterns and Wood et al. (1985) and Harris (1989) on intraday anomalies.

the close and that it is more intense on quarter-end days. They attribute this phenomenon to manipulation by fund managers. Similarly, Hillion and Suominen (2004) find on the Paris Bourse that significant rises in volatility, volume and bid-ask spreads occurs mainly in the last minute of trading and they attribute this to manipulation. This chapter extends these findings by isolating the impact of closing price manipulation from unrelated day-end phenomena and seasonal effects by using actual manipulation cases and the method of difference-in-differences.

Empirical research using manipulation cases is scarce. Chapter 2 reviews the small number of studies examining corners[34], squeezes[35], the stock pools of the 1920s[36] and longer period manipulation schemes commonly referred to as 'pump-and-dump' manipulation. In a pump-and-dump scheme the manipulator attracts liquidity to a stock while inflating its price so that he can profit from selling the stock at the inflated price. Closing price manipulation is far more mechanical. The manipulator seeks only to create a short-term liquidity imbalance, in many instances just a matter of minutes, and is prepared to accept a loss on the manipulative trades. Whereas pump-and-dump manipulators profit directly from the manipulated stock by buying low and selling high, closing price manipulators typically profit outside the manipulated market, for example, greater remuneration for a fund manager, greater payoff from a derivatives position or a more profitable takeover.

Aggarwal and Wu (2006) analyse pump-and-dump manipulation cases obtained from The US Securities and Exchange Commission (SEC) litigation releases. They find that in their sample of prosecution cases stocks generally experience a price increase during the manipulation period, a subsequent decrease during the post-manipulation period and increased volatility. Their sample of cases is more concentrated in illiquid stocks and most of the manipulation is conducted by informed

[34] See Allen et al. (2006).

[35] See Merrick et al. (2005), Jegadeesh (1993) and Jordan and Jordan (1996).

[36] Although these stock pools are the main reason for the current anti-manipulation laws in the USA, Mahoney (1999) and Jiang et al. (2005) find little evidence of price manipulation.

insiders such as management, substantial shareholders, market-makers or brokers. This chapter is similar to Aggarwal and Wu (2006) in that it analyses prosecuted manipulation cases but differs in that it examines a substantially different form of market manipulation.

4.3 Predicted effects of manipulation

Based on litigation releases and discussions with exchange surveillance personnel and regulators, in this section I describe the typical approaches taken by closing price manipulators and predict how manipulation affects trading characteristics. Although manipulators may attempt to push a stock's price in either direction, I limit this discussion to upward closing price manipulation. As there are no cases involving price decreases in the examined litigation releases it is not possible to empirically examine this type of manipulation using prosecution cases.

The manipulator's intent is to inflate the closing price. Therefore, as long as manipulators are successful at least some of the time day-end returns should on average be positive in the presence of manipulation. This is consistent with Carhart et al. (2002) who find that equity price inflation is localised in the last half hour before the close, attributing this to manipulation. Similarly, Hillion and Suominen (2004) use manipulation to explain the finding that changing the closing price mechanism on the Paris Bourse eliminated abnormal day-end returns.

Most investors view price impact as an undesirable side-effect of making large trades relative to the liquidity in the market because it increases the cost of trading. For a manipulator, the opposite is true and therefore closing price manipulators often submit large buy orders just before the close.[37] This consumes depth on the ask side of the order book by executing a number of limit orders, thus raising the ask price and widening the spread. This prediction is consistent with Hillion and Suominen (2004)

[37] For a typical example, see SEC v. Schultz Investment Advisors and Scott Schultz (http://www.sec.gov/litigation/admin/33-8650.pdf).

who argue that manipulation is the cause of the significant rise in the spread during the last minutes of trading on the Paris Bourse. Given overnight for new orders to enter the market and resolve the liquidity imbalance, prices should revert towards their original levels the following morning as demonstrated by Carhart et al. (2002).

Manipulators trade to influence closing prices and in doing so can also induce trading by speculators and arbitrageurs. For example, price increases caused by the manipulator may induce buying by momentum traders or selling by sophisticated investors and arbitrageurs that recognise the opportunity to profitably counteract the manipulator. Indeed, the latter is the mechanism by which manipulators increase liquidity in a microstructure model by Hanson and Oprea (2009). Therefore, trading activity is expected to increase in the presence of manipulation; the extent of which is likely to depend on the liquidity of the stock, the regulatory environment, the manipulator's incentives and amount of available funds. Hillion and Suominen (2004) argue that manipulation is the cause of the rise in volatility and volume in the last minutes of trading on the Paris Bourse.

The effect of manipulation on the size of trades is less obvious as it depends on the aggressiveness of a manipulator. In its least aggressive form, manipulation can simply involve making one small trade to close the stock at the ask quote. If this is the manipulator's intent, the trade size chosen by the manipulator is likely to be smaller than the average trade size, thereby decreasing the average size of trades in the last part of the day relative to trades during the day. Non-aggressive manipulation is more likely to occur in thinly traded stocks that have wide spreads or when a manipulator intends to influence closing prices over many days because making large trades over many days is costly.

Aggressive manipulators make many large trades to consume ask-side depth and increase the price beyond the ask quote. Such manipulation increases the relative trade size at the end of the day. Aggressive manipulation is more likely to occur in liquid stocks and when the manipulator has a lot of resources and incentive, such as a fund manager on the last day of a reporting period. Therefore, the effect of manipulation on the size of trades is expected to depend on the factors that influence the aggressiveness of a manipulator and the nature of stocks being manipulated. For this reason, the analysis in this chapter is conducted separately for high turnover stocks, low turnover stocks, stocks manipulated on several consecutive days and stocks manipulated as separate occurrences on month-end days.

In summary, closing price manipulation is expected to increase day-end returns, spreads, return reversals and trading activity. Manipulation's effect on trade size is expected to depend on the aggressiveness of a manipulator and the nature of stocks being manipulated.

4.4 Data

This chapter uses the manually collected sample of closing price manipulation cases, which is described in Chapter 3. I obtain intra-day trade and quote data from a *Reuters* database maintained by the *Securities Industry Research Centre of Asia-Pacific* (*SIRCA*). I filter these data to remove erroneous entries and stock-days that do not contain at least one trade and one quote.

During most of the sample period the Canadian exchanges, TSX and TSX-V, have simple closing mechanisms. Trade occurs continuously until 4:00pm at which time the market closes and the closing price is the price of the last trade.[38] There is no facility to allow trading at the closing price, nor do the designated market makers have discretion in setting the closing price, other than by adjusting their quotes.

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[38] Subsequently the TSX introduced an automated closing call auction in 2004. In a comment during the consultation process prior to adopting the closing call auction, the TSX highlight the inadequacies of the "last sale" method and potential for manipulation: "the current 'last sale' methodology for determining closing prices … is often arbitrarily based on the market participant with the 'fastest fingers' who is able to successfully place an order in the final few seconds before the close" (The TSX Notice of Amendments and Commission Approval, July 25, 2003). Hillion and Suominen (2004), among others, demonstrate that a closing call auction reduces price manipulation.

In contrast, the closing mechanisms on the NYSE and AMEX are more complicated. They allow orders to be specified for execution at the closing price and the specialists intervene in setting closing prices. Although the NYSE and AMEX closing procedures are sometimes described as auctions, they bear little resemblance to any other auction procedure (Hasbrouck, 2007), particularly automated closing call auctions, such as the ones currently used at Euronext Paris and the London Stock Exchange, for example. On the NYSE and AMEX, traders can enter market-on-close (MOC) and limit-on-close (LOC) orders to be executed at the closing price. In each stock, the specialist determines the buy or sell on-close order imbalance and may publish the imbalance, in which case MOC and LOC orders can only be entered on the other side of the imbalance.[39] At 4:00pm no more orders are accepted and the specialist pairs off on-close orders at a single price (the closing price) and supplies additional liquidity to execute any remaining on-close order imbalance.

In order to describe the characteristics of the manipulated stock sample I compare manipulated stocks to all other stocks on the same exchange. Table 4.1 reports medians of variables in a two-month period prior to each manipulation, for the manipulated stocks and all other stocks on the corresponding exchange during the same time period.

[39] MOC and LOC orders of any kind can be entered until 3:40pm, after which time these orders cannot be cancelled. If there is a large imbalance, the specialist, at his/her discretion, may publish an imbalance announcement between 3:00pm and 3:40pm. At 3:40pm the specialist must publish imbalances of 50,000 shares or more (25,000 on the AMEX). If there is no imbalance, traders cannot place further MOC or LOC orders, however, if there is an imbalance, traders may place MOC and LOC orders that decrease the imbalance. If an imbalance is published at 3:40pm, the specialist must update this information at 3:50pm. See Bacidore and Lipson (2001) for details.

Table 4.1
Characteristics of manipulated stocks compared to all other stocks on the same market

Rows (I) report the median values for manipulated stocks in a two-month period ending one month prior to the manipulation date. Similarly, rows (II) report medians for non-manipulated stocks over the same two-month periods. Differences are calculated by subtracting (II) from (I). Significance at the 5% and 1% levels is indicated by * and **, respectively, using Wilcoxon z-tests. *n* is the number of two-month periods used in calculating the medians. For manipulated stocks this is equal to the number of instances of manipulation (not necessarily the number of stocks because some stocks are manipulated more than once) and for non-manipulated stocks is equal to the number of instances of manipulation multiplied by the number of non-manipulated stocks on the market. *Mean daily spread* is calculated as the average of the bid-ask spreads at every trade and quote revision during the day. *AMEX* is the American Stock Exchange, *NYSE* is the New York Stock Exchange, *TSX* is the Toronto Stock Exchange and *TSX-V* is the TSX Venture Exchange.

Market		n	Closing Price ($)	Trades Per Day	Mean Trade Frequency (trades per hour)	Daily Traded Value x$1000	Mean Trade Size x$100	Mean Daily Spread (%)
AMEX	Manipulated stocks (I)	29	10.25	10	1.45	70.5	61.8	2.4
	Non-manip. stocks (II)	11,629	7.38	5	0.76	30.1	55.5	2.7
	Difference (I-II)		2.88**	5**	0.69**	40.4**	6.3**	-0.3**
NYSE	Manipulated stocks (I)	31	18.39	19	2.87	266.1	132.6	0.7
	Non-manip. stocks (II)	106,299	19.38	80	12.25	1055.5	131.4	0.5
	Difference (I-II)		-0.98	-61**	-9.37**	-789.3**	1.3	0.3**
TSX	Manipulated stocks (I)	90	3.95	8	1.23	74.5	86.1	2.8
	Non-manip. stocks (II)	105,380	4.83	11	1.69	61.7	55.6	2.7
	Difference (I-II)		-0.88**	-3**	-0.46**	12.8*	30.5**	0.1*
TSX-V	Manipulated stocks (I)	34	1.40	6	0.88	14.5	24.3	3.6
	Non-manip. stocks (II)	18,520	0.35	5	0.77	9.5	18.3	6.6
	Difference (I-II)		1.05**	1	0.12	5.0*	6.0	-3.0**

The manipulated stocks on the larger of the two exchanges in each country, the NYSE and the TSX, tend to be less liquid than the exchange median. Manipulated stocks on these exchanges trade fewer times per day and have larger spreads than the market median. On the other hand, the manipulated stocks on the AMEX and the TSX-V tend to be more liquid than the exchange median as indicated by the smaller spread, more trades per day and higher daily traded value. Overall, this suggests that the manipulated stocks on different exchanges within the same country are more alike in their level of liquidity than non-manipulated stocks and the stocks preferred by manipulators are at neither end of the liquidity spectrum. This result is consistent with the fact that on one hand, very liquid stocks are difficult to manipulate and on the other, the potential gains from manipulating the closing prices of illiquid stocks are small.

These results contrast with Aggarwal and Wu (2006) who find that pump-and-dump manipulation is concentrated in illiquid stocks. The differences in these two sets of results are explained by the differences between the two types of manipulation. Because pump-and-dump manipulators profit directly from their trading, manipulating illiquid stocks can be profitable. However, closing price manipulators typically profit outside the manipulated market from contracts based on closing prices and such contracts are less prevalent or less valuable in illiquid stocks. For example, illiquid stocks represent a small proportion of fund manager portfolios and broker trading for institutional clients and are less likely to have options trading on them.

4.5 Effects on trading characteristics

This section reports the effects of closing price manipulation on five trading characteristics using two different methods: difference-in-differences and matched stocks.

4.5.1 Measurement of trading characteristics

I estimate manipulation's effect on returns, return reversals, trade frequencies, spreads and trade sizes. Appendix C contains formulae for these variables. Return is calculated as the natural logarithm of the closing price divided by the bid-ask midpoint at a specified time (defined later) before the close. Return reversal is the return from the closing price to the midpoint the following morning at 11am, allowing time from the open for price discovery to occur and temporary volatility to disappear. Trade frequency, a proxy for trading activity, is calculated as the average number of trades per hour in the last part of the day. Spread is measured at the close proportional to the bid-ask midpoint. Trade size is the average dollar volume of trades at the end of the day relative to the average dollar volume of trades during the day.

The substantial variation in the timing of closing price manipulation presents a challenge in both its characterisation and detection. If the day-end interval in which the effect of manipulation is measured is too wide the measures are diluted with non-manipulative trading activity, but if the interval is too narrow some of the manipulator's effect is missed.[40] Highly liquid stocks are likely to be manipulated shortly before the close because in such stocks it is costly to sustain the liquidity imbalance that causes the inflated price. The effects of manipulation can be adequately measured in a short real-time interval prior to the close, such as the last 20 minutes of trading. On the other hand, a thinly traded stock can be manipulated with a single trade considerably earlier in the day. A short real-time interval would fail to capture the manipulator's trades. Here, the use of a transaction-time interval is more effective, for example, the last two trades of the day.

To handle different levels of liquidity I use several real-time and transaction-time intervals and select the interval in which manipulation is most likely to occur. The real-time intervals are the last 15, 20, 30, 60 and 90 minutes prior to the close and the transaction-time intervals are from the last, the second last, third last and fourth last trades before the close. For each stock-day, I calculate variables for the smallest real-time interval containing at least one trade[41] and the transaction-time interval that has the largest value of return from the bid-ask midpoint to the closing price. The real-time interval is as small as possible to avoid diluting the effects of the manipulator's trades with non-manipulative trading activity. The transaction-time interval is likely to contain the manipulator's trades, if manipulation is present, with the least amount of non-manipulative trading. This is because the manipulator's trades are expected to have greater price impact, on average, than other trades. For each variable I take the maximum of its values in the real-time and transaction-time

[40] To illustrate this, consider a stock that usually trades at a rate of one trade every five minutes and has one additional trade made by a manipulator just before the close. The increase in trade frequency in the last 10 minutes is 50%, but in the last 30 minutes it is only 17%.

[41] If a stock has no trades in the 90 minute interval, then the variables are measured from the last trade.

intervals to obtain a single measure that can be applied across stocks of different levels of liquidity.[42]

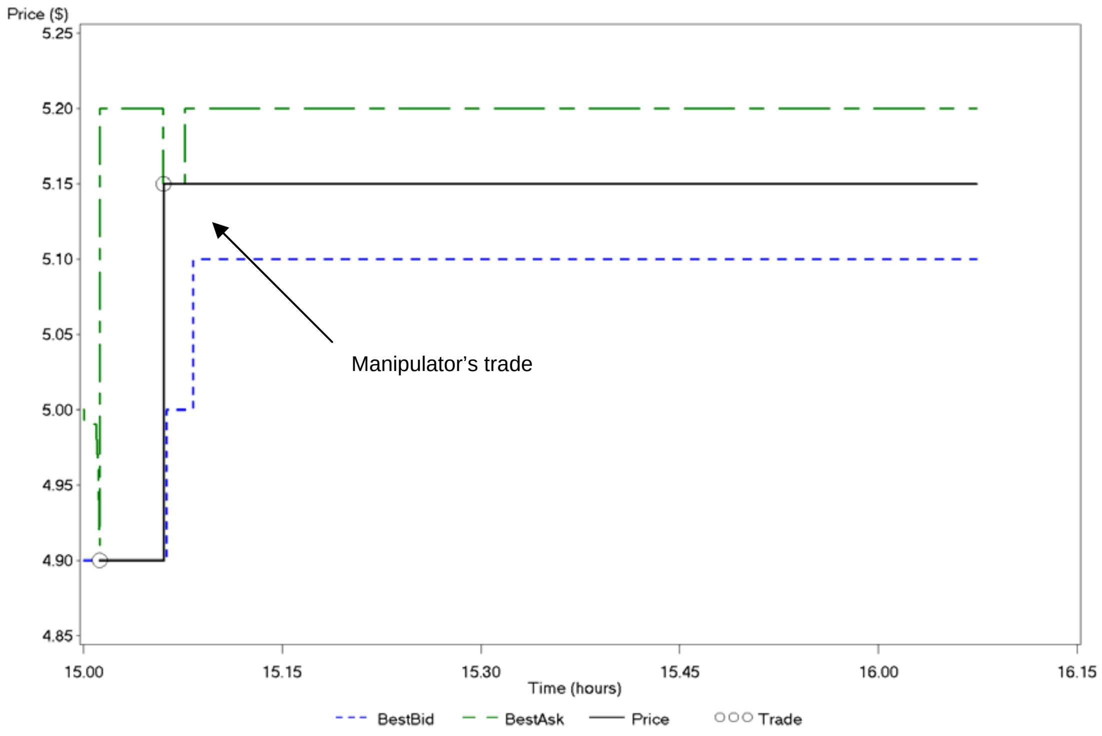
To illustrate how this method of combining multiple intervals works, consider two instances of manipulation from the sample, which involve stocks of different levels of liquidity. Figure 4.1 plots the best quotes and trade prices for the last hour of trading.

In the first example (Panel A), the manipulated stock is relatively illiquid. The manipulator makes only one trade approximately one hour before the close, setting the closing price at the ask quote (up approximately 5% from the last trade price). In this example, the day-end variables are calculated from the transaction-time window corresponding to the last trade. Many of the real-time windows (e.g., the last 30 minutes before the close) fail to capture the manipulator's trade and therefore incorrectly measure the effects of manipulation. Although the 90 minute real-time window contains the manipulator's trade it provides a less accurate measure of the effects of manipulation because it contains half an hour of non-manipulative trading before manipulation begins. In even less liquid stocks manipulators can place the closing trade hours before the close, in which case none of the real-time intervals correctly measure the effects of manipulation.

In the second example (Panel B), the manipulated stock is more liquid. The manipulator makes seven trades in the last 20 minutes of trading (trades made in close succession may appear in Figure 4.1 as a single trade due to overlapping symbols), increasing the price from $19.875 to $20.50 (3.1%). In this example, the day-end variables are calculated from the real-time window corresponding to the last 15 minutes before the close. This window contains most of the manipulator's trades and captures most of the manipulator's effects on trading characteristics. On the other hand, due to the relatively large number of trades in this example, the transaction-time intervals miss a significant part of the manipulation's effects.

[42] The upward bias in individual values caused by the use of the maximum operator is removed through differencing in both the difference-in-differences and matched stock methodologies.

Panel A: Helix BioPharma Corporation on 21 March 2000



Panel B: Southern Union Company on 22October 1999

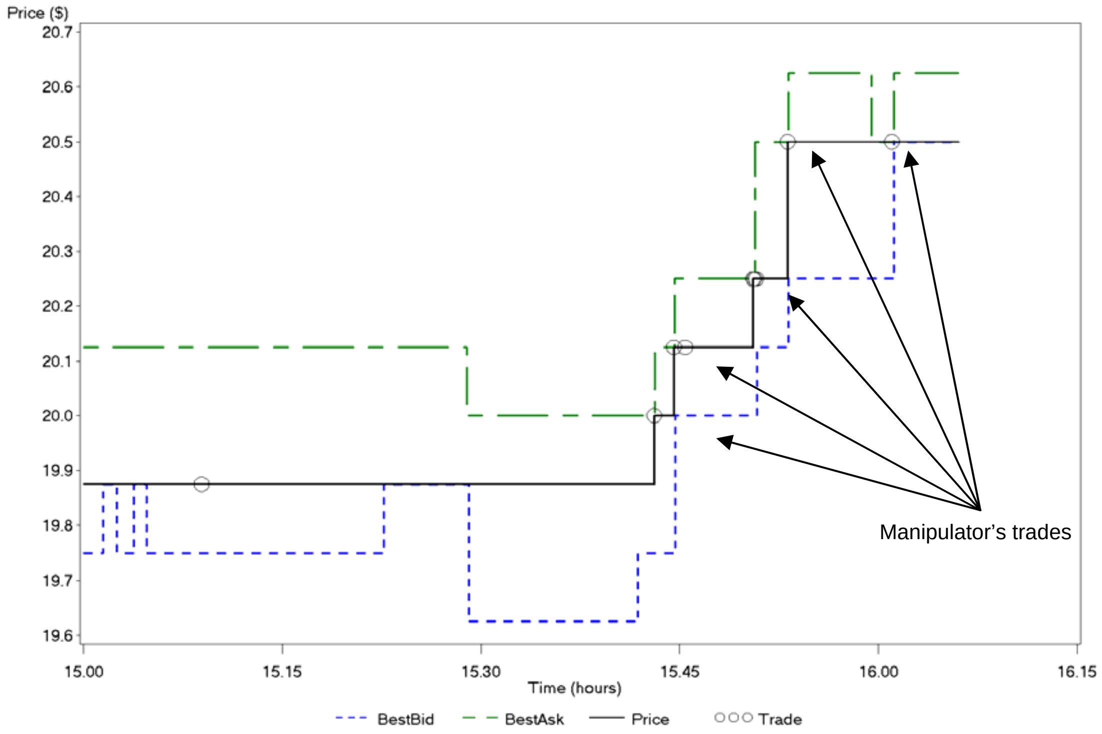


Figure 4.1 Day-end trading in two instances of closing price manipulation
This figure plots the best quotes and trades during the last hour of trading for two instances of closing price manipulation. The close of trading is approximately 16:00.

4.5.2 Difference-in-differences estimates

I estimate the effects of manipulation on trading characteristics using difference-in-differences estimation and differences in matched stocks. These methods control for selection bias, which can arise from manipulators choosing: (i) stocks that systematically differ from other stocks in observable or unobservable characteristics (e.g., liquidity); or (ii) days that differ systematically from other days, for example, month-end days. These methods also control for differences in detection rates across groups of stocks and types of days. The difference-in-differences estimator can provide a more robust selection-controlled estimate of the effects of a treatment than the commonly used Heckman selection estimators and instrumental variables estimators when longitudinal data are available (Blundell and Costa Dias, 2000).

The difference-in-differences estimator first computes changes in day-end variables on manipulation days relative to other trading days for each stock and then compares the differences of manipulated stocks to those of non-manipulated stocks. This is expressed in the following equation,

$$\Delta_{DD} = \left(Y_{it_1}^{M} - Y_{it_0}^{M}\right) - \left(Y_{it_1}^{0} - Y_{it_0}^{0}\right), \tag{4.1}$$

where, for the i^{th} manipulation, Y_i^M and Y_i^0 are the values of a day-end variable for the manipulated stock and corresponding non-manipulated stocks (all other stocks on the same exchange) respectively, time period t_1 is the day of the manipulation and t_0 is a period of 42 trading days (approximately two months) ending one month prior to the date of the manipulation.

The first term, $\left(Y_{it_1}^{M} - Y_{it_0}^{M}\right)$, the before-after estimator for manipulated stocks, indicates how much larger the values of the day-end variables are on the day of manipulation relative to the two-month benchmark in the same stock.[43] This term

[43] The length of this benchmark is somewhat arbitrary. There is a trade-off between not being responsive to changes in market characteristics through time if the benchmark is too long, and not being representative of normal inter-day variation if the benchmark is too short. The benchmark is

removes the effects of stock-specific characteristics thereby overcoming possible bias from manipulators selecting non-random stocks.

The second term, $\left(Y_{it_1}^{0} - Y_{it_0}^{0}\right)$, is the before-after estimator for non-manipulated stocks on the same exchange and day as the i^{th} manipulation. Subtracting this from the first term removes market-wide trends on the manipulation day and overcomes possible bias from manipulators choosing non-random days, such as month-end days.

Table 4.2 reports median difference-in-differences estimates. Using medians avoids the results being overly affected by the detection process, which is influenced by extreme observations as discussed later.[44] I analyse stocks by their level of turnover because liquidity is likely to affect the impact of manipulation. I also analyse different types of closing price manipulation separately. Using the litigation releases, I divide the sample of cases into those in which manipulation takes place over consecutive (or approximately consecutive) days and those in which manipulation is in separate occurrences on month-end days.[45] The manipulator in each of these types has different incentives, different resources and is likely to target stocks with different characteristics. Also, manipulation over several days may have different effects on the return reversal variable because its calculation involves the following day's price.

lagged by one month so that any abnormal trading or other forms of market misconduct prior to the manipulation reported in a litigation release is excluded.

[44] Implementation with medians is used in Meyer et al. (1995), for example, and discussed more formally as a special case of quantile difference-in-differences in Athey and Imbens (2006).

[45] An example of the first type of manipulation is influencing the price of a seasoned equity issue that is based on the average closing price over a certain period. An example of the second type is a fund manager manipulating closing prices at the end of a reporting period.

Table 4.2
Effects of manipulation on day-end trading characteristics using difference-in-differences

Panel E reports difference-in-differences estimates of the effects of manipulation,

$$\Delta_{DD} = med_i\{[Y^M_{it_1} - med_d(Y^M_{it_0d})] - med_s[Y^0_{ist_1} - med_d(Y^0_{ist_0d})]\}$$

Panels A to D report components of the difference-in-differences estimator as follows: Panel A, $med_i(Y^M_{it_1})$; Panel B, $med_i[med_d(Y^M_{it_0d})]$; Panel C, $med_i[Y^M_{it_1} - med_d(Y^M_{it_0d})]$; Panel D, $med_i\{med_s[Y^0_{ist_1} - med_d(Y^0_{ist_0d})]\}$; where index i represents the instances of manipulation, index s represents the non-manipulated stocks on the same exchange as manipulation i, index d represents the days in the pre-manipulation periods, subscript t_0 represents the pre-manipulation period of 42 trading days ending one month prior to manipulation i, subscript t_1 represents the day of manipulation i, superscript M represents the stock involved in manipulation i and 0 represents a non-manipulated stock traded on the same exchange as M, Y represents the day-end variables defined in Appendix C and med_x is the median operator applied across index x. *High turnover* stocks are defined as having more than ten trades per day on average in the pre-manipulation period and vice versa. *Consecutive* refers to stocks that are manipulated over several consecutive days, *Month-end* refers to non-consecutive occurrences of manipulation on month-end days and n is the number of stock-days used in the calculation. In Panels C, D and E significance at the 5% and 1% levels is indicated by * and **, respectively, using non-parametric sign tests.

Panel	Group	n	Return (%)	Reversal (%)	Frequency (trades per hour)	Spread (%)	Abnormal Trade Size (%)
A: Manipulated stocks on manipulated days	ALL	184	2.60	1.71	12.00	3.27	-5.0
	Consecutive	124	2.94	2.12	12.17	3.36	-31.3
	Month-end	60	2.20	1.10	12.00	2.26	37.8
	High turnover	113	2.16	1.38	16.06	2.53	-13.3
	Low turnover	71	3.58	2.10	10.12	3.91	0.0
B: Manipulated stocks prior to manipulation	ALL	7,728	1.25	0.00	5.63	2.76	-10.2
	Consecutive	5,208	1.25	-0.25	5.63	2.76	-10.5
	Month-end	2,520	0.33	0.00	1.67	2.36	0.0
	High turnover	4,746	1.25	-0.15	5.63	2.42	-18.3
	Low turnover	2,982	1.06	0.00	1.61	3.00	-5.0
C: Before-after estimator for manipulated stocks	ALL	7,912	1.42**	1.71**	7.77**	0.39**	5.8
	Consecutive	5,332	1.35**	2.16**	7.77**	0.56**	-17.1
	Month-end	2,580	1.76**	1.07**	8.68**	0.14	44.5**
	High turnover	4,859	0.97**	1.11**	7.69**	0.51**	17.2
	Low turnover	3,053	2.23**	2.10**	7.85**	0.37	0.0
D: Before-after estimator for non-manipulated stocks	ALL	5,954,856	0.00	0.00	0.08	0.00	0.0
	Consecutive	4,193,920	0.00	0.00	0.00	0.02	0.0
	Month-end	1,760,936	0.04	-0.40**	1.12**	-0.01	3.8*
	High turnover	4,095,032	0.00	0.00	0.02	0.04*	0.0
	Low turnover	1,859,824	0.01	-0.06	0.47*	-0.04**	0.0
E: Median difference-in-differences estimator	ALL	5,962,768	1.46**	1.85**	7.90**	0.36**	0.0
	Consecutive	4,199,252	1.37**	1.96**	8.02**	0.63**	-15.8
	Month-end	1,763,516	1.62**	1.65**	7.60**	0.11	15.5
	High turnover	4,099,891	1.05**	1.33**	8.07**	0.37*	4.7
	Low turnover	1,862,877	2.24**	2.29**	7.57**	0.34	-0.1

The before-after estimates reported in Panel C indicate highly statistically significant and economically meaningful increases in each of the day-end variables for manipulated stocks on the day of manipulation relative to their trading activity prior to manipulation. The before-after estimates for stocks that are not manipulated (Panel D) are all near zero suggesting there are no strong market-wide trends on the manipulation days that can explain the significant increases for manipulated stocks. This is confirmed by Panel E which indicates that manipulation causes a significant increase in returns, reversals, trade frequencies and spreads after controlling for stock- and time-specific effects.

Low turnover stocks experience a much larger increase in day-end returns in the presence of manipulation compared to high turnover stocks (2.24% and 1.05% respectively). Low turnover stocks are likely to have less depth in the order book and hence a large trade will have more substantial price impact. Additionally, the manipulator of a low turnover stock has to compete with fewer trades for control over the price and therefore is more likely to be successful in making the last trade of the day. Consistent with this result, low turnover stocks also exhibit the largest return reversals from the closing price to the following morning.

A 15.5% increase in the size of month-end trades is attributable to manipulation after controlling for the tendency for trades to be larger on month-end days. Combined with a proportionally larger increase in day-end trade frequency, this suggests that month-end manipulators spend more per closing price manipulation than consecutive day manipulators. The difference may be because fund managers have access to greater amounts of capital or because they have stronger incentives to manipulate. Aggressive closing price manipulation increases the probability of detection. The manipulators willing to bear this risk are likely to be those for whom manipulation is most profitable.

4.5.3 Matched stock estimates

Abnormal trading activity in a stock's prior trading benchmark, particularly in manipulated stocks, can lead to problems in inference using difference-in-differences. To ensure the results are robust with respect to this potential problem I examine the effect of manipulation using an alternative method of matched stocks. Abnormal trading in a stock's prior trading benchmark could occur if the stock was manipulated before the first instance of manipulation reported in the litigation documents. This could also occur if particular abnormal trading characteristics cause manipulation.

I match each manipulated stock to another stock from the same exchange in a manner similar to Huang and Stoll (1996).[46] Matched stocks must meet the price criterion in Equation 4.2 and are selected as those with the smallest scores of the loss function in Equation 4.3.

$$\left| \frac{price^{M} - price^{0}}{(price^{M} + price^{0})/2} \right| < 1 \qquad (4.2)$$

$$\sum_{j=1}^{2} \left(\frac{x_i^{M} - x_i^{0}}{(x_j^{M} + x_j^{0})/2} \right)^2 \qquad (4.3)$$

In Equations 4.2 and 4.3 the superscripts *M* and *0* refer to manipulated and non-manipulated stocks (all other stocks on the corresponding exchange), respectively. The x_j are two liquidity related stock characteristics: daily traded dollar volume and mean daily spread. Both *price* and the two stock characteristics are calculated over a two month period ending one month prior to the manipulation. The price criterion eliminates matching candidates for which price levels are extremely far apart and the loss function ensures matched stocks have similar liquidity.[47]

[46] As a robustness test I also use one-to-twenty matching and find similar results.

[47] The median differences in the manipulated and matched stocks' closing prices, trades per day, daily traded dollar volume and mean daily spread are all less than 8% suggesting the matching is relatively precise.

Table 4.3 compares the manipulated and matched stocks on manipulation days. The estimated effects of manipulation (Panel C) support the previous conclusions. Estimates of abnormal returns increase from 1.46% using difference-in-differences to 1.90% using matched stocks and estimates of return reversals increase from 1.85% to 2.09%. The matched stock results support the previous finding that low turnover stocks experience larger abnormal day-end returns and reversals. Abnormal day-end trade size for month-end manipulations is significantly positive (12.0%), whereas manipulation on consecutive days is estimated to decrease the average size of trades by 20.5%.

Table 4.3
Effects of manipulation on day-end trading characteristics using matched stocks

Medians of day-end variables for manipulated stocks on manipulation days (Panel A), matched stocks on manipulation days (Panel B), and differences between manipulated stocks and matched stocks on manipulation days (Panel C). High turnover stocks are defined as having more than ten trades per day on average in the benchmark period (42 trading days lagged one month) and vice versa. *Consecutive* refers to stocks that are manipulated over several consecutive days, *Month-end* refers to non-consecutive occurrences of manipulation on month-end days and *n* is the number of stock-days. The variables are defined in Appendix C. In Panel C significance at the 5% and 1% levels is indicated by * and **, respectively, using non-parametric sign tests.

Panel	Group	n	Return (%)	Reversal (%)	Frequency (trades per hour)	Spread (%)	Abnormal Trade Size (%)
A: Manipulated stocks on manipulation days (I)	ALL	184	2.60	1.71	12.00	3.27	-5.0
	Consecutive	124	2.94	2.12	12.17	3.36	-31.3
	Month-end	60	2.20	1.10	12.00	2.26	37.8
	High turnover	113	2.16	1.38	16.06	2.53	-13.3
	Low turnover	71	3.58	2.10	10.12	3.91	0.0
B: Matched stocks on manipulation days (II)	ALL	184	0.32	0.00	3.52	2.20	0.0
	Consecutive	124	0.37	0.00	3.01	2.52	-2.9
	Month-end	60	0.31	-0.27	4.44	1.62	15.1
	High turnover	113	0.31	-0.29	4.00	1.79	0.5
	Low turnover	71	0.56	0.00	2.00	3.08	-5.0
C: Cross-sectional differences (I-II)	ALL	184	1.90**	2.09**	7.24**	0.36**	-11.5
	Consecutive	124	2.01**	2.45**	7.61**	0.35*	-20.5*
	Month-end	60	1.63**	1.42**	3.50**	0.39*	12.0*
	High turnover	113	1.32**	1.44**	7.34**	0.37**	-25.3
	Low turnover	71	3.04**	2.82**	6.56**	0.30	0.6

4.5.4 Discussion and robustness tests

The estimation of median effects rather than means in both analyses is important to ensure the results are not overly affected by the detection process. Details of the mechanisms that regulators use to detect manipulation are kept confidential to make it more difficult for manipulators to work around the mechanisms and avoid detection (Cumming and Johan, 2008). However, it is known that surveillance systems are largely automated and based on patterns of abnormal trading characteristics such as price movements. Discussions with regulators suggest that price and volume are among the most common variables in surveillance systems and that trade size and spreads are not commonly used.

Each of the eight manipulation cases in the sample contain on average 23 instances of closing price manipulation. It is likely that only the most abnormal price movements would have triggered alerts in automated market surveillance systems. Investigation of trading records around these events would have revealed other instances of manipulation, attempted manipulation or conspiring manipulators that did not trigger automated alerts. The instances that trigger alerts, being relatively few in number but having large abnormal characteristics, are likely to influence mean estimates but have a minimal effect on medians. Consequently, median estimates are less affected by the detection process and more accurately reflect the characteristics of all manipulation: detected and undetected.

I perform a number of robustness tests. The full set of results are in Appendix D. First, I estimate the difference-in-differences and matched stock differences with means instead of medians.[48] The results are similar to estimation with medians, but tend to be slightly larger. I replicate the difference-in-differences analysis with a

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[48] As Harris (2005) points out, the mean difference-in-differences model can be estimated using the panel regression model: $Y_{it} = \beta_0 + \beta_D D_{it} + \mu_i + \mu_t + \varepsilon_{it}$ where β_D is the impact estimator, D_{it} is an indicator for a manipulated stock-day and the μ are the panel data terms that pick up stock- and time-specific effects. Estimating this model with double clustered standard errors as suggested by Thompson (2009) produces similar results to those reported in Table 4.2.

randomly chosen single day from the prior trading benchmark (rather than 42 days) and find similar point estimates and levels of statistical significance. I conduct the difference-in-differences analysis separately for each legal manipulation case. Although there are differences in magnitudes, the overall effects of manipulation in individual cases are qualitatively consistent with the main conclusions of this chapter. Specifically, in each case manipulation causes abnormal returns, reversals and abnormal trading frequency, most cases lead to wider spreads, and the effects of manipulation on trade size are mixed. I examine the influence of the way the day-end variables are calculated by estimating the effects of manipulation in each real-time and transaction-time window separately (not using a maximum operator). The findings that manipulation increases returns, reversals, trade frequency and spreads are robust to measuring the variables over different intervals.

4.6 Conclusions

This chapter quantifies the effects of closing price manipulation on the trading characteristics of stocks on US and Canadian stock exchanges. Unlike previous studies, this analysis isolates the effect of closing price manipulation from unrelated day-end and seasonal effects. This chapter uses methods that control for selection bias that can result from the non-random occurrence of manipulation. The use of two methods in conjunction with generally consistent findings allows greater confidence in the estimated effects of manipulation.

This chapter's findings are important in evaluating the benefits or harm caused by manipulators. In that regard, one of the key findings is that closing price manipulation has a significantly detrimental effect on price accuracy. Manipulation causes abnormal day-end returns of between 1.4% and 1.9% - approximately six times larger than their usual levels. Most of these abnormal returns are reversed by the following morning. Although the price distortions generally exist only for a short period of time before the close, their effects are of great consequence because of the widespread use of closing prices and the frequency with which they are manipulated.

The results also indicate that trading frequencies more than triple and spreads increase by between 0.11% and 0.63% in the presence of manipulation. Illiquid stocks that have wide spreads can be manipulated with a single small trade that closes the stock at the bid or ask quote (depending on the manipulator's intended direction). For a liquid stock, this approach would have little effect on the price. Therefore, liquid stocks are commonly manipulated with several large trades. Fund managers have strong incentives to manipulate and they typically use large trades in manipulation. When manipulating a stock over several days manipulators tend to use smaller trades.

By enhancing our understanding of how closing price manipulation affects trading characteristics, this chapter sheds light on how manipulation can be identified in markets. These findings are used in constructing a manipulation index in Chapter 6. The next chapter complements these findings by analysing the broader effects of manipulation, such as the effects on overall market liquidity.

Chapter 5

The effects of closing price manipulation on market quality

5.1 Introduction

Two fundamentally important aspects of financial market quality are pricing accuracy and liquidity. Pricing accuracy, the precision with which market prices reflect the underlying value of an asset, determines the informativeness of prices and their ability to encourage efficient resource allocation.[49] Liquidity allows efficient transfer of risk. The presence of traders with incentives to manipulate prices is a feature of markets that may limit their informational and transactional efficiency.

The purpose of this chapter is to identify how closing price manipulation affects pricing accuracy and liquidity, in order to evaluate manipulation's effects on economic efficiency and social welfare. In their discussion of how to define illegal market manipulation, Kyle and Viswanathan (2008) argue that forms of manipulation should only be illegal if they are detrimental to *both* pricing accuracy and liquidity. Their argument is based on the premise that if a manipulator distorts pricing accuracy but brings about greater liquidity, or vice versa, depending on the relative social value of these two externalities, it may be economically efficient to allow such forms of manipulation.

The small body of existing evidence on the effects of manipulation is mixed and inconclusive, largely due to the difficulties in empirically studying manipulation.

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[49] Kyle and Viswanathan (2008) point out that "pricing accuracy" does not mean the same thing as "market efficiency".

There is little doubt that manipulators are able to influence prices.[50] However, it is not clear how consistently and to what extent manipulators distort prices. Rational expectations theory predicts that if market participants are able to recognise manipulation they should profitably counteract it, thereby offsetting any price distortion. This intuition is central to the microstructure model in Hanson and Oprea (2009) where manipulation causes prices to be *more* accurate due to increased liquidity from rational profit seeking investors.

Further evidence of manipulation attempts that do not impair pricing accuracy are found in experimental and field studies. In an experimental market involving asset trading via an electronic limit order book, Hanson et al. (2006) find no evidence that manipulators are able to distort prices. In a field experiment involving attempts to manipulate horse racing odds, Camerer (1998) reports that manipulation failed to distort prices.

On the second important aspect of market quality, liquidity, the evidence is more scarce, but similarly inconclusive. Hanson and Oprea (2009) report that in their microstructure model the possibility of manipulation increases liquidity due to rational traders' attempts to profitably counteract manipulation. In contrast, other studies argue that manipulation reduces participation in markets resulting in lower liquidity, higher trading costs and higher costs of capital (e.g., Prichard (2003)).

A further issue is how regulation affects manipulators' strategies, pricing accuracy and liquidity. In an inter-jurisdiction study, Cumming and Johan (2008) find that more detailed market manipulation rules increase trading activity through enhanced investor confidence. Bhattacharya and Daouk (2002) find in a sample of 103 countries that the *enforcement* of laws governing financial conduct, rather than

[50] There are many examples in the litigation releases of the US and Canadian regulators (see www.sec.gov/litigation/litreleases.shtm and www.osc.gov.on.ca/Enforcement/Proceedings/ep_index.jsp), direct empirical evidence in Aggarwal and Wu (2006) and Chapter 4 of this thesis, indirect empirical evidence in Carhart et al. (2002), Hillion and Suominen (2004), Khwaja and Mian (2005), Ni et al. (2005) and evidence from theoretical analyses in Allen and Gale (1992) and Kumar and Seppi (1992).

simply their presence, affects markets in a positive way. Little is known about how manipulation strategies change in response to regulation.

Empirical examination of these issues is difficult. In order to provide direct evidence a researcher must be able to observe manipulation. In practice, regulators only observe the non-random subset of manipulation that they detect. Researchers, due to the opaqueness of regulation, are generally only able to observe the fraction of detected manipulation that gets prosecuted. As documented in Chapter 3, this is a small non-random proportion of manipulation. The nature of this partial observability problem is such that conventional approaches to overcoming endogeneity or sample selection issues, such as Heckman two-stage procedures or instrumental variables, can not be applied to correct the bias. Further, key variables such as true asset values, incentives and information sets, as well as important counterfactuals such as manipulation free markets, are generally not observable. In order to control incentives and information, observe true asset values and counterfactual manipulation free markets, and to avoid the significant partial observability or endogeneity biases, this chapter studies closing price manipulation in an experimental market.

The results indicate that manipulators, given incentives similar to many actual manipulation cases, decrease price accuracy (ex-post) and liquidity (ex-post and ex-ante). The mere possibility of manipulation alters market participants' behaviour causing reduced liquidity. This chapter finds some evidence that ordinary traders attempt to profitably counteract manipulation, but their effect is not strong enough to prevent the harm caused by manipulation. Finally, this chapter provides examples of the strategies employed by manipulators, illustrates how these strategies change in the presence of regulatory scrutiny and assesses the ability of market participants to identify manipulation.

Hanson et al. (2006) conduct the first laboratory work on price manipulation in asset markets. Their main result is that manipulators are unable to distort price accuracy throughout trading sessions because other traders counteract the actions of the manipulator.

This chapter extends Hanson et al. (2006) in several important ways. First, it considers not only pricing accuracy, but also the effect of manipulation on liquidity – the second externality that must be understood to draw conclusions about manipulation's social harm or benefit. Second, by making the presence of manipulators uncertain, the experimental market used in this chapter creates a more realistic setting and allows analysis of how the possibility of manipulation alters trading characteristics (ex-ante effects). Third, this chapter examines how regulation affects manipulators' strategies and other traders' reactions. Finally, and perhaps most importantly, this chapter examines a different form of manipulation - closing price manipulation - by giving manipulators incentive to realise high *closing* prices as opposed to high prices throughout a trading session. The results indicate that this last difference is critical in determining how manipulation affects markets.

Manipulation of closing prices differs from manipulation of prices within a trading period in several important ways. Closing price manipulation is arguably more mechanical in nature and consequently easier to carry out because the manipulator needs only to sustain a liquidity imbalance for a short time period just prior to the close. A typical example involves aggressive buying or selling in the final moments of trading. In contrast, trading to maintain an artificially inflated or deflated price for a longer period of time is more costly. Consequently, manipulators of intraday prices typically use different strategies such as rumours, wash sales and attempts to corner the market.

5.2 Experiment design and procedure

The experiment design consists of three treatments: a control with no manipulators, a treatment to examine the ex-ante and ex-post effects of manipulation and a treatment to examine the effects of regulation. In all treatments 12 subjects trade shares of a common asset in an electronic continuous double auction market.[51] Each experimental session consists of 16 trading periods of 200 seconds each, under one of the treatments.

Treatment 1 replicates a variation of a classic design developed by Plott and Sunder (1988) to study information aggregation, and is similar to the control treatment used by Hanson et al. (2006). The fundamental value of the asset, V, is unknown to individual subjects during the course of trading and is revealed at the end of each period. However, it is made common knowledge among subjects that $V \in \{20,40,80\}$ with an equal probability of each value occurring. At the start of each trading period subjects are endowed with four shares of the common asset, 200 experimental currency units (ECU) and a clue about V. The clue is knowledge of one of the three possible values that V will certainly not take in that period. For example, if $V = 40$, half the traders (chosen at random) are told $V \neq 80$ and the other half are told $V \neq 20$. Although no individual knows the true fundamental value, V, in aggregate subjects have enough information to determine V.

At the end of each period the shares owned by participants are converted to cash at their fundamental value, V, and, together with any remaining cash, added to the traders' payoff pools. The traders' payoff pools determine how much they are paid for participating in the experiment as explained later. Traders' endowments are reset to the original amount of four shares and 200 ECU at the beginning of each period.

Treatment 2 introduces the possibility of manipulation by giving some subjects incentives to manipulate the closing price. In a randomly selected half of the trading periods, a trader drawn at random is informed that they will assume the role of manipulator for that period. The remaining traders, from the beginning of the

[51] Forsythe and Lundholm (1990) examine the effect of the number of traders in a similar experimental market and find that 12 traders is a suitable number for competition among traders to drive the market to perform as predicted by a rational expectations model. Hanson et al. (2006) also use 12 traders in their experimental markets.

experimental session, are aware that manipulators will be chosen at random in some periods, but they do not know which periods or traders.

Manipulators receive the same initial endowment as other traders (including the clue about V) but different payoffs. A manipulator's payoff at the end of a trading period is $15(P_{closing} - P_{median}) + 250$, where $P_{closing}$ and P_{median} are the closing price (the last traded price) and median price, respectively. This payoff provides incentive for manipulators to try and increase the last trade price irrespective of V. The median price is chosen as the reference point for calculating manipulation profits because it is difficult to manipulate (as demonstrated by Hanson et al. (2006)) and is consistent with many real examples in which manipulation profits are a function of closing prices relative to prevailing intraday market prices. Unlike several other forms of market manipulation, closing price manipulators often profit from sources external to the market, for example, from overstated fund performance. This is simulated by the payoff provided to manipulators. Periods with a manipulator allow the ex-post effects of manipulation to be analysed, and periods without a manipulator provide evidence on the ex-ante effects of manipulation (the effect of possible manipulation).

At the end of each period ordinary traders submit guesses as to whether or not a manipulator was present in the market. Correct (incorrect) guesses earn (cost) the subject 50 ECU. Manipulators guess how many of the other 11 traders will have guessed that a manipulator was present and also earn (lose) 50 ECU for correct (incorrect) guesses. The purpose of the guesses in this treatment is to examine the accuracy with which market participants are able to identify manipulation, and to gauge the manipulators' perceptions of how easily market participants can identify manipulation.

Treatment 3 simulates possible manipulation with a regulator by introducing a penalty for manipulators that are 'detected' by the other traders. In each period a randomly selected trader assumes the role of manipulator. Manipulators start with the same endowment as other traders (including the clue about V) and choose whether or not to trade, given knowledge of the following payoffs. A manipulator that chooses to trade is ‘detected’ if eight or more of the other 11 traders (approximately three quarters) guess that the manipulator traded, and evades ‘detection’ otherwise.[52] Undetected manipulators receive a manipulation profit of 15($P_{closing}$ - P_{median}) and detected manipulators receive a detection penalty of negative the manipulation profit. In addition to the manipulation profit or detection penalty (which is zero if the manipulator does not trade) manipulators also receive 250 ECU to make their average payoffs close to those of the ordinary traders. This payoff structure and the choice offered to the manipulator allow the effects of regulation on manipulation to be analysed.

At the end of each period, ordinary traders submit guesses as to whether or not the manipulator traded. Traders are paid for correct guesses and penalised for incorrect guesses as in Treatment 2. The guesses determine if a manipulator that chooses to trade is ‘detected’. As explained in more detail below, traders, in making their guesses about manipulation, are able to observe similar information to what regulators use in market surveillance, for example, trader IDs, orders, trade prices and volumes, both graphically and in tabulated form. At the end of each period, the manipulator guesses how many of the other 11 traders will have guessed that the manipulator traded. Table 5.1 contains a summary of the payoffs from trading and guessing in each of the treatments.

[52] The choice of three quarters of guesses as the threshold at which ‘detection’ occurs is somewhat arbitrary. However, the chosen threshold results in behaviour consistent with real markets. For example, some would-be manipulators choose not to manipulate because of the risk of being caught, yet others manipulate despite the risk of being caught.

Table 5.1
Summary of end of period trader payoffs by treatment

This table summarises the payoffs earned by manipulators and ordinary traders (all other traders) at the end of each trading period. N and C are the number of shares and amount of cash, respectively, owned at the end of the period. $V \in \{20,40,80\}$ is the payoff of each share at the end of a period. $P_{closing}$ and P_{median} are the last and median trade prices, respectively, in a trading period. In Treatment 3 manipulation (defined as a manipulator choosing to trade) is 'detected' if at least eight of the other 11 traders guess that the manipulator traded and 'not detected' otherwise. Ordinary traders guess whether or not a manipulator was present and manipulators guess how many of the ordinary traders will guess that a manipulator was present. All amounts are denominated in experimental currency units.

Treatment	Trader type	Trading payoff	Guessing payoff
1	Ordinary	$NV + C$	
2	Ordinary	$NV + C$	+50 if correct, -50 if incorrect
	Manipulator	$15(P_{closing} - P_{median}) + 250$	+50 if correct, -50 if incorrect
3	Ordinary	$NV + C$	+50 if correct, -50 if incorrect
	Manipulator	$15(P_{closing}$ - P_{mec}if not detected $-15(P_{closing}$ - P_{mec}if detected if no trade	+50 if correct,-50 if incorrect

Subjects trade using computer terminals running a trading simulator (Rotman Interactive Trader) that allows them to place market and limit orders.[53] Subjects, on their terminals, are able to see the full order book, a list and chart of trade prices and volumes and a countdown of the time remaining to the end of the period. Conversion between stocks and cash occurs instantaneously after a trade and there are no brokerage costs, short selling or margin buying. The prohibition of short selling and margin buying simply constrains the buying and selling power of the traders (including the manipulator) to the supply of stocks and cash set by the initial endowments.[54] To avoid biasing the prices up or down, the initial endowments of

[53] A screenshot of the trading interface is in Appendix E.

[54] Allowing short selling and margin buying for an equal amount of shares is expected to increase buying and selling power equally and not affect the experimental outcomes significantly. Allowing one but not the other would distort the balance between buying and selling power, making manipulation either easier or more difficult. For example, allowing short selling but not margin buying would make manipulation more difficult as ordinary traders would have more selling power to counteract manipulation.

stock and cash are set such that buying and selling power are on average approximately equal. Subjects are not allowed to communicate with one another and are aware of the payoffs that each type of participant faces. The asset values, *V*, clues and the manipulator allocations are randomly drawn prior to the study and the ordering kept the same for each session, as detailed in Table 5.2.[55] The instructions provided to subjects consist of a core set common to all treatments, with additional instructions added for Treatments 2 and 3.[56]

Eight sessions are conducted; two sessions in Treatments 1 and 3 and four sessions in Treatment 2. Twice as many sessions are run in Treatment 2 than the other two treatments because Treatment 2 contains two sub-treatments (periods that have a manipulator and periods that do not). With 16 trading periods in each experimental session there are 32 trading periods in Treatment 1, Treatment 3 and each of the sub-treatments of Treatment 2. I collect data on all trades and orders including prices, volumes, trade/order direction, trade initiator, trader IDs and timestamps, as well as snapshots of the full order book at five-second intervals. Each session takes approximately two hours and subjects receive an average payment of \$30.[57] Subjects are not allowed to participate in more than one session so in total 96 subjects are recruited. The subjects are undergraduate and graduate students from the Faculty of Economics and Business at the University of Sydney.

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[55] In Treatment 2 the periods in which a manipulator is present are drawn at random subject to the conditions that for each of the asset values and each half of the experimental session (periods 1-8 and 9-16) there are an equal number of periods with and without a manipulator. This condition allows a more equal comparison of the sub-treatments (manipulator and no manipulator) in Treatment 2.

[56] The instructions are in Appendix E.

[57] At the end of an experimental session subjects are ranked in descending order by their total payoff pools. The subject with the highest payoff receives \$45, the second and third ranked subjects receive \$40 each, the next two receive \$35 each and so on down to subjects ranked 10 and 11 who receive \$20 each and the lowest ranked subject who receives \$15. This payout method, which is similar to the method used by Bloomfield and O'Hara (1999), ensures that average payoffs are equal across the three treatments and guarantees that the subjects receive at least \$15.

Table 5.2
Asset values, clues and manipulator allocations

V is the payoff in experimental currency for each share of the asset at the end of a trading period. The clue given to each subject is knowledge of one of the three possible values that V will certainly not take in that period. For example, Subject 1 in Period 1 is told $V \neq 20$. For each period in the three treatments Panel B describes which subject, if any, is assigned the role of manipulator (given a different payoff schedule as described in Table 5.1).

Panel A: Asset values and clues

	Practice	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7	Period 8	Period 9	Period 10	Period 11	Period 12	Period 13	Period 14	Period 15	Period 16
V	40	40	20	80	80	40	20	40	80	20	80	40	20	20	40	80	20
Subject 1 clue	20	20	80	40	20	80	40	20	20	80	40	80	40	80	20	40	80
Subject 2 clue	80	80	40	20	40	80	80	20	40	80	20	80	80	40	80	20	40
Subject 3 clue	20	80	80	40	40	80	40	80	20	40	40	20	40	80	80	20	80
Subject 4 clue	80	20	80	20	20	80	80	80	40	40	20	20	80	40	20	40	40
Subject 5 clue	80	20	40	40	20	80	40	80	20	80	20	20	80	40	20	40	80
Subject 6 clue	80	80	40	20	40	20	80	20	40	40	20	80	40	80	80	20	40
Subject 7 clue	20	20	80	20	20	20	80	20	40	40	40	80	40	40	80	20	80
Subject 8 clue	80	80	80	20	40	20	80	80	20	40	40	80	40	80	80	40	40
Subject 9 clue	20	80	40	40	20	80	40	20	40	40	40	20	40	80	20	20	80
Subject 10 clue	20	80	40	40	20	20	40	80	20	80	40	20	80	40	20	40	40
Subject 11 clue	20	20	40	40	40	20	40	80	20	80	20	20	80	80	20	20	80
Subject 12 clue	80	20	80	20	40	20	80	20	40	80	20	80	80	40	80	40	40

Panel B: Manipulator allocations

Treatment	Practice	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7	Period 8	Period 9	Period 10	Period 11	Period 12	Period 13	Period 14	Period 15	Period 16
1	None	None	None	None	None	None	None	None	None	None	None	None	None	None	None	None	None
2	None	None	Subject 5	Subject 2	None	Subject 7	None	None	Subject 4	Subject 1	None	Subject 6	None	None	Subject 8	None	Subject 3
3	None	Subject 10	Subject 4	Subject 7	Subject 9	Subject 1	Subject 11	Subject 2	Subject 6	Subject 8	Subject 3	Subject 12	Subject 5	Subject 1	Subject 3	Subject 2	Subject 4

5.3 Analysis

As a starting point, I replicate part of the analysis in Hanson et al. (2006) to examine the effect of manipulation on closing price accuracy. I then extend this analysis to examine intra-period effects and apply it to liquidity variables. Next, I characterise the trading strategies used by manipulators with and without a regulator and examine how manipulation affects the behaviour of ordinary traders. Finally, I assess the ability of market participants to identify manipulation and conduct some robustness tests. Throughout most of the analysis Treatment 2 is split into its two sub-treatments, 2a and 2b, according to whether or not a manipulator is present. This chapter refers to Treatments 1, 2a, 2b and 3 as the 'control' treatment, 'possible manipulation', 'manipulation', and 'possible manipulation with a regulator', respectively.

5.3.1 Effects on price accuracy

This analysis of the effect of manipulation on price accuracy begins by replicating tests conducted by Hanson et al. (2006). Figure 5.1 plots the prices of the last trade in each period (equivalent to the closing price in many stock exchanges), the averages of these prices by treatment, and the fundamental asset value, *V*, in each period. Similar to Hanson et al. (2006), prices are attracted towards *V* in each period but display 'stickiness' to a value around 40. From Figure 5.1 it appears price convergence (the degree to which market prices track *V*) is stronger in this experiment than in that of Hanson et al. (2006).

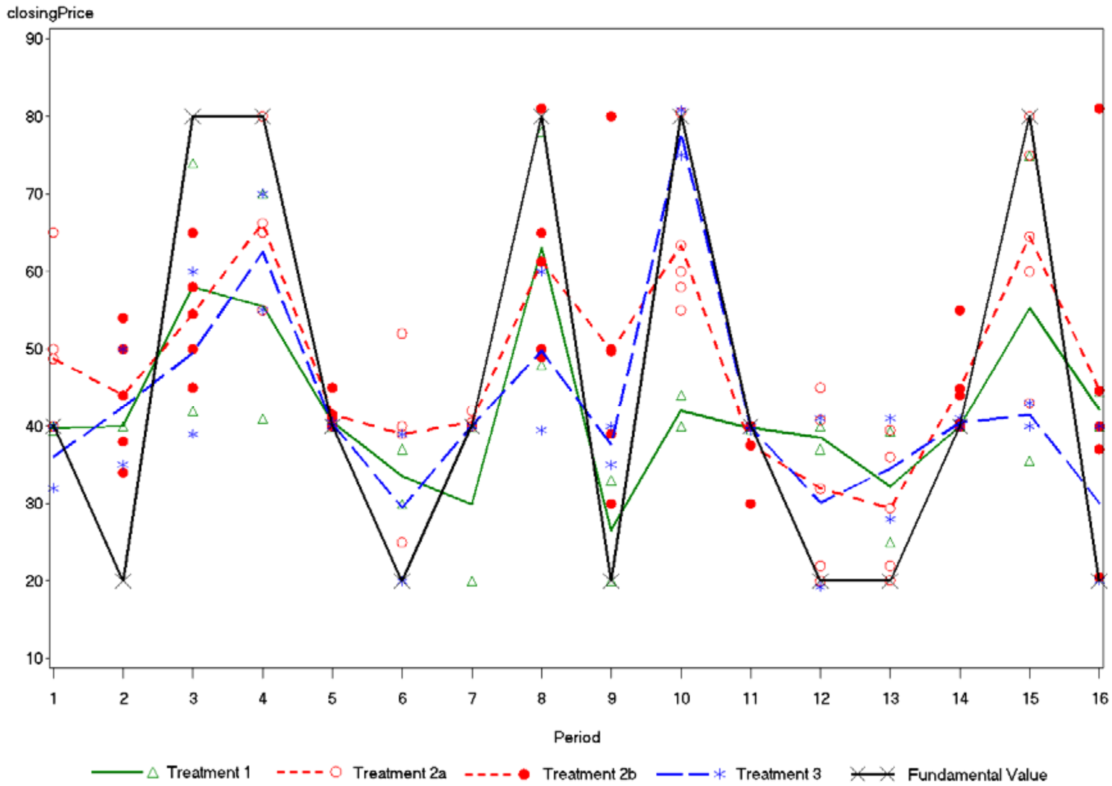


Figure 5.1 End of period prices by period
This figure plots the prices of the last trade in each period of each experimental session (the various shaped and coloured points) as well as the average of these prices in each period by treatment (lines). The solid black line indicates the fundamental asset value in each period.

I quantify the price convergence properties and test for the effect of manipulation on the ability of prices to track V using the following linear mixed effects models (replicating Hanson et al. (2006), but with two additional treatments):

$$\begin{aligned} price_{ij} &= (\alpha + \alpha_i) + (\beta_1 + \beta_{1i})possible_{ij} + (\beta_2 + \beta_{2i})manipulation_{ij} + (\beta_3 + \beta_{3i})regulator_i \\ &\quad + (\beta_4 + \beta_{4i})V_j + (\beta_5 + \beta_{5i})possible_{ij} \times V_j + (\beta_6 + \beta_{6i})manipulation_{ij} \times V_j \\ &\quad + (\beta_7 + \beta_{7i})regulator_i \times V_j + \varepsilon_{ij} \end{aligned} \tag{5.1}$$

$$\begin{aligned} (price_{ij} - V_j)^2 &= (\alpha + \alpha_i) + (\beta_1 + \beta_{1i})possible_{ij} + (\beta_2 + \beta_{2i})manipulation_{ij} \\ &\quad + (\beta_3 + \beta_{3i})regulator_i + \varepsilon_{ij} \end{aligned} \tag{5.2}$$

$Price_{ij}$ is the average of the last three trade prices in period j of session i.[58] $Possible_{ij}$, $manipulation_{ij}$ and $regulator_i$ are indicator variables that take the value of 1 if the trading period is under Treatment 2a, 2b or 3 respectively. V_j is the fundamental asset value in period j. Parameters α_i and β_{1i} to β_{7i} are random effects for session i. All random effects and the error term, ε_{ij}, are assumed to be distributed independently and normally with a mean of zero. Consequently, this model allows composite errors to be heteroscedastic and correlated between trading periods within an experimental session, but assumes sessions are independent of one another. If prices were to converge perfectly to V, α (in Equation 5.1) would be zero and β_4 would be one. If manipulation had no effect on prices or price accuracy β_1, β_2, β_3, β_5, β_6, and β_7 would be zero.

Table 5.3 reports the estimated model coefficients.[59] Price convergence is not perfect; in Equation 5.1, α (25.84) is significantly larger than zero and β_2 (0.36) is just over a third of its value under perfect convergence. However, price convergence is better than in the experimental markets of Hanson et al. (2006) where the equivalents of α and β_4 are estimated as 48.58 and 0.2, respectively. A few design modifications may explain the difference. In the experimental market used in this chapter: $V \in \{20,40,80\}$ as opposed to $V \in \{0,40,100\}$; the instructions are more explicit in explaining how to profit when market prices are away from V; the initial endowment makes buying and selling power more equal on average; the trading interface provides information on executed trades as well as current limit orders; and the subjects are drawn from a different university.

[58] For robustness I replace the average of the last three prices (used by Hanson et al. (2006)) with the last trade price and find similar results.

[59] All models are estimated using Restricted Maximum Likelihood (REML).

Table 5.3
Effect of manipulation on end of period price accuracy

This table reports estimates from a linear mixed effects model with random intercepts and random slopes. *Price* and *Squared error* are the dependent variables. *Price* is the average of the last three trade prices in a trading period. *Squared error* is the square of the difference between *Price* and the fundamental asset value. *Possible*, *Manipulation* and *Regulator* are indicator variables that take the value of 1 if the trading period is under Treatment 2a, 2b or 3, respectively. $V \in \{20,40,80\}$ is the fundamental asset value. *n* is the number of observations. Significance at the 10%, 5% and 1% levels is indicated by *, ** and ***, respectively, and t-statistics are reported in parentheses.

Covariate	Price	Squared error
Intercept	25.84***	374.43***
	(7.49)	(3.23)
Possible	-0.27	-106.50
	(-0.06)	(-0.68)
Manipulation	20.01**	296.91
	(2.17)	(0.89)
Regulator	-1.50	-81.53
	(-0.31)	(-0.50)
V	0.36***	
	(3.98)	
Manipulation x V	-0.33*	
	(-1.93)	
Possible x V	0.14	
	(1.21)	
Regulator x V	0.05	
	(0.43)	
n	128	128

In contrast to Hanson et al. (2006), Table 5.3 suggests that closing price manipulation has a large and detrimental ex-post effect on prices and their accuracy. Estimates from the first mixed effects model suggest that end of period prices in the presence of a closing price manipulator (Treatment 2b) are on average approximately 20 ECU higher than when there is no manipulator. This, in the second model, translates to a large increase in squared price error (a large decrease in price accuracy) in the presence of a manipulator. The increase in squared price error attributable to manipulation (297 ECU^2) is very large relative to the underlying level (374 ECU^2).[60]

[60] In this model, which replicates Hanson et al. (2006), although the increase in price error due to manipulation is large it is not statistically significant. This may be due to low statistical power in the test given that it only utilises one observation per trading period. In the more detailed analysis that follows, the increase in error due to manipulation is statistically significant.

The results reported in Table 5.3 indicate that possible manipulation, i.e., when there is no manipulator but traders are under the belief that there may be a manipulator, does not have a significant effect on prices or their accuracy. This suggests that closing price manipulation does not have a significant ex-ante effect on prices, but does have significant detrimental ex-post effects. This is consistent with the main theoretical prediction in Hanson and Oprea (2009).

Table 5.3 also indicates that possible manipulation in the presence of a regulator (when potential manipulators face a penalty if detected) does not have a significant effect on prices. This could be because the risk of incurring a penalty deters manipulation, or simply that manipulators distort prices less to avoid detection. As shown in the following subsections, both effects are at play.

I extend the replicating analysis to examine the effects of manipulation on price accuracy in more detail. Given that the manipulation incentive in this chapter is focused at the end of a trading period rather than throughout, I also analyse price accuracy within a trading period. Figure 5.2 plots the average absolute price error (the absolute of the difference between trade price and fundamental asset value) for each treatment in ten-second intervals within a trading period. Average price error decreases through the course of a trading period as a result of price discovery. The experimental market gradually incorporates information into the price – a feature consistent with behaviour observed on equity markets and existing literature. Price error appears to increase sharply in the last 20 seconds of the trading period in the presence of manipulation (Treatment 2b), but does not increase in any of the other treatments.

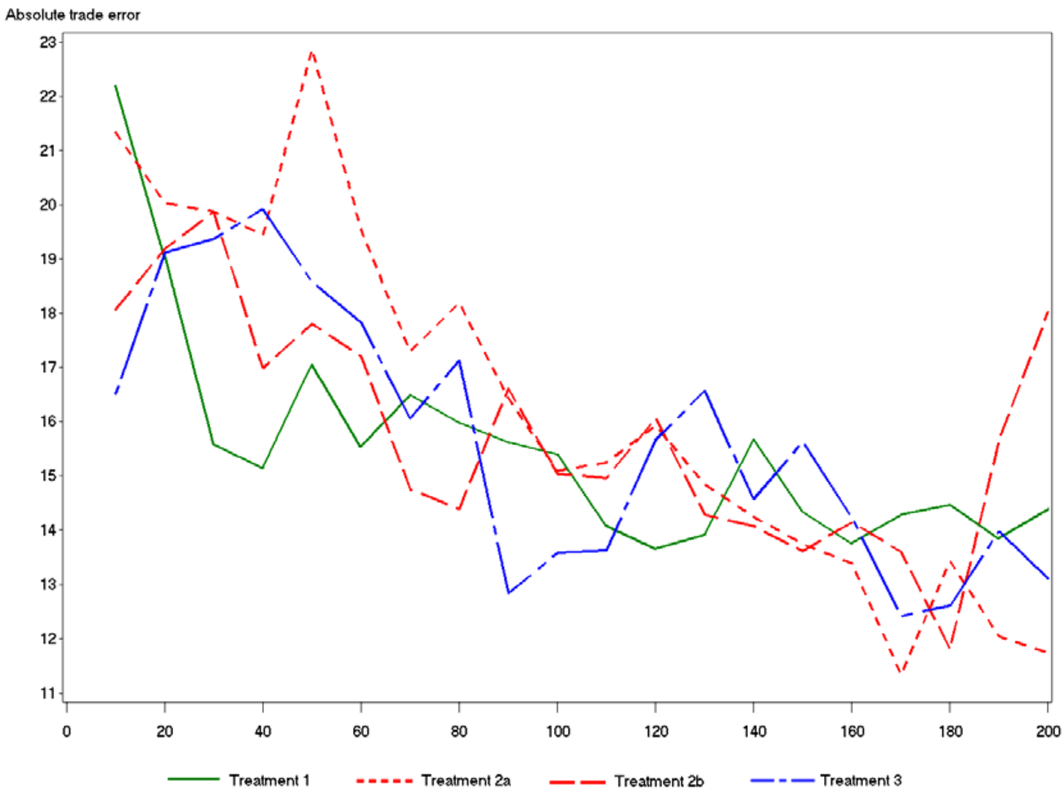


Figure 5.2 Average absolute pricing errors within a trading period
This figure plots the average (by treatment) of the absolute pricing error at the end of each ten-second interval within a trading period. Absolute pricing error is calculated as the absolute difference between the price of the trade immediately prior to the end of a ten-second interval and the fundamental asset value. The horizontal axis measures time (in seconds).

I formally test manipulation's effects on price accuracy within a trading period using a linear mixed effects model:

$$\begin{aligned}\left|price_{ijk}-V_j\right| &= (\alpha+\alpha_i+\alpha_{ij})+(\beta_1+\beta_{1i})possible_{ij}+(\beta_2+\beta_{2i})manipulation_{ij}\\ &+(\beta_3+\beta_{3i})regulator_i+(\beta_4+\beta_{4i})V20_j+(\beta_5+\beta_{5i})V80_j+(\beta_6+\beta_{6i})period_j\\ &+(\beta_7+\beta_{7i})interval_k+(\beta_8+\beta_{8i})interval_k^2+(\beta_9+\beta_{9i})last_k+(\beta_{10}+\beta_{10i})last_k\times possible_{ij}\\ &+(\beta_{11}+\beta_{11i})last_k\times manipulation_{ij}+(\beta_{12}+\beta_{12i})last_k\times regulator_i+\varepsilon_{ijk}\end{aligned} \tag{5.3}$$

Price$_{ijk}$ is the price of the trade immediately prior to the end of the k^{th} ten-second interval in period j of session i. *Possible*$_{ij}$, *manipulation*$_{ij}$ and *regulator*$_i$ are indicator variables that take the value of 1 if the trading period is under Treatment 2a, 2b or 3, respectively. $V20_j$ and $V80_j$ are indicator variables that take the value of 1 if $V=20$ and $V=80$, respectively. *Period*$_j$ is the trading period number within the experimental session, which takes values from 1 to 16. $Interval_k$ is the number of the ten-second interval within a trading period, which takes values from 0 to 19. $Last_k$ is an indicator variable which takes the value of 1 for the last interval of the trading period. Parameters α_i and β_{1i} to β_{12i} are random effects for session *i* and α_{ij} is a random effect for period *j* of session *i*. All random effects and the error term, ε_{ijk}, are assumed to be distributed independently and normally with a mean of zero. Consequently, this model allows composite errors to be heteroscedastic and correlated between trading periods within an experimental session and between intervals within a trading period, but assumes sessions are independent of one another.[61]

Table 5.4 reports the estimated model coefficients. Manipulation (Treatment 2b) causes prices to be less accurate on average throughout a trading period (by 4.82 ECU) and even less accurate in the last ten seconds of the trading period (an increase of 5.49, or total of 10.3 ECU). The magnitude of this effect is economically meaningful. The end-of-period increase in absolute trade price error that is attributable to manipulation is, as a percentage of *V*, between 13% and 52% (for $V = 80$ and $V = 20$, respectively). The other treatments do not appear to have a significant effect on price accuracy, consistent with the previous analysis. The coefficients of $interval_k$ and $interval_k^2$ suggest price accuracy improves (at a decreasing rate) through the course of a trading period, consistent with the pattern in Figure 5.2. Price accuracy also tends to improve through the course of an experimental session as participants learn to aggregate information more accurately. Prices are significantly less accurate for $V = 20$ and $V = 80$ than $V = 40$, consistent with the previously observed 'stickiness' of prices to a value around 40.

[61] A covariance structure that allows the correlations between intervals within a period to decline with time-separation (e.g., a first-order autoregressive process) may seem more appropriate than constant correlation if random price shocks take several intervals to dissipate. However, if price shocks are random, because the data are from repeated measures the effects of gradual adjustment to price shocks will average out leaving the estimates unbiased.

Table 5.4
Effect of manipulation on price accuracy within a trading period

This table reports estimates from a linear mixed effects model with random intercepts and random slopes. The dependent variable is the absolute difference between the price of the last trade and the fundamental asset value at the end of each ten-second interval within a trading period. *Possible*, *Manipulation* and *Regulator* are indicator variables that take the value of 1 if the trading period is under Treatment 2a, 2b or 3, respectively. *V20* and *V80* are indicator variables that take the value of 1 if the fundamental asset value in that trading period is 20 or 80, respectively, and *Period* is the trading period number within the experimental session, which takes values from 1 to 16. *Interval* is the number of the ten-second interval within a trading period, which takes values from 0 to 19. *Last* is an indicator variable which takes the value of 1 for the last interval of the trading period. *n* is the number of observations. Significance at the 10%, 5% and 1% levels is indicated by *, ** and ***, respectively.

Covariate	Estimate	t-statistic
Intercept	9.58***	4.43
Possible	1.81	0.81
Manipulation	4.82**	2.03
Regulator	0.97	0.41
V20	14.6***	8.95
V80	20.6***	9.48
Period	-0.29**	-2.00
Interval	-0.89***	-5.23
Interval^2	0.03***	3.50
Last	-0.21	-0.13
Last x Possible	-1.83	-0.81
Last x Manipulation	5.49	1.56
Last x Regulator	-0.39	-0.16
n	2,560	2,560

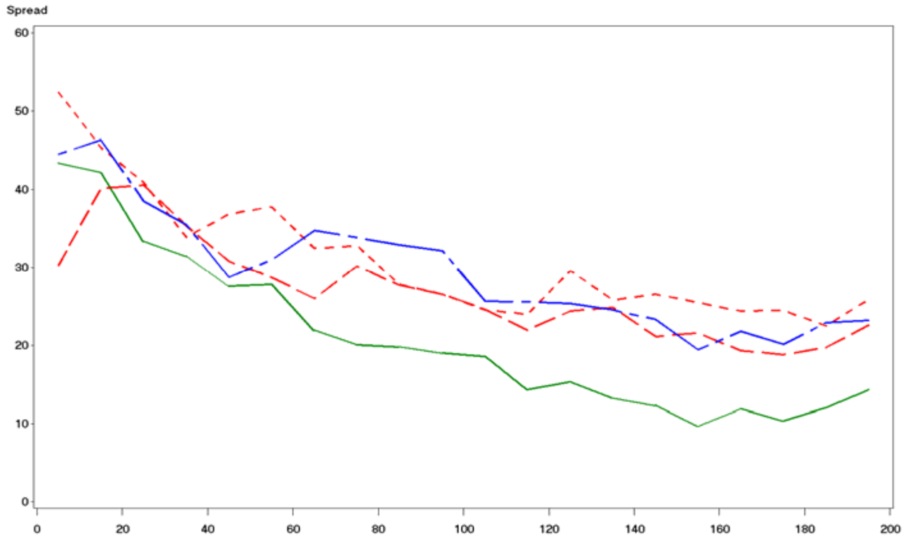
The finding that closing price manipulation has a large and detrimental effect on prices and their accuracy is not contradictory to Hanson et al. (2006), but rather, complimentary. Given the similarity in the experiment designs used in this chapter and in Hanson et al. (2006), the findings of the two studies together demonstrate that the manipulators' incentives, defined by the payoff structure, are critical in determining the effect of manipulation on prices. Manipulators in my experimental market have less market power because one manipulator trades against 11 other traders, compared to six manipulators trading against six other traders in Hanson et al. (2006). However, of critical importance is that the manipulator in my experimental market is concerned about influencing only the last trade price, not prices throughout the entire period (as in Hanson et al. (2006)) and for this reason the manipulators are detrimental to price accuracy. The difference highlighted by the comparison of manipulator incentives is of particular concern given the many real examples of market participants with incentives to realise high closing prices and the numerous important uses of closing prices.

5.3.2 Effects on liquidity

The previous subsection suggests that closing price manipulation has a significant detrimental ex-post effect on price accuracy. In order to evaluate closing price manipulation's overall social harm I now examine its effects on the second important market externality, liquidity. I use three alternative measures of liquidity: bid-ask spread, depth and volume.

Figure 5.3 plots the evolution of the liquidity variables through the course of a trading period. The patterns exhibited by these variables are generally consistent with behaviour observed in equity markets (see, for example, Cai et al. (2004)) and other experimental markets (see, for example, Bloomfield et al. (2005)). Bid-ask spreads decline through the trading period but increase at the end of the period, depth tends to increase through the trading period at a decreasing rate and volume increases sharply at the end of the trading period. The most apparent difference between the treatments is that spreads (depth) tend to be smaller (greater) in the control treatment than in the other treatments.

Panel A: Bid-ask spread



Panel B: Depth

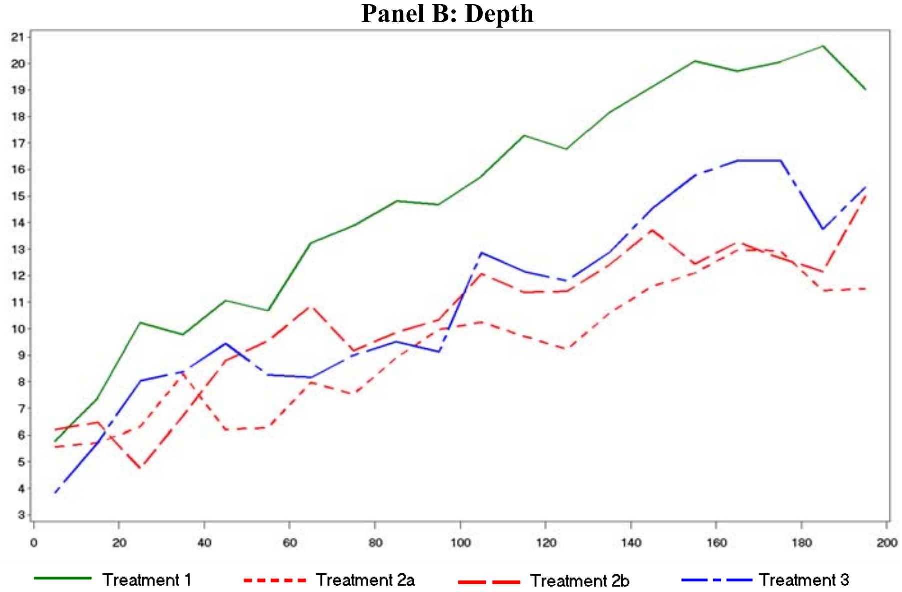


Figure 5.3 Evolution of liquidity variables
This figure plots average bid-ask spread (difference between the best bid and best ask as a percentage of the bid-ask midpoint), depth (total number of shares demanded or offered within 20% either side of the bid-ask midpoint) and volume (number of shares traded in each ten-second interval) within a trading period for each of the treatments. The horizontal axis measures time (in seconds).

Panel C: Volume

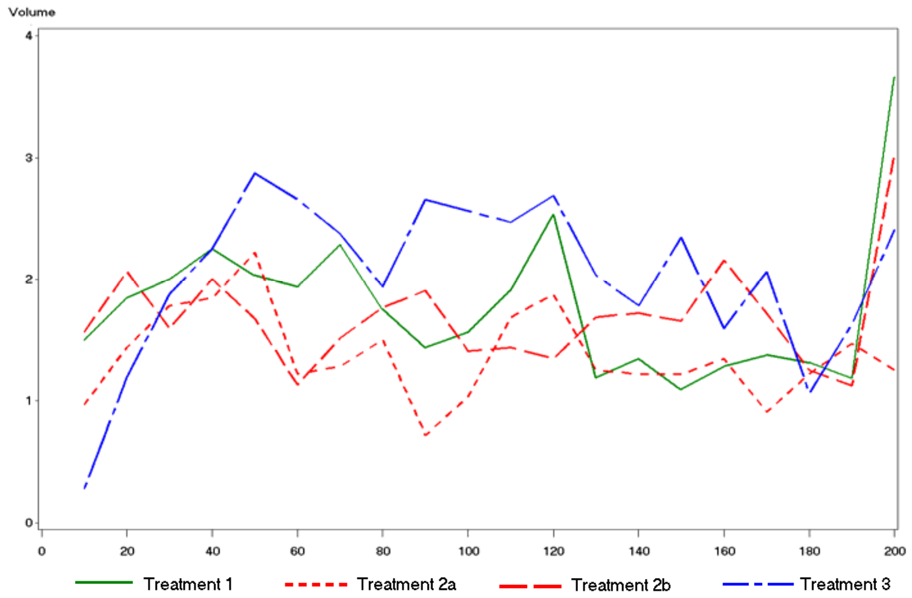


Figure 5.3 (continued)

I formally test manipulation's effects on liquidity with a linear mixed effects model, similar to the models used to examine price accuracy:

$$Y_{ij} = (\alpha + \alpha_i) + (\beta_1 + \beta_{1i}) possible_{ij} + (\beta_2 + \beta_{2i}) manipulation_{ij} + (\beta_3 + \beta_{3i}) regulator_i + (\beta_4 + \beta_{4i}) V20_j + (\beta_5 + \beta_{5i}) V80_j + (\beta_6 + \beta_{6i}) period_j + \varepsilon_{ij} \quad (5.4)$$

Y_{ij} represents the liquidity variable in period j of session i. Bid-ask spreads and depth values are averaged across the ten-second intervals within a period, similar to a time-weighted average. Volume is measured as the total number of shares traded in the period. $Possible_{ij}$, $manipulation_{ij}$ and $regulator_i$ are indicator variables that take the value of 1 if the trading period is under Treatment 2a, 2b or 3, respectively. $V20_j$ and $V80_j$ are indicator variables that take the value of 1 if $V = 20$ and $V = 80$, respectively. $Period_j$ is the trading period number within the experimental session, which takes values from 1 to 16. Random effects parameters α_i and β_{1i} to β_{6i}, as well as the error term, ε_{ij}, are assumed to be distributed independently and normally with a mean of zero. Consequently, this model allows composite errors to be heteroscedastic and correlated between trading periods within an experimental session, but assumes sessions are independent of one another.

Table 5.5 reports the estimated model coefficients. Bid-ask spreads are approximately eight to ten percent wider in Treatment 2 relative to the control treatment regardless of whether a manipulator is actually present or not. Similarly, spreads are approximately nine percent wider when manipulation is possible in the presence of a regulator (Treatment 3) than in the control treatment. These effects are statistically significant at the 5% level and meaningful relative to the grand mean spread of approximately 20% corresponding to the control treatment. Spreads are also wider for $V = 20$ and $V = 80$ than $V = 40$, and tend to decrease through the course of an experimental session. These results are consistent with notion that spreads are wider when there is greater uncertainty about V and that manipulation, or even the mere possibility of manipulation, causes greater uncertainty.

Fundamental values $V = 20$ and $V = 80$ cause greater uncertainty than $V = 40$ due to the nature of the clues provided to traders. An obvious initial strategy for traders with the clue $V \neq 20$ is to buy the asset at prices below 40 knowing that either $V = 40$ or $V = 80$. Similarly, for the clue $V \neq 80$ an obvious initial strategy is to sell the asset at prices above 40. Consequently, when $V = 40$ and the set of clues is $\{V \neq 20, V \neq 80\}$ there tends to be no shortage of buyers at prices up to 40 and sellers at prices down to 40, so prices converge quickly and accurately with little uncertainty. As a secondary strategy, after having inferred the clues of other traders by observing order flow, a trader may choose to post limit orders above and below V, thereby acting as a market maker and earning the spread for supplying liquidity.

In contrast, when $V = 80$, only the traders with the clue $V \neq 20$ have an obvious initial strategy – to buy at prices up to 40. The other half, with the clue $V \neq 40$, only know with certainty that either $V = 20$ or $V = 80$ and therefore have to infer which of these possibilities is true by observing other traders' order flow. Consequently, states $V = 20$ and $V = 80$ induce greater uncertainty and cause traders to set wider spreads.

Table 5.5
Effect of manipulation on liquidity

This table reports estimates from a linear mixed effects model with random intercepts and random slopes. *Bid-ask spread*, *Depth* and *Volume* are the dependent variables. *Bid-ask spread* is the difference between the best ask and best bid prices divided by the bid-ask midpoint (average of the best bid and best ask) expressed as a percentage and averaged across the ten-second intervals within a trading period. *Depth* is the total number of shares demanded or offered within 20% either side of the bid-ask midpoint averaged across the ten-second intervals within a trading period. *Volume* is the number of shares traded in a trading period. *Possible*, *Manipulation* and *Regulator* are indicator variables that take the value of 1 if the trading period is under Treatment 2a, 2b or 3, respectively. *V20* and *V80* are indicator variables that take the value of 1 if the fundamental asset value in that trading period is 20 or 80, respectively, and *Period* is the period number within the experimental session, which takes values from 1 to 16. *n* is the number of observations. Significance at the 10%, 5% and 1% levels is indicated by *, ** and ***, respectively, and t-statistics are reported in parentheses.

Covariate	Bid-ask spread	Depth	Volume
Intercept	20.43***	16.21***	31.36***
	(5.11)	(7.72)	(7.41)
Possible	8.48**	-5.19**	-12.25**
	(2.23)	(-2.26)	(-2.45)
Manipulation	10.41**	-5.33**	-3.84
	(2.46)	(-2.22)	(-0.74)
Regulator	9.34**	-3.82	-5.53
	(2.41)	(-1.51)	(-0.51)
V20	19.51***	-7.70***	9.15***
	(5.68)	(-6.22)	(3.31)
V80	14.81***	-5.69***	12.67***
	(4.41)	(-4.33)	(4.26)
Period	-1.38***	0.35***	0.19
	(-4.57)	(3.18)	(0.48)
n	128	128	128

The presence of manipulators that have no regard for the fundamental asset value, V, increases the probability of observing a false signal in order flow, and therefore increases the chance of incorrectly inferring V. As a result, price uncertainty is greater and traders set wider spreads.

Consistent with the effects on spreads, depth is reduced by manipulation and the mere possibility of manipulation. Depth (the number of shares offered or demanded in the limit order book within 20% of the bid-ask midpoint) is reduced by approximately five shares in Treatment 2 relative to the control treatment regardless of whether a manipulator is actually present or not. The reduction in depth is approximately four shares when manipulation is possible in the presence of a regulator (Treatment 3). These effects are meaningful relative to the grand mean depth of approximately 16 shares, corresponding to the control treatment.

Volume is significantly lower when manipulation is possible (Treatment 2a) relative to the control treatment, suggesting that the possibility of manipulation creates a greater reluctance to trade. This effect may stem from the fact that, all else being equal, manipulation and the possibility of manipulation increase spreads and therefore increase trading costs. This explanation is supported by the finding of Barclay et al. (1998) that wider spreads lead to reduced volume. The effect on trading volume is not as strong when manipulation actually occurs (Treatments 2b and 3) because the manipulators, in trading to manipulate prices, offset the reduced trading levels of other market participants.

The results in this subsection on spreads, depth and volumes suggest that manipulation, and even the mere possibility of manipulation, has a significant detrimental effect on market liquidity.

5.3.3 Manipulation strategy

This subsection focuses on the trading strategies employed by closing price manipulators. I characterise manipulators' use of different order types and the timing of their trades in the presence and absence of a regulator. To do this, I classify orders into four categories of aggressiveness: market orders (and marketable limit orders, i.e., limit orders that cause immediate execution) that execute all of the depth at the best quote and at least some of the depth at the next best quote; market orders that execute at the best quote; limit orders that are at least part filled; and limit orders that are not at all filled.

Figure 5.4 reports a breakdown of order types submitted by manipulators and other traders in each treatment. Panel A compares the orders used by manipulators to those used by other traders in the absence of a regulator (Treatment 2b). Panel B makes the same comparison, but in the presence of a regulator (Treatment 3).

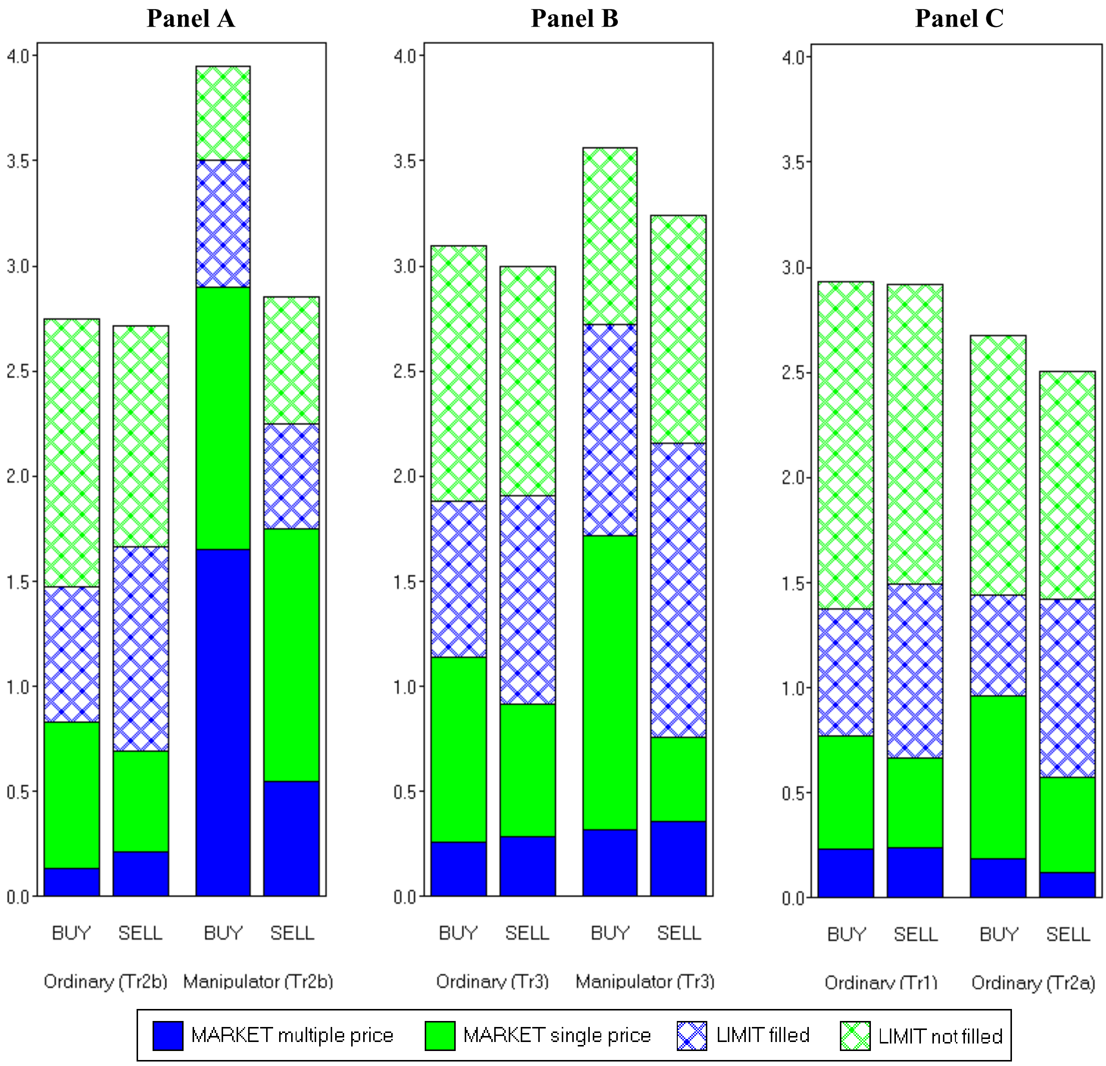


Figure 5.4 Order types used by manipulators and ordinary traders
This figure shows the average number of various types of order, per trader, per trading period. Panel A compares the orders of non-manipulators (*Ordinary*) with those of manipulators (*Manipulator*) in Treatment 2b (manipulation without a regulator). Panel B compares the orders of non-manipulators with those of manipulators in Treatment 3 (possible manipulation with a regulator). Panel C compares the orders of non-manipulators in Treatments 1 and 2a (control and possible manipulation). *MARKET multiple price* and *MARKET single price* are orders that execute instantaneously (either market orders or marketable limit orders) at more than one price level (cause price impact), and only one price level, respectively. *LIMIT filled* and *LIMIT not filled* are limit orders that are at least part filled, and not at all filled, respectively. For Treatment 3 only the trading periods in which the manipulator chose to trade are included to allow comparison between manipulators and other traders.

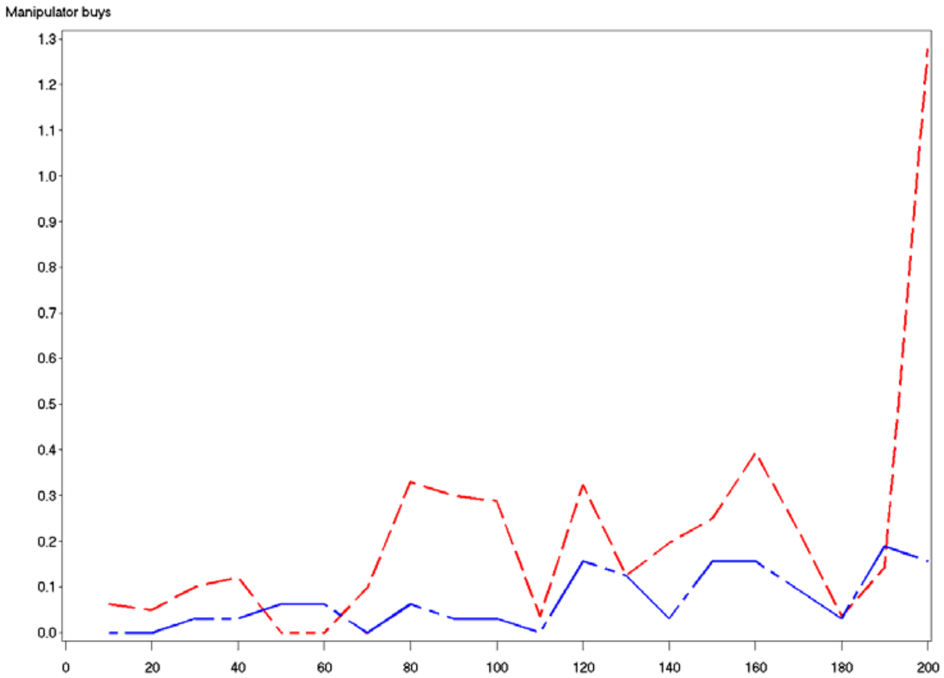
The most striking difference in the use of different order types is the large number of very aggressive buy orders used by manipulators in the absence of a regulator (1.65 multiple-price market orders per period per manipulator compared to 0.14 for ordinary traders). This difference is statistically significant at the 1% level using a paired t-test (t-statistic of 4.87). In the presence of a regulator, manipulators tend to use considerably less aggressive orders. It appears that manipulators in such circumstances use more of the second most aggressive order type (1.40 single-price market orders per period per manipulator compared to 0.88 for ordinary traders), although the difference is not statistically significant.

Figure 5.5 illustrates the timing of buy and sell trades initiated by manipulators. In the absence of a regulator, manipulators tend to sell stock around the middle of a trading period to increase their buying power and then buy heavily in the last ten seconds of trading. In the presence of a regulator, however, the buying activity of manipulators is less intense and peaks earlier. Buying activity is highest in the second to last ten-second interval, as opposed to the last interval, and involves less than a quarter of the amount of trades that a manipulator uses when there is no regulator.

To test the differences in trading times between manipulators and ordinary traders I calculate a measure of how late in the trading period most trading takes place - the volume weighted average trade time (VWATT) measured in seconds from the start of the trading period. Paired t-tests comparing the VWATT of manipulators' buy and sell volume with that of ordinary traders confirm that manipulators in both Treatments 2 and 3 tend to buy later than ordinary traders (significant at the 5% level). There is no significant difference in the timing of sell orders for manipulators compared to ordinary traders.

The results reported in this subsection suggest that in the experimental setting used in this chapter the introduction of a regulator, i.e., imposing a penalty on detected manipulators, is successful in reducing the intensity of manipulation. This helps explain why price accuracy is not significantly harmed by a manipulator accompanied by a regulator.

Panel A: Buys



Panel B: Sells

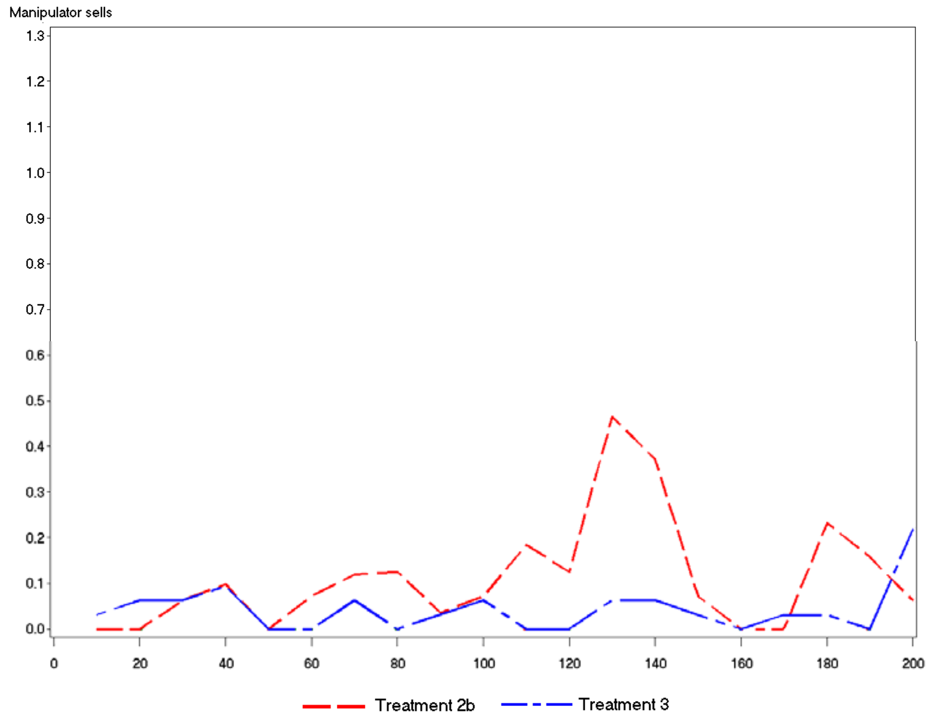


Figure 5.5 Manipulator buying and selling activity within a trading period
This figure plots the average number (by treatment) of buys (Panel A) and sells (Panel B) initiated by the manipulator in each ten-second interval within a trading period. The horizontal axis measures time (in seconds). For Treatment 3 only the trading periods in which the manipulator chose to trade are included to allow comparison across the two treatments.

However, there is a second factor at play here. The penalty imposed on detected manipulation in Treatment 3 also reduces the frequency of manipulation. Twenty-two percent of the subjects given the opportunity to manipulate the market in Treatment 3 choose not to manipulate. This fraction roughly corresponds to the perceived detection probability. Twenty-four percent of manipulators in Treatment 2 (no regulator) guess that at least eight out of the other 11 traders would guess that a manipulator was present (the equivalent of being detected in Treatment 3). The perceived detection probability in Treatment 3 is likely to be somewhat less than 24% because manipulators choose to act in a more subtle manner than in Treatment 2. Of the 78% that do attempt manipulation in Treatment 3, 40% are detected and receive a penalty and 60% avoid detection. Therefore, the actual detection probability given the decision to manipulate (40%) is higher than the perceived probability of detection (less than 24%).

To conclude, in this chapter's experimental market the imposition of a penalty on detected manipulators helps restore price accuracy, both by deterring manipulation and by reducing the intensity of the remaining manipulation. The ability of regulation to reduce the harm caused by manipulation is likely to depend on the credibility of the regulator, the size of the penalty and the probability of being caught. I have only simulated a specific instance of these parameters, which could be viewed as that of a successful regulator.

5.3.4 Effects on ordinary traders' behaviour

The previous results indicate that ordinary traders set wider spreads in the presence of manipulators in a reaction to increased price uncertainty. This subsection examines how manipulators affect other traders' order submission strategies and tests specific predictions about trader reactions to manipulation. Figure 5.4 Panel C compares the order types submitted by ordinary traders under the control treatment and possible manipulation (Treatment 2a). There are no obvious differences in the aggressiveness of orders, and none of the paired t-tests by order type indicate any significant differences in order submission strategy between the two treatments.

Hanson and Oprea (2009) report that in their microstructure model the possibility of manipulation increases liquidity due to the desire of rational traders to profitably counteract manipulation attempts. In the context of closing price manipulation, a rational trader might increase depth on the ask side of the limit order book to profit from a manipulator's aggressive buying at prices above fundamental value.

To test whether ordinary traders attempt to profit from manipulation I use the mixed effects model in Equation 5.3 replacing the dependant variable with depth at the best ask price and an alternative measure, the average depth at the best three ask prices. If ordinary traders increase depth on the ask side throughout the trading period to try and profit from manipulation we should observe a significant positive coefficient on $possible_{ij}$. If ordinary traders increase depth on the ask side at the end of the trading period we should observe a positive coefficient on $last_k$ x $possible_{ij}$.

Estimating the mixed effects model with depth at the best ask as the dependent variable I find that possible manipulation causes an increase in depth of 1.44 shares at the best ask price in the last ten-second interval of a trading period. This increase is meaningful compared to the grand mean, α, of 2.71 shares and is statistically significant at the 10% level. However, there is no evidence of an increase in depth at the ask throughout a trading period, nor does this effect hold for average depth at the best three ask quotes. Therefore, there is some evidence of ordinary traders attempting to profitably counteract manipulation by offering more shares at the best ask. These traders believe the manipulator, if present, is likely to trade in the last ten-second interval. However, the effect of this behaviour is not strong enough to prevent manipulators from distorting prices, nor is it strong enough to restore the bid-ask spread and depth to the levels in the control treatment.

5.3.5 Ability of market participants to recognise manipulation

This final part of the analysis assesses the accuracy with which market participants are able to identify manipulation by observing the limit order book, a real-time list of trades, and a chart of trade prices and volumes. The ability for market participants to identify manipulation is important in facilitating trading strategies that exploit manipulators and help restore price accuracy. It is also important for the efficient functioning of the allocative role of prices because if market participants are unable to recognise when prices have been distorted, biased signals will be used in resource allocation.

Table 5.6 reports two-way frequencies of the guesses submitted by ordinary traders to the question of whether or not a manipulator was present in the market, as well as the percentage of correct guesses. I test the null hypothesis that the percentages of correct guesses are equal to 50%, i.e., guessing ability is only as good as chance. Despite having found that manipulation has a substantial impact on prices, surprisingly, market participants have poor ability in identifying manipulation. In Treatment 2, overall only 53.2% of guesses are correct, only marginally better than chance. When a manipulator is present, market participants correctly identify this with an accuracy of 49.0% - no better than chance. In Treatment 3, the accuracy of guesses is higher: 59.8% overall and 64.9% when manipulation takes place.

Table 5.6
Ability of traders to identify manipulation

Two-way frequency tables of state (whether a manipulator was present in the market or not) and traders' guesses of whether a manipulator was present or not. *% Correct* is the percentage of correct guesses. Significance at the 10%, 5% and 1% levels is indicated by *, ** and ***, respectively, for two-sided binomial proportion tests with the null hypothesis that *% Correct* equals 0.5, i.e., the accuracy of guesses is not different from chance.

Panel A: Without regulator (Treatment 2)				
	Guess			
State	No manipulator	Manipulator	Total	% Correct
No manipulator	214	161	375	57.1***
Manipulator	175	168	343	49.0
Total	389	329	718	
% Correct	55.0**	51.1		53.2*
Panel B: With regulator (Treatment 3)				
	Guess			
State	No manipulator	Manipulator	Total	% Correct
No manipulator	30	42	72	41.7
Manipulator	92	169	261	64.8***
Total	122	211	333	
% Correct	24.6***	80.1***		59.8***

The difference in guessing accuracy between Treatments 2 and 3 is partly explained by the difference in perceived prior probabilities of manipulation. In Treatment 2, a manipulator, with no reason not to manipulate, is selected in a randomly chosen 50% of trading periods. However, participants are not aware of the proportion of periods with a manipulator. On the other hand, in every period of Treatment 3, a manipulator is given the choice of whether to manipulate or not. Because participants are aware of all payoffs that are relevant to deciding whether or not to manipulate, arguably, participants are better able to estimate the prior probability of manipulation and therefore guess more accurately whether or not a manipulator was present. The generally poor accuracy with which market participants identify manipulation is concerning because, among other things, it limits the ability for market participants to profitably counteract manipulation and attenuate its detrimental effects.

5.3.6 Robustness tests

I test the robustness of the results to using alternative measures of price accuracy and liquidity, disregarding the first four trading periods in each session to allow participants learning time, and simplification of the mixed effects regression models to random intercept models by dropping the random slopes. The main results are robust to these tests.

5.4 Discussion and conclusions

Understanding how trading strategies commonly labelled as 'manipulation' affect price accuracy and market liquidity is critical in determining whether such strategies are harmful to markets and should be illegal (Kyle and Viswanathan, 2008). However, the limited evidence that exists regarding the effects of manipulation on markets is mixed and inconclusive. This is largely because of the significant variation in manipulation strategies, the general lack of data on manipulation and the inability to observe key variables such as true asset values, and counterfactuals such as manipulation free markets. By studying manipulation in an experimental market this chapter overcomes these limitations and provides important insights into the effects of a particular and common form of manipulation – manipulation of the closing price.

The first key result arises from contrasting the particular incentives given to manipulators in this chapter's experimental market with those in the closely related study by Hanson et al. (2006). The results indicate that the manipulators' incentives are critical in determining the harm caused by a particular type of manipulation. Consequently, different types of manipulation should be considered separately in formulating policy decisions or in conducting academic research.

The second key finding is that closing price manipulation harms both price accuracy and liquidity. In fact, even the mere possibility of manipulation decreases liquidity and increases trading costs by increasing price uncertainty. Therefore, in line with the argument put forward by Kyle and Viswanathan (2008), closing price manipulation undermines economic efficiency, creates social harm and should be prohibited. These findings about closing price manipulation are particularly concerning given the many examples of market participants with incentives to manipulate closing prices and the numerous important uses of closing prices.

The third important result is that price accuracy can be restored by imposing a credible mechanism that monitors the market and issues penalties to detected manipulators. However, the restoration of liquidity through the imposition of penalties for manipulation is more difficult. The decrease in price accuracy caused by manipulation is largely an ex-post effect resulting directly from the manipulators' actions, whereas the decrease in liquidity is an ex-ante effect caused by ordinary traders' reactions to the perceived probability of manipulation. While regulation may have an immediate impact on the behaviour of manipulators and therefore help restore price accuracy, changing the behaviour of ordinary traders to restore liquidity requires that market participants believe regulation will eliminate manipulation. This was not the case in the experimental markets; regulation restored price accuracy but not liquidity. This finding is consistent with Bhattacharya and Daouk (2002) who report that the perception of credibility gained by a regulator through the enforcement of laws governing financial conduct, rather than simply their presence, affects markets in a positive way.

The last significant contribution of this chapter is in characterising a typical closing price manipulation strategy and the reactions of ordinary traders. Manipulators of a stock with a reasonable level of liquidity, in the absence of a credible regulator, submit many highly aggressive buy orders in the last seconds of trading. In the presence of a regulator, manipulators trade less aggressively and earlier in a trading period, trading off some of the benefits they stand to gain from manipulation against the probability of being caught.

The results suggest that some ordinary traders attempt to profit from manipulators by offering more shares for sale shortly before the close when they perceive manipulation to be likely. Such a strategy, motivated by self-interest, offers hope to markets for attenuating the detrimental effects of manipulation and minimising the need for regulatory intervention.

However, in order for ordinary traders to successfully counter manipulation, they must be capable of identifying manipulation. In this chapter's experimental market, despite the fact that manipulators have a substantial impact on prices, market participants have great difficulty in identifying manipulation. This result suggests the need for regulatory intervention, as opposed to leaving markets to their own devices, particularly in light of the finding that closing price manipulation imposes a social cost. Further, this also suggests that regulators need more advanced monitoring mechanisms than human judgment in order to detect a meaningful fraction of manipulation. The next chapter constructs an index of manipulation and a closely related detection tool that can be used by regulators to improve the accuracy of their market surveillance systems.

Chapter 6

Detecting and measuring closing price manipulation

6.1 Introduction

The previous chapters find that only a small fraction of closing price manipulation is detected and prosecuted by regulators and closing price manipulation harms both price accuracy and liquidity. Therefore, reducing the prevalence of closing price manipulation is likely to enhance market integrity and economic efficiency. One way in which this can be achieved is by improving the accuracy of detection methods.

Another issue highlighted by this thesis is that although closing price manipulation is common, our understanding of it is limited because of the scarcity of data and opaqueness of regulatory authorities. In a large number of markets, cases of prosecuted closing price manipulation either do not exist or are not publicly available, thus making it impossible to directly study closing price manipulation. These two issues suggest the need for improved methods to detect and measure closing price manipulation.

The purpose of this chapter is twofold. The first is to develop an index of closing price manipulation that can be used to study manipulation in markets and time periods in which prosecution data are not readily available. The second purpose is to extend the index to produce a closing price manipulation detection tool that can be used by regulators to improve the accuracy of automated market surveillance systems.

The reason for constructing separate tools for research and for market surveillance comes down to data requirements. The index, intended mainly as a tool for research, is constructed so that it can be calculated using only readily available trade and quote data. This maximises the number of markets and time periods in which the index can be calculated. On the other hand, regulators are likely to have access to more detailed information within the markets they regulate. Some of this additional information can be used to more accurately detect manipulation. Therefore, using the index as base, this chapter constructs a more detailed manipulation detection tool by incorporating the findings of Chapter 3 about factors that drive manipulation.

Given that closing price manipulation is generally not observable, the manipulation index is useful in empirical research similar to the way in which the Easley et al. (1996) probability of informed trading (PIN) is commonly used to proxy for informed trading, or the Huang and Stoll (1997) adverse selection component of the spread is used to measure information asymmetry. To illustrate this point, a simple application of the index would be to analyse the effect of a regulatory change on the level of manipulation by examining index values around the change. The index can also be used to examine how the nature of manipulation varies across market structures, firm characteristics and through time. The ability to use this index in such a manner, which is confirmed by analysing out-of-market and out-of-time classification characteristics, is largely due to the index's explicit controls for market trends, stock-specific characteristics and variance of the underlying variables.

The manipulation detection tool incorporates into the index the underlying probability of manipulation based on factors that influence the decision to manipulate, such as information asymmetry, market capitalisation, regulatory budget and so on. It can be used by regulators in their surveillance systems to aid in the identification of possible manipulation for further investigation, or in enforcement as statistical evidence of manipulation.

6.2 Data

This chapter uses the manually collected sample of closing price manipulation cases, which is described in Chapter 3. I obtain intra-day trade and quote data, expiry dates for listed options, and index composition data from a *Reuters* database maintained by the *Securities Industry Research Centre of Asia-Pacific* (*SIRCA*). From this database I also obtain trade and quote data on all of the stocks in each of the four markets. I filter these data to remove erroneous entries and stock-days that do not contain at least one trade and one quote. The remaining data are from *Thomson's Datastream* and the websites of the regulators.

6.3 Closing price manipulation index

The findings of Chapter 4 suggest that returns, spreads, trading frequencies and return reversals can be used to distinguish manipulated closing prices from those occurring in normal trading. Therefore, I base the index on standardised measures of the abnormality of these variables and use logistic regression to obtain weights. I analyse the classification characteristics of the index out of market and out of time and perform robustness tests.

6.3.1 Components

To make use of the index across different stocks, markets and time, changes in market conditions and cross-sectional differences in the central tendency and dispersion of variables such as trade frequency, return and spread must not cause systematic differences in the value of the index. For example, the fact that trading frequency tends to increase through time must not in itself cause higher index values in later time periods. Similarly, the fact that large price changes occur more frequently in illiquid stocks due to their wider spreads, lower depth and higher risk, must not cause the index to suggest on this basis that illiquid stocks are more frequently manipulated. As a final example, particular days are associated with more intensive trading activity by speculators, arbitrageurs, and hedgers, for example, options expiry days, month-end days and macroeconomic announcement days. This additional trading activity, which is unrelated to manipulation, must not in itself influence the index's estimate of the manipulation rate on these days.

The difference-in-differences estimator used in Chapter 4 eliminates differences in central tendency, thus allowing the identification of abnormal variable values while controlling for stock- and time-specific effects. However, in constructing the index it is necessary to account for differences in the dispersion of the variable distributions. If dispersion is neglected, volatile stocks (and therefore volatile markets and time periods) for example, would more frequently cause large absolute values of the difference-in-differences estimators and therefore result in more manipulation alerts than in stable stocks, regardless of the underlying manipulation rates. Therefore, I modify the difference-in-differences estimator by standardising the differences between a stock-day and that stock's prior trading. The standardisation makes use of sign statistics (from non-parametric sign tests). The sign statistics combine each set of differences into a single standardised measure of the day-end variable's abnormality (in the positive direction) relative to that stock's prior trading.[62]

Taken together, the differencing in time, differencing in cross-section and standardisation of the differences using a nonparametric statistic insulates the index from changing market conditions and cross-sectional differences in the levels and dispersion of variables. A disadvantage of this approach is that although manipulation may cluster in time and by exchange, the index cannot detect the full extent of this clustering.

The sign statistics for the day-end variables used in Chapter 4 (*i=return*, *reversal*, *frequency, spread*) are defined as,

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[62] In unreported results I substitute the sign statistics for non-parametric Wilcoxon signed-rank statistics and robust parametric winsorised means. I find that the index using the sign statistics is superior in classification accuracy.

$$S_i = \frac{n_+ - n_-}{2} \tag{6.1}$$

where n_+ and n_- are the number of positive and negative differences respectively. The period of prior trading is the same as in Chapter 4 (42 trading days ending one month before the examined day). This allows the index to detect closing prices manipulated over several consecutive days. For each variable there are 42 differences and the sign statistics are standardised to the range -21 to +21. A score of -21 indicates the value of the underlying variable is the lowest reading in the 42 day benchmark and +21 indicates a value higher than each reading in the benchmark. Based on the findings of Chapter 4, the sign statistics of differences corresponding to day-end returns, spreads, trading frequencies and return reversals will be significantly positive for manipulated stock-days whereas they will be on average zero for non-manipulated days.

Differencing the sign statistic for a particular stock from the cross-sectional median sign statistic that day removes market trends and produces the following modified difference-in-differences estimator, the *difference-in-signs*,

$$\Delta_i^{sign} = S_i - med_s(S_{si}) \tag{6.2}$$

where S_i is the sign statistic for variable *i* on a particular stock-day and $med_s(S_{si})$ is the median sign statistic for all other stocks, *s*, on the same exchange and day.

The way return and reversal are defined, the index measures the probability of upward price manipulation – the only form of manipulation in the sample of prosecutions. It is straightforward to modify the index to also account for downward price manipulation. However, without cases of downward manipulation for calibration, this modification would require the assumptions that downward manipulation is similar to upward manipulation in trade characteristics (except for the direction of price movements) and is equally common.

6.3.2 Functional form and coefficients

The functional form of the index is obtained from the following logit model used to estimate weights for the index components,

$$\ln\left(\frac{P}{1-P}\right) = \alpha + \beta_1 \Delta_{return}^{sign} + \beta_2 \Delta_{reversal}^{sign} + \beta_3 \Delta_{frequency}^{sign} + \beta_4 \Delta_{spread}^{sign} + \varepsilon \qquad (6.3)$$

where $\ln\left(\frac{P}{1-P}\right)$ is the log-odds of the probability of manipulation, *P*, and the Δ_i^{sign} are the difference-in-signs estimators defined in Equation 6.2. An attractive feature of the logit model is that it accommodates non-linearity between the probability of manipulation and the explanatory variables. For example, an increase in abnormal return from 8% to 9% can have less of an effect on the probability of manipulation than an increase from 1% to 2%.

I estimate the coefficients of this model on the sample of manipulated and non-manipulated stock-days. The non-manipulated stock-days (n = 241,828) are obtained by taking, for each manipulated stock-day (n = 184), all other stocks on the corresponding exchange on that day. Consequently, the non-manipulated stock-days are an accurate match of the manipulated stock-days by market and time.

Table 6.1 reports the results of the regression. All coefficient estimates are statistically significant at the 1% level and the signs are consistent with expectations. That is, abnormally positive day-end returns, trade frequencies, spreads and return reversals increase the probability that a closing price has been manipulated. The largest marginal contribution to maximising the log-likelihood (and predicting manipulation) is from the difference-in-signs statistic corresponding to frequency, followed by reversal, return and then spread. This means that returns and reversals, the main criteria for alerting regulators to manipulation, are not the sole factors (or even the best two factors) in predicting manipulation from trading characteristics. In subsection 6.3.4 I examine the differences between the US and Canada in how the factors contribute to predicting manipulation.

Table 6.1
Index coefficients from logistic regression

This table reports coefficient estimates from binary logistic regression of manipulated (n=184) and non-manipulated stock-days (n=241,828) using the regression model:

$$\ln\left(\frac{P}{1-P}\right) = \alpha + \beta_1\Delta^{sign}_{return} + \beta_2\Delta^{sign}_{reversal} + \beta_3\Delta^{sign}_{frequency} + \beta_4\Delta^{sign}_{spread} + \varepsilon$$

where $\ln\left(\frac{P}{1-P}\right)$ is the log-odds of the probability of manipulation and Δ^{sign}_{i} are the difference-in-signs estimators defined as:

$$\Delta^{sign}_{i} = S_i - med_s(S_{si})$$

where $med_s(S_{si})$ is the median sign statistic for all other stocks, *s*, on the corresponding exchange. The sign statistics are standardised differences between the stock-day being examined and each of the stock-days in a 42 trading day period lagged one month, and are scaled by a factor of 100.

Variable	Estimate	p-value
Constant	-7.49	< 0.0001
Δ^{sign}_{return}	4.22	< 0.0001
$\Delta^{sign}_{reversal}$	3.58	< 0.0001
$\Delta^{sign}_{frequency}$	8.46	< 0.0001
Δ^{sign}_{spread}	1.83	0.002

The manipulation index is obtained from the regression model by setting the index equal to the probability of manipulation. Rearranging the regression equation and inserting the coefficient estimates produces the following calibrated index,

$$I_{manip} = \frac{1}{1+e^{-(-7.5+4.2\Delta^{sign}_{return}+3.6\Delta^{sign}_{reversal}+8.5\Delta^{sign}_{frequency}+1.8\Delta^{sign}_{spread})}} \qquad (6.4)$$

If the index were calibrated on a random sample of manipulation cases it would be an unbiased measure of the probability of manipulation (including detected and undetected manipulation). However, I calibrate the index on a sample of prosecuted manipulation cases and consequently the index, I_{manip}, which varies between zero and one, represents the probability of a prosecuted closing price manipulation.[63] The index can be expected to flag prosecuted manipulation as well as

[63] If the population rate of manipulation differs from the proportion of manipulation to non-manipulation cases used in the regression the constant must be adjusted to obtain unbiased probabilities (Joanes, 1993). However, this is not required when the index is used as a classifier using a classification threshold chosen to obtain the desired type I to type II error trade-off. This also does not affect the analysis of classification characteristics in the following subsection because I use a method that is independent of prior probabilities.

a proportion of undetected manipulation which is most similar in characteristics to the prosecuted sample.

6.3.3 Issues in using the index

A threshold value of I_{manip} can be chosen to classify stock-days as manipulated depending on the desired trade-off between type I and type II errors (false positives and false negatives). Stock-specific late-day news is likely to create abnormal day-end trading activity that can resemble manipulation and therefore lead to false positive classifications. In an academic application of the index, this component of the error can be minimised by combining the index with a news database and disregarding manipulation classifications that coincide with late-day news.

End-of-day program trading by participants such as leveraged ETFs is likely to increase volume and volatility at the end of the day (Cheng and Madhavan, 2009). The increase in volatility is equivalent to adding noise to the data in which the index looks for evidence of manipulation. If the behaviour of manipulators does not change in response to the additional volatility, then effectively the signal-to-noise ratio is reduced by the end-of-day program trading, making manipulation more difficult to detect.

However, the index is relatively well equipped to deal with end-of-day phenomena without causing excessive false alerts. This is achieved by the differencing in the 42 day own-stock benchmark and the differencing in cross-section. To illustrate this, consider the following examples. If the presence of leveraged ETFs on average increases the volume of trading at the close by say 50%, then not only will any particular stock-day on average have 50% greater volume at the close but so too will each stock-day in the 42 day prior trading benchmark. Therefore, the difference of a stock-day's day-end volume and the median day-end volume in the 42 day prior trading benchmark will eliminate the overall effect of leveraged ETFs on day-end volume.

A similar argument holds for volatility. If the day-end price of any specific stock-day is more volatile, then large positive or large negative day-end returns will occur more often, not only in a specific stock-day, but also in the 42 day prior trading benchmark. In high volatility, for a particular day-end return to give an abnormal reading, it must be abnormal relative to 42 highly volatile day-end returns. Consequently, high volatility does not cause more false alerts than low volatility simply as a result of volatility.

The cross-sectional differences help insulate the index from phenomena that have market-wide effects, such as end-of-day trading by leveraged ETFs, macroeconomic news, quarter-end days and so on. The following example illustrates this. Leveraged ETFs rebalance in the same direction as the market movement that day (Cheng and Madhavan, 2009). Consider a day in which due to some exogenous reason, the market increases substantially during the day, and the increase is the largest single day increase in the past three months. Leveraged ETFs would be expected to buy heavily at the end of the day across multiple stocks, causing abnormal day-end volume and abnormal positive day-end returns in many stocks. The day-end returns and volumes are likely to be abnormal relative to the prior trading 42 day benchmarks of many stocks, however, when differenced in cross-section, the market wide abnormal characteristics are eliminated and only stocks with abnormal trading relative to the overall market would be flagged as abnormal.

As well as its use as a dichotomous classifier of manipulation, the index also measures the intensity of manipulation's adverse effects on the market. The index is increasing in the abnormality of day-end returns, trade frequencies, return reversals and spreads. Abnormal day-end return and return reversals measure the extent to which a price has been driven away from its natural level and hence the magnitude of errors when decisions are based on closing prices. Increased trade frequency is an indication of the proportion of trades made by the manipulator and the uncertainty induced by the manipulator's actions. Finally, increased spread is an adverse effect because it increases trading costs.

6.3.4 Validation and robustness testing

I analyse the classification characteristics of the index on markets and in time periods not used in its estimation. The purpose of this is twofold. First, this assesses the practical applicability of the index. Application of the index to cross-market studies or to predicting manipulation on a daily basis forward in time from the calibration data requires good out-of-market and out-of-time accuracy, respectively. Second, this analysis tests whether model overfitting is at play.

I divide the sample of manipulated and non-manipulated stock-days into their four markets and into two time periods – earliest and latest – each period containing half of the manipulation instances. For each market I calculate manipulation probabilities predicted by the index, with the index parameters estimated using the other three markets. Similarly, for the two time periods I calculate manipulation probabilities for the later time period using the index estimated on the earlier time period and vice versa. To perform leave-one-out cross-validation I in turn leave out one instance of manipulation (and the corresponding non-manipulation stock-days), fit the index to the rest of the data and calculate the manipulation probabilities for the left out data. Figure 6.1 plots the Receiver Operating Characteristics (ROC) curves generated by all three cross-validation techniques.

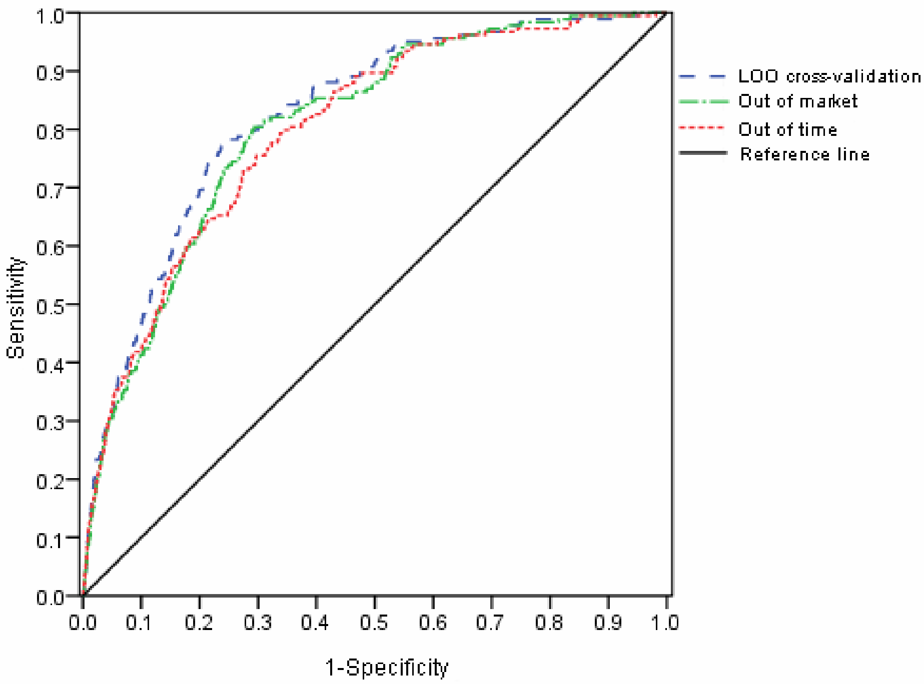


Figure 6.1 Out of sample classification characteristics of the manipulation index
This figure plots the Receiver Operating Characteristics (ROC) curves of the manipulation index for leave-one-out cross-validation, out-of-time cross-validation and out-of-sample cross-validation. Leave-one-out cross-validation is performed by in turn leaving out one instance of manipulation and the corresponding non-manipulation stock-days, fitting the index to the rest of the data and calculating the manipulation probabilities for the left out data. Out-of-time cross-validation is performed by dividing the manipulation instances and the corresponding non-manipulated stock-days into two time periods (earliest half and latest half), fitting the index on one of the time periods, calculating the manipulation probabilities for the other time period, and repeating this process for the other time period. Similarly, in out-of-market cross-validation the index is fitted on three markets, the manipulation probabilities are calculated for the fourth market, and this process is repeated for each of the markets. Sensitivity is the true positive rate and 1-specificity is the false positive rate.

The ROC curve is a performance measure independent of prior probabilities and classification thresholds.[64] It describes the trade-off between the proportion of true positives (sensitivity) and the proportion of false positives (one minus the specificity). In the context of the manipulation index, the ROC curve describes the proportion of stock-days from the non-manipulation sample that will be classified as manipulated in order to correctly classify a certain proportion of the prosecuted manipulation instances. ROC curve analysis is more general than count based

[64] For a more detailed description of ROC curves applied in a financial modelling context see Tang and Chi (2005) and Stein (2005).

measures because it examines classification accuracy under all possible classification thresholds as opposed to a specific threshold. The area under the ROC curve (AUROC) represents the probability of correct prediction and is a robust measure by which to compare the performance of a classifier across different samples.[65]

Due to the presence of undetected and not prosecuted manipulation, the data do not allow the absolute accuracy of the index to be estimated, only the relative accuracy across different samples. This is because when the index detects manipulation that has not been prosecuted it is penalised because the data record those observations as not manipulated. Unless undetected manipulation can be observed independently of the index classifications, one minus specificity (the usual measure of false positives) is in fact a measure of false positives *and* correctly flagged manipulation that has not been prosecuted. Therefore, this analysis estimates the lower bound of the index's classification accuracy. The underestimation of the true accuracy is greater the larger the fraction of not prosecuted manipulation.

The ROC curves under all three cross-validation regimes are significantly above the ascending diagonal line that represents a classifier only as good as chance. Consistent with this, the AUROC reported in Table 6.2 are well above 0.5 indicating that even the lower bound accuracy in predicting manipulation out of market and out of time is considerably better than chance. The 95% confidence intervals for the AUROC of the three cross-validation techniques overlap and the point estimates differ by less than 4%. This is strong evidence that the index is robust to different markets and time periods and can, with a relatively high level of accuracy, predict manipulation in markets and time periods not used in its estimation.

The classification accuracy of the index is also very similar across the two countries. The AUROC is 0.819 in the US and 0.826 in Canada, and the difference is not statistically significant. This suggests that it is not significantly easier to detect manipulation in one country or the other using the index.

[65] The AUROC is equivalent to the Mann-Whitney-Wilcoxon two independent sample non-parametric test statistic (Hanley and McNeil, 1982).

Table 6.2

Comparison of the manipulation index classification performance out of time and out of market

AUROC is the area under the ROC curves in Figure 6.1. Leave-one-out cross-validation is performed by in turn leaving out one instance of manipulation and the corresponding non-manipulation stock-days, fitting the index to the rest of the data, and calculating the manipulation probabilities for the left out data. Out-of-time cross-validation is performed by dividing the manipulation instances and the corresponding non-manipulated stock-days into two time periods (earliest half and latest half), fitting the index on one of the time periods, calculating the manipulation probabilities for the other time period, and repeating this process swapping the time periods. Similarly, in out-of-market cross-validation the index is fitted on three markets, the manipulation probabilities are calculated for the fourth market, and this process is repeated for each of the markets. The p-values are for a non-parametric test of the null hypothesis that the area is equal to 0.5.

Cross-validation technique	AUROC	p-value	95% Confidence interval for the area	
			Lower bound	Upper bound
Leave-one-out	0.825	< 0.0001	0.797	0.853
Out-of-time	0.806	< 0.0001	0.777	0.835
Out-of-market	0.800	< 0.0001	0.770	0.830

I compare the US and Canadian stock exchanges in the contribution made by each of the four factors (return, reversal, frequency and spread) to predicting manipulation. I do this by constructing the index with and without each of the four factors and measuring the change in model log-likelihood and classification accuracy. The order of contribution for the four factors is the same using log-likelihood and classification accuracy and therefore Table 6.3 reports only the results using classification accuracy.

In the US stock exchanges the factors ordered from greatest to least in their contribution to classification accuracy are frequency, return, reversal and spread. In the Canadian stock exchanges the order is frequency, reversal, return and spread. This suggests that despite the differences in the way closing prices are set in the US and Canadian exchanges, the contributions of the factors that predict manipulation are relatively consistent.

Table 6.3
Marginal contribution of predictor variables to index classification accuracy

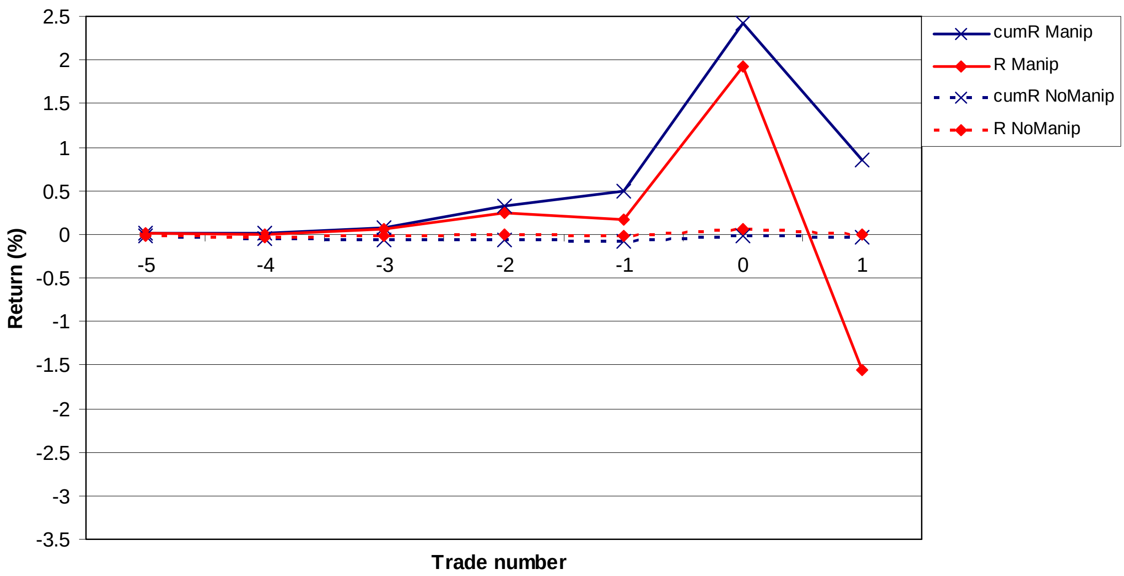
This table reports the marginal contribution of the predictor variables (difference-in-signs corresponding to return, reversal, frequency and spread) to the classification accuracy of the index. Classification accuracy is measured by the area under the ROC curve in leave-one-out cross-validation (AUROC). The marginal contribution of a predictor variable to the AUROC is calculated as the difference in the AUROC for the index constructed without the predictor variable and the index with the predictor variable. The numbers in parentheses indicate the rankings of the variables in their marginal contributions.

Country	n	Δ^{sign}_{return}	$\Delta^{sign}_{reversal}$	$\Delta^{sign}_{frequency}$	Δ^{sign}_{spread}
All	241,828	0.020 (2)	0.014 (3)	0.082 (1)	0.003 (4)
US	117,928	0.024 (2)	0.006 (3)	0.138 (1)	0.003 (4)
Canada	123,900	0.017 (3)	0.018 (2)	0.059 (1)	0.002 (4)

I compare day-end trading characteristics between stock-days flagged by the index as likely manipulation (top 2% quantile of index probabilities) and the sample of prosecuted manipulations. The threshold for forming the probable manipulation sample is somewhat arbitrary, but is chosen to be similar to the underlying rate of manipulation estimated in Chapter 3.

The plots in Figure 6.2 illustrate that the shape and magnitude of the day-end price run-ups are quite similar for the stock-days with high index scores (Panel B) and the prosecution cases (Panel A) suggesting the index is effective in identifying stock-days which look like prosecuted manipulation. Both proxies for manipulation have a median price run-up of just over 2% by the close and a significant price reversal the following morning. These plots also shed insight on the timing of manipulation. In the median instance most of the price distortion occurs with the last trade. Performing the same analysis in real-time indicates that almost all of the price run-up occurs in the five minutes before the close.

Panel A: Prosecuted manipulation v no prosecuted manipulation



Panel B: High index probability of manipulation v low index probability

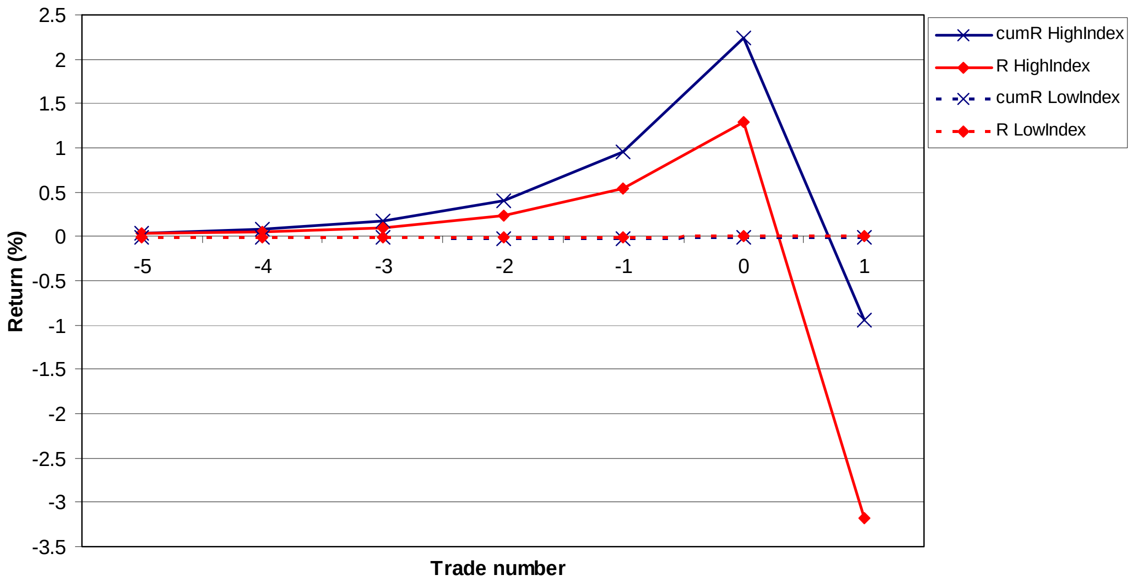


Figure 6.2 Day-end trade-by-trade returns

This figure plots the median returns on trades at the end of the day for manipulated and not manipulated stocks using two alternative proxies for manipulation. In Panel A the manipulation proxy is the sample of prosecuted manipulation instances, and in Panel B the proxy is the top 2% quantile of stock-days by manipulation index score. Returns, *R*, are computed as the logarithm of the ratio of trade prices. Trade number 0 corresponds to the last trade of the day, -1 corresponds to the second to last and so on. Trade number 1 corresponds to the last traded price at 11am the following morning. Cumulative returns, *cumR*, are computed by summing the returns on trades -5 to the current trade.

The sample composed of the highest 2% of index scores contains a mix of prosecuted manipulation, undetected or not prosecuted manipulation, and stock-days not involving manipulation (false positives). This analysis does not suggest that 2% of stock-days are manipulated. The 2% threshold can be interpreted as an upper bound on the rate of manipulation for similar reasons to why the ROC analysis estimates a lower bound on the classification accuracy.

As an additional robustness test, I examine the stability of the index coefficients through time. I estimate the index multiple times on half the sample rolled forward chronologically in each re-estimation. The coefficients remain relatively stable through time. [66] This supports the usefulness of the index in making forward predictions when estimated using past data.

6.4 An instrument for detecting closing price manipulation

Most market surveillance systems are automated (Harris, 2002; Clayton et al., 2006) and rely on real-time computer systems that alert surveillance staff of unusual trading activity (Cumming and Johan, 2008). Discussions with regulators suggest that 'alerts' are often based on prices or volumes and are triggered when changes in these variables exceed predetermined thresholds. The findings of Chapter 5 suggest that even in a relatively simple laboratory experiment in which the parameters and information structure are common knowledge, participants have great difficulty in identifying manipulation based on price and volume movements. Considering also

[66] In each iteration, the coefficients maintain the same order in their magnitudes (frequency, return, reversal, spread) and remain within a +/- 50% band from their full sample values. Given that the sample spans several years and eight manipulation prosecution cases, much of the variation in the absolute values of the coefficients can be explained by changes in the intensity of manipulation through time or across cases as cases enter or exit the rolling sample used in this test. Therefore, the order of the coefficients is the better indicator of whether the nature of manipulation changes through time and whether the approach to detecting manipulation needs to be regularly updated.

that only a small fraction of manipulation is detected and prosecuted, this suggests more accurate market surveillance systems would enhance market integrity.

So far, this thesis has produced two different measures of the probability of closing price manipulation. The first is based on the detection controlled estimation (DCE) model (Chapter 3, Equations 3.17 and 3.18). The second is the manipulation index constructed in the previous section using only trade and quote data. This section compares the strengths and weaknesses of both measures and describes how the two can be combined to produce a detection tool suitable for regulatory applications.

6.4.1 Comparison of manipulation metrics

The main strength of the DCE model (in Chapter 3) is its ability to estimate the probability of manipulation based on stock-, time- and market-specific characteristics such as liquidity, information asymmetry, index constituency, month-end days, level of regulatory budget and so on. These factors clearly affect the probability of manipulation and therefore should be considered when trying to detect manipulation. The DCE model estimates the influence of each factor on the probability of manipulation. Combining these estimates with observed values of the factors gives an estimate of the probability of manipulation.

The main weakness of this model as a detection tool is that it only considers factors affecting the decision to manipulate not the effects or 'footprint' left behind by manipulation. In that sense it does not utilise all of the information that is available. Most of the factors that affect the decision to manipulate are measured at a relatively aggregated level and consequently the predictions are most useful at similar levels of aggregation. For example, useful predictions from this model are that manipulation is more likely on quarter-end days and in stocks of low to mid levels of liquidity.

The second metric, the closing price manipulation index, has higher resolution, i.e., it is constructed specifically to estimate probabilities at the stock-day level. Unlike the DCE model, which is based on relatively aggregated stock-, time- and market-specific characteristics, the index is based on day-end trading characteristics (returns, price reversals, trade frequency and spreads). Not only is the resolution of these variables higher but also they measure a different aspect of manipulation – the effects or 'footprint' left behind by manipulation rather than factors affecting the decision to manipulate.

A weakness of the index as a predictor of manipulation is that it ignores the factors that affect the decision to manipulate, such as index constituency, regulatory budget and so on. This is done so that the index can be used in the large number of markets in which detailed information is not available. The index starts with the prior that manipulation is equally likely in all stock-days and then identifies stock-days that have abnormal day-end trading characteristics similar to prosecuted instances of manipulation. Abnormality is measured relative to a stock's past trading and the prevailing market-wide conditions to minimise the number of false positives due to volatility or macroeconomic news announcements, for example.

Overall the DCE model is best suited for identifying long-term changes in levels of manipulation, periods of increased likelihood of manipulation and stocks with characteristics that make them susceptible to manipulation. The index is best suited to identifying stock-days with abnormal day-end trading characteristics similar to actual manipulation cases.

6.4.2 Combined detection tool

In a regulatory application, in which the availability of data and ability to process it is not a significant constraint, the two metrics can be combined. The combined detection tool first estimates the likelihood of manipulation from the factors that affect the decision to manipulate and then, taking into consideration this likelihood, estimates the probability of manipulation by comparing the day-end trading characteristics to the typical 'footprint' left behind by manipulation. The combined detection tool overcomes the weaknesses of each of the individual metrics by utilising what is known about both the drivers and the 'footprint' of manipulation.

Following Joanes (1993) the combined detection tool is defined as,

$$C_{manip} = \frac{1}{1 + \frac{(1 - I_{manip})}{I_{manip}} \frac{n_M}{n_0} \frac{(1 - \pi_M)}{\pi_M}} \tag{6.5}$$

where I_{manip} is the value of the manipulation index defined in Equation 6.4, n_M (n_0) is the number of closing prices with (without) detected and prosecuted manipulation used in estimating the index, and π_M is the DCE conditional probability of manipulation given by Equation 3.17 (or Equation 3.18 if using the two-equation model).

An estimate of the probability of manipulation is more useful than a binary alert because higher manipulation probabilities have a lower rate of misclassification. Therefore, a market regulator would first investigate instances with the highest probability of manipulation and continue to investigate lower probability instances as far as their resources allow. Stock-specific late-day news is likely to create abnormal day-end trading activity that can resemble manipulation and therefore lead to false positive classifications. In a regulatory application this is relatively easily managed by checking for late-day news when examining manipulation alerts.

6.5 Conclusions

The previous chapters find that a large proportion of closing price manipulation remains undetected or not prosecuted and closing price manipulation harms economic efficiency. In a large number of markets, prosecuted closing price manipulation cases either do not exist or are not publicly available, thus making it impossible to directly study closing price manipulation. This chapter addresses both of these issues by constructing an index of closing price manipulation that can be used to study manipulation where prosecution data are not readily available, and then extending the index to provide a detection tool that can be used by regulators to improve the accuracy of market surveillance systems.

The index can be used to identify probable instances of manipulation across markets and through time. This capability is largely due to the controls incorporated into the index for market trends, stock-specific characteristics, and variance of the underlying variables. The index creates opportunities for research on issues such as how the nature of manipulation varies across market structures, regulatory environments, firm characteristics, and through time. Such insights would allow more efficient use of regulatory and surveillance resources.

The trading characteristics, in order of their contribution to correctly classifying manipulation (from greatest to least), are frequency, reversal, return and spread. Despite the differences in the way closing prices are set in the US and Canadian exchanges the order of these factors is similar across the two countries. The index classification accuracy is also similar across the countries suggesting it is not significantly easier to detect manipulation in one country or the other using the index. The shape and magnitude of day-end price run-ups for closing prices with high index values and the prosecution cases suggest the index is effective in identifying stock-days which look like prosecuted manipulation. The results also suggest that in the median instance of closing price manipulation, most of the price distortion occurs with the last trade, within five minutes of the close.

The combined manipulation detection tool constructed in this chapter utilises what is known about both the drivers of manipulation, and the ‘footprint’ in trading characteristics left behind by manipulators. In a regulatory application a market regulator could rank suspected manipulation cases based on the probability of manipulation and investigate cases from the highest probability downwards as far as resources allow. This approach minimises false positives.

Chapter 7

Conclusions

This chapter summarises the conclusions that can be drawn from this thesis about: (i) why closing prices are manipulated; (ii) how closing prices are manipulated; (iii) how often closing prices are manipulated; (iv) what makes closing price manipulation and detection more likely; (v) how closing price manipulation affects markets; and (vi) the implications of closing price manipulation for economic efficiency and policy. This chapter ends with suggestions for future research.

7.1 Why are closing prices manipulated?

The existing literature and anecdotal evidence suggest a number of reasons why closing prices are manipulated: (i) to overstate a fund's performance at the end of a reporting period; (ii) to profit from a derivatives position, particularly on expiry of the derivatives contract; (iii) to influence the price of a seasoned equity issue; (iv) to affect a takeover price; (v) to influence the perceived execution ability of a broker that is benchmarked against closing prices; (vi) to maintain a stock's listing on an exchange with minimum price requirements; (vii) to avoid margin calls; and (viii) to influence an index rebalancing.

The prosecuted closing price manipulation cases used in this thesis provide evidence that (i), (iii), (iv) and (vii) have motivated closing price manipulation on US and Canadian stock exchanges. The sample of prosecution cases also contains manipulation with more general motivations such as the intent to create a misleading appearance of strength and stability in the price of a stock. The empirical analysis in this thesis suggests manipulation by fund managers on month-end and quarter-end days is among the most common reasons for closing price manipulation.

Manipulation can either increase or decrease closing prices. The sample of closing price manipulation cases suggests manipulation that increases prices is more common.

7.2 How are closing prices manipulated?

Typically, closing price manipulation is conducted by aggressively buying or selling stock at the end of a trading day. A manipulation strategy can be characterised by the timing and aggressiveness of the manipulator's trades.

The timing of a manipulator's trades depends on the liquidity of the manipulated stock and the strength of regulatory enforcement. Highly liquid stocks tend to be manipulated in the final minutes or seconds before the close because it is costly to sustain the liquidity imbalance that causes the inflated price. Thinly traded stocks, on the other hand, can be manipulated earlier in the day and still have the price distortion carry through to the close. In the median instance of prosecuted closing price manipulation, most of the price inflation occurs with the last trade of the day, within five minutes of the close. In a simulated stock market with 200-second periods of continuous trading, closing price manipulators trade most actively in the last ten seconds. The possibility of incurring penalties from regulatory enforcement causes manipulators to trade earlier in the day, making closing price manipulation more difficult to detect.

The aggressiveness of manipulation (number and size of trades) depends on factors such as the stock's liquidity, the magnitude of the manipulation incentive, the number of times the manipulator intends to manipulate closing prices, and the strength of regulatory enforcement. Illiquid stocks that have wide spreads can be manipulated with a single small trade that closes the stock at the bid or ask quote (depending on the manipulator's intended direction). For a liquid stock, this approach would have little effect on the price. Therefore, liquid stocks are commonly manipulated with several large trades. Fund managers have strong incentives to manipulate and they typically use large trades in manipulation. When manipulating a stock over several days manipulators tend to use smaller trades. Regulatory enforcement causes manipulators to use less aggressive order types to conceal their manipulation.

7.3 How often are closing prices manipulated?

Using an empirical model that takes into consideration the incomplete and non-random detection and prosecution of manipulation, this thesis estimates that on US and Canadian stock exchanges approximately 1.1% of closing prices are manipulated (during the period 1997-2008). For every prosecuted closing price manipulation there are approximately 300 instances of closing price manipulation that remain undetected or not prosecuted. Closing price manipulation is more prevalent on larger exchanges than smaller ones, but detected at a higher rate on small exchanges.

7.4 What makes closing price manipulation and detection more likely?

The likelihood of closing price manipulation is greater in: (i) jurisdictions with smaller regulatory budgets because the probability of detection is lower; (ii) stocks with higher information asymmetry because market participants find it more difficult to distinguish between informed trading and manipulation; (iii) stocks with mid to low levels of liquidity because very illiquid stocks do not have large incentives for manipulation and highly liquid stocks are difficult to manipulate; (iv) month-end days due to manipulation by fund managers; and (v) stocks with lower volatility because volatility draws the attention of the regulator.

Manipulation is more likely to be detected and prosecuted when regulatory budgets are larger because more cases can be investigated and prepared for prosecution. Manipulation is also more likely to be detected and prosecuted when it causes abnormal trading characteristics because such manipulation is more likely to trigger alerts in automated surveillance systems. Evidence from a laboratory experiment reinforces the finding that regulation deters some would-be manipulators and makes remaining manipulation less aggressive.

7.5 How does closing price manipulation affect markets?

Using a sample of prosecution cases, this thesis finds that closing price manipulation is associated with large day-end returns, subsequent return reversals, increased day-end spreads and increased day-end trading activity. Manipulation is associated with abnormal day-end returns of between 1.4% and 1.9% - approximately six times larger than their usual levels, most of which is reversed by the following morning. Price distortions are larger in less liquid stocks. Trading frequencies more than triple and spreads increase by between 0.11% and 0.63% in the presence of manipulation.

At the broader level of market quality, this thesis provides evidence that closing price manipulation decreases both price accuracy and liquidity. In fact, even the mere possibility of manipulation decreases liquidity and increases trading costs because uncertainty is greater.

7.6 Implications for economic efficiency and policy

This thesis finds that the manipulators' incentives are critical in determining the harm caused by a particular type of manipulation. Consequently, different types of manipulation should be considered separately in formulating policy decisions.

Closing price manipulation is significantly more prevalent than the number of prosecution cases would suggest. Further, it harms both pricing accuracy and liquidity and therefore, following the argument of Kyle and Viswanathan (2008), closing price manipulation undermines economic efficiency, creates social harm and should be prohibited. These findings are particularly concerning given the many examples of market participants with incentives to manipulate closing prices and the numerous important uses of closing prices. Therefore, reducing the prevalence of closing price manipulation is likely to enhance market integrity and economic efficiency.

The findings of this thesis and the review of literature suggest four ways to reduce the prevalence of closing price manipulation: (i) increase regulatory budgets; (ii) improve the accuracy of detection methods; (iii) take measures to aid the ability for market participants to identify manipulation; and (iv) implement closing mechanisms that are difficult to manipulate. Each of these is discussed below drawing on the findings of this thesis.

This thesis finds that by deterring some would-be manipulators and making remaining manipulation less aggressive, credible regulation helps reduce the harm manipulators cause to price accuracy. However, restoring the liquidity that is lost due to manipulation is more difficult because it requires that market participants believe regulation will reduce manipulation. This conclusion is consistent with Bhattacharya and Daouk (2002) who find that the perception of credibility gained by a regulator through the enforcement of laws governing financial conduct, rather than simply their presence, affects markets in a positive way. The empirical models used in this thesis estimate that in the US and Canada, a 1% increase in government regulatory budgets would decrease the amount of closing price manipulation by 3.3% and increase in the rate of prosecution by 2.9%. The benefits from the estimated reduction in manipulation need to be weighed against the costs of regulation.

This thesis develops an index of closing price manipulation and a tool for the detection of manipulation, which can be used by regulators in automated surveillance systems. These tools can be used to increase the accuracy with which manipulation is detected. A higher rate of detection is likely to deter manipulation.

This thesis finds some evidence that ordinary traders attempt to profit from manipulators by offering more shares for sale shortly before the close when they perceive manipulation to be likely. Such a strategy, motivated by self-interest, offers hope to markets for attenuating the detrimental effects of manipulation and reducing the need for regulatory intervention. However, this requires market participants to be capable of identifying manipulation. In the laboratory experiment used in this thesis, despite the fact that manipulators have a substantial impact on prices, market participants have great difficulty in identifying manipulation. Therefore, measures that improve the ability for market participants to identify manipulation are likely to enhance the ability for markets to self-attenuate the detrimental effects of manipulation. This might be achieved, for example, by increasing market transparency or introducing a system to alert market participants to potential manipulation. Further research on how markets can be structured to improve the ability for market participants to identify manipulation would be valuable.

Finally, closing mechanisms can be designed to make closing price manipulation more difficult. For example, closing call auctions, which are becoming increasingly popular among exchanges, reduce the price distortions caused by manipulation (Hillion and Suominen 2004; Comerton-Forde and Rydge, 2006). Closing call auctions have relatively few disadvantages.

Based on the discussion above, the recommended methods of reducing closing price manipulation are implementing closing mechanisms that are difficult to manipulate, such as closing call auctions, and improving the accuracy of market surveillance systems using the detection tools developed in Chapter 6. Both of these approaches have relatively few downsides. Increased regulatory budgets would reduce the frequency of manipulation, but the benefits need to be weighed against the costs of regulation. Future research should examine how markets can be structured to improve the ability for market participants to identify manipulation. These actions should enhance market integrity and economic efficiency.

7.7 Avenues for future research

Many instances of closing price manipulation are not detected or not prosecuted. Future research might attempt to disentangle detection from prosecution, thereby enhancing our understanding of which of these processes plays the larger role in allowing manipulation to occur without penalty.

The manipulation index developed in this thesis can be used to examine how the nature of manipulation varies across market structures, firm characteristics and through time. It can also be used to study the effects of events, such as regulatory changes, on manipulation.

As suggested in the previous section, further research on how markets can be structured to improve the ability for market participants to identify manipulation would be valuable. Finally, future research might apply some of the methods used in this thesis, such as detection controlled estimation, index construction, and laboratory experiments, to other types of manipulation.

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Appendix A

Alternative detection controlled estimation models

A.1 Two-equation model of manipulation and detection

Using the same notation as for the three-equation model and omitting much of the explanation the two-equation model of manipulation and detection is as follows.

$$Y_{1i}^{*} = X_{1i}\beta_1 + \varepsilon_{1i} \tag{A1}$$

$$Y_{1i} = \begin{cases} 1 \ \text{(manipulated)} & \text{if} \ Y_{1i}^{*} > 0 \\ 0 \ \text{(not)} & \phantom{\text{if}} \ Y_{1i}^{*} \leq 0 \end{cases} \tag{A2}$$

$$Y_{2i}^{*} = X_{2i}\beta_2 + \varepsilon_{2i} \tag{A3}$$

$$Y_{2i} = \begin{cases} 1 \ \text{(detected)} & \text{if} \ Y_{2i}^{*} > 0 \\ 0 \ \text{(not)} & \phantom{\text{if}} \ Y_{2i}^{*} \leq 0 \end{cases} \tag{A4}$$

$$M\left(X_{1i}\beta_1\right) = \Pr\left(Y_{1i} = 1\right) \tag{A5}$$

$$D\left(X_{2i}\beta_2\right) = \Pr\left(Y_{2i} = 1 | Y_{1i} = 1\right) \tag{A6}$$

$$\log L_A = \sum_{i \in A} \log\{M(X_{1i}\beta_1) D(X_{2i}\beta_2)\} \tag{A7}$$

$$\log L_{A^c} = \sum_{i \in A^c} \log\{[1 - M(X_{1i}\beta_1)] + M(X_{1i}\beta_1)[1 - D(X_{2i}\beta_2)]\} \tag{A8}$$

$$\log L = w_A \sum_{i \in A} \log\{M(X_{1i}\beta_1) D(X_{2i}\beta_2)\} + w_{A^c} \sum_{i \in A^c} \log\{[1 - M(X_{1i}\beta_1)] + M(X_{1i}\beta_1)[1 - D(X_{2i}\beta_2)]\} \tag{A9}$$

A.2 Three-equation model of manipulation and detection with expectations simultaneity

$$Y_{1i}^{*} = X_{1i}\beta_1 + \varepsilon_{1i} \tag{A10}$$

$$Y_{1i} = \begin{cases} 1 \text{ (manipulated)} \\ 0 \text{ (not)} \end{cases} \text{ if } \begin{matrix} Y_{1i}^{*} > 0 \\ Y_{1i}^{*} \le 0 \end{matrix} \tag{A11}$$

$$M(X_{1i}\beta_1) = \Pr(Y_{1i} = 1) \tag{A12}$$

$$Y_{2i}^{*} = X_{2i}\beta_2 + M(X_{1i}\beta_1)\delta_2 + \varepsilon_{2i} \tag{A13}$$

$$Y_{2i} = \begin{cases} 1 \text{ (directly detected)} \\ 0 \text{ (not)} \end{cases} \text{ if } \begin{matrix} Y_{2i}^{*} > 0 \\ Y_{2i}^{*} \le 0 \end{matrix} \tag{A14}$$

$$D\big(X_{2i}\beta_2, M(X_{1i}\beta_1)\delta_2\big) = \Pr(Y_{2i} = 1 | Y_{1i} = 1) \tag{A15}$$

$$Y_{3i}^{*} = X_{3i}\beta_3 + M(X_{1i}\beta_1)\delta_3 + \varepsilon_{3i} \tag{A16}$$

$$Y_{3i} = \begin{cases} 1 \text{ (indirectly detected)} \\ 0 \text{ (not)} \end{cases} \text{ if } \begin{matrix} Y_{3i}^{*} > 0 \\ Y_{3i}^{*} \le 0 \end{matrix} \tag{A17}$$

$$I\big(X_{3i}\beta_3, M(X_{1i}\beta_1)\delta_3\big) = \Pr(Y_{3i} = 1 | Y_{1i} = 1, Y_{2i} = 0) \tag{A18}$$

Representing $M(X_{1i}\beta_1)$ by M, $D\big(X_{2i}\beta_2, M(X_{1i}\beta_1)\delta_2\big)$ by D and $I\big(X_{3i}\beta_3, M(X_{1i}\beta_1)\delta_3\big)$ by I:

$$\log L_A = \sum_{i \in A} \log\{MD + M[1-D]I\} \tag{A19}$$

$$\log L_{A^c} = \sum_{i \in A^c} \log\{[1-M] + M[1-D][1-I]\} \tag{A20}$$

$$\log L = w_A \sum_{i \in A} \log\{MD + M[1-D]I\} + w_{A^c} \sum_{i \in A^c} \log\{[1-M] + M[1-D][1-I]\} \tag{A21}$$

Appendix B

Details of prosecution cases

This appendix describes each of closing price manipulation cases used in the empirical analysis. The purpose of this is to illustrate the circumstances surrounding each case of closing price manipulation, the incentives of the manipulators as well as to provide some examples of how regulators detect and prosecute closing price manipulation.

Table A.1 provides a summary of the manipulators, motivations and outcomes involved in each case. A discussion of each case follows.

Table A.1
Summary of manipulation cases

Case	Exchange	Date range	Manipulator(s)	Motivation	Outcomes
Competitive Technologies Inc. et al	AMEX	Jul. 1998 - Jun. 2001	Several brokers, former brokers and company CEO.	Increase value of personal stock position, avoid margin calls.	Conviction by a federal jury and settlements.
RT Capital Management Inc. et al.	TSX	Oct. 1998 - Mar. 1999	Several fund managers.	Inflate reported performance for fund to collect more management fees and managers to get greater remuneration.	Settlement, fines and suspensions.
Spear, Leeds & Kellogg / Baron Capital Inc. et al.	NYSE	Oct. 1999 - Nov. 1999	A substantial shareholder.	Affect the takeover price for a company acquisition for personal profit.	Settlement and fines.
John Andrew Scott et al.	TSX	Feb. 2000 - Jul. 2000	Investment advisor, company insiders and substantial shareholders.	Affect the price protection level of private placements of equity.	Settlements, fines and suspensions.
Douglas Christie	TSX	Feb. 2001 - Jun. 2001	A trader in a small trading firm.	Increase personal remuneration, which was paid by the firm based on market value of the trading account.	Settlement and fines.
Schultz Investment Advisors Inc.	NYSE	Jun. 2002 - Dec. 2003	A fund manager.	Inflate reported performance to collect more management fees.	Settlement, fines and suspension.
Research Capital Corporation	TSX-V	Nov. 2003 - Dec. 2003	An investment advisor on behalf of private clients.	Create misleading appearance of strength and stability in the market for the company's shares.	Settlements, fines and suspensions.
Luc St Pierre	TSX-V	Oct. 2004 - Sep 2005	An investment advisor on behalf of private clients including a company director.	Create misleading appearance of trading in the company's shares.	Conviction by a Disciplinary Panel, fines and suspension.

Case 1: Competitive Technologies Inc. et al.

The US SEC alleges that several brokers, former brokers and the CEO of Competitive Technologies Inc. (CTT) created a false or misleading appearance in the market for CTT stock and artificially raised CTT's stock price using a prolonged multi-faceted manipulation scheme.[67] The manipulation scheme was carried out between July 1998 and June 2001 with the main incentive for most of the manipulators being profit from inflated prices and avoidance of margin calls. Most of the seven brokers and former brokers that were involved in the manipulation scheme, their families and/or their clients had substantial positions in CTT stock. In addition, one of the defendants held the title of interim CEO of CTT at the start of the manipulation period and believed that increasing the price of CTT stock would help him to be named permanent CEO.

The ringleader of the manipulation scheme was a broker named Chauncey Steele. In thousands of telephone calls Steele discussed with the other brokers and former brokers the timing, sequence and quantity of manipulative trades and directed the CEO of CTT to make trades that further the manipulation scheme using CTT's stock repurchase plan. Although other trade-based manipulation techniques were involved, such as matched trades, the principal focus of the manipulation scheme was closing price manipulation. More than 40% of the manipulators' purchases of CTT were made within the last hour before the market close and more than 20% were made in the last half hour. During the manipulation period Steele telephoned his customers urging them buy CTT. Steele also placed buy orders without obtaining his customers' consent. Steele often divided his customers' orders into several late-day purchases in a single customer's account, for example, on one occasion he placed four buy orders in the last 15 minutes of trading for one client.

The outcomes of this case are different for the eight defendants and include conviction by a federal jury and various settlements. Defendants McPike and Kocherhans have been ordered to pay civil penalties of $60,000 and $50,000 respectively, Steele ordered to pay disgorgement of $47,439 and a civil penalty of $110,000, plus prejudgment interest, Steel barred from association with any broker, dealer or investment adviser Glushko ordered to pay $10,000 disgorgement plus

[67] SEC v. Competitive Technologies, Inc et al. Civil Action No. 304 CV 1331 JCH (District of Connecticut). See http://www.sec.gov/litigation/complaints/comp18827.pdf.

$8,308 pretrial interest (which was waived based on Gushko's financial condition) and Glushko barred from association with any broker or dealer.

Case 2: RT Capital Management Inc. et al.

The Ontario Securities Commission (OSC) alleges that RT Capital Management Inc. (RT Capital), a managed investment company with approximately $34 billion under management, intentionally engaged in 53 instances of closing price manipulation between October 1998 and March 1999 in 26 different Canadian equity securities.[68] The manipulation was conducted by several fund managers on month-end days with the intention of inflating reported performance for the fund to collect more management fees and managers to earn greater remuneration.

Most of the closing price manipulations were ordered by Peter Larkin, a director of RT Capital and the senior portfolio manager in the Canadian Equities section to whom the six other portfolio managers in that section report. Larkin instructed two of RT Capital's "order executioners" or Senior Equity Traders to conduct the manipulative trades. The remaining closing price manipulations were ordered by Gary Baker, RT Capital's Canadian Equity Small Capitalization Fund's sole manager.

RT Capital determined the value of the Canadian Equity component of any given portfolio by multiplying the number of shares in a particular security by the closing price for each security in the portfolio. Larkin's and Baker's closing price manipulations resulted in a total increase in the RT Capital Canadian Equities component of approximately $30,186,168 and $8,376,110 respectively. RT Capital benchmarked its equity portfolio performance to the TSE300 index and the managers were expected to match or better the index. RT Capital Management charged management fees based on a percentage of the average value of the client's assets

[68] OSC litigation releases in the matter of RT Capital Management Inc et al. (http://www.osc.gov.on.ca/Enforcement/Proceedings/SOA/soa_20000629_rtcapitaletal.jsp).

under management. Portfolio managers and trade executioners received a base salary and participated in the company's profit sharing plan by receiving phantom equity and annual bonuses based on the profitability of RT Capital.

The outcome of this case was a settlement with RT Capital ordered to pay the OSC $3,000,000 and the costs of the investigation and hearing (approximately $150,000) to be used for the benefit of investors in Ontario as well as being ordered to submit an expert review of their trading practices, restate misleading fund values and results and configure a telephone recording system for all conversations between fund managers and order executioners. The individuals involved in the manipulation were ordered to pay the OSC $8,000 each, had their registrations suspended for periods of between one month and life, were suspended from trading and barred from holding the title of director or officer of any market participant for varying periods of time up to life.

Case 3: Spear, Leeds & Kellogg/ Baron Capital Inc. et al.

The US SEC alleges that Baron Capital Inc. manipulated the closing prices of stock in Southern Union Company (SUG) by placing buy orders at or near the close of the market.[69] This manipulation was conducted during a period when the closing price of SUG determined the consideration paid by SUG in a pending corporate acquisition.

Baron Capital, during the period of closing price manipulations, was a broker-dealer for several affiliated investment advisory firms that had approximately $8.6 billion under management. SUG and Pennsylvania Enterprises (PNT) entered into a merger agreement whereby SUG would acquire PNT for a combination of cash and stock determined by the average closing price of SUG over a 10-day period starting

[69] SEC Administrative Proceeding file number 3-11189 (http://www.sec.gov/litigation/admin/34-48199.htm) and SEC Administrative Proceeding file number 3-11096 (http://www.sec.gov/litigation/admin/34-47751.htm).

on 19 October 1999. The higher the closing price of SUG during this period, the less cash SUG would pay for the acquisition. As of 15 October 1999, the client accounts managed by the Baron affiliates owned more than 10% of the shares in SUG.

The CEO of Baron Capital instructed Baron Capital's traders to place the manipulative buy orders. During the five trading days from 20 October the largest single purchases of SUG by Baron occurred at 15:59 or 16:00, when the NYSE closes. Baron Capital made the closing trade on seven of the 10 days in the pricing period and accounted for approximately 78% of the volume in that period. Baron Capital traded an average of 70,230 shares in SUG per day during the pricing period whereas their daily average in the two weeks preceding the pricing period was 19,530.

The SEC, in their litigation documents, use recorded telephone conversations between the CEO of Baron Capital, Baron's traders and Spear, Leeds & Kellogg (SLK) trading clerks to clearly demonstrate that the CEO of Baron Capital placed orders with the intent of closing price manipulation.[70] These recorded telephone conversations also demonstrated that two of Baron Capital's traders were knowingly partaking in the manipulation and that SLK order clerks executed Baron's orders without regard for the lowest or best price available. Consequently SLK also had legal action taken against them by the SEC for failing to reasonably supervise employees that aided and abetted closing price manipulation.

The outcome of this case was a settlement with Baron Capital ordered to pay a civil penalty of $2,000,000, the CEO of Baron Capital ordered to pay a civil penalty of $500,000 and two of Baron Capital's traders ordered to pay civil penalties of $125,000 and $75,000. SLK also settled and among other requirements was ordered to pay civil penalties and fines totalling $450,000.

[70] Some examples of recorded conversation provided in the litigation materials include: instructions such as "drive the price up a little bit", "I had trouble yesterday when it didn't close where I wanted it to close so make sure it closes"; questions such as "it's the closing price that matters, right?"; requests such as "give me some more sugar to buy. Somebody came in through the system with 16,000"; and comments such as "making the world believe there's a rally happening in this stock".

Case 4: John Andrew Scott et al.

RS alleges that an investment advisor, John Scott, and his sales assistant, Linda Malinowski, knowingly placed trades intended to manipulate the closing prices of stock in Helix BioPharma Corp. (HBP).[71] The manipulative trades were placed on behalf of clients in relation to private placements of HBP shares. One of the clients was in charge of investor relations at HBP and another was the managing director of a company that entered into a finder's fee agreement with HBP for the private placements (client D).

In January 2000, HBP shareholders passed a resolution allowing HBP to issue, in one or more private placements, common shares up to the total number of issued and outstanding common shares as at November 1999. Scott attended the meeting at which the resolution was passed. Around the time of applications made by HBP to the TSX for price protection for the private placements Scott and Malinowski submitted trades on behalf of clients with the intent of manipulating the closing prices of HBP stock. On 37 trading days in the relevant period orders executed by Scott or Malinowski set the closing price on an uptick (a trade at a price higher than the previous trade) and most of the orders placed during this period resulted in trades that took out the offer and moved it up. The trades made by client D set the closing price on the days that HBP's initial application for price protection was based upon and on the day that the TSX's extension of price protection was based upon. It is not made clear in the litigation documents exactly how Scott and Malinowski benefited from their knowing participation in the manipulation or how their clients benefited besides the fact that some of the clients had interests in the private placements and the statement that the manipulation increased the value of the shareholdings of the clients.

The outcome of this case was settlements for Scott, Malinowski and Matthew Linden, the supervisor of Scott and Malinowski, with RS. Scott was suspended from

[71] RS Statement of allegations (OOS 2003-010) (http://docs.rs.ca/ArticleFile.asp?Instance=100&ID=F78AB14F67984C7BBE6AC9F512D86445)

access to the marketplace for two years and ordered to pay a fine of $150,000, an additional fine of $53,757 representing the financial benefit to Scott and costs of $35,000. Malinowski was ordered to pay a fine of $10,000 and re-sit the Conduct and Practices Handbook exam to continue to act as a registered representative. Linden was ordered to re-sit the Examination for Branch Managers and pay a fine of $50,000 and costs of $12,500.

Case 5: Douglas Christie

Market Regulation Services Inc. (RS) alleges that Douglas Christie, a trader and partner with the small Toronto firm the Independent Trading Group, knowingly manipulated the closing prices and bids of stock in computer chip manufacturer, Mosaid Technologies Inc (MSD).[72] RS alleges Christie did this to benefit his own financial position on the basis that his remuneration from Independent Trading Group was calculated on the marked-to-market value of his trading account.

Christie commenced employment with Independent Trading Group in 1994. Independent Trading Group paid Christie 100% of his trading profits after deducting trading costs. In calculating trading profits from the value of Christie's trading account, Independent Trading Group priced long positions at the closing bid. As an example of how Christie's manipulation affected his remuneration, on 28 February 2001, Christie's account was long 20,372 shares of MSD, representing 53% of the total value of his trading account. By manipulating the MSD, Christie reduced his unrealised loss on MSD by $14,260 and therefore also increased his remuneration by $14,260.

The outcome of this case was a settlement for Douglas Christie with RS. Christie agreed to pay a fine of $15,000, plus $6,000 in regulatory costs.

[72] RS Statement of allegations (OOS 2002-002) (http://docs.iiroc.ca/DisplayDocument.aspx?DocumentID=8A7BF830C66B451F84F0183C654B006B&Language=en).

Case 6: Schultz Investment Advisors Inc.

The US Securities and Exchange Commission (SEC) alleges that Scott Schultz, President and founder of Schultz Investment, engaged in closing price manipulation of four thinly-traded closed-end funds to boost the reported performance results of their client's portfolios.[73] Shultz Investments held approximately 90% of clients' assets in the funds which it manipulated. As a result of the manipulation Schultz Investment benefited by collecting more management fees from the overstated portfolio performance results. Schultz Investment, at the time of manipulation charges fees based on a percentage of assets under management calculated based on the quarterly value of client holdings.

The closing price manipulations were conducted on quarter-end days over a period of at least 18 months. They were conducted by placing large buy orders at the end of the trading day, often within five minutes of the market close. The trades used to manipulate closing prices often constituted approximately one-third to one-half of the day's trading volume. As an example, at 3:57pm, three minutes before the market close, on the last trading day of the fourth quarter of 2003, Schultz investments placed a market buy order on the NYSE for 80,750 shares of BIF. This order constituted 76% of the day's trading volume in BIF. As a result, the price of BIF rose from $5.90 prior to the trade to close at $6.30. In addition to closing price manipulation Schultz Investment misrepresented its investment strategies to its clients. According to the calculations contained in the SEC litigation release[74] the closing price manipulation conducted by Schultz Investment on the last trading day of 2003 caused an increase in the value of four of Schultz Investment's portfolios of $1,322,763 from a value of

[73] SEC v. Schultz Investment Advisors and Scott Schultz (http://www.sec.gov/litigation/admin/33-8650.pdf)

[74] SEC v. Schultz Investment Advisors and Scott Schultz (http://www.sec.gov/litigation/admin/33-8650.pdf)

$28,863,328 immediately prior to the manipulation. It is alleged that the overstated performance of Schultz Investment as a result of manipulation contributed to increased media coverage and significant growth in assets under management.

The SEC, in their litigation documents, use recorded telephone conversations between Scott Schultz and the employees of a brokerage firm's trading desk to clearly demonstrate that Schultz placed orders with the intent of closing price manipulation.[75] The outcome of this case was a settlement with Schultz Investment ordered to pay disgorgement, prejudgment interest and civil penalties totalling $114,534.00.

Case 7: Research Capital Corporation

Market Regulation Services Inc. (RS) alleges that Alfred Gregorian, an investment advisor at Research Capital Corporation knowingly participated in his clients' use of closing price manipulation of securities in International Wex Technologies (WXI).[76] The manipulation, which occurred between September 2002 and January 2004, was ordered by insiders of WXI with the purpose of supporting the market in WXI shares by creating a misleading appearance of strength and stability.

Insiders at WXI, including the COO and two employees in the investor relations/corporate communications department, used accounts of two of Gregorian's clients (identity withheld in litigation documentation) in which they held trading authorisations to place the manipulative orders. The price support strategy involved placing buy orders, particularly at the end of the trading day, when the price was under pressure. The vast majority of buy orders were for small volumes and resulted in no economic benefit to the clients. Many purchases were entered at prices significantly above the last traded price in the final minutes of a trading session.

[75] Some examples of recorded conversation provided in the litigation materials include, "I need the last tape… it's important. I am at quarter end…the last trade has to show $15.50… the newspaper will show $14.98… that costs me a lot of money… I bill on a quarterly basis".

[76] RS Litigation release (DN 2006-003) (http://docs.rs.ca/ArticleFile.asp?Instance=100&ID=6283C3A64E2244BCAB8AE71730EE55E8)

There was also a pattern of periodically selling WXI shares in larger volumes, often at prices below the purchase price, to provide the necessary cash flow in the clients' accounts to enable further buying of WXI shares. As a result there is no indication that the accounts used for the manipulative trading were intended to be profitable. At least one way in which Gregorian benefited from knowing participation in the manipulation scheme was the commissions he earned from the high level of trading activity ($19,850 of which Gregorian's share was 50%). However, it is not made clear in the litigation documents what the incentive of WXI's insiders was in ordering the manipulative trades.

The outcome of this case is a settlement between RS and Gregorian whereby Gregorian was suspended from access to the marketplace for five years and ordered to pay a fine of $55,260.

Case 8: Luc St Pierre

Market Regulation Services Inc. (RS) alleges that Luc St Pierre knowingly manipulated the closing prices of two TSX Venture Exchange listed stocks: Halo Resources Ltd (HLO) and Golden Hope Mines Ltd (GNH).[77] St Pierre was an investment advisor at Union Securities. The manipulation occurred between October 2004 and September 2005. RS alleges St Pierre did this on behalf of a group of clients: a director of GNH, clients associated with the director of GNH and a sophisticated investor. The clients of St Pierre that were involved in the manipulation remain anonymous in the litigation documents and the motivation behind the manipulation is not clear beyond creating misleading appearance of trading in the companies' shares.

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[77] RS Statement of allegations (OOS 2007-010) (http://docs.iiroc.ca/DisplayDocument.aspx?DocumentID=4430E8DA2D8340C98071D0299C0A4B35&Language=en).

The outcome of this case was conviction of Luc St Pierre by the Market Regulation Services Inc. Hearing Panel. St Pierre was ordered to pay a fine of $30,000, plus $70,000 in regulatory costs. The Panel also suspended St Pierre from all marketplaces regulated by the Investment Industry Regulatory Organization of Canada (IIROC) for a period of five years.

Appendix C

Formulae for day-end trading characteristics

All variables are calculated in 'real-time' and 'transaction-time'. The real-time intervals are defined by x, which takes the values of x = 15, 20, 30, 60, 90 minutes prior to the close of the market. The transaction-time intervals are defined by y, which takes the values of y = 1, 2, 3 and 4 representing the last trade before the close, the second, third and fourth to last trades before the close, respectively.

Formulae of day-end variables in real-time and transaction-time are as follows.

i	Real-Time Variable, $R_{i,x}$	Transaction-Time Variable, $T_{i,y}$
Return (%)	$\ln\left(\frac{P_{close}}{M_x}\right)\times 100$	$\ln\left(\frac{P_{close}}{M_y}\right)\times 100$
Reversal (%)	$\ln\left(\frac{P_{do,close}}{M_{d1,morning}}\right)\times 100$	$\ln\left(\frac{P_{do,close}}{M_{d1,morning}}\right)\times 100$
Frequency (trades per hour)	$\left(\frac{n_x}{x}\right)\times 60$	$\left(\frac{y}{t_{close}-t_y}\right)\times 60$
Spread (%)	$\left(\frac{S_{close}}{M_x}\right)\times 100$	$\left(\frac{S_{close}}{M_y}\right)\times 100$
Abnormal trade size (%)	$\left(\frac{Value_x - Value_{daily}}{Value_{daily}}\right)\times 100$	$\left(\frac{Value_y - Value_{daily}}{Value_{daily}}\right)\times 100$

The other variables are defined as follows:

P_{close} is the closing price;

M_x is the bid-ask midpoint x minutes before the close;

M_y is the bid-ask midpoint just prior to the y^{th} last trade;

$P_{do,close}$ is the closing price on the current day;

$M_{d1,morning}$ is the bid-ask midpoint at 11am the following day;

n_x is the number of trades in the last x minutes before the close;

t_{close} is the time of the close;

t_y is the time of the y^{th} last trade;

S_{close} is the bid-ask spread at the close equal to the ask price minus the bid price;

$Value_x$ is the mean value per trade of the trades in the last x minutes before the close;

$Value_{daily}$ is the mean value per trade of all the values traded during the day; and

$Value_y$ is the mean value per trade of the last y trades before the close.

The value of x used in the real-time analysis is the smallest of the intervals 15, 20, 30, 60 and 90 minutes prior to the close that has at least one trade in the interval. If a stock has no trades in the 90 minute interval, then the variables are measured from the last trade. This allows the interval to capture the trades that take place closest to the close while making the interval as small as possible so as to not dilute the effects of the manipulator's trades. The value of y in transaction-time is the value from the set {1, 2, 3, 4} that maximises the return from bid-ask midpoint to the close. Trades made by manipulators are likely to have high values of return to the close and therefore this interval is likely to capture the manipulator's trades (if present) with the least amount of dilution from non-manipulative trading activity. The real-time and transaction-time variables are combined by taking the maximum of corresponding variables in both transaction-time and real-time.

Formulae of day-end variables that combine intervals from real-time and transaction-time are as follows.

	Real-Time	Transaction-Time
Combined interval variable i=1,2,...5 corresponding to the five previously defined variables	$R_i^{combined} = R_{i,x} \;\Big|$ $x = \min\{15,20,30,60,90\}$ minutes for which there is at least one trade in the interval	$T_i^{combined} = T_{i,y} \;\Big|$ y maximises the value of $\left[\ln\left(\frac{P_{last}}{M_y}\right)\times 100\right]$
Day-end variable i=1,2,...5 corresponding to the five previously defined variables	$Y_i = \max\{R_i^{combined}, T_i^{combined}\}$	

Appendix D

Selected robustness tests

This appendix reports the results of selected robustness tests from Chapter 4. Tables D.1 and D.2 replicate the difference-in-differences and matched stock analysis (Tables 4.2 and 4.3) using means instead of medians. The results using means are similar to those using medians. The mean estimates tend to be larger than the medians, consistent with the fact that the few extreme instances of manipulation (likely to be those that lead to detection) influence the mean more than the median. The means across different groups also tend to be more dispersed and some of the mean estimates appear to be influenced by outliers, not only among the prosecuted manipulation but also in the other stock-days.

Table D.1
Replication of Table 4.2 with means

This table replicates Table 4.2 (effects of manipulation on day-end trading characteristics) estimating difference-in-differences with *means* instead of *medians*.

Panel	Group	n	Return (%)	Reversal (%)	Frequency (trades per hour)	Spread (%)	Abnormal Trade Size (%)
A: Manipulated stocks on manipulated days	ALL	184	3.12	2.63	17.56	3.82	22.4
	Consecutive	124	2.99	1.67	17.75	3.78	-10.0
	Month-end	60	3.40	4.69	17.15	3.90	92.1
	High turnover	113	2.68	1.26	21.05	3.40	18.4
	Low turnover	71	3.78	4.69	12.33	4.44	28.5
B: Manipulated stocks prior to manipulation	ALL	7,728	1.31	-0.27	6.39	3.06	-0.7
	Consecutive	5,208	1.64	-0.31	7.03	3.21	-5.7
	Month-end	2,520	0.60	-0.18	5.02	2.75	10.1
	High turnover	4,746	1.52	-0.33	8.82	2.57	-3.0
	Low turnover	2,982	0.99	-0.17	2.74	3.81	2.7
C: Before-after estimator for manipulated stocks	ALL	7,912	1.81**	2.90**	11.17**	0.75*	23.1
	Consecutive	5,332	1.35**	1.98**	10.72**	0.57*	-4.3*
	Month-end	2,580	2.80**	4.86**	12.14**	1.15*	82.0*
	High turnover	4,859	1.16**	1.59**	12.22**	0.83	21.3
	Low turnover	3,053	2.79**	4.86**	9.59**	0.63	25.8
D: Before-after estimator for non-manipulated stocks	ALL	5,954,856	0.07	-0.32	2.24*	-0.12	8.9**
	Consecutive	4,193,920	0.02	0.18	0.42	-0.17	0.6
	Month-end	1,760,936	0.17	-1.35**	5.99*	-0.02	26.0**
	High turnover	4,095,032	0.01	-0.02	2.41	0.09**	11.5
	Low turnover	1,859,824	0.15	-0.81	1.96*	-0.46**	4.8**
E: Median difference-in-differences estimator	ALL	5,962,768	1.75**	3.26**	8.83**	0.86*	15.4
	Consecutive	4,199,252	1.34**	1.84**	10.08**	0.71**	-5.0**
	Month-end	1,763,516	2.63**	6.32**	6.14**	1.19	59.2*
	High turnover	4,099,891	1.15**	1.63**	9.71**	0.71*	11.8
	Low turnover	1,862,877	2.65**	5.71**	7.51**	1.08*	20.8

Table D.2
Replication of Table 4.3 with means

This table replicates Table 4.3 (effects of manipulation on day-end trading characteristics) estimating matched stock differences with *means* instead of *medians*.

Panel	Group	n	Return (%)	Reversal (%)	Frequency (trades per hour)	Spread (%)	Abnormal Trade Size (%)
A: Manipulated stocks on manipulation days (I)	ALL	184	3.12	2.63	17.56	3.82	22.4
	Consecutive	124	2.99	1.67	17.75	3.78	-10.0
	Month-end	60	3.40	4.69	17.15	3.90	92.1
	High turnover	113	2.68	1.26	21.05	3.40	18.4
	Low turnover	71	3.78	4.69	12.33	4.44	28.5
B: Matched stocks on manipulation days (II)	ALL	184	0.72	-1.19	7.19	3.04	19.7
	Consecutive	124	0.56	-0.66	6.60	3.39	16.5
	Month-end	60	1.06	-2.34	8.48	2.30	26.4
	High turnover	113	0.70	-0.44	8.85	2.42	29.7
	Low turnover	71	0.75	-2.33	4.71	3.97	4.7
C: Cross-sectional differences (I-II)	ALL	184	2.40**	3.83**	10.37**	0.78**	2.8
	Consecutive	124	2.42**	2.33**	11.15**	0.39*	-26.5*
	Month-end	60	2.34**	7.03**	8.68**	1.61**	65.6*
	High turnover	113	1.98**	1.70**	12.20**	0.98**	-11.3
	Low turnover	71	3.02**	7.01**	7.62**	0.47	23.8

As an alternative to the median difference-in-differences analysis, I estimate a panel regression with a dummy variable for manipulation. This is econometrically similar to mean difference-in-differences. I use double clustered Thompson (2009) standard errors. Table D.3 reports the results.

Table D.3
Panel regression with manipulation dummy variable

This table reports the results of the panel regression:

$$Y_{it} = \beta_0 + \beta_D D_{it} + \mu_i + \mu_t + \varepsilon_{it}$$

with each of the trading characteristics (return, reversal, frequency, spread and trade size - defined in Appendix C) in turn as the dependent variable (Y_{it}), manipulation dummy variables (D_{it}), stock and date fixed effects (μ_i and μ_t) and Thompson (2009) double clustered standard errors. T-statistics are reported in parentheses and significance at the 1%, 5% and 10% levels is indicated by ***, ** and *, respectively. *High turnover* stocks are defined as having more than ten trades per day on average in the benchmark period (42 trading days lagged one month) and vice versa. *Consecutive* refers to stocks that are manipulated over several consecutive days. *Month-end* refers to non-consecutive occurrences of manipulation on month-end days.

Group	Return (%)	Reversal (%)	Frequency (trades per hour)	Spread (%)	Abnormal Trade Size (%)
ALL	2.68***	2.99***	7.71***	0.78	-22.96
	(6.25)	(2.61)	(2.86)	(1.34)	(-0.87)
Consecutive	2.56***	2.09***	10.70***	0.65	-38.29**
	(4.88)	(4.27)	(5.65)	(0.78)	(-2.17)
Month-end	2.94***	4.90**	5.83	1.25*	4.37
	(3.98)	(2.09)	(0.31)	(1.67)	(0.09)
High turnover	2.15***	1.41**	9.19***	1.00	-32.11
	(3.14)	(2.50)	(4.14)	(0.98)	(-0.99)
Low turnover	3.52***	5.43**	6.83	0.29	-21.84
	(6.92)	(2.13)	(1.24)	(0.40)	(-0.62)

The signs of the coefficients are largely consistent with the median difference-in-difference estimates, but the estimated magnitudes of the effects tend to be larger. The larger magnitude is consistent with the fact that outliers or extreme instances of manipulation (such as those that would have triggered alerts in regulator surveillance systems) have a larger influence on the coefficients in the panel regression than in an analysis of medians. The levels of statistical significance are similar to those in the median difference-in-differences analysis, although they tend to be lower for frequency and spreads. This may be partly due to the presence of outliers.

Table D.4 replicates the difference-in-differences analysis with a randomly chosen single day from the 42 day benchmark. The results are similar to those using a 42 day benchmark, in terms of the point estimates and levels of statistical significance.

Table D.4
Replication of Table 4.2 with single day benchmark

This table replicates Table 4.2 (effects of manipulation on day-end trading characteristics) but instead of using 42 days in the trading history benchmark, one day is selected at random from the 42 day benchmark.

Panel	Group	n	Return (%)	Reversal (%)	Frequency (trades per hour)	Spread (%)	Abnormal Trade Size (%)
A: Manipulated stocks on manipulated days	ALL	184	2.60	1.71	12.00	3.27	-5.0
	Consecutive	124	2.94	2.12	12.17	3.36	-31.3
	Month-end	60	2.20	1.10	12.00	2.26	37.8
	High turnover	113	2.16	1.38	16.06	2.53	-13.3
	Low turnover	71	3.58	2.10	10.12	3.91	0.0
B: Manipulated stocks prior to manipulation	ALL	184	0.89	-0.16	3.18	1.80	-11.0
	Consecutive	124	1.07	-0.61	3.18	1.80	-13.3
	Month-end	60	0.24	0.07	1.70	2.42	35.1
	High turnover	113	0.16	-0.61	3.18	1.54	-13.3
	Low turnover	71	1.07	0.00	1.00	3.23	0.0
C: Before-after estimator for manipulated stocks	ALL	368	1.68**	1.82**	8.92**	0.60**	0.0
	Consecutive	248	1.41**	2.65**	9.22**	0.90**	-15.4
	Month-end	120	2.13**	0.68**	7.75**	-0.25	25.3
	High turnover	226	1.54**	1.46**	9.80**	0.49*	-3.0
	Low turnover	142	2.29**	2.03**	8.00**	0.75	0.0
D: Before-after estimator for non-manipulated stocks	ALL	241,644	0.00	0.00	0.07*	0.00	0.0
	Consecutive	170,186	0.00	0.00	0.00	0.02	0.0
	Month-end	71,458	0.01	-0.37**	0.47**	0.00	3.5*
	High turnover	166,173	0.00	0.00	0.02	0.03*	0.0
	Low turnover	75,471	0.00	-0.16	0.17*	-0.07**	0.0
E: Median difference-in-differences estimator	ALL	242,012	1.76**	1.93**	8.48**	0.58**	-6.7
	Consecutive	170,434	1.46**	2.57**	9.20**	1.35**	-13.3
	Month-end	71,578	2.05**	1.08**	7.47**	-0.24	0.0
	High turnover	166,399	1.57**	1.47**	9.76**	0.53*	-12.6
	Low turnover	75,613	2.05**	2.05**	7.63**	0.83**	0.0

Table D.5 reports the results of the difference-in-differences analysis conducted separately for each manipulation prosecution case. The results demonstrate the variation in the effects of manipulation across cases. Most of the variation is due to differences in the manipulator's incentives, strategy and targeted stock. Overall, the effects of manipulation in individual cases are consistent with the main conclusions of Chapter 4. In each case manipulation causes abnormal returns, return reversals and abnormal trading frequency. In most cases manipulation leads to wider spreads and the effects of manipulation on trade size are mixed.

Table D.5
Replication of Table 4.2 separately for each prosecution case

This table replicates Table 4.2 (effects of manipulation on day-end trading characteristics), estimating difference-in-differences separately for each manipulation prosecution case (*Prosec. case*). The case numbers correspond to the cases (in Appendix B) as follows: 1=RT Capital; 2=John Scott; 3=Alfred Gregorian; 4=Schultz Investment Advisors; 5=Spear, Leeds & Kellogg; 6=Competitive Technologies; 7=Luc St Pierre; and 8=Douglas Christie.

Panel	Prosec. case	n	Return (%)	Reversal (%)	Frequency (trades per hour)	Spread (%)	Abnormal Trade Size (%)
A: Manipulated stocks on manipulated days	1	39	2.95	1.44	11.23	4.44	5.88
	2	47	4.06	2.70	8.60	4.93	-49.68
	3	14	3.29	2.59	14.00	1.92	-28.76
	4	21	0.47	0.40	18.29	0.45	306.00
	5	10	1.47	1.10	13.97	1.24	126.33
	6	29	1.94	0.83	24.00	2.96	-30.35
	7	20	3.73	2.36	8.31	4.12	-35.79
	8	4	0.87	0.58	14.62	0.23	-58.62
B: Manipulated stocks prior to manipulation	1	1,638	0.72	0.00	1.00	3.00	0.00
	2	1,974	2.09	-0.46	5.63	2.76	-34.52
	3	588	1.96	0.56	1.61	2.97	-10.45
	4	882	0.22	-0.15	8.00	0.36	7.79
	5	420	0.45	0.15	8.00	1.18	0.00
	6	1,218	1.25	0.59	6.07	2.42	-10.19
	7	840	1.06	-0.25	2.27	3.73	-5.05
	8	168	0.16	-0.05	10.96	0.51	-18.51
C: Before-after estimator for manipulated stocks	1	1,677	2.18**	1.37**	10.23**	0.22	5.88
	2	2,021	1.97**	3.17**	2.97**	2.17**	-15.16
	3	602	1.33	2.03**	12.39**	-1.05	-18.31
	4	903	0.25	0.48	7.06**	0.04	298.21**
	5	430	1.02**	0.94	5.97**	0.06	126.33**
	6	1,247	0.69	0.24	17.93**	0.53	-20.16
	7	860	2.67**	2.61**	6.03**	0.39	-30.74
	8	172	0.71	0.63	3.66	-0.28	-40.10
D: Before-after estimator for non-manipulated stocks	1	1,236,438	0.10	-0.46**	0.77	-0.04**	0.13**
	2	1,800,540	-0.01	0.00	-0.28**	-0.01	0.00
	3	331,422	-0.09	-0.01	0.48	-0.96*	0.00*
	4	483,546	-0.02	-0.10	3.96**	0.02	192.36**
	5	1,182,006	0.01	-0.24	0.70**	0.05**	2.81
	6	374,976	0.00	0.00	0.06	0.07*	0.00
	7	354,480	0.08	0.26*	0.01	-0.60	0.00
	8	62,580	-0.05	0.06	-0.38	0.06	0.00
E: Median difference-in-differences estimator	1	1,238,115	2.02**	2.29**	8.89**	0.34	5.52
	2	1,802,561	1.83**	3.10**	3.04**	2.21**	-10.10
	3	332,024	1.46*	2.11**	12.07**	0.16	-16.44
	4	484,449	0.29*	0.44	5.59**	-0.02	84.66*
	5	1,182,436	1.01**	1.08*	4.04	0.01	126.67*
	6	376,223	0.60	0.24	17.64**	0.37*	-20.16
	7	355,340	2.30*	2.10**	6.07**	0.63*	-30.74*
	8	62,752	0.82	0.82	3.70	-0.08	-39.02

I examine the robustness of the results to the way the day-end variables are calculated. Table D.6 reports estimates of the effects of manipulation in each real-time and transaction-time window separately (not using a maximum operator).

Table D.6

Replication of Table 4.2 with alternative day-end windows

This table replicates Table 4.2 (effects of manipulation on day-end trading characteristics) using each of the real- and transaction-time intervals separately. *Combined* refers to the variables calculated by combining values from the real- and transaction-time intervals as detailed in Appendix C. *Re15*, *Re30*, *Re60* and *Re90* refer to variables calculated in the real-time intervals of 15, 30, 60 and 90 minutes prior to the close. *Tr1*, *Tr2*, *Tr3* and *Tr4* refer to variables calculated in the transaction-time intervals corresponding to the last, second to last, third to last and fourth to last trades for the day. To maintain a consistent sample, when the value of a variable cannot be calculated in a particular interval the value is taken from the closest interval in which it can be calculated (e.g., if a stock only has three trades on a particular day, return in the *Tr4* interval is calculated from the third to last trade). Reversal does not depend on the interval because it is calculated from the closing price to the following morning's bid-ask midpoint.

Panel	Interval	n	Return (%)	Reversal (%)	Frequency (trades per hour)	Spread (%)	Abnormal Trade Size (%)
A: Manipulated stocks on manipulated days	Combined	184	2.60	1.71	12.00	3.27	-4.98
	Re15	184	1.81	1.71	8.00	3.27	-27.17
	Re30	184	2.07	1.71	6.00	3.25	-20.15
	Re60	184	2.06	1.71	4.00	3.25	-2.03
	Re90	184	2.04	1.71	3.33	3.25	-4.09
	Tr1	184	1.31	1.71	11.15	3.25	-50.08
	Tr2	184	1.65	1.71	12.63	3.27	-32.85
	Tr3	184	1.75	1.71	8.66	3.27	-14.73
	Tr4	184	1.99	1.71	6.20	3.25	0.00
B: Manipulated stocks prior to manipulation	Combined	7,728	1.25	0.00	5.63	2.76	-10.19
	Re15	7,728	0.42	0.00	4.00	2.72	-22.29
	Re30	7,728	0.46	0.00	4.00	2.72	-17.82
	Re60	7,728	0.53	0.00	3.00	2.73	-10.49
	Re90	7,728	0.60	0.00	2.33	2.71	-7.64
	Tr1	7,728	0.31	0.00	6.21	2.75	-30.55
	Tr2	7,728	0.60	0.00	5.23	2.76	-9.40
	Tr3	7,728	0.42	0.00	3.46	2.74	0.00
	Tr4	7,728	0.32	0.00	2.71	2.72	0.00
C: Before-after estimator for manipulated stocks	Combined	7,912	1.42**	1.71**	7.77**	0.39**	5.79
	Re15	7,912	1.26**	1.71**	4.00**	0.41**	6.52
	Re30	7,912	1.63**	1.71**	4.00**	0.43**	5.43
	Re60	7,912	1.51**	1.71**	2.00**	0.43**	10.77**
	Re90	7,912	1.53**	1.71**	1.33**	0.44**	7.76**
	Tr1	7,912	0.97**	1.71**	6.08**	0.36**	-5.85
	Tr2	7,912	1.17**	1.71**	8.20**	0.35**	-5.84
	Tr3	7,912	1.35**	1.71**	5.02**	0.37**	0.00
	Tr4	7,912	1.48**	1.71**	2.77**	0.38**	0.00
D: Before-after estimator for non-manipulated stocks	Combined	5,954,856	0.00	0.00	0.08	0.00	0.00
	Re15	5,954,856	0.00	0.00	0.00	0.00	0.00
	Re30	5,954,856	0.00	0.00	0.00	0.00	0.00
	Re60	5,954,856	0.00	0.00	0.00	0.00	0.00
	Re90	5,954,856	0.00	0.00	0.00	-0.01	0.00
	Tr1	5,954,856	0.00	0.00	0.05	0.00	0.00
	Tr2	5,954,856	0.00	0.00	0.02	-0.01	0.00
	Tr3	5,954,856	0.01	0.00	0.00	0.00	0.00
	Tr4	5,954,856	0.00	0.00	0.00	-0.01	0.00
E: Median difference-in-differences estimator	Combined	5,962,768	1.46**	1.85**	7.90**	0.36**	0.00
	Re15	5,962,768	1.27**	1.85**	4.00**	0.37**	4.65
	Re30	5,962,768	1.65**	1.85**	2.00**	0.36**	2.06
	Re60	5,962,768	1.53**	1.85**	1.00**	0.34**	8.85
	Re90	5,962,768	1.47**	1.85**	0.83**	0.36**	5.13
	Tr1	5,962,768	0.97**	1.85**	5.54**	0.35**	-10.63*
	Tr2	5,962,768	1.13**	1.85**	7.64**	0.36**	-12.86*
	Tr3	5,962,768	1.43**	1.85**	4.77**	0.37**	-7.39*
	Tr4	5,962,768	1.55**	1.85**	2.58**	0.37**	0.00

Measuring the day-end variables in the different intervals does not alter the general findings about the effects of manipulation. The main difference is that the magnitude of the effects varies depending on how the day-end variables are measured. This is likely to be because, as discussed in Chapter 4, a 'one size fits all' approach to choosing an interval will either include too much normal trading in the window or miss some of the manipulator's trades, if dealing with stocks of different levels of liquidity. This is most apparent in the reduced magnitude of the frequency estimates when using the 'one size fits all' approach. To understand why this occurs, consider a stock that usually trades at a rate of one trade every five minutes and has one additional trade made by a manipulator just before the close. The increase in trade frequency in the last 10 minutes is 50%, but in the last 30 minutes it is only 17%.

Appendix E

Experiment instructions an screen layout

E.1 Instructions provided to participants

The following pages are a copy of the written instructions handed to participants in the experiment prior to the commencement of the experiment.

Experiment instructions

Welcome to this experiment in market decision making. The instructions are simple and if you follow them carefully and make good decisions you might earn a considerable amount of money which will be paid to you in cash. Before we start, there are three ground rules:

1. No communication with other subjects of any kind. If you have a question, bring it to the attention of the researchers by raising your hand.
2. All mobile phones turned off.
3. When told to use the terminal do not close any windows or rearrange the layout of the windows on your screen.

In this experiment you will trade shares of a hypothetical company XYZ with the other 11 participants in several rounds of trading. All prices and values are denominated in laboratory dollars. Once the experiment is over participants will be ranked according to how many laboratory dollars they have earned and then paid out in real dollars according to a scale ranging from $15 to $45.

How to trade

You will now learn how to use your computer to trade. Watch the demonstration on the large screen.

Notice at the bottom of the screen a countdown of the time remaining in seconds in the current trading period. Each of the trading rounds will last for 200 seconds – that does not apply to this demonstration.

Next, notice in the top right hand corner your broker ID. This ID allows you to identify your trades and orders. Below your broker ID is the amount of cash in laboratory dollars that you currently have and next to the word “Position” is the number of shares you currently own. You will start every round of trading with $200 and 4 shares.

To trade you will use the "Order Entry" window to submit orders. Orders are requests to buy or sell shares. You can toggle between buy or sell orders by clicking on the "BUY/SELL" button. In the field labelled "Volume" you will enter the amount of shares you wish to buy or sell. You can toggle between market and limit orders using the "MKT/LMT" button. A limit order is a request to buy or sell shares at a specified price, whereas a market order is an instruction to buy or sell at whatever the best available price is in the market at the time. For limit orders you specify the price at which you wish to buy or sell in the price field. Notice that when you toggle a market order the price field becomes inactive. Once you have specified information about your order you can submit it to the market by clicking on the "Submit" button. In this example I am submitting a limit order to buy 2 shares at a price of $45.

I will now demonstrate how to submit a limit order to buy 1 share at a price of $47.
I will now demonstrate how to submit a limit order to sell 3 shares at a price of $53.
I will now demonstrate how to submit a limit order to sell 1 share at a price of $51.

Notice that all of the limit orders are recorded in the "Market Depth View" window in order of price with the buy orders on the "Bid" side and the sell orders on the "Ask" side. This window will show the orders submitted by every participant. Each record shows the submitter's broker ID, the number of shares and price of the order.

Notice that your orders, while they are still active, are displayed in the "Trade Blotter" window. You can use this window to cancel your orders by clicking on the grey "C". Watch the demonstration.

Let's practice submitting limit orders. Submit a limit order to BUY 3 shares at a price equal to your trader number (Broker ID). For example, if you are "Trader 6" then submit a limit order to BUY 3 shares at a price of $6. Do this now. Were there any problems?

Submit a limit order to SELL 2 shares at a price equal to 30 plus your trader number (Broker ID). For example, if you are "Trader 6" then submit a limit order to BUY 2 shares at a price of $36 (30+6). Do this now. Were there any problems? Notice all of the orders in the "Market Depth View" window and your order in the "Trade Blotter" window.

Watch what happens when I submit a market SELL order for 1 share. The best price at which I can sell is $12 because that is the highest any participant has offered to buy shares at, so a trade occurs at this price. Notice my cash changes and "Position" (number of shares I own) also changes. Watch what happens when I submit a market BUY order for 1 share. The best price at which I can buy is $31 because that is the lowest price any participant has offered to sell shares at, so a trade occurs at this price.

Let's practice submitting market orders. Submit a market order to BUY 1 share. Do this now. Were there any problems? Submit a market order to SELL 2 shares. Do this now. Were there any problems?

Now cancel all of your remaining orders by clicking on the grey "C" in the "Trade Blotter" window. Do this now.

Notice that all of the trades are recorded in the "Time & Sales" window in the sequence that they occur. Take a look at the "Ticker Chart View" window. From the second drop-down box select "1". This window plots the prices of all trades through time. Green bars indicate trades that increase the price from the previous trade price (usually from buy orders) and white bars indicate trades that decrease the price from the previous trade price (usually from sell orders). The blue lines at the bottom of this window indicate the number of shares traded.

There are no brokerage costs associated with trading and short selling is not allowed, i.e., you cannot sell more shares than you own at that point in time. There is no margin buying, which means that the trading simulator will not allow you to place limit orders to buy shares at a cost greater than the amount of cash you have at the time. This includes the value of any active limit buy orders you have at the time. For example, if I have $200 cash and an active limit buy order for three shares at $50, i.e., value of $150, then effectively I can only place new buy limit orders for up to $50 value. This does not apply to market orders – they are executed regardless of your cash position.

Payoffs

You will now learn about the payoffs you can earn from trading. Shares in the hypothetical company XYZ have one of three possible values at the end of each round – either $20, $40 or $80 – with equal probability. At the beginning of each round, your clue sheet, the spreadsheet to the left of your trading simulator, will tell you one of the three values that will not be the ending value of the shares. This leaves two possible ending values. For example, if your clue sheet says the value is NOT $20 then the ending value of the shares must be either $40 or $80. Other participants may receive different clues.

At the end of each round the shares you own will be converted to cash using the actual ending value and added to your total payoff pool together with any cash you have left. This amount is calculated automatically and displayed at the end of the round in the "Cash" field. The actual ending value of the shares, i.e., $20, $40 or $80 will be displayed at the end of each round on your clue sheet. Your payoff for each round will be saved to a database and your total payoff pool will determine how much real money you are paid at the end of the experiment. As an example, if at the end of a round you own six shares that have an actual ending value of $40 and have $80 cash, your shares are worth 6x$40=$240, which is added to your cash amount of $80, so in total $320 is added to your payoff pool.

If your clue is that the shares do not have an ending value of $20, then you know that the ending value will be either $40 or $80 per share. In this case you could increase your payoff by buying shares for less than $40, for example $30, because at the end of the round they will be converted to either $40 or $80. You can also learn from observing other traders' orders. For example, if you know the ending value is not $40, i.e., it must be $20 or $80, and you see other traders submitting buy orders at say

$30, you might infer that those traders have been told the ending value is not $20 and therefore deduce that the ending value is likely to be $80. You can then profit by buying shares at prices less than $80. Alternatively, if you see other traders submitting sell orders at say $60, you might infer that those traders know the ending value is not $80 and therefore, if you know the ending value is not $40, you might deduce that the ending value is likely to be $20. In that case you would increase your payoff by selling shares at prices above $20.

Specific instructions for treatment 1

Take a look at the clue sheet. The first line reports the current round, in this case "Practice round". The second piece of information is the clue about the actual value of the shares. At the end of a round your clue sheet will change as will now be demonstrated. The clue sheet now reports the actual value of the shares and asks and asks you to type "OK" and hit enter. Do that now. Notice how the clue sheet now displays new information for the next round. When this occurs, read the information and wait for the next round to start.

Specific instructions for treatment 2

In some rounds, one participant may be selected at random to be a "manipulator". When this occurs, the selected participant will be informed of this fact on their clue sheet. Not all rounds will have a manipulator, the rounds which do are chosen at random. The manipulator starts each round with the same amount of shares and cash as the ordinary traders; however, the payoff for a manipulator is different from what has just been described. The manipulator receives a payoff of 15 times the difference between the price of the last trade for the round and the median price for the round. This payoff occurs regardless of the actual stock value and the manipulator's final amount of shares and cash. In addition the manipulator gets $250. The median price is the middle price when trade prices are ordered from lowest to highest. For example, if trades occur at $38, $41, $44, $52 and $58 then the median price is $44. If the last trade in the round occurs at a price of $58 then the payoff for the manipulator in this example is (\$58-\$44)x15 + \$250 = \$210 + \$250 = \$460. This example illustrates that the payoff of the manipulator is larger the higher the price of the last trade, so the manipulator should try to maximise the last trade price.

At the end of each round the clue sheet will ask ordinary traders to submit a guess as to whether or not they thought a manipulator had been selected in that round. Guesses are entered into the clue sheet using "Y" for yes and "N" for no. Correct guesses earn a bonus of \$50 added to your payoff pool and incorrect guesses cost you \$50 from your payoff pool. If you do not submit a guess you will receive a penalty of \$50. If a manipulator was selected for the round, their clue sheet will ask them to guess how many of the other 11 traders they think will guess that a manipulator was selected. Correct and incorrect guesses will earn the same bonuses and penalties as just described.

Take a look at the clue sheet. The first line reports the current round, in this case "Practice round". The second piece of information is the clue about the actual value of the shares. The third piece of information informs you whether or not you have been selected to be a manipulator for this round.

At the end of a round your clue sheet will change as will now be demonstrated. The clue sheet now reports the actual value of the shares and asks a question that must be answered before the next round starts. Let's practice answering. No one was selected as a manipulator in the practice round so enter "N" in the yellow box and hit enter. Notice how after automatically recording your guess the clue sheet displays new information for the next round. When this occurs, read the information and wait for the next round to start.

A final word of caution for those selected to be manipulators. The trading simulator does not allow limit orders with value exceeding your cash holdings. To avoid having an order rejected at a critical point in time, ensure the value of your limit orders (including any active limit buy orders you have in the market) does not exceed the amount of cash you have. For example, if you have no active limit buy orders and have \$400 cash, you may submit a buy order for 5 shares at \$80 (value of \$400), but an order for 6 shares at $80 (value of $480) would be rejected. Alternatively you may wish to use market orders as they are executed regardless of your cash position.

Specific instructions for treatment 3

In each round one participant will be selected at random to be a “manipulator”. The selected participant will be informed of this fact on their clue sheet. The manipulator starts each round with the same amount of shares and cash as the ordinary traders; however, the payoff for a manipulator is different from what has just been described.

If the manipulator trades and less than eight of the other 11 traders (approximately three quarters) guess that the manipulator traded they have avoided detection and receive a manipulation payoff of 15 times the difference between the price of the last trade for the round and the median price for the round. This payoff occurs regardless of the actual stock value and the manipulator’s final amount of shares and cash. The median price is the middle price when trade prices are ordered from lowest to highest. For example, if trades occur at $38, $41, $44, $52 and $58 then the median price is $44.

If the manipulator trades and eight or more of the other 11 traders guess that the manipulator traded they have been detected and receive a detection penalty of negative 15 times the difference between the price of the last trade for the round and the median price for the round. In addition to manipulation payoffs and detection penalties (which are zero if the manipulator does not trade) all manipulators also receive $250.

In the previous example in which the median price was $44, if the last trade in the round occurs at a price of $58 and the manipulator traded then the payoff for the manipulator that is not detected would be ($58-$44)x15 + $250 = $210 + $250 = $460. The payoff for a manipulator that is detected would be -($58-$44)x15 + $250 = -$210 + $250 = $40 and the payoff for a manipulator that chooses not to trade would simply be the $250. This example illustrates that the payoff of the manipulator that is able to avoid detection is larger the higher the price of the last trade, so the manipulator should try to maximise the last trade price.

At the end of each round the clue sheet will ask ordinary traders to submit a guess as to whether or not they thought a manipulator traded in that round. Guesses are entered into the clue sheet using “Y” for yes and “N” for no. Correct guesses earn a bonus of $50 added to your payoff pool and incorrect guesses cost you $50 from your payoff pool. If you do not submit a guess you will receive a penalty of $50. The manipulator’s clue sheet will ask them to guess how many of the other 11 traders they think will guess that they traded. Correct and incorrect guesses will earn the same bonuses and penalties as just described.

Take a look at the clue sheet. The first line reports the current round, in this case “Practice round”. The second piece of information is the clue about the actual value of the shares. The third piece of information informs you whether or not you have been selected to be a manipulator for this round.

At the end of a round your clue sheet will change as will now be demonstrated. The clue sheet now reports the actual value of the shares and asks a question that must be answered before the next round starts. Let’s practice answering. The manipulator did not trade in the practice round so enter “N” in the yellow box and hit enter. Notice how after automatically recording your guess the clue sheet displays new information for the next round. When this occurs, read the information and wait for the next round to start.

A final word of caution for those selected to be manipulators. The trading simulator does not allow limit orders with value exceeding your cash holdings. To avoid having an order rejected at a critical point in time, ensure the value of your limit orders (including any active limit buy orders you have in the market) does not exceed the amount of cash you have. For example, if you have no active limit buy orders and have $400 cash, you may submit a buy order for 5 shares at $80 (value of $400), but an order for 6 shares at $80 (value of $480) would be rejected. Alternatively you may wish to use market orders as they are executed regardless of your cash position.

Are there any questions?

The following page contains a quick reference guide of the payoffs earned in each round. If at any time you have a question please raise your hand. You must now wait for the first round of trading to start.

Payoffs at the end of each round (Tr1)

(NumberOfSharesOwned x ActualShareValue) + RemainingCash

Payoffs at the end of each round (Tr2)

For an ordinary trader (everyone unless your clue sheet says you are a manipulator)

For trading

(NumberOfSharesOwned x ActualShareValue) + RemainingCash

For guessing

$50 for a correct guess
-$50 for an incorrect guess or no guess

For a manipulator

For trading

(PriceOfLastTrade - MedianPrice) x 15 + $250

For guessing

$50 for a correct guess
-$50 for an incorrect guess or no guess

Payoffs at the end of each round (Tr3)

For an ordinary trader (everyone unless your clue sheet says you are a manipulator)

For trading

(NumberOfSharesOwned x ActualShareValue) + RemainingCash

For guessing

$50 for a correct guess
-$50 for an incorrect guess or no guess

For a manipulator

For trading

(PriceOfLastTrade - MedianPrice) x 15 + $250	if less than 8/11 of the other traders guessed that the manipulator traded
- (PriceOfLastTrade - MedianPrice) x 15 + $250	if at least 8/11 of the other traders guessed that the manipulator traded
$250	if the manipulator does not trade

For guessing

$50 for a correct guess
- $50 for an incorrect guess or no guess

E.2 Layout of experiment participants' trading screen

Figure E.1 shows a screenshot of the trading simulator and clue sheet used by participants in the experiment.

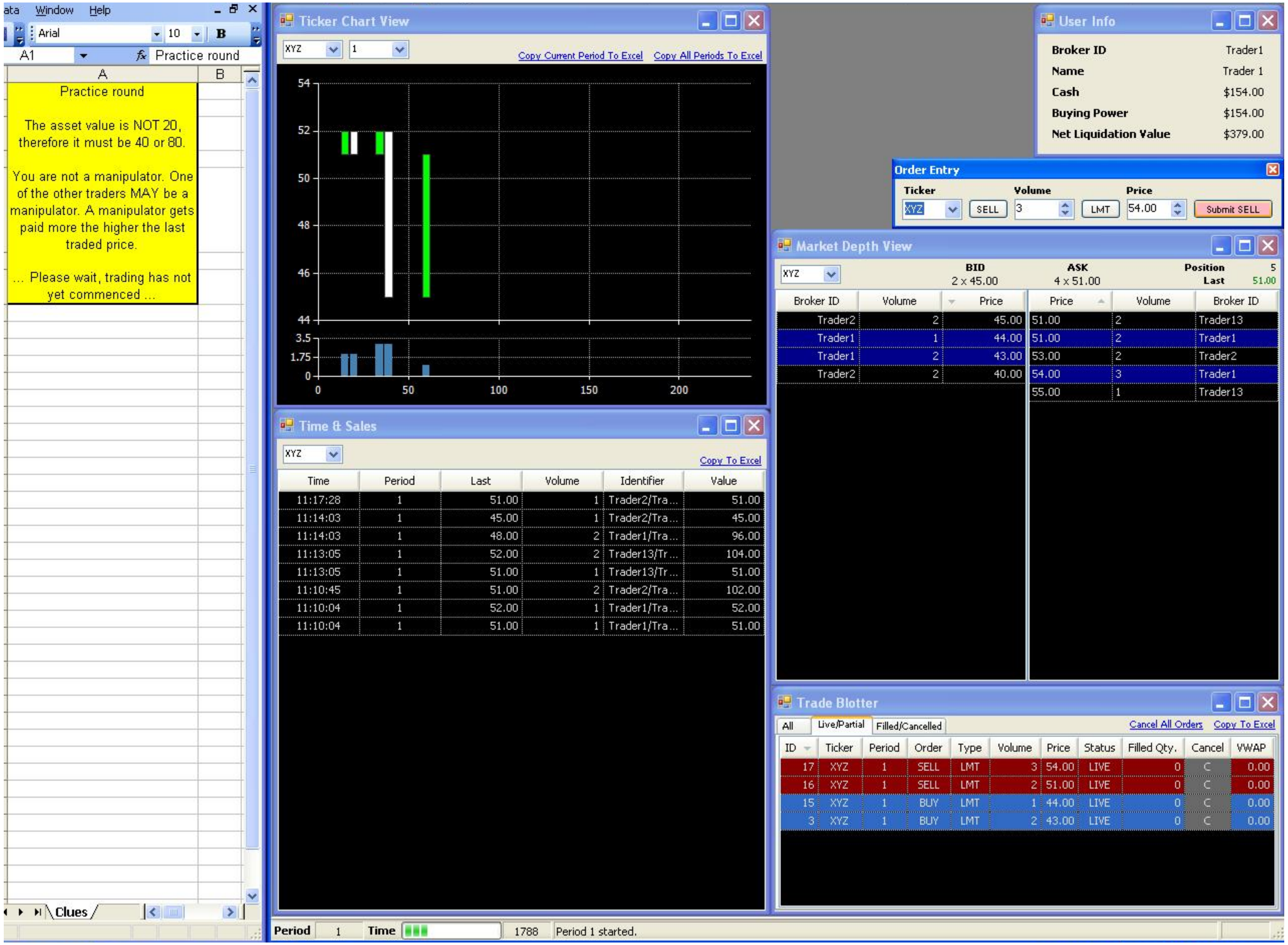

Figure E.1 Layout of experiment participants' trading screen