ABSTRACT

Title of Document: ESSAYS ON MARKET MICROSTRUCTURE

Masahiro Yamada, Doctor of Philosophy, 2012

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This dissertation studies topics on market microstructure. The first chapter theoretically studies market manipulation in stock markets in a linear equilibrium. The second chapter empirically examines the presence of opportunities for liquidity arbitrage. The last chapter develops and examines a method to capture a co-movement of informed trading.

In chapter 1, I study a theory of trade-based price manipulation in markets. I compare two different types of price manipulation studied in previous literature, uninformed and informed manipulation, in the same linear equilibrium model. I show that the presence of positive-feedback traders creates an incentive for the informed trader to bluff, but the opportunity is absent if a sufficient number of uninformed traders behave strategically. Numerical comparable statics results show that informed manipulation is more likely and more profitable when the noise trading is more volatile and that market efficiency could become worse under the presence of

manipulation. A financial transaction tax can not prevent informed manipulation, but it reduces the liquidity of the market.

Chapter 2 empirically investigates intra-day price manipulation in a stock market. My microstructure model is specifically designed to define the conditions under which a manipulation opportunity arises from the variation in liquidity as measured by price impact. My empirical analysis using data from the Tokyo Stock Exchange suggests that while there is a significant chance of uninformed manipulation across time and stock codes, it is not profitable enough to affect price fluctuations. Analysis of intraday price and trade sizes shows that the opportunity begins to disappear in 10 minutes.

Chapter 3 studies contagion in a financial market by using a market microstructure model. We extend the Easley, Kiefer, and O'Hara (1997) model to a multiple-asset framework. The model allows us to identify whether the driving forces of informed trading common or idiosyncratic information events are. We apply the method to three groups of stocks listed on the New York Stock Exchange: American Depositary Receipts (ADRs) of developed and emerging countries, and blue chips. We find contagion among emerging-country ADRs during the Asian Financial Crisis of 1997, in the sense that informed trades were mostly driven by common information events.

ESSAYS ON MARKET MICROSTRUCTURE

By

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Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2012

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To my parents.

Acknowledgements

This dissertation could not be completed without the advice and encouragement of my advisors at the University of Maryland.

First and foremost, I would like to thank my chair advisor, Albert S. Kyle for his persistent encouragement and assistance. He taught me not only about how do research, but also what a true academic profession will be like. His comments and advice have always kept me in a right track. I am really thankful to his generosity. Also, his passion and insight for economic and finance problems have enlightened me, and it is invaluable experience in my life.

I also thank the members of my dissertation committee, Prof. John Rust, Prof.Anton Korinek, Prof.Anna Obizhaeva, Prof.Steve Heston, and Prof.John Shea. They gave me insightful comments and questions, and encouraged me in every aspect of this research.

I owe a lot to Prof.Marco Cipriani, my co-author of the last chapter of this dissertation. During this joint-work at the IMF, I have learned a lot about collaborating, and how great it can be.

I would like to thank my friends and colleagues in Maryland and Japan for their encouragement and influence. I would also like to thank Vickie Fletcher for all her help on my PhD life at the University of Maryland.

Above all I would like to dedicate this dissertation to my parents Eiichi and Emiko, who have allowed me to study economics in the U.S.

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Chapter 1

Trade-Based Price Manipulation in a Linear Equilibrium

1.1. Introduction

Motivation Recently, high-frequency algorithmic trading has become widely used in markets. In the United States, high-frequency trading firms account for 73% of all equity order volume according to a recent survey[1]. Different from traditional automated trading, the algorithms run by high-tech hedge funds are finely tuned and repeat orders and cancellations millions of times a day. More surprisingly, such high-frequency trading (HFT) can earn profits consistently throughout the day, according to recent research by Kirilenko, Kyle, Samadi, and Tuzun (2011). They have net zero position at the end of a day, indicating a clear contrast with long-term buy-and-hold investment. The public's concern with HFT is growing because the public believes that such trades can potentially harm market efficiency and increase the volatility of markets.

Can traders potentially make a profit like the HFTs, using information about how stock prices are determined by strategic interactions rather than information about a firm's future cash flows? How can we identify and measure the potential profit

[1] Rob Iati, The Real Story of Trading Software Espionage, AdvancedTrading.com, July 10, 2009

opportunities? Can we regulate HFTs to improve market efficiency? In this paper, I theoretically study intraday asset trading to investigate such questions. The work presented here is strongly connected to the study of trade-based price manipulation found in the market microstructure literature. Trade-based price manipulation is a buying or selling securities in markets to earn profits by misleading other participants about the value of the securities without communication other than the trading itself.

In practice, various strategies can be utilized in trade-based manipulation, and some such strategies have been theoretically studied. Allen and Gale (1992) presents a theoretical model which supports uninformed manipulation in equilibrium when uninformed traders believe that there is informed trading. Examining a special case of trade-based manipulation, Kumar and Seppi (1992) studied theoretical price manipulation in cash settled contracts, and Brunnermeier and Pedersen (2005) theoretically investigated predatory trading which attacks stop-loss orders to drive down the price. Recently, Hasbrouck and Saar (2009) noted how the mechanism of HFT allows for the repeated cancellation and resubmission of limit orders within a second to take advantage of potential profits (called "fleeting orders"). Kirilenko, Kyle, Samadi, and Tuzun (2011) examined empirically the trading of high-frequency traders in Standard and Poor's E-mini S&P 500 futures contract and find that their positions were correlated with the past return within the space of one minute and one second. Working against these algorithmic traders, some market participants have also been known to take advantage of predictable features of algorithmic trading and to make a profit by placing spoof limit orders[2]. The algorithmic trading strategy was designed to submit market orders in response to changes in the limit order book, even though the limit orders were intended to "spoof" the algorithmic traders. In one such case, the trader was eventually ac-

[2] SESC cases on the manipulation of Hokuetsu Kishu Seishi (3865), on June 14 and 15, 2010.

cused of manipulative trading by the concerned authority. The party that actually manipulated the market is, however yet to be determined. This example illustrates that the definition of "manipulation" is wide-ranging and somewhat confusing. Therefore, before proceeding with the explanation of the measure I have devised, I will formally define the term "manipulation" in the context of this paper.

I study trade-based manipulation in a stylized model that does not consider outside of trading in the market. This implies that market participants trade and manipulate prices based on their private information and strategic interactions, but they do not spread rumors nor trade on them. I assume that there are no regulatory or administrative causes of manipulation, such as cash settlement and stop-loss orders enabling predatory trading. My study does not rely on any specific empirical events, and I can construct the model as an extension of the standard market microstructure model of Kyle (1985, 1989).

Definition of Manipulation My theory-based definitions of manipulation, or the profitability of intraday stock trading, are simple; they are described as a profitable of a round-trip trade (i.e., uninformed manipulation) or trade in a direction counter to the manipulator's private information (i.e., informed manipulation defined by Chakraborty and Yilmaz (2006)). These trading strategies differ from the strategy the Kyle model suggests; in the Kyle model, an insider should splits the trades to minimize the price impact but does not trade against her private information.

A round-trip trade is a set of offsetting purchases and sales during a certain interval. A net-zero-position round trip trade should not earn any profits on average if uniformed manipulation is not allowed. Uninformed manipulation is called "uninformed" because it does not require the manipulator to have private information: i.e., the manipulator uses only public information.

Informed manipulation can be viewed as an exercise in profitable front running. When dealers can sell a stock to their customers at prices higher than the market price, would they have an incentive to sell the stock in the market? Apparently, the dealers are reluctant to trade lower prices in the market. The answer can be yes, however, if dealers are able to manipulate the market price and buy more shares at an even lower price than the price at which they sold at the market.

These trading strategies differ from insider trading. Insiders can trade along with their private information and split their orders to minimize price impacts, as a result of which the market price can gradually reveal the insiders information. With the manipulation, the market price does not necessarily reflect the true fundamental value: the market price can move in the opposite direction of the fundamental value.

My market microstructure model provides clear conditions for manipulation opportunities. These conditions are described only by the variation in the liquidity of the stock: permanent price impact (PPI) and immediate price impact (IPI). PPI has been traditionally studied in the field of empirical market microstructure (e.g., Hasbrouck (1991)). , A theoretical definition of PPI is also known as Kyle's lambda. I can estimate the PPI as a regression coefficient of price changes on order imbalances defined as buyer-initiated order minus seller-initiated orders. IPI is defined by the price difference between the midpoint of the limit order book and the executed price.

The advantage of separating IPI and PPI is empirical. Some electronic trading platforms have pre-trade transparency, i.e., the trading platform reveals to traders the quantities of buy and sell orders in the limit order book. In markets with pre-trade transparency, IPI can be calculated by traders from order book data. Thus, IPI is available to any trader in many electrical trading markets, but PPI can only be estimated from the price and order sequences. In many market microstructure models, including the Kyle model, the trading game is modeled as a simultaneous-move game and the IPI and PPI become identical. The trading game is more like a sequential-move game in limit order markets. In such an environment, the execution price can overshoot, implying that the IPI and PPI is not identical. Recent literature on intraday stock markets[3] also focuses on the dynamics of the limit order book (i.e., IPI), and my model provides a simple strategic framework to consider the limit order market.

Theoretical Implication Kyle (1985) considers uniformed manipulation a theoretical possibility: the informed trader is allowed to engage in trade-based manipulation, but he chooses not to do so in equilibrium. Instead, he always trades so that he is pushing prices in a direction which reveals his private information. Informed manipulation was proposed by Chakraborty and Yilmaz (2004). They consider the information structure that implies that the manipulator pushes the prices in a direction opposite from his private information. My study considers both in a consolidated framework. My aim in constructing this model is to present a measure of manipulation opportunity analogous to an arbitrage opportunity. My theory suggests that, to preclude arbitrage opportunities, my manipulation measure should not be greater than zero.

I show that theoretically informed manipulation may occur if I allow rule-of-thumb traders to trade. Without rule-of-thumb traders, whose demand function is not strategically determined, I show that manipulation is never observed because uninformed traders respond optimally to the informed manipulators. Uninformed manipulation is even more difficult to obtain in theoretical models because the manipulator can make an unbounded profit by taking an unbounded position, an

[3] e.g., Roşu (2006).

outcome not supported as an equilibrium. Technically speaking, the condition of uninformed manipulation necessarily implies violation of second order condition of informed traders. The absence of uninformed manipulation holds for any extension of the Kyle model in which manipulators do not have a wealth limit.

When informed manipulation takes place, the market price moves in a direction opposite from the true fundamental value. The price is no longer a sufficient measure of fundamental value. Market efficiency, in the sense of the distance between the market price and the true fundamental value, deteriorates. It has been argued that a transactions tax would improve market efficiency by reducing the trading activity of HFTs who engage in trade-based manipulation. I investigate this idea theoretically, by simulating the efficiency of the market both with a transactions tax and without a transactions tax. I show that a transactions tax does not discourage manipulators from trading and can not improve market efficiency. Instead, it reduces liquidity. The tax discourages the informed trader from executing large quantities at the last period, which reduces the profit from private information. To compensate for the loss, the informed trader tends to manipulate more aggressively in earlier period.

Literature Theorecital model provides an environment in which the manipulation opportunity assumed by Huberman and Stanzl (2004). In their model, each IPI and PPI function is exogenously given. Their model analyzes conditions which preclude uninformed price manipulation, defined as a risk-less profitable round-trip trade. The resulting no-arbitrage condition is that, for the single asset case, PPI should be less than the sum of current and future IPIs. My model recovers the same condition (the uninformed manipulation condition) in a linear equilibrium framework in which IPI and PPI are derived endogenously. The condition is never satisfied in equilibrium, however, because the second order condition of the informed trader's maximization problem is not satisfied. Thus, uninformed price manipulation is not supported as a linear equilibrium.

My notion of informed price manipulation, characterized by trading against private information, is similar to that studied by Chakraborty and Yilmaz (2004a, b). The differences between my framework and theirs are the following: first, that I model an equilibrium with linear strategies, whereas their structure deals with a discrete sets of strategies, and second, while I ascribe the informed price manipulation opportunity to a non-strategic reaction of uninformed traders, the Chakraborty and Yilmaz framework does not require such traders.

Mei, Wu, and Zhou (2004) study uninformed price manipulation generated by the presence of behavioral traders, and they consider the empirical plausibility of manipulation. They introduce rule-of-thumb "momentum" traders in a manner similar to those of De-Long et al. (1990) and Hong and Stein (1999). As a result, they propose that there could be uninformed manipulation. In my framework, while the non-strategic traders follow a similar strategy, uninformed price manipulation is not supported as an equilibrium because the profit becomes unbounded. Also, their model focuses on the contrarian behavior of traders, while in my model contrarian traders cannot be a profitable source of manipulation. This difference arises because my model deals with a two-period trading game while they model a T-periods game and because my model incorporates strategic traders who successfully respond to a manipulator's strategy. Such strategic traders push pushes the price back in an unprofitable direction for manipulators, at least in a pure strategy equilibrium. Similarly, the price does not necessarily deviate from the fundamentals in the way that De-Long, Shleifer, Summers, and Waldmann (1990) propose because my model has strategic uninformed traders while the uninformed traders in the model of De-Long et al. trade non-strategically.

The model of Mendel and Shleifer (2011) is also comparable. They propose that positive uninformed "Outsider" traders could have an upward sloping demand curve when the uninformed traders confuse noise traders with informed traders. This effect is not observed in my model simply because my model highlights the presence of monopolistic informed traders while all the agents in Mendel and Shleifer's model are price takers. The monopolistic traders can affect the price and make an unbounded profit from the uninformed trader's upward sloping demand, but the uninformed traders can avoid this effect by creating a downward sloping demand. My model has a structure similar to Kumar and Seppi (1992), who study price manipulation of future markets which are cash settled. I will discuss their model in detail in the next section.

Kyle and Viswanathan (2008) do not consider these trading strategies to be manipulation because they do not harm market efficiency. In line with their argument, my manipulation opportunity can be considered a liquidity arbitrage. In my model, also, the trading game is zero-sum, and the market price may deviate from the fundamental during the game, but it does not affect the total profit that the agents will earn. Thus, I do not look further into the welfare consequence of price manipulation.

This paper proceeds as follows. Section 2 analises the model of price manipulation. Section 3 discusses additional propositions of the model, including market efficiency under manipulation, a financial transaction tax, and other comparative statics results. Section 4 concludes.

1.2. Theoretical Model

Motivation for the Model I present a model to provide an analytical framework to study the conditions under which manipulation can occur in equilibrium. I can also study how the volatility of noise trading, the risk aversion of traders, and the number and attitude of rule-of-thumb traders influence manipulation opportunities. In contrast to the frameworks of Huberman and Stanzl (2004) and De-long, Shleifer, Summers, and Waldman (1990), in which the level of liquidity is exogenously specified, my framework endogenously derives an equilibrium level of liquidity, which is determined by the amount of asymmetric information and the risk aversion of traders. Also, I do not allow an exogenous liquidity provision based on regulatory or investment requirements such as cash settlement (Kumar and Seppi (1992)), predatory trading (Brunnermeier and Pedersen (2005)), and currency attacks. I show that a weak and plausible assumption about exogenous liquidity provision, the presence of positive feedback rule-of-thumb traders is sufficient to generate manipulative trading.

1.2.1. The Model Environment

The model resembles a multiple trading period version of the model of Kyle (1989). An informed trader, who is the "manipulator", can affect the market price to obtain larger profits. Uninformed traders observe the order imbalance, which is caused by the informed trader and noise traders, update their expectations of fundamentals, and trade against the informed trader strategically.

Trade Opportunities In this model, there are two trading opportunities at $t = 1$ and $t = 2$. In addition, the entire risky asset is liquidated at the fundamental value v after the two trading periods. Five types of agents — informed, uninformed (denoted A at $t = 1$ and B at $t = 2$), rule-of-thumb and noise traders — trade against each other. At the end of each period, the market price is determined by an auctioneer to clear the demand and supply of traders.

Assets and Agents There is a risky stock and a risk-less asset. The risky stock is liquidated at the exogenous price v in the last period, and its unconditional expectation is v_0. The informed trader knows the fundamental value, but the uninformed traders know only its distribution, $\tilde{v} \sim N(v_0, \sigma_v^2)$.

The informed trader stays in the market throughout this trading game, but uninformed traders can exit and entrer. A fraction θ of uninformed traders at $t = 1$ remain in the market, but the rest of the uninformed traders leave by the liquidation period. At $t = 2$, new uninformed traders join the market. I allow these uninformed traders traders to have different risk aversions (γ_1, γ_2). These assumptions are made to control the number of uninformed traders and to keep the solution tractable. I assume that $\theta \in [0,1)$, and $\gamma_1, \gamma_2 > 0$.

The utility function of uninformed traders is a negative exponential $-exp(-\gamma_i \tilde{W}_U)$ in their terminal wealth $\tilde{W}_U$ for $i = 1,2$. This specification, together with the normally distributed $\tilde{W}$, introduces a linear functional form for the traders' demand and the supply curves for the risky stock. Traders are allowed to short both assets without limitations.

The informed trader is risk neutral and optimizes his position dynamically. At $t = 1$ and $t = 2$, the noise traders, denoted $z_1$and z_2, submit a market order following to a normal distribution $N(0, \sigma_z^2)$.

The rule-of-thumb traders are risk averse, and their demand function is given exogenously:

$$x_{2,R} = \phi\left(\kappa P_{t-1} + (1-\kappa)v_0 - p_t\right), \quad \phi > 0. \tag{1.2.1}$$

Here, P_{t-1} is the last transaction price and p_t is the current price. This trader is considered a contrarian trader if $\kappa < 0$ and a momentum follower if $\kappa > 0$. If $\kappa = 0$, they do not update their expectation of the fundamental value v. Assuming a risk aversion parameter of one, the parameter ϕ measures the number of momentum traders. The rule of thumb traders are assumed to have a negative exponential utility function with risk aversion ϕ and the expectation $E[v|\mathscr{F}] = \kappa P_{t-1} + (1-\kappa)v_0$. Without loss of generality, the conditional variance is set to one, since reducing the conditional variance is equivalent to increasing the risk aversion by the same proportion.

The conditional variance under their information set is set to 1 for normalization. I can also assume the conditional variance is σ_v^2 or $\hat{\sigma}_v^2$, but it is the same to define different ϕ.

This specification is essentially the same as that of De-Long et al. (1990), Hong and Stein (1999), or Mei, Wu, and Zhou (2004). In other words, the rule-of-thumb trader's expectation of the fundamental price is based on a simple adaptive learning process. In fact, this type of trading strategy includes many of the rule-based trading strategies, such as the Kalman filter forecasting and technical analysis.

At $t = 1, 2$, the information set of each trader is described as follows.

$$\mathscr{F}_{1,U} = \{\emptyset\}, \ \mathscr{F}_{2,U} = \{P_1\}$$

$$\mathscr{F}_{1,I} = \{v, P_1\}, \ \mathscr{F}_{2,I} = \{v, P_1, P_2\}.$$

Information about the distribution is common knowledge. Here, I assume that overlapping old and young agents have the same information set, and so I do not use different notation.

For random variables, I assume that $\tilde{v}, \tilde{z}_1, \tilde{z}_2$ follows a multivariate Normal distribution:

$$\begin{bmatrix} \tilde{v} \\ \tilde{z}_1 \\ \tilde{z}_2 \end{bmatrix} \sim N\left(\begin{pmatrix} v_0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_v^2 & 0 & 0 \\ 0 & \sigma_z^2 & 0 \\ 0 & 0 & \sigma_z^2 \end{pmatrix} \right).$$

Thus, the random variables are independently distributed.

I assume that uninformed traders and and rule-of-thumb traders are perfectly competitive price takers and that the informed trader is monopolist. Uninformed traders behave like agents in an inventory model.

Timing of the game The timing of this game is described in Fig. 1.2.1. At period $t = 0$, uninformed traders A submit to the market their limit orders $X_{A1}(\cdot)$, which are price contingent supply-demand schedules for the risky asset. The thickness of the limit order book is determined by the variance of the fundamentals and uninformed traders' risk aversion.

At period $t = 1$, an informed trader and noise traders enter the market. Looking at the limit order book composed of $X_{A1}(\cdot)$, the informed trader submits limit orders $X_{I1}(\cdot)$ strategically. Noise traders submit market orders $\tilde{z}_1$ after the informed trader.[4] At the end of the period $t = 1$, an auctioneer sets a uniform price $\tilde{p}_1 = P_1(\tilde{z}_1; X_{A1}, X_{I1})$ to clear the market.

At period $t = 2$, uninformed traders A and B realize that there were informed trades, and they update the expectation of the fundamental value to submit limit orders $X_{A2}(\cdot)$ and $X_{B2}(\cdot)$. Here, I note that the A-group uninformed traders already have positions from $t = 1$ trades, but these positions were not planned at $t = 0$.

[4] The informed trader incurs the price fluctuation risk made by noise traders, but it does not matter for *risk neutral* monopolistic informed traders.

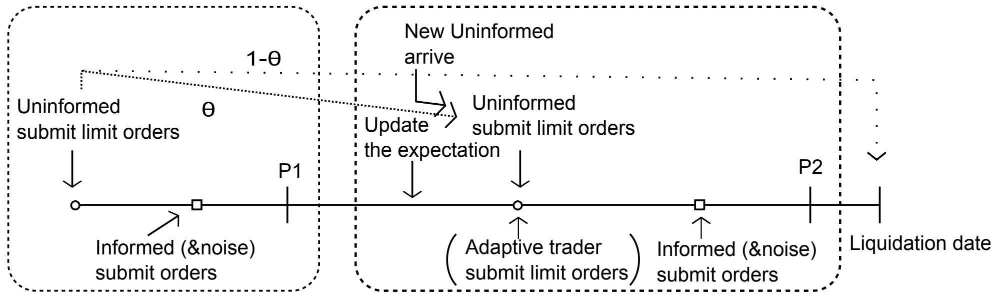

Figure 1.2.1. The time-line of the game.

The trade at $t = 1$ is *unexpected* for uninformed traders. This assumption makes their optimization problem static rather than dynamic. The rule-of-thumb traders submit limit orders $X_{R2}(\cdot)$.

Lastly, the noise and informed traders submit final orders $\tilde{z}_2$ and $X_{I2}(\cdot)$ as period $t = 1$. Noise and informed traders are allowed to have a positive or negative position. Because I assume that noise trading follows a normal distribution, the expectation of the net position of noise traders is zero mean.

After $\tilde{p}_2 = P_2(\tilde{z}_1; X_{A2}, X_{B2}, X_{I2}, X_{R2})$ is determined, the private information becomes public, and infinite liquidity is then provided to determine a final liquidation price. Therefore, the net profit (per unit) for each trader is the difference between the purchasing (shorting) prices P_1 and $P_2$and the liquidation price v.

Strategy Uninformed traders A and B, informed trader I, and rule-of-thumb trader R submit price schedules, noise $\tilde{z}_1$ and $\tilde{z}_2$ submit quantities. I denote the strategies as follows:

$$X_{A1} = X_{A1}(p_1),\ X_{A2} = X_{A2}(P_1, p_2),$$

$$X_{R2} = X_{R2}(P_1, p_2),\ X_{B2} = X_{B2}(P_1, p_2),$$

$$X_{I1} = X_{I1}(v, p_1),\ X_{I2} = X_{B2}(v, P_1, p_2).$$

The strateges of the rule-of-thumb traders are exogenously defined by ϕ and κ. Each trader's strategy is a function from their information set to their limit order schedule. I also denote the demand schedule using the notation $X_{I1}(\cdot) = X_{I1}(v, \cdot)$. I can change the informed trader's strategy to submiting market orders rather than demand schedules. Because informed traders internalize the price impacts, this different setup gives identical outcomes.

Pricing and market clearing An auctioneer combines schedules to obtain the market clearing prices

$$\tilde{p}_1 = P_1(\tilde{v}, \tilde{z}_1; X_{I1}, X_{A1})$$

which satisfies the market clearing condition $X_{A1} + X_{I1} + z_1 = 0$. Similarly, at period 2, the market price

$$\tilde{p}_2 = P_2(\tilde{v}, \tilde{z}_2; X_{I2}, X_{A2}, X_{B2}, X_{R2}).$$

is determined to satisfy the market clearing condition $X_{A2} + X_{B2} + X_{R2} + X_{I2} + z_2 = 0$.

Maximization problems The optimal strategies are solutions to maximization problems. To state how the strategies are dependent on the other agent's strategies, we denote the dependence explicitly. The market clearing price P_2 is a function of the previous market clearing price P_1 as well as other strategies

$$P_2(\tilde{v}, \tilde{z}_2; P_1(\tilde{v}, \tilde{z}_1; X_{A1}, X_{I1}), X_{A1}, X_{I1}, X_{A2}, X_{B2}, X_{R2}, X_{I2}).$$

Uninformed traders A and B are perfect competitors with negative exponential utility γ_A and γ_B. Trader B's wealth is $(v-P_2)x_{B2}$. As a perfect competitor he realizes how P_2 is determined. The solution to B's problem is denoted:

$$X_{B2}^*(P_1,p_2) = \underset{X(\cdot,\cdot)}{argmax}\, E\left\{(\tilde{v}-P_2(\tilde{v},\tilde{z}_2;P_1(\tilde{v},\tilde{z}_1;X_{A1},X_{I1}),X_{all}))\cdot X(\cdot,\cdot)|P_1(\tilde{v},\tilde{z}_1;X_{I1},X_{A1})=p_1\right\}. \tag{1.2.2}$$

Trader B chooses $X(\cdot)$, taking everything else as given. Like a rational expectation's equilibrium, he understandes distributions of $\tilde{v},\tilde{z}_1,\tilde{z}_2$. Trader B observes P_1, and conditions on p_2. I use the notation $X_{all}=\{X_{A1},X_{I1},X_{A2},X_{B2},X_{R2},X_{I2}\}$ to denote all strategies.

Trader A's wealth is $(v-P_1)x_{A1}+(v-P_2)x_{A2}$ if he trades in period 2, and $(v-P_1)x_{A1}$ if he does not trade in period 2. For simplicity, the possibility of trading in period 2 is not considered when trader A chooses his period 1 trade. Period 2 trade is a surprise for A (See discussion later). Therefore trader A solves two static optimization problems one for each period. The solution to the period 2 problem for A is

$$X_{A2}^*(P_1,p_2) = \underset{X(\cdot,\cdot)}{argmax}\, E\left\{(\tilde{v}-P_2(\tilde{v},\tilde{z}_2;P_1(\tilde{v},\tilde{z}_1;X_{A1},X_{I1}),X_{all}))\cdot X(\cdot,\cdot)|P_1(\tilde{v},\tilde{z}_1;X_{I1},X_{A1})=p_1\right\}. \tag{1.2.3}$$

The solution to the period 1 problem for A:

$$X_{A1}^*(p_1) = \underset{X(\cdot)}{argmax}\, E\left\{(\tilde{v}-P_1(\tilde{v},\tilde{z}_1;X_{A1},X_{I1}))\cdot X(\cdot)\right\}. \tag{1.2.4}$$

Note that trader A takes the price $P_1(\tilde{v},\tilde{z}_1;X_{A1},X_{I1})$ as given.

The informed trader is risk neutral, maximizing expected profits $(v-P_1)x_{A1}+(v-P_2)x_{A2}$. The informed trader exercises monopoly optimally in dynamically consistent manner over periods 1 and 2. The problem is complicated because informed trading at period 1 needs to take account of the effects of her trading on prices on both periods. From the perspective of the informed trader, the price is considered as a function of his own strategy as well as other trader's strategies.

The optimal strategy in period 2 is influenced by the choice in period 1. $X^*_{I2}(v, P_1, p_2; X_{I1}, X_{-I})$ can be thought of $X_{I2}(\cdot) = X_{B2}(v, P_1, \cdot; X_{I1}, X_{-I})$ as a demand schedule which reflects X_1, v, and P_1 as given. I denote $X_{-I} = \{X_{A1}, X_{A2}, X_{B2}, X_{R2}\}$ to economize on notation. The solution to the informed trader's problem is

$$X^*_{I2}(v, P_1, \cdot; X_{I1}, X_{-I}) = \underset{X(\cdot,\cdot,\cdot)}{argmax} E \Bigg\{ (\tilde{v} - P_1(\tilde{v}, \tilde{z}_1; X_{I1}, X_{A1})) \cdot X_{I1} \tag{1.2.5}$$
$$+ (\tilde{v} - P_2(\tilde{v}, \tilde{z}_2; P_1(\tilde{v}, \tilde{z}_1; X_{I1}, X_{-I}), X(\cdot,\cdot,\cdot), X_{I1}, X_{-I}) \cdot X(\cdot,\cdot,\cdot) | \tilde{v} = v, P_1(\tilde{v}, \tilde{z}_1; X_{I1}, X_{A1}) = p_1 \Bigg\}.$$

The first term is a profit from period 1 trade, and it is pre-determined. Therefore it does not influence on the period 2 solution.

In period 1, the informed trader takes into account that he will adjust X_{I2} to changes in X_{I1} through $X^*_{I2}(X_{I1})$. The solution to the informed trader's period 1 problem is

$$X^*_{I1}(v, \cdot; X^*_{I2}, X_{-I}) = \underset{X(\cdot,\cdot)}{argmax}\, E \Bigg\{ (\tilde{v} - P_1(\tilde{v}, \tilde{z}_1; X(\cdot,\cdot), X_{-I})) \cdot X(\cdot,\cdot) \tag{1.2.6}$$
$$+ (\tilde{v} - P_2(\tilde{v}, \tilde{z}_2; P_1(\tilde{v}, \tilde{z}_1; X(\cdot,\cdot), X_{-I}), X^*_{I2}(v, P_1, \tilde{p}_2; X(\cdot,\cdot), X_{-I}), X(\cdot,\cdot), X_{-I})) \cdot X^*_{I2}(v, P_1, \tilde{p}_2; X(\cdot,\cdot), X_{-I}) | \tilde{v} = v \Bigg\}.$$

At $t = 1$, the informed trader realizes that he influences the price in period 2, and optimizes his trade in period 1.

Linear equilibrium conjecture A sequentially rational Bayesian Nash equilibrium of this game is given by strategies $X_{A1}, X_{I1}, X_{A2}, X_{B2}, X_{R2}, X_{I2}$, and the market clearing price P_1 and P_2 such that all maximization problems (1.2.2), (1.2.3), (1.2.4), (1.2.5), (1.2.6) solved. The conditional expectations are derived using Bayes' rule in a way consistent with the equilibrium strategies.

The equilibrium is solved with following linear conjecture for strategies:

$$X_{A1}(p_1) = \mu - \lambda_1 p_1, \quad X_{A1}(P_1, p_2) = \mu_{2,A} + \delta_A P_1 - \lambda_{2,A} p_2, \quad X_{B2}(P_1, p_2) = \mu_{2,B} + \delta_B P_1 - \lambda_{2,B} p_2,$$

$$X_{I1}(v, p_1) = \alpha_1 + \beta_1 v - \zeta_1 p_1, \quad X_{I2}(v, P_1, p_2) = \alpha_2 + \beta_2 v + \xi_2 P_1 - \zeta_2 p_2. \tag{1.2.7}$$

For uninformed trader A and B, market clearing implies $\tilde{p}_1 = P_1(\tilde{v}, \tilde{z}_1; X_{I1}, X_{A1})$ and $\tilde{p}_2 = P_2(\tilde{v}, \tilde{z}_2; X_{I2}, X_{A2}, X_{B2}, X_{R2})$.

For the informed trader, the residual demand schedule at each period is $X_{M1}(\cdot) = X_{A1}(\cdot)$ and $X_{M1}(\cdot) = X_{A2}(\cdot) + X_{B2}(\cdot) + X_{R2}(\cdot)$. This implements a solution to the period 2 problem. The informed trader's demand function at period 2 does not depend on P_1 (i.e., $\xi_2 = 0$), because the informed trader knows the information of P_1 and his exercise of monopoly power is expressed in their demand function of v and p_2.The characterization of equilibrium is found in Appendix A.

Model discussion Even without the rule-of-thumb uninformed traders, this model differs from the Kyle (1989) model in at least three ways: multiple trading periods, overlapping generations of uninformed traders, and the assumption of an alternating rather than simultaneous game. The multi-period framework is essential to my analysis because price manipulation is a dynamic trading strategy, but the OLG feature for uninformed traders is just for tractability.

In this model, uninformed trader A at period 2 trades as if the arrival of informed and noise is a surprise. Thus I avoid considering the hedging demand for long-lived uninformed trader A. Because uninformed trader A is risk averse, he would have a hedging demand for the risk associated with the trade in period 2. Also, I assume that some fraction of uninformed trader A does not to trade in period 2. Otherwise, at period 2, he liquidates all the positions acquired in period 1. This discourages the informed trader from trading in period 1, considering the information leakage and the price impact made by the uninformed trader.

For this issue, I can propose an alternative interpretation. I can assume that uninformed trader A is a long term investor and holds the position until the liquidation period, but the rule-of-thumb trader will liquidate a fraction of the position of trader A. This liquidation can be thought of as a contrarian pressure. This pressure is combined with the original κ, and it defines the new value for κ. Setting the mass of uninformed trader B as $\frac{1}{\gamma_B} + \frac{\theta}{\gamma_A}$, and I can obtain a new model that provides the same results.

Finally, the largest simplification is that the uninformed trader is limited to one update. This restriction reflects the fact that the limit order trades are more like an alternating game rather than a simultaneous game. In addition, there are two benefits from this assumption. The first is tractability. Because the uniformed trader's problem at $t = 1$ is not affected by the informed trader's strategy, it is treated as exogenous. As a result, the simultaneous equation that characterizes equilibrium becomes much simpler. Another benefit is that I can separate the price impact into an informational component (PPI) and a risk aversion component (IPI).

The comparison with the Kumar and Seppi (1992) model is interesting. They study the manipulation of the price at a future contract, which is settled at the price of cash assets, and their model also allows for multi-trading periods. In their model, at $t = 2$, the manipulator switches from an uninformed trader to an informed one. The manipulator also has upward demand curve, and the manipulator invests all of his wealth at $t = 1$. This result resembles uninformed manipulation

End. variables		Ex. variables	
$x_{t,U}, x_{t,I}$	Trade vol.	γ_A, γ_B	Risk aversion param.
P_t	Transaction price	$\sigma_v,\ \sigma_z$	Std. of stochastic var.
Strategic variables		$\tau_v,\ \tau_z$	Precisions $\tau \equiv \sigma^{-2}$
$\mu_t,\ \lambda_t,\ \delta$	Decision rules for uninf.	$\tilde{z}_t$	Noise trading vol.
$\alpha_t,\ \beta_t,\ \xi,\ \zeta_t$	Decision rules for inf.	$\tilde{v}$	True fundamental value
$m_0,\ m_1$	coef. of $E[\tilde{v}\|\mathscr{F}_{t,U}]$	θ	Probability of retuning
		κ	Adaptive expectation parameter
	$t = 1,2$	ϕ	Risk capacity of non-strategic.

Table 1.1. Variables used in this model. Tilde means it is a stochastic variable, and hat means it is a estimated variable. Note that x and z mean the trading volume. They mean buy if the value is positive, and sell if negative. Some literature employ notation that x is a position. In this paper, the position at t is $\sum_{t=1}^{T} x_t$.

in my model, but I prohibit the degenerate equilibrium in which the manipulator invests infinitely many times.

1.2.2. Characterization of the Equilibrium

Here, I outline how I solved for the equilibrium. The detailed characterization can be found in the Appendix.

I solve for the equilibrium in reverse. For the first step, I calculate the conditional expectation of the fundamental value for the uninformed traders' problem. Then, I solve the $t = 2$ maximization problems given any realization at $t = 1$. Lastly, I the solve $t = 1$ problem.

Uninformed trader's problem Uninformed traders have a negative exponential utility function. The maximization problems for the $i = A, B$ generations of uninformed traders are described as follows:

$$max_{x_{2,i}}\ E\left[-exp(-\gamma_i\left\{(\tilde{v}-p_2)x_{2,i}+(\tilde{v}-P_1)x_{1,i}\right\})|\mathscr{F}_{2,U}\right],$$

$$max_{x_{1,A}} \; E\left[-exp(-\gamma(\tilde{v}-p_1)x_{1,A})|\mathscr{F}_{1,A}\right].$$

I note that the conditional expected value and variance of $\tilde{v}$ are calculated with the projection theorem: $\hat{v}_U \equiv E[\tilde{v}|\mathscr{F}_{U_{i,2}} = \{P_1\}]$ and $\hat{\sigma}_U^2 \equiv Var(\tilde{v}|\mathscr{F}_{U_{i,2}} = \{P_1\})$. Because $\tilde{v}$ and P_1 are jointly normally distributed, so is their terminal wealth, and I can use the moment generating function to simplify the expected utility.

Uninformed trader B has no position at $t = 2$, and $x_{1,B} = 0$. The first order conditions determine their demand function:

$$x_{2,i}^*(p_2) = \frac{\hat{v}_U - p_2}{\gamma_i \hat{\sigma}_U^2} - x_{1,i} \quad i = A, B.$$

$$x_{1,A}^*(p_1) = \frac{v_0 - p_1}{\gamma_A \sigma_v^2}.$$

The conditional volatility of the fundamental decreases because of the information leakage from the informed trades, yielding $\hat{\sigma}_U^2 < \sigma_v^2$. The informed trader submits more limit orders (implying deeper limit order book) when they are less risk averse (small γ). At $t = 2$, the A traders unwind their position acquired into $t = 1$. Thus, $\theta = 1$ implies the trade at $t = 1$ to be trivial.

Permanent price impact is defined like a Kyle's lambda:

$$\hat{v}_U - v_0 = \frac{(1 + \frac{\theta\gamma_B}{\gamma_A})\delta + \theta\lambda_1 + \phi\kappa}{\lambda_1\left((1 + \frac{\theta\gamma_B}{\gamma_A})\lambda_2 + \phi\right)}(x_{1,I} + z_1).$$

The price has a martingale property. This property is implied by the assumptions that uninformed traders are risk neutral price takers.

Informed trader's problem The maximization problems for the informed trader are described as follows:

$$max_{x_{2,I}}\, E\left[(v-\tilde{P}_2(x_{2,I}))x_{2,I}|\mathscr{F}_{2,I}\right],$$

$$max_{x_{1,I}}\, E\left[(v-P_1)x_{1,I}+(v-\tilde{P}_2)x^*_{2,I}+B_0|\mathscr{F}_{1,I}\right].$$

At $t=2$, the informed trader does not take the position at $t=1$ into account because the informed trader is risk neutral. The residual demand curves for the informed trader (X_{M2} and X_{M1}) are

$$\tilde{P}_2 = \frac{1}{(1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi}\left((1+\frac{\theta\gamma_B}{\gamma_A})\mu_2-\theta\mu_1+\left((1+\frac{\theta\gamma_B}{\gamma_A})\delta+\theta\lambda_1+\phi\kappa\right)P_1+x_{2,I}+\tilde{z}_2\right),$$

$$\tilde{P}_1=\frac{1}{\lambda_1}(\mu_1+x_{1,I}+\tilde{z}_1).$$

The immediate price impact at $t=1$ and $t=2$, $\frac{\partial P_2}{\partial x_{2,I}}$ and $\frac{\partial P_1}{\partial x_{1,I}}$, are given by

$$\frac{1}{\lambda_1},\ \frac{1}{(1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi}.$$

These expressions are determined by the risk aversion of uninformed traders. Substituting these terms into the residual demand curve, I can derive the first order and second order conditions for the informed trader. With the demand functions derived above, I can characterize the equilibrium.

1.2.3. Analysis

Existence of equilibrium A linear equilibrium is characterized by (A.1.3), (A.1.7), and (A.1.9). Assuming $v_0 = 0$ yields $\mu_1 = \mu_2 = m_0 = 0$.[5] Because the conditional expectation and the informed trader's strategic variables can be expressed as a function of uninformed trader's strategic variables, the system equation is then simplified to a cubic equation for δ which characterizes the equilibrium.

Proposition 1. *Assuming $v_0 = 0$, we let all the constant terms equal to zero: $\alpha_1 = \alpha_2 = \mu_1 = \mu_2 = m_0 = 0$. A linear equilibrium is characterized by a root of the cubic equation for δ and the informed trader's second order conditions. The existence of the equilibrium is shown using examples.*

The expression of the equation is tedious, so I do not include it here. The equilibrium may or may not exist depending on the parameters because they fail to satisfy the S.O.C.

Definition of price manipulation In my model, the monopolistic trader, or informed trader, can be a manipulator. I analyze two types of manipulation: *uninformed manipulation* and *informed manipulation*. Uninformed manipulation is a zero information, zero net cost trading strategy that yields a positive payoff, while informed manipulation is a trading strategy that utilizes private information.

Uninformed manipulation is also called a pump and dump scheme. This scheme aims to make a profit just by repeating purchases and sales[6]. I call this strategy "uninformed" because it does not require private information. In my model, I assume that the manipulator has information and that uninformed traders believe

[5] The fundamental value can be negative. Traders can make profit by shorting the stock even in that case. While they are allowed to dispose of the stock, such an action cannot be optimal.

[6] Ususally pump and dump scheme also involves spreading rumors. In this paper, however, I do not consider spreading rumor to make the argument simpler.

the existence of information based trades; otherwise, there is no permanent price impact[7]. The appearance of an informed trader is disguised by the noise trading. As the volatility of noise trading becomes larger, the fraction of informed trade becomes relatively smaller and informed traders can trade more aggressively.

Informed manipulation is illustrated as follows. Informed traders' first trade against their private information. For example, they first sell if they know the asset value is higher than the market price. This action causes a loss to the manipulator, but they can make a more advantageous position with the resulting better price. In this sense, they are "bluffing." Different from uninformed manipulation, the informed manipulator has non-zero net position at the end of trading.

I provide the formal definition of the two manipulations that are found in my model. Uninformed manipulation is defined as follows.

Definition. Uninformed price manipulation is defined as a round-trip trade by *the monopolistic trader* who makes a positive profit. In my environment, uninformed manipulation is profitable when

$$\underbrace{\frac{(1+\frac{\theta\gamma_B}{\gamma_A})\delta+\theta\lambda_1+\phi\kappa}{\left((1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi\right)\lambda_1}}_{Permanent\ P.I.}-\underbrace{\frac{1}{(1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi}}_{Immediate\ P.I_{t+1}}-\underbrace{\frac{1}{\lambda_1}}_{Immediate\ P.I_t}>0.$$

I can derive this condition by imposing a round-trip restriction on the problem of the manipulator. The detailed derivation is found in Appendix.

Uninformed price manipulation requires a trade at t to have an impact on the $t+1$ price that is more than the sum of the slippage at t and $t+1$. The impact on the next period is expressed as $\frac{\partial P_2}{\partial x_{1,I}}=\frac{(1+\frac{\theta\gamma_B}{\gamma_A})\delta+\theta\lambda_1+\phi\kappa}{(1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi}\cdot\frac{1}{\lambda_1}$. The numerator is the demand change of uninformed traders due to the price change at the first period. The

7

Ross and Tinn (2010) assumes the probability of the presence of informed traders to be a random variable. Uninformed traders update the probability by using Bayesian learning.

first term is from information leakage, the second term is from liquidation of first period trade, and the last term $\phi\kappa$ is from rule-of-thumb traders. The price impact on the current price (immediate price impact) is $\frac{\partial P_1}{\partial x_{1,I}} = \frac{1}{\lambda_1}$ and $\frac{\partial P_2}{\partial x_{2,I}} = \frac{1}{(1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi}$.

Next, I define informed manipulation: a trade in direction different from the trader's private information. Since $\beta_2 = (1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2 > 0$ always holds because slippage $1/\lambda_i$ is always positive, I focus on the sign of $\beta_1 = 2\lambda_1 - ((1+\frac{\theta\gamma_B}{\gamma_A})\delta + \theta\lambda_1 + \phi\kappa)$.

Definition. Informed manipulation is defined as a trading strategy that can have an position opposite to the private information and a nonzero net holding at the liquidation date.

In my environment, a monopolistic trader could take a manipulative position if $\beta_1 = \lambda_1 - ((1+\frac{\theta\gamma_B}{\gamma_A})\delta + \theta\lambda_1 + \phi\kappa) < 0$.

The condition can be rewritten as $\frac{(1+\frac{\theta\gamma_B}{\gamma_A})\delta+\theta\lambda_1+\phi\kappa}{\left((1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi\right)\lambda_1} - \frac{1}{(1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi} > 0$. Since $sign(\delta) = sign(\beta_1) < 0$, I need to rely on $\phi\kappa$ to satisfy the condition.

This type of definition of price manipulation also appears in Chakraborty and Yilmaz (2004a,b). In their framework, as long as unformed traders believe there is an informed trades, the monopolistic informed traders can trade in a direction opposite to his private information.

Back and Baruch (2004) also show the presence of bluffing in equilibrium. In both models, bluffing is a possibility in a mixed strategy equilibrium, and it cannot occur without rule-of-thumb traders in my model, in which I only consider the linear pure-strategy equilibrium.

Price manipulation in equilibrium Comparing the two conditions, I observe that both conditions state that the degree of momentum trading $(1+\frac{\theta\gamma_B}{\gamma_A})\delta + \theta\lambda_1 +$

$\phi\kappa$ should be low enough to exclude manipulation in equilibrium. The S.O.C also takes a similar form.

— The S.O.C for a linear equilibrium is

$$\left((1+\frac{\theta\gamma_B}{\gamma_A})\delta+\theta\lambda_1+\phi\kappa\right)^2 < 4\lambda_1\left((1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi\right).$$

— The condition implying absence of uninformed manipulation is

$$(1+\frac{\theta\gamma_B}{\gamma_A})\delta+\theta\lambda_1+\phi\kappa < \lambda_1+\left((1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi\right)$$

— The condition implying absence of informed manipulation trade is

$$(1+\frac{\theta\gamma_B}{\gamma_A})\delta+\theta\lambda_1+\phi\kappa < \lambda_1.$$

From the definition, it is evident that uninformed manipulation does not occur in equilibrium. It is ruled out by the second order condition.

Proposition 2. *Uninformed manipulation does not occur in equilibrium.*

The proof is from the inequality of arithmetic and geometric means: $\lambda_1+\left((1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi\right) > 2\sqrt{\lambda_1\left((1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi\right)}$. Each term is assumed to be positive, and the uninformed manipulation opportunity necessarily implies that the S.O.C does not hold. However, informed manipulation could occur in equilibrium:

Proposition 3. *If there are no rule-of-thumb traders (ϕ=0) or if they are contrarian ($\phi > 0$ and $\kappa < 0$), informed manipulation does not occur in equilibrium.*

Existence of an informed manipulation opportunity implies the presence of rule-of-thumb momentum traders. Unfortunately, I cannot fully identify the presence of rule-of-thumb traders empiricallly, but I can draw an inference by checking the manipulation condition.

Comparing the three conditions and the definition of each strategic variable δ, λ_1, and β_1 , I can complete the proof[8].

Supposing that either ϕ=0 or $\phi > 0, \kappa < 0$ and the existence of informed manipulation leads to a contradiction. Note that the sign of δ and β_1 should be the same. If $\beta_1 < 0$, there is an informed manipulation by definition. Then, $(1+\frac{\theta\gamma_B}{\gamma_A})\delta + (\theta-1)\lambda_1 + \phi\kappa > 0$. However the left hand side should be negative, because $\delta < 0$, $0 \le \theta < 1$, and $\theta\kappa \le 0$. Here, λ_1 is strictly positive because of the definition of γ_1 and σ_v: uninformed traders must have downward sloping demand curve. Thus, I have shown a contradiction.

To derive examples of informed manipulation, I use the following remark for my numerical analysis.

Remark 4. Setting $\phi = 2(1-\theta/2)\lambda_1$, I obtain $\beta_1 = \lambda_1(1-\theta/2)(1-\kappa) - (1+\frac{\theta\gamma_B}{\gamma_A})\delta/2$. Because the signs of β_1 and δ are always the same, $\kappa > 1$ implies $\beta_1 < 0$. The condition $\kappa = 1$ implies $\beta_1 = 0$.

1.3. Discussion

Simulated Price and the Price Efficiency

I would like to evaluate the efficiency of the price when there is a informed manipulation opportunity. I generated a sample price path with simulations and examined the distance between the market price and the fundamental.

[8] Caldentey and Stacchetti (2010) consider a variant of the Kyle model in which the fundamental is described by Brownian motion, and they propose that bluffing and boundless profit (uninformed manipulation) are not supported as an equilibrium.

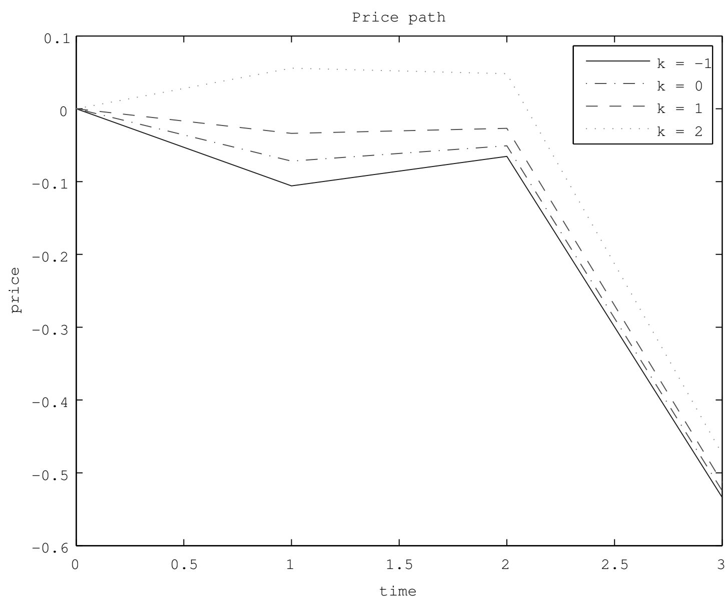

Figure 1.3.1. Simulated price path. Parameters are, $[v, v_0, \theta, \gamma_A, \gamma_B, \sigma_z^2, \sigma_v^2, \phi]$=[-1, 0, 0.2, 1/3, 1/3, 1,1, $2(1-\theta/2)\lambda_1$]. The true fundamental price is $v = -1$. The informed trader conducts informed manipulation when $\kappa > 1$. Trades were executed at $t = 1$ and $t = 3$, and the price at $t = 0$ and $t = 2$ are the mid-price or the expected fundamental for uninformed traders.

Fig. 1.3.1 shows the simulated price path. Trades were executed at $t = 1$ and $t = 3$, and the prices at $t = 0$ and $t = 2$ are the mid-price or the expected fundamental for uninformed traders. I set the true fundamental equal to -1 and generated the noise trading in 500 iterations. The presented price is an average over the 500 simulations. Here, I can observe how the market price deviates from the fundamental price.

Because I set $\phi = 2(1-\theta/2)\lambda_1$, $\kappa > 1$ implies informed manipulation. When there is informed manipulation, the price at $t = 1$ always deviates from the fundamental. We know this derivation from the market clearing condition (Eq. (A.1.1)). The coefficient of v is $\frac{\beta_1}{\lambda_1+\zeta_1}$. The denominator is always positive, and the negative β_1 pushes the price in the direction opposite to the true fundamental.

Thus, when there is manipulation, the price at $t = 1$ goes up even though the true fundamental is less than the current price $v_0 = 0$. When $\kappa < 1$, the informed trader starts to sell from the beginning. When $\kappa = 1$, the informed trader does not trade. At $t = 2$, the uninformed traders observe the order imbalance at $t = 1$, and update their expectations. Because the rule-of-thumb contrarian traders ($\kappa < 0$) trade in the direction opposite to the first executed price, the price goes up at $t = 2$ when $\kappa < 0$. At the last period, the informed traders exploit their monopolistic power, and the price goes to nearly the half of the true fundamental (-0.5).

The inefficiency in this paper is defined as an average distance from the fundamental value $\sum_{t=1,\ldots 4} \frac{(v-P_t)^2}{4}$. The executed price P_1 and P_2 are not semi-strong efficient in the sense that the price does not include all the information obtained by uninformed traders after each trade. Uninformed traders, however, could make a profit at period 2 because of rule-of-thumb traders are less rational. In this sense, each executed price satisfies a weak form of maket efficiency. $\hat{v}_U$ is a semi-strong efficient price, but it still can deviate more from the true fundamental than unconditional expectation v_0. The calculated market inefficiencies for the simulation above are 0.863, 0.848, 0.823, and 0.799, for $\kappa = 2, 1, 0, -1$, respectively. Thus, the market is more efficient, in terms of the incorporation of private information when the rule of thumb traders are contrarian because the informed trader can trade more aggressively against these rule of thumb traders, who provide the liquidity to informed traders.

Financial Transaction Tax

I can examine policy implications desigined to prevent the manipulation. Because informed manipulation undermines market efficiency, government regulation might recover the efficiency. Recently, introduction of the financial transaction tax (FTT) has been discussed as a policy to suppress the activity of HFTs and to stabilize the markets. In practice, I expect that FTT could reduce manipulation because HFTs may avoid the transaction tax. This intuition is, however, not necessarily true in the model.

To study the effect of FTT, I incorporated a quadratic transaction cost (or tax). Both uninformed and informed traders pay $\frac{c}{2}x^2$ to trade x units. Assuming that $\gamma_1 = \gamma_2$, I express the coefficient β_1 and ζ_1 as follows:

$$\begin{aligned} \beta_1 &= \left[1 - \zeta_2 PPI\left(1 - \frac{\zeta_2 IPI_2}{1+\zeta_2 IPI_2}\right)\right] \cdot (IPI_1 + c)^{-1}. \\ \zeta_1 &= \left(1 - \frac{PPI^2}{IPI_1 IPI_2} \cdot \frac{\zeta_2 IPI_2}{1+\zeta_2 IPI_2}\right) \cdot (IPI_1 + c)^{-1} \end{aligned}$$

Here, $\zeta_2 = \left[\left((1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2 + \phi\right)^{-1} + c\right]^{-1}$, $IPI_1 = \frac{1}{\gamma_A \sigma_v^2 + c}$ $IPI_2 = \frac{1}{(1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi}$, $\lambda_2 = \frac{1}{\gamma_B \hat{\sigma}_U^2 + c}$, and $PPI = ((1+\theta)\delta + \theta\lambda_1\lambda_2\gamma\hat{\sigma}_U^2 + \phi\kappa) \cdot IPI_1 \cdot IPI_2$. Higher costs increase both IPI and PPI, implying a loss of liquidity in the market. When $c = 0$,

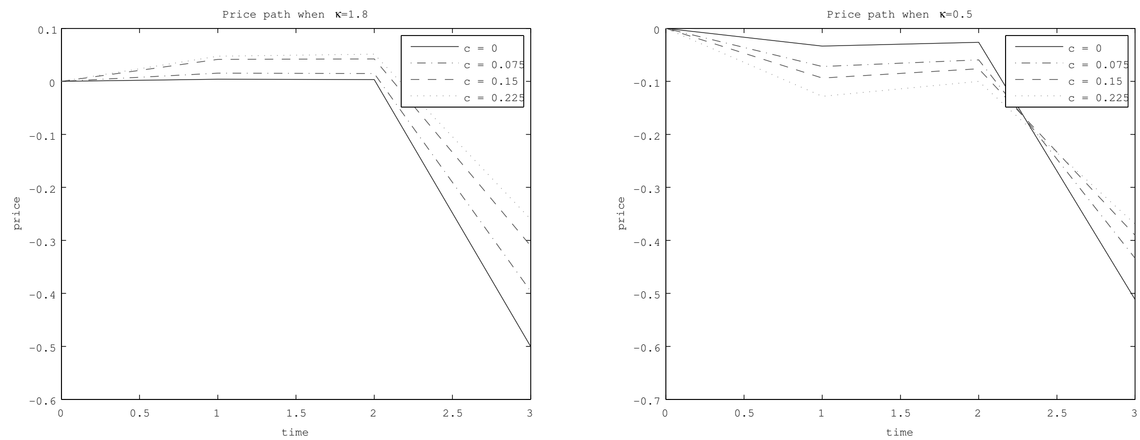

Figure 1.3.2. Simulated price path. Parameters are, $[v, v_0, \theta, \gamma_A, \gamma_B, \sigma_z^2, \sigma_v^2, \phi]$=[-1, 0, 0.2, 1/3, 1/3, 0.5,1, $2(1-\theta/2)\lambda_1$]. The true fundamental price is $v=-1$. $\kappa = 1.8$ for left graph, and the informed trader conducts informed manipulation. $\kappa = 0.5$ for right graph, and the informed trader does not conduct informed manipulation. Trades were executed at $t = 1$ and $t = 3$, and the price at $t = 0$ and $t = 2$ are the mid-price or the expected fundamental for uninformed traders.

$\zeta_2 = IPI_2^{-1}$, and we can confirm every strategic variable is identical to those of the no-transaction-cost case.

The effect of the adjustment cost c is ambiguous when it is moderately small. The manipulator cannot trade aggressively at time $t = 2$ because of the transaction cost. This restriction increases the motivation for manipulation at $t = 1$, and the price deviates more from the fundamental when $\kappa > 1$ and informed manipulation occurs. However, the transaction cost can also smooth the price path when $\kappa < 1$.

The simulations of price path, for both the $\kappa > 1$ and $\kappa < 1$ cases, are described in Fig 1.3.2. The higher cost even helps the price to deviate from the fundamental $v = -1$ when $\kappa > 1$. High costs also discourage the informed trader from trading at the last period, preventing the price from approaching the fundamentals. For $\kappa = 1.8$, the calculated market inefficiencies are 0.859, 0.901, 0.941, and 1.059, for $c = 0, 0.05, 0.10, 0.15$, respectively. The market inefficiency gets worse when the transaction tax is higher. For $\kappa = 0.5$, the market inefficiencies are 0.796, 0.799, 0.794, and 0.788. The inefficiency does not change a lot depending on the level of transaction tax.

Heterogeneous Belief

The assumption of the rule-of-thumb traders is a key device in this model, but it also seems ad-hoc. We can, however, reinterpret the model as a kind of heterogeneous belief model on the random variables, under certain conditions on the parameters. Thus, I can investigate whether heterogeneous beliefs could imply momentum trading which can lead informed manipulation.

I study whether if the model with rule of thumb traders can be replicated by two models with heterogeneous belief: (1) the uninformed traders believe that the noise trading is correlated with the fundamental, (2) the uninformed traders believe that the precision of the noise is high. I assume that the traders agree to disagree about the noise structure. More specifically, I assume (1) $Cov(z_1, v) = \sigma_{zv} \neq 0$, and (2) $Var(z_1) = k\sigma_z^2,\ 0 < k < 1$ to calculate the demand function of uninformed traders. Because the noise only becomes important when uninformed traders update their expectation, I only have to consider the change of uninformed traders and rule-of-thumb traders.

Combining the demand function of the uninformed traders (Eq.A.1.4) and the rule-of-thumb traders (Eq.1.2.1), I obtain

$$X_{2,B}(\cdot)+X_{2,R}(\cdot) = \frac{1}{\gamma_B \hat{\sigma}_U^2}\left\{\left(\frac{Cov(P_1,v)}{Var(P_1)} + \gamma_B \hat{\sigma}_U^2 \phi \kappa\right)(P_1 - E[P_1]) + \left(1+\gamma_B \hat{\sigma}_U^2 \phi\right) v_0 - \left(1+\gamma_B \hat{\sigma}_U^2 \phi\right) p_2\right\}.$$

Thus, I find that the aggregated demand $X_{2,B}(\cdot)+X_{2,R}(\cdot)$ becomes a linear transformation of $X_{2,B}(\cdot)$ except for the different coefficient of $(P_1 - E[P_1])$. I investigate the condition that the aggregated demand can be transformed as changes in the assumption (1) and (2).

The changes of (1) and (2) alter the conditional variance $\hat{\sigma}_U^2$ and the projection coefficient $\frac{Cov(P_1,v)}{Var(P_1)}$ at the same time. Because I have two free parameters ϕ and κ, the implicit function theorem guarantees that I can determines the transformation of the rule-of-thumb traders model into the different noise structure models (1) and (2).

To simplify the analysis, I assume that $\Phi = \frac{\phi}{\gamma_B \hat{\sigma}_U^2}$,i.e., the risk capacity of the rule-of-thumb traders is a linear transformation of that of uninformed trader at $t = 2$.

Proposition 5. *The model with rule-of-thumb traders (Φ, κ) can be transformed to (1) the model with agreement to disagree about noise-fundamental correlation ($Cov(z_1, v) = \sigma_{zv}$), and (2) the model with agreement to disagree about noise precision ($Var(z_1|\mathscr{F}_u) = k\sigma_z^2$) when we set ϕ and κ as follows:*

(1) $\Phi = \frac{\sigma_{zv} A \beta_1}{\sigma_p^2(\sigma_v^2\sigma_z^2 - \sigma_{zv}^2)}$, $\kappa = \frac{\beta_1\sigma_v^2\sigma_{zv} + \sigma_v^2\sigma_z^2}{A} \cdot \left(\frac{\beta_1}{\lambda_1+\zeta_1}\right)^{-1}$ *and* $A = \beta_1\sigma_v^2\sigma_{zv} + 2\sigma_v^2\sigma_z^2 + \sigma_{zv}^2\sigma_z^2/\beta_1$,

(2) $\Phi = \frac{(1-k)}{k}\rho^2$, $\kappa = \left(\frac{\beta_1}{\lambda_1+\zeta_1}\right)^{-1}$.

I can find the expressions by solving following simultaneous equations for Φ and κ:

$$
\begin{aligned}
(1) \quad \frac{Cov(P_1,v) + \frac{\sigma_{zv}}{\lambda_1+\zeta_1}}{Var(P_1) + \frac{2\beta_1\sigma_{zv}}{(\lambda_1+\zeta_1)^2}} &= \frac{Cov(P_1,v)}{Var(P_1)} \cdot \frac{1}{1+\Phi} + \frac{\Phi\kappa}{1+\Phi}, \; \sigma_v^2 - \frac{\left(Cov(P_1,v) + \frac{\sigma_{zv}}{\lambda_1+\zeta_1}\right)^2}{Var(P_1) + \frac{2\beta_1\sigma_{zv}}{(\lambda_1+\zeta_1)^2}} = \frac{1}{1+\Phi} \cdot \hat{\sigma}_U^2 \\
(2) \quad \frac{Cov(P_1,v)}{\frac{\beta_1^2\sigma_v^2}{(\lambda_1+\zeta_1)^2} + \frac{k\sigma_z^2}{(\lambda_1+\zeta_1)^2}} &= \frac{Cov(P_1,v)}{Var(P_1)} \cdot \frac{1}{1+\Phi} + \frac{\Phi\kappa}{1+\Phi}, \; \sigma_v^2 - \frac{Cov(P_1,v)^2}{\frac{\beta_1^2\sigma_v^2}{(\lambda_1+\zeta_1)^2} + \frac{k\sigma_z^2}{(\lambda_1+\zeta_1)^2}} = \frac{1}{1+\Phi} \cdot \hat{\sigma}_U^2
\end{aligned}
$$

Thus, I can propose that the model with informed manipulation ($\beta_1 < 0$, $\kappa > 0$) cannot be transformed to the model (2). However, numerical examples show that informed manipulation can occur in the model (1).

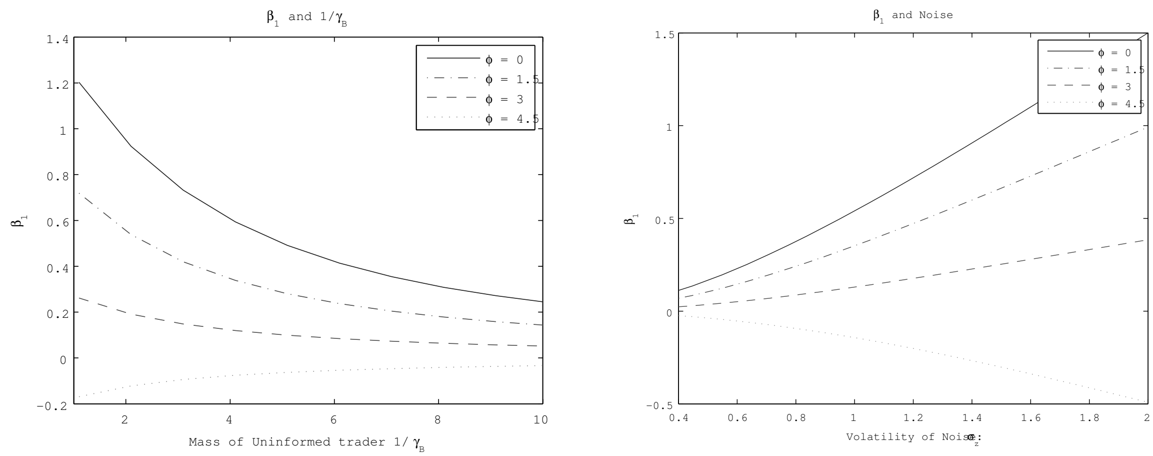

Figure 1.3.3. Numerical comparative statics for β_1. $\beta_1 < 0$ indicates presence of informed manipulation.
(Left) (horizontal) Mass of Uninformed trader $(1/\gamma_2)$, (vertical) β_1
(Right) (horizontal) Volatility of noise trading (σ_z), (vertical) β_1
Note: Other parameters: (Left) $[\theta, \gamma_A, \sigma_z^2, \sigma_v^2, \kappa]$=[.2, 1/5, 3, 1, 1],
(Right) $[\theta, \gamma_A, \gamma_B, \sigma_v^2, \phi]$=[.2, 1/5, 1/3, 1, $(1-\theta)\lambda_1$]

Numerical Comparative Statics

The equilibrium is characterized by a cubic equation. I can solve this equation numerically[9], but the solution may not be unique or there may not be an equilibrium under some parameter sets because the solution will violate the second order condition.

The role of rule of thumb traders I am interested in determining when manipulation (informed manipulation, indicated by negative β_1) is more likely. One obvious connection is the inflow of momentum traders at $t = 2$, which is indicated by ϕ. The more momentum traders that trade, the easier it is for manipulation to occur. The left graph of the Fig. 1.3.3 confirms this intuition.

When ϕ increases, $\beta_1$decreases. If $\phi > (1-\theta)\lambda_1$, β_1 changes sign. In the case of $\phi = (1-\theta)\lambda_1$and $\kappa = 1$, $\beta_1 = 0$. This relation implies that informed traders

[9] I used Matlab to calculate the cubic equation that governs the equilibrium. Then I determine whether the second order conditions are satisfied for the candidate solution.

trade independently of their private information because the loss from information leakage and the gain from manipulating rule-of-thumb traders are equal. The informed traders only trade to obtain the advantage of the variation of the number of uninformed traders (described in ζ_1 terms).

When $1/\gamma_B$ increases (implying that the liquidity provision at $t = 2$ increases), the informed trader takes smaller position to minimize their information leakage and wait for $t = 2$ to trade. Thus, β_1 decreases as $1/\gamma_B$ increases.

Noise trading and the manipulation measure The right graph of Fig. 1.3.3 describes the connection between the volatility of noise and β_1. Here, I assume that $\phi = (1-\theta)\lambda_1$. Again, $\kappa = 1$ implies $\beta_1 = 0$ regardless of the value of σ_z.

Because the informed trader can hide behind the noise trading, he can trade more aggressively (aggressive manipulation or aggressive informed trading) by using private information. When informed manipulation is more profitable than honest trading, informed traders tend to manipulate more.

Profitability Lastly, I would like to note the profit from the manipulation. Fig. 1.3.4 describes the changes in profit depending on the number of uninformed traders and the volatility of noise trading.

When there are more strategic uninformed traders, as shown in the left graph, the profitability declines because the liquidity also declines. This relationship is true even when the informed trader conducts manipulation. An increase in the number of uninformed traders, which is the same as the number of rule-of-thumb traders, increases the total profit of the informed trader. Because uninformed traders take more risk and submit orders more aggressively, and it implies more liqidity provision to the informed traders.

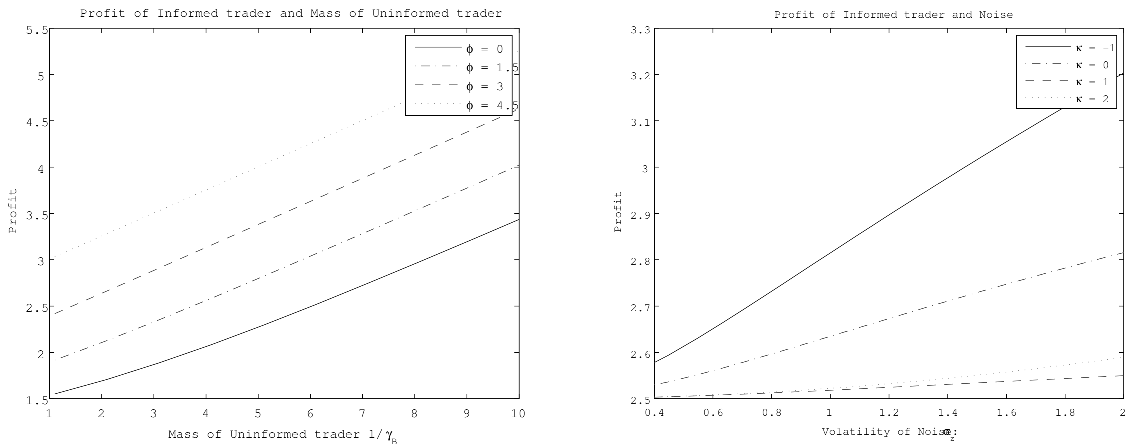

Figure 1.3.4. Numerical comparative statics for the total profit for informed traders.
(Left) (horizonal) Mass of Uninformed trader ($1/\gamma_B$), (vertical) profit
(Right) (horizontal) Volatility of noise trading (σ_z), (vertical) profit
Note: Other parameters: (Left) $[\theta, \gamma_A, \sigma_v^2, \sigma_z^2, \kappa]$=[.2, 1/5, 3, 1, 1],
(Right) $[\theta, \gamma_A, \gamma_B, \sigma_v^2, \phi]$=[.2, 1/5, 1/3, 1, $(1-\theta)\lambda_1$]

The higher noise trading decreases permanent price impact. This decrease improves the profitability of non-manipulative trading but at the same time dampens the profit from manipulation. The contribution of more volatile noise trading to the profit is high for non-manipulative trading and low for manipulative trading. This result is described in the right graph of Fig. 1.3.4.

Even though manipulative trading can make as much profit as non-manipulative trading, the "rate" of profit is even higher when contrarian traders are the majority because informed manipulation requires much greater funds to pump and dump the prices. The liquidity provided by the contrarian traders is more favorable for informed traders.

1.4. Conclusion

I study the intraday opportunity of stock price manipulation. The model suggests two conditions for price manipulation, which are obtained as restrictions on the variation of liquidity: uninformed and informed price manipulation. The model views the price manipulation as an arbitrage opportunity regarding expected liquidity changes. Uninformed price manipulation is not supported in a Bayesian Nash Equilibrium because the manipulator can earn unbounded profit. The model gives an equilibrium framework to the model of Huberman and Stanzl (2004).

Informed manipulation is easier to conduct because it has only to pay one-way slippage, but it requires private information about the fundamental. The opportunity for informed manipulation is available in an equilibrium when there are positive feedback (momentum) rule-of-thumb traders, who do not trade strategically and are naively influenced by manipulators. The manipulation cannot be successful without the rule-of-thumb traders because uninformed traders optimally respond to the manipulation.

Numerical comparable statics show that informed manipulation is more likely and more profitable when the noise trading is more volatile and that the market efficiency could become worse under the presence of manipulation. Financial transaction tax does not prevent informed manipulation and reduces the liquidity of the market.

Chapter 2

Intraday Liquidity Trading Opportunities

2.1. Introduction

Need for this study Can traders deceive their counterparts to make a bigger profit even when they do not have access to private information on fundamentals and liquidity? If they can accomplish this, how can one identify and measure this opportunity? For example, high-frequency trading (HFT) apparently allows steadly accumulation of profit by repeating trades during a day (Kirilenko, Kyle, Samadi, and Tuzun (2011)). How do the traders discover opportunities to make a profit? The concerns about HFT and resulting market efficiency have attracted growing concern, but not much academic research has been conducted in this area. I shall attempt to answer these questions in this paper. I present a measure designed to discover the manipulation opportunity based on a market microstructure model and test it empirically.

Various real-life examples depict ways in which market prices may be manipulated. Most of these are regulated by the authorities. Aggarwal and Wu (2006) investigated cases from the United States Securities and Exchange Commission (SEC), and summarized the ways in which profits may be made through manipulation: trade-based manipulation, rumors, wash sales, and corners.

In practice, various strategies can be utilized in trade-based manipulation, and some such strategies have been theoretically studied. Allen and Gale (1992) presents a theoretical model which supports uninformed manipulation in equilibrium when uninformed traders believe that there is informed trading. Examining a special case of trade-based manipulation, Kumar and Seppi (1992) studied theoretical price manipulation in cash settled contracts, and Brunnermeier and Pedersen (2005) theoretically investigated predatory trading which attacks stop-loss orders to drive down the price. Recently, Hasbrouck and Saar (2009) noted how the mechanism of HFT allows for the repeated cancellation and resubmission of limit orders within a second to take advantage of potential profits (called "fleeting orders"). Kirilenko, Kyle, Samadi, and Tuzun (2011) examined empirically the trading of high-frequency traders in Standard and Poor's E-mini S&P 500 futures contract and find that their positions were correlated with the past return within the space of one minute and one second. Working against these algorithmic traders, some market participants have also been known to take advantage of predictable features of algorithmic trading and to make a profit by placing spoof limit orders[1]. The algorithmic trading strategy was designed to submit market orders in response to changes in the limit order book, even though the limit orders were intended to "spoof" the algorithmic traders. In one such case, the trader was eventually accused of manipulative trading by the concerned authority. The party that actually manipulated the market is, however yet to be determined. This example illustrates that the definition of "manipulation" is wide-ranging and somewhat confusing. Therefore, before proceeding with the explanation of the measure I have devised, I will formally define the term "manipulation" in the context of this paper.

In this paper, I intend to study trade-based manipulation in light of the predictability of intraday liquidity. This means that I do not consider rumors to affect the par-

[1] SESC cases on the manipulation of Hokuetsu Kishu Seishi (3865), on June 14 and 15, 2010.

ticipant's belief of the fundamentals, and the relation between the market price and its fundamentals. I assume there are no regulatory and/or administrative causes of manipulation, such as cash settlements and stop loss orders for predatory trading. While my study does not rely on specific real-life events, I construct a manipulation opportunity measure for every listed stock as if it were a general arbitrage opportunity.

Modern portfolio theory tells us how to measure risk using mean-variance analysis. The profitability of manipulation is also associated with risk, given that the market price may fluctuate due to unanticipated reasons. However, there is a twist when it comes to the consideration of risk: the profit from manipulation bacause of market power is quadratic in the amount of trading. Thus, a comparison with the usual stock trading where the return is linear is not straightforward. My model provides insights on how to account for the risk. I also recognize that my analysis is about the ex-ante hypothetical profitability of a manipulation opportunity, and clarify that I do not aim to detect whether a manipulation has actually occurred.

Different from my approach, the majority of empirical studies concerning market manipulation resort to anecdotal evidence. Aggarwal and Wu (2006) studied data related to enforcement actions by the SEC. They concluded that manipulators are usually informed parties like insiders, brokers, and large shareholders and that their manipulation influences liquidity, price volatility, returns, etc. Khwaja and Mian (2005) documented a trade-based "pump and dump" scheme exercised by colluding principal brokers to generate an artificial momentum.

Definition of Manipulation Our theory-based definitions of manipulation can be applied to intraday stock trading. They are described as follows: "uninformed manipulation" refers to the profitability of a round trip trade, and "informed manipulation" addresses whether a manipulator could trade in a direction opposite to their private information. A “round trip trade” is an offsetting set of buying and selling trades in a certain interval. This zero-net-position trade should not earn any profit on average in a very short time interval. Informed manipulation is related to the following practical question—if traders have information that the stock fundamental is better than the market price, would they like to sell the stock? The answer can be in the affirmative, provided they are able to buy more shares at the lower price after the sale.

Note that these trading strategies are different from insider trading. Insiders could trade along with their private information, and they might split their orders to minimize price impacts. In this case, the market price incorporates the true fundamentals. However, under manipulate trading, the market price does not necessarily reflect true fundamentals.

In this paper, I attempt to model the dynamics of the limit order book (LOB) and incoming market orders. The dynamics involves an exogenous stochastic process, whereby a manipulator tries to maximize his profit by manipulating the environment. This allows us to analyze the conditions enabling a profitable opportunity for the manipulator. The conditions are described by the variation of liquidity and the volatility of the price; in order to find an opportunity for manipulation, I need to measure both Permanent Price Impact (PPI), and Immediate Price Impact (IPI). PPI has been traditionally studied in the field of empirical market microstructure (e.g., Hasbrouck (1991)). It is also known as the Kyle’s lambda (λ). Theoretically, we can estimate PPI as a regression coefficient of price changes on the order imbalances (buyer-initiated orders minus seller- initiated orders). In order to calculate IPI, we need rich information about the market. Therefore, I calculate IPI by using LOB data.

Literature The two types of manipulation strategies, uninformed manipulation and informed manipulation, have been studied previously. Uninformed manipulation has been referred to as a theoretical possibility by Kyle (1985). Informed manipulation was proposed by Chakraborty and Yilmaz (2004). I am going to study both strategies within a consolidated framework.

My aim in building the model is to present a measure of the manipulation opportunity, like the arbitrage opportunity implied by the alpha of the CAPM. As the CAPM assumes that the alpha is not significantly different from zero as the absence of arbitrage, my theory suggests that the manipulation opportunity measure should not be greater than zero as the absence of arbitrage, which means there is no opportunity of uninformed manipulation.

My model resembles the environment of Huberman and Stanzl (2004), where each IPI and PPI function is exogenously given. Their model analyzesconditions which preclude uninformed price manipulation, defined as a risk-less profitable round trip trade. The resulting no arbitrage condition mandates that for the single asset case, PPI should be less than the sum of current and future IPIs. My model considers a risk-averse manipulator reluctant to take the risk of price changes. The resulting manipulation condition tells us how to consider the risk of manipulation.

My notion of informed price manipulation, characterized by the trading against private information, is similar to the argument studied by Chakraborty and Yilmaz (2004a, b). I can consider informed manipulation in a framework similar to that proposed by Huberman and Stanzl (2004). Mei, Wu and Zhou (2004) studied uninformed price manipulation generated by the presence of behavioral traders, and considered its empirical plausibility. They introduced a rule of thumb for "momentum" traders in a manner similar to that of De-Long et al. (1990) and Hong and Stein (1999). While I do not specifically assume such a rule of thumb for traders in my model, I empirically examine whether the return or abnormal volume can affect the manipulation measure I am proposing. If they do, it implies that the predictable behavior of rule of thumb for traders leads the profitability of manipulation.

This paper proceeds as follows. In section 2 presents the model to define the profitability of manipulation. Section 3 describes the data. Section 4 explains the empirical formulation and presents the results. I conclude in section 5.

2.2. The Model

Motivation for the Model I present a model to define the conditions of manipulation. The conditions motivate my empirical formulation. To simplify the model, I assume the incoming orders are exogenous, and the manipulator maximizes his profit based on the environment. I assume a very short time for the trade, and that the dividend from the trade is zero.

2.2.1. The Model Environment

I model the state of the LOB s_t, at time t as pairs of the amount of limit order and the price:$s_t = \{(b_{t,i}, pb_{t,i}), (a_{t,i}, pa_{t,i})\}_{i=1,\dots I}$. Here, b and a denote the quantities in bid and ask side of the book, respectively. $pb_{t,i}$ and $pa_{t,i}$ denote bid and ask prices of the ith step at time t. From LOB orders up to I steps of the ask and bid are publicly observable. I define the mid price of the book mp_t as the weighted average of the best bid and ask prices

$$mp_t = \frac{a_{t,1}pb_{t,1} + b_{t,1}pa_{t,1}}{b_{t,1} + a_{t,1}}.$$

I also define effective spreads for bid and ask as $es_{b,t}$ and $es_{a,t}$, respectively. For example, $es_{b,t} = mp_t - pb_{t,1}$.

I assume incoming market orders between t and $t-1$, and arrivals of public information that affect the book without inducing any executions. Combining with a PPI λ_t, I model the changes in the mid price as follows:

$$mp_t - mp_{t-1} = \lambda_t v_t + i_t. \tag{2.2.1}$$

v_t denotes the executed order imbalances between t and $t-1$, and i_t is the price change from public information. This formulation is motivated by Kyle (1985). λ_t represents the update of belief of market participants (or market makers) about the fundamental. If the order imbalances do not have any content of private information, $\lambda_t = 0$.

In addition to the PPI, I want to know the instantaneous price change which is made by my own execution at time t after observing the state of the book. This leads to the definition of IPI. I can define an IPI at t from the state of the book s_t. When I buy x units of the stock at time t, the IPI is a function of x, and the buyer pays an *averaged purchase price* $- pa_{t,1}$ per unit that can be calculated from s_t.[2]

Based on a system represented by s_t, v_t, i_t, λ_t, I set up the maximization problem of a manipulator at $t-1$ and t. I examine two cases: a case when the manipulator

[2] In reality, for the limit order book, I would observe the maximum purchase price rather than the averaged purchase price. My definition employs the latter so as to simplify the maximization problem of a manipulator.

make a round trip trade in the market, and another case when the manipulator does front-running. The first setup derives the condition for uninformed manipulation, while the second setup gives the condition for informed manipulation.

Uninformed manipulation A round trip trade is a set of two trades with zero net position at the end. The manipulator first buys (sells) a stock, and liquidates the position after some time interval. I will examine whether the round trip trade between $t-1$ and t could make a positive profit. To simplify the notation, the IPI at t and $t+1$ of x unit execution are denoted as $IPI_t(x)$ and $IPI_{t+1}(x)$. If the LOB is discrete, the function of IPI is described as a step function depending on s_t. I assume $IPI_t(x), v_t, i_t, \lambda_t$ follow stochastic processes, and the manipulator maximizes the profit based on the information set at $t-1$.

I also assume the manipulator has a negative exponential utility function in the terminal wealth W_t: $u(W_t) = -exp(-\gamma W_t)$. The maximization problem for the manipulator who conducts a round trip trade of $x \in \mathbb{R}^+$ units of stocks [3] is,

$$max_x E_{t-1}\left[-exp\left(-\gamma\left(P_t(x,-x) - P_{t-1}(0,x)\right)\cdot x\right)\right]. \tag{2.2.2}$$

Here $P_t(x,y)$ is an averaged execution price when the manipulator trades x at $t-1$ and y at t. The restriction of a round trip trade can be denoted as $y=-x$. Combining Equation (2.2.1) and the definition of IPI gives us,

$$P_t(x,-x) = \lambda_t(v_t+x)+i_t+IPI_t(-x)-es_{b,t}+mp_{t-1},\ P_{t-1}(0,x) = es_{a,t-1}+IPI_{t-1}(x)+mp_{t-1},$$

when $x \geq 0$. To simplify this argument, I assume $IPI(x)$ is a linear function: $IPI(x) = IPI \cdot x$.

[3] I assume manipulators start with buying rather than selling. This is because anecdotal evidence suggests that more than 90% of manipulators start with buying in order to manipulate the price. The analysis of selling manipulation is mostly symmetric to this analysis.

I further assume $(IPI_t, es_{b,t}, v_t, i_t, \lambda_t)$ are jointly normally distributed and uncorrelated. Their means are assumed to be $(I\bar{P}I, e\bar{s}_{b,t}, 0, 0, \bar{\lambda})$ and their variances are $(\sigma^2_{IPI}, \sigma^2_{es_b}, \sigma^2_v, \sigma^2_i, \sigma^2_\lambda)$. The maximization problem can be rewritten as,

$$
\begin{aligned}
max_x \quad & -E_{t-1}\left[exp\left(-\gamma x\left(\tilde{i}_t - xI\tilde{P}I_t - \tilde{e}s_{b,t}\right)\right)\right] \\
& \cdot E_{t-1}\left[exp\left(-\gamma x \cdot \tilde{\lambda}_t(\tilde{v}_t + x)\right)\right] \\
& \cdot exp\left(-\gamma x\left(-es_{a,t-1} - xIPI_{t-1}\right)\right).
\end{aligned}
$$

because $(v_t + x)$ and the other terms are independent, and $P_{t-1}(0,x)$ is a deterministic term. The randam variables are marked with tilde. Taking out the expectation, I obtain

$$
\begin{aligned}
max_x \quad & -exp\left[-\gamma x\left(-xI\bar{P}I - \bar{e}s_{b,t}\right) + \frac{\gamma^2 x^2}{2}\left(\sigma_i^2 + x^2\sigma^2_{IPI} + \sigma^2_{es_b}\right)\right] \\
& \cdot exp\left[\frac{2\bar{\lambda}x(-\gamma x) + \gamma^2 x^2(\sigma^2_\lambda x^2 + \sigma^2_v \bar{\lambda}^2)}{2(1-\gamma^2 x^2 \sigma^2_\lambda \sigma^2_v)}\right] / (1 - \gamma^2 x^2 \sigma^2_\lambda \sigma^2_v)^{\frac{1}{2}} \\
& \cdot exp(-\gamma x[-es_{a,t-1} - xIPI_{t-1}]).
\end{aligned}
\tag{2.2.3}
$$

Here, the first term is from a moment generating function of a normal distribution, and the second term is from that of a product-normal distribution. Note that taking $\gamma \to 0$ generates a risk neutral case, and taking $\sigma_\lambda \to 0$ leads the product-normal to a normal distribution. The maximization problem seen in Equation (2.2.3) should have its second order condition satisfied in order to preclude the profitable uninformed manipulation. Taking the second order derivative, I find that it takes the form of $f''(x)e^{f(x)} + f(x)'^2 e^{f(x)}$ for a function $f(x)$. When the second order condition is positive, the manipulator buys stocks infinitely (unbounded solution). When the condition is negative, it is optimal to set $x = 0$ (denoting an absence of uninformed manipulation). Since $f(x)'^2$, $e^{f(x)}$ are positive, I focus on $f(x)''$ to test the sign of the second order condition. Taking a Taylor expansion of $f(x)''$ around $x = 0$, I obtain

$$2\gamma\left(-\bar{\lambda}+I\bar{P}I+IPI_{t-1}\right)+\gamma^2\left(\bar{\lambda}^2\sigma_v^2+\sigma_i^2+\sigma_{es_b}^2+\sigma_\lambda^2\sigma_v^2\right)+\gamma^3\left(\bar{es}_{b,t}+es_{a,t-1}\right)\sigma_\lambda^2\sigma_v^2 x+O(x^2). \tag{2.2.4}$$

The first term is the same as the risk neutral uninformed manipulation condition $-\lambda + IPI_t + IPI_{t-1} < 0$, which is the condition to obtain positive expected profit[4]. The second term represents the risk, and this is interpreted as the volatility of mid price changes, and the volatility of effective spread incurred in the liquidation period. The third term is related to the bid and ask spread, but I ignore it because I realize the solution should be either $x = \infty$ or $x = 0$.

Equation (2.2.4) motivates my risk-averse uninformed manipulation measure M_t, which I define as follows,

$$M_t \equiv E_{t-1}\left[\lambda_t - IPI_t\right] - IPI_{t-1} - \frac{\gamma^2\sigma_{price}^2}{2}. \tag{2.2.5}$$

When $M_t > 0$, I find an opportunity to make a profit from uninformed manipulation between $t-1$ and t. I can empirically test this manipulation opportunity with market data.

Informed manipulation Informed manipulation is defined as a profitability of front running. I assume that the manipulator can liquidate their position at $t+1$ at a price P_{exit} (to denote front running). They have two options to earn a profit: dividing their order to mitigate the price impacts, or trading in the opposite direction

[4] The risk neutral manipulation condition is the same as the one proposed by Huberman and Stanzl (2005).

at $t-1$ to take an advantage of the price at t. Assuming that the manipulator would take the second strategy, I can formulate the maximization problem as follows:

$$max_{x_{t-1},x_t} E_{t-1}\left[-exp\left(-\gamma(P_{exit}\cdot(x_t+x_{t-1})-P_t(x_{t-1},x_t)x_t-P_{t-1}(0,x_{t-1})x_{t-1})\right)\right]. \tag{2.2.6}$$

Here, I assume that the manipulator has private information indicating better fundamentals and sells at $t-1$ and then buys at t. The execution price depends on whether the manipulator buys or sells because of different effective spreads. When it is selling (buying), the price is associated with $es_{b,t}(es_{a,t})$. The problem at t gives the solution $x_t^* = \frac{P_{exit}-(\lambda(x+v)+es_{z,t}+i+mp_{t-1})}{2IPI}$. Given x_t^*, the problem can be transformed into

$$max_x E_{t-1}\left[-exp\left(-\gamma\frac{\left(P_{exit}-\left(\lambda(x+\tilde{v})+\tilde{e}s_{a,t}+\tilde{i}_t+mp_{t-1}\right)\right)^2}{4IPI_t}-\gamma x\left(P_{exit}-(mp_{t-1}-es_{b,t-1}-IPI_{t-1}\cdot x)\right)\right)\right],$$

to obtain $x_{t-1}=x^*$. For tractability, here I assumed that the PPI and IPI are deterministic. Based on this assumptions, I can take out the expectation by using the momentum generating function of a non-central Chi-square distribution. The second term is pre-determined. I may write,

$$max_{x_{t-1}} \quad -\frac{exp\left[\frac{-\gamma\sigma^2}{\sigma^2(1+2\gamma\sigma^2)}\frac{\left[P_{exit}-(mp_{t-1}+\lambda x_{t-1}+\bar{e}s_{a,t})\right]^2}{4IPI_t}\right]}{(1+2\gamma\sigma^2)^{\frac{1}{2}}}$$
$$\cdot exp\left[-\gamma\left(P_{exit}-(mp_{t-1}-es_{b,t-1}-IPI_{t-1}\cdot x_{t-1})\right)x_{t-1}\right].$$

I denote $\sigma^2 = \frac{\lambda^2\sigma_v^2+\sigma_{es_{a,t}}^2+\sigma_i^2}{4IPI_t}$, and $E_{t-1}[es_{a,t}] = \bar{e}s_{a,t}$.

I want to show the solution $x^*<0$ when $P_{exit} > E_{t-1}[es_{a,t}]+mp_{t-1}$. The first order condition is

$$\frac{-2\gamma\sigma^2\lambda}{\sigma^2(1+2\gamma\sigma^2)^{\frac{3}{2}}}\left(\frac{P_{exit}-(\lambda x_{t-1}+\bar{e}s_{a,t}+mp_{t-1})}{4IPI_t}\right)+\gamma\left(P_{exit}-(mp_{t-1}-es_{b,t-1}-2IPI_{t-1}\cdot x_{t-1})\right)=0.$$

I drop the exponential term. After solving for x_{t-1}, the condition for $x^*_{t-1} < 0$, the risk averse informed manipulation condition, is

$$\lambda > \frac{P_{exit} - (mp_{t-1} - es_{b,t-1})}{P_{exit} - E_{t-1}[\bar{es}_{a,t} + mp_{t-1}]} \cdot 2IPI_t \cdot (1 + 2\gamma\sigma^2)^{\frac{3}{2}}. \tag{2.2.7}$$

When the manipulator is risk neutral and the effective spreads are zero, $\gamma = 0$ and $es_a = es_b = 0$, then the condition reduces to $\lambda > 2IPI_t$.

2.2.2. Summary for the Empirical Study

In this section, I summarize the empirical implication obtained from this model. The manipulation opportunity can be examined by estimating the IPI and PPI. Each price impact is identified without estimating the structural parameters that govern the behavior of the traders. The PPI is identified as Kyle's lambda, and if I allow a linear approximation, the IPI should be the slope of the demand and supply curve implied by the LOB.

The fundamental question about the manipulation opportunity is whether if it is arbitraged or not. If market participants recognize the presence of the arbitrage opportunity, it should be exploited. To answer this question, I develop following empirical questions: (1) what is the likelihood of the manipulation measure (defined in Eq.(2.2.5), and Eq.(2.2.7)) being positive (implying the presence of manipulation opportunity), (2) is it profitable enough for risk averse manipulators, and (3) whether it changes along with an intraday time range. I explore these questions by taking look at the descriptive statistics.

Other questions about the measure are its cross-sectional and time series properties. Which stock is more likely to present a high opportunity for manipulation? During a day, what is the driver of the time-variant manipulation measure? These questions assume significance when I implement the manipulation strategy, and therefore, I think it is prudent to explore the link between the manipulation measure and other market variables.

For the cross-sectional analysis, I look at the relation between the measure and number and volume of trade(s), volatility of noise trading, and market capitalization. In my time series regression model, I use lagged return, order imbalance, and abnormal volume, which are supposed to be correlated with "attention-based trading," as per the findings of Barber and Odean (2008). If these market variables stimulate the behavior of momentum follower, the stock price is more easily manipulated.

2.3. Data

2.3.1. Description of Data

In this analysis, I use tick-by-tick transactions and LOB data provided by the Nikkei Tick data[5]. Transaction data contain the code of equities, quantities, prices, up-tick or down-tick flags, and time-stamp (minute-by-minute for the Tokyo Stock Exchange (TSE), second-by-second for the Osaka Securities Exchange (OSE)). There are no flags to identify market orders from limit orders. The LOB data contains every snapshot of the LOB, which is revised at every new order arrival. The LOB in the TSE is described as five-step best bid and ask prices associated with the total order volume. Note that my data does not include block-trading and basket-trading transactions conducted during off-auction hours through the Tokyo Stock Exchange Trading Network or ToSTNet.

[5] I appreciate Prof.Takatoshi Ito, and Center for Advanced Research in Finance at University of Tokyo for the access to this data.

The trading system, rules, and basic characteristics are documented in Lehmann-Modest (1994). The dealing system of the TSE starts at 9:00 AM with an auction. It has a break between 11:00 AM to 12:30 PM, and ends at 3:00 PM. The dealing system at the OSE ends at 3:10 PM. There is a price limit that ranges from 7% to 20% of each equity price, depending on its price range. Each equity's minimum tick size ranges between 3bp to 100%, and is characterized by a relatively bigger minimum tick size than that of the New York Stock Exchange or NYSE. The total quoted trade volume was the fourth largest in the world in 2009. Currently, there are about 3,000 listed stocks. Unlike other Electronic Trading Systems (ETS), the TSE does not allow hidden orders, and traders can use either a market or limit order. The pricing system has price and time priority. Each order is anonymous, and traders cannot identify whether if it comes from institutional investors or retail dealers.

The advantages of the TSE and OSE data are as follows: (1) it is one of the biggest markets using ETS, and is the most liquid, (2) whole LOB data are available, (3) index and bond futures and option data are also available, and (4) relatively new data (ranging between 2004 to 2009) are available. The defects of the data are as follows: (1) the time-stamp is sparse (minute-by-minute), (2) order identities are hidden, (3) old data (before 2004) are not available, (4) the tick size is large, and (5) there are price limits. For the purposes of my study, the liquidity and availability of LOB data are essential. [6]

2.3.2. Descriptive Statistics

Table 2.1 shows the descriptive statistics of my paper. These statistics are calculated for the sample time range from November 1, 2004 to November 1, 2005.

[6] The presence of a price limit may distort the results. Therefore, I omit data approaching the price limit for a particular stock day.

Variable	Mean	Std. Dev.
Immediate Price impact (ask,yen/unit)	.084	.143
Immediate Price impact (bid,yen/unit)	.091	.165
Bid and Ask spread (yen)	1.469	1.141
Permanent price impact (yen/unit)	.063	.237
Ask side depth (million yen)	2.31	7.47
Bid side depth (million yen)	2.12	6.74
Number of trades perday	339.4	321.8
Daily volume (# of shares)	2.46 million	9.28 million
Order imbalances(in unit)	4.849	523.8
$sd(return)$	.002	.001
market capitalization (log yen)	25.99	1.158
	Obs.	432

Table 2.1. Descriptive statistics. The return is a 5-minutes return. “unit” means the minimum shares to trade which depends on the stock’s face value.

Since the Kalman filter does not necessarily converge and I focus on one-minimum tick size stocks, the number of samples reduces from 1000 to 432.

To calculate PPI and IPI correctly, each stock needs large enough activity. I can measure the activity, or liquidity, by trading volume, trade numbers, and depth. For the 432 sample stocks, the mean trading volume is 2.46 million shares, and the mean trading number is 339.4 per day. Also, the mean ask and bid side depth are 2.31 and 2.12 million yen, respectively. Thus, the sample stocks are liquid enough in terms of both depth and volume. Further, the mean PPI (0.63 yen per unit) is lower than the IPI 0.84 yen per unit for ask, and 0.91 yen per unit for bid). This indicates there is no opportunity for manipulation on average.

2.4. Empirical Analysis

2.4.1. Empirical Formulation

2.4.1.1. Immediate Price Impact (IPI)

I consider measuring the IPI (also called slippage). Theoretically, slippage is measured by estimating the slope of the demand-supply schedule implied by each snapshot of the LOB. However, my empirical estimate of the IPI differs from the theoretical definition. My model assumes that the IPI is defined on the average purchase price that depends on the amount of executed volume, but in reality, the IPI is the executed price for the last one unit. In order to draw the IPI to simply represent the state of the book, I approximate the real LOB with a linear demand and supply curve.

From a snapshot of the LOB, I conjecture the price schedule as a linear function to define the IPI for the ask side of the book. Then I conduct the following regression:

$$\text{Slippage estimation:} \qquad p(V_k) - pa_{t,1} = IPI_A \cdot V_k + \varepsilon_k, \quad V_k = \sum_{i=1}^{k} order\ volume_i \tag{2.4.1}$$

where $i = 1, 2, \cdots 5$ because I have only five best bid and ask orders from the data. I repeat the regression for the bid side of the LOB to obtain IPI_B. Here I do not consider the presence of bid and ask spread, as I do not have to heed the spread while considering the uninformed manipulation condition.

As indicated previously, I want to define the IPI based on the average purchase price rather than the last marginal purchase price. This necessitates a modification such that the IPI is denoted as half of the linear price impact inferred from the LOB, or IPI/2. The details of this modification are located in the Appendix.

2.4.1.2. Permanent Price Impact (PPI)

The PPI is a price change led by information leakage. The PPI is identified by the order imbalance and the mid-price change in the LOB. The empirical regression equation is as follows:

$$\text{Permanent price impact estimation:} \qquad \Delta\tilde{p}_{t+1} = PPI \cdot v_{t+1} + \varepsilon_{t+1}, \quad t = 1, 2, \cdots T, \tag{2.4.2}$$

where v_{t+1} denotes order imbalance between t and $t+1$, and $\Delta\tilde{p}_{t+1} \equiv \tilde{p}_{t+1} - \tilde{p}_t$ is a mid-price change[7]. The order imbalance is defined as a difference between the buy volume and sell volume, or the sum of signed volume in shares. According to the standard market microstructure model, the PPI is determined endogenously; the trading of manipulator does not affect the PPI itself.

2.4.1.3. The Kalman Filter

The price impact coefficients, IPI and PPI, are assumed to be time varying. The IPI_t and PPI_t are price impacts which are estimated at the ending of each time segment t, and are conditional on the past realization of price and trade up to

[7] In practice, defining $\tilde{p}_{t+1}$ can be a problem. The LOB price $\tilde{p}_{t+1}$ is defined either as the mid-point of bid and ask price, or depth-weighted average of bid and ask price. The latter method is an approximation of estimating the crossing point of demand and supply schedule implied by the LOB. I define $\tilde{p}_t$ as a depth-weighted average price. This also relieves the bid-ask bounce problem. Cao, Hansch, and Wang (2009) discussed the use of share weighted mid-quote in more detail.

$t-1$. To calculate them, I employ the Kalman filtering algorithm. The equations are expressed as a state space as noted below.

$$\text{Observation equation:} \quad \begin{pmatrix} \Delta\tilde{p}_t \\ IPI_t \end{pmatrix} = \begin{pmatrix} v_t & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} P\tilde{P}I_t \\ I\tilde{P}I_t \end{pmatrix} + \begin{pmatrix} \varepsilon_{U,t} \\ 0 \end{pmatrix}$$

$$\text{Transition equation:} \quad \begin{pmatrix} P\tilde{P}I_{t+1} \\ I\tilde{P}I_{t+1} \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} PPI_t \\ I\tilde{P}I_t \end{pmatrix} + \begin{pmatrix} u_{U,t} \\ u_{S,t} \end{pmatrix}$$

I distinguish the state of slippage $I\tilde{P}I$ from the observed slippage IPI. The error terms are further assumed as follows:

$$\begin{bmatrix} \varepsilon_{U,t} & \\ u_{U,t} & |\mathscr{F}_{t-1} \\ u_{S,t} & \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma^2_{\varepsilon,U} & 0 & 0 \\ 0 & \sigma^2_U & 0 \\ 0 & 0 & \sigma^2_S \end{bmatrix} \right) \tag{2.4.3}$$

The Kalman Filtering provides one-period ahead estimation $\theta_t|\mathscr{F}_{t-1} \sim N(\hat{\theta}_{t|t-1}, V_{t|t-1})$, where θ_t is the parameter vector $(PPI_t\ IPI_t)'$. $V_{t|t-1}$ is the conditional variance and is recursively defined. Also, I can estimate an initial parameter PPI_0, and the standard deviations $\sigma_{\varepsilon,U}$, $\sigma_{u,U}$, $\sigma_{u,S}$ by maximum likelihood estimation. Abbreviating the observation function as $y_t = Z_t\theta_t + H_t$, I can express the log likelihood function as follows:

$$\begin{aligned} \sum_{t=1}^{T} log\ f(y_t|X_t, \mathscr{F}_{t-1} : \lambda_0, \sigma_\varepsilon, \sigma_\lambda, \sigma_\mu) \quad = \quad & -\frac{T}{2} log(2\pi) - \frac{1}{2}\sum_{t=1}^{T} log\ det(Z_t' V_{t|t-1} Z_t + H_t) \\ & -\frac{1}{2}\sum_{t}^{T} (y_t - y_{t|t-1})'(Z_t' V_{t|t-1} Z_t + H_t)^{-1}(y_t - y_{t|t-1}) \end{aligned}$$

Eventually, I obtain $PPI_{t|t-1}$ and $IPI_{t|t-1}$ by the information up to $t-1$: $\mathscr{F}_{t-1} = \{\Delta\tilde{p}_{t-1}, v_{t-1}, IPI_{t-1}, \mathscr{F}_{t-2}\}$. I apply this empirical framework to the LOB data in the TSE. I take 5, 15, and 30 minute intervals to calculate the order imbalance v_t and the mid-price change Δp_t. Each slippage IPI_t is calculated from the snapshot of the LOB at the beginning of every five minutes.

As mentioned previously, for this formulation, I estimate the standard deviation of the transition and observation errors with maximum likelihood lstimation. Because the optimization program might not always converge, I confirm that the rolling Ordinary Least Squares (OLS) Method leads to similar results.

2.4.1.4. Regression formulation

The objective of this empirical study is to show the existence of manipulation opportunity and its driving force. Here, I implement cross-sectional and intraday time series regression analysis.

Cross-sectional analysis For cross-sectional analysis, I examine the frequency of the manipulation opportunity averaged over a year. This analysis aims to explore what sort of stock is more likely to be manipulated. For explanatory variables, I calculate the amount of noise trading on the basis of the probability of informed trading (PIN) model, log market capitalization, short-term price volatility, averaged trade volume, and frequency.

Intraday time series analysis I assume that the manipulation opportunity measure M_t is driven by the mass of momentum traders. However, I cannot estimate the behavior of momentum traders. As a plausible proxy, I used lagged return, order imbalances, and abnormal volume as defined by Barber and Odean (2008). Independent variables also include abnormal volume and trade frequency defined as a percentage deviation from the means. Independent variables introduced in the cross-sectional analysis are also included. This empirical methodology is similar to the time series regression adopted by Ahn, Bae, and Chan(2001), and Breen, Hodrick, and Korajczyk (2002).

The manipulation opportunity would not be persistent if manipulators exploit it. I examine this intuition by adding dummy variables indicating the opportunity: $1_{M_t>0}$. If the manipulation measure lies towards one end of the no-manipulation region, the coefficient of the interaction variable $M_t \cdot 1_{M_t>0}$ should be significantly negative. This specification follows a threshold auto-regressive model, which was also used to test the opportunity of index arbitrage (Dwyer, Locke, Yu (1996)).

I focus on "buy and sell" manipulation rather than "sell and buy" manipulation. This is because manipulation through short sell is not popular[8].

2.4.2. Descriptive Results

2.4.2.1. Relative frequency of manipulation opportunity

I examine the ease of manipulation measured by the price impacts. I define the uninformed manipulation condition as $M_t = E[PPI_t - IPI_{t+1}] - IPI_t > 0$. Thus, the sign of the measure is essential to infer the manipulation opportunity. As a measure of the ease of manipulation, I use the frequency of positive M_t observations divided by the number of total observations. This represents the average possibility of manipulation. Along with the theoretical implication, I also look into the risk adjusted manipulation opportunity measure $E[PPI_t - IPI_{t+1}] - IPI_t - \frac{\gamma Var(\Delta P_t)}{2}$, the informed manipulation condition $E[PPI_t - 2IPI_{t+1}]$, and their frequency of the manipulation opportunity.

Table 2.2 summarizes the results about the descriptive statistics. The descriptive statistics are calculated for different sampling intervals: 5 minutes, 15minutes,

[8] More than 90% of trade-based stock manipulation is ignited by buy trades (Aggarwal and Wu (2006)).

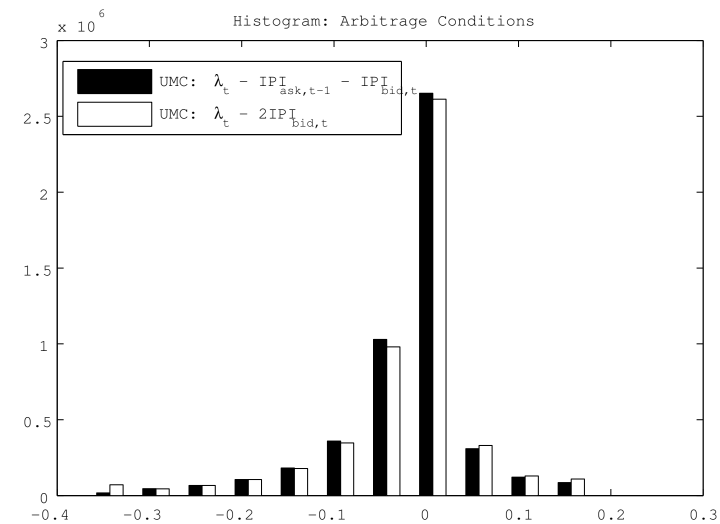

Figure 2.4.1. Overall frequency of the two different manipulation opportunity measures: uninformed manipulation measure and informed manipulation measure. The horizontal line denotes the value of each measure, and the vertical line the density.

and 30 minutes. Since the PPI, becomes smaller as the time interval becomes longer, the possibility of manipulation opportunity $\sum 1_{M_t>0}/\#obs$ also reduces for the longer time interval examinations. For five minutes sampling case, the uninformed manipulation opportunity can be found in 32% of overall intervals. For the 15 minutes sampling case, the possibility of uninformed manipulation opportunity reduces to around 29%. For 30 minutes intervals, it becomes 26%. When the price fluctuation risk is considered, however, the five minutes interval manipulation opportunity declines to 0.6% [9]. This drop in the opportunity can be observed in different time intervals as well. I will look more details on the risk of manipulation in later section.

When it comes to informed manipulation, the frequency ratio goes up to 58% for the five minutes interval case. This implies that there are slightly more of manipulation possibilities for those who have strong private information and exit

[9] To construct the risk adjusted measure, I set the risk aversion parameter $\gamma = 1$.

plans (or indulge in front running). This is due to the fact that liquidity shows increasing during a day, which confirms the well-know inversed J shape of intraday liquidity. Informed manipulation, or bluffing trading, could make the market price deviated from the true fundamentals. Figure 2.4.1 shows the distribution of each manipulation opportunity measure that are sampled across each stock and interval. The horizontal axis is the value of measure, and the vertical axis is the number of observations. The informed manipulation measure is more skewed to the left, which indicates the informed manipulation can be more easily conducted. It is hard to see that the manipulation opportunity is exploited in markets, however, the opportunity almost disappears when the risk is considered as shown in later section.

2.4.2.2. Time range and manipulation opportunity

So far, I have examined the descriptive statistics of the manipulation opportunity. I find that there are occasional chances of manipulation. From this section, I should focus our attention on the determinants of the measure. First of all, I start from examining the intraday variation of the possible opportunities.

I can see an intraday pattern of price impacts and manipulation opportunity measure in Figure 2.4.1. I stratified intraday time bins by each 30 minutes, and took the cross-sectional mean of price impacts (PPI and IPIs) and manipulation opportunity measure. PPI and IPI decrease monotonically during a day. At the end of a day, PPI drops by 35% from the beginning of the day. While IPI-bid (ask) drops by 47% (38%). Thus, PPI shows a slightly more moderate drop than IPI. As a result, M_t is low in the morning (-0.54 at 9:00-9:30 bin), and increases during the middle of a day (-0.20 at 12:30-1:00 bin). At the end of a day, it becomes lower once more (-0.26 at 2:30-3:00 bin). The standard deviation of the measure is high at the beginning of a day and the afternoon session.

		5 minutes		15 minutes		30 minutes	
Variable	Variable definition	Mean	S.D	Mean	S.D	Mean	S.D.
Uninformed manip.	$PPI_t - IPI_t - IPI_{t+1}$	-.024	.232	-.037	.348	-.048	.447
Freq/obs of U.M.	$\frac{\sum 1_{PPI_t - IPI_t - IPI_{t+1} > 0}}{\#obs}$.	.324	.052	.288	.063	.256	.081
Risk adjusted U.M.	$PPI_t - IPI_t - IPI_{t+1} - \frac{\gamma}{2}\sigma_p^2$	-.691	1.657	-1.139	3.119	-1.644	4.818
Freq/obs of R.A.U.M.	$\frac{\sum 1_{PPI_t - IPI_t - IPI_{t+1} - \gamma\sigma_p^2/2 > 0}}{\#obs}$.	.006	.016	.002	.014	.003	.025
Informed manip.	$PPI_t - IPI_{t+1}$	-.028	.248	-.042	.363	-.056	.466
Freq/obs of I.M.	$\frac{\sum 1_{PPI_t - IPI_{t+1} > 0}}{\#obs}$.	.336	.0526	.300	.060	.265	.073
Uninformed manip. (rolling)	$PPI_t - IPI_t - IPI_{t+1}$	-.035	.104	-	-	-	-
Freq/obs U.M.(rolling)	$\frac{\sum 1_{PPI_t - IPI_t - IPI_{t+1} > 0}}{\#obs}$.	.242	.057	-	-	-	-
Uninf manip (2006)	$PPI_t - IPI_t - IPI_{t+1}$	-.037	.348	-	-	-	-
Freq/obs U.M.(2006)	$\frac{\sum 1_{PPI_t - IPI_t - IPI_{t+1} > 0}}{\#obs}$.	.288	.063	-	-	-	-

Table 2.2. Averaged manipulation opportunity measure and the frequency of manipulation opportunity. This table shows the ease of manipulation implied by the manipulation opportunity measure dictated by the model. Each three panel is a result for 5, 15, and 30-minute intervals of price impacts obtained by the Kalman Filter. Results from different definitions of the ease of manipulation are presented for each row. $E[PPI_t - IPI_{t+1}] - IPI_t$ is the manipulation opportunity measure of uninformed manipulation, and it implies manipulation opportunity whenever it is positive. $E[PPI_t - IPI_{t+1}] - IPI_t - \gamma\sigma_p^2/2$ is a risk adjusted uninformed price manipulation measure, where I take $\gamma = 1$ for this experiment. $E[PPI_t - 2IPI_{t+1}]$ is the informed price manipulation measure without any bid-ask spread loss. Each measure also gives a frequency of manipulation opportunity intervals.

Time Dummy	PPI_t	s.d	IPI_t ask	s.d	IPI_t bid	s.d	$PPI_t - IPI_t ask - IPI_{t+1} bid$	s.d
9:00-9:30	.071	.430	.114	.196	.137	.264	-.054	.444
9:30-10:00	.080	.211	.099	.165	.107	.186	-.023	.199
10:00-10:30	.073	.178	.088	.145	.095	.161	-.019	.160
10:30-11:00	.066	.166	.085	.140	.091	.151	-.022	.151
12:30-1:00	.065	.247	.081	.139	.090	.165	-.020	.239
1:00-1:30	.059	.155	.074	.124	.079	.134	-.018	.143
1:30-2:00	.054	.139	.073	.122	.076	.129	-.020	.129
2:00-2:30	.051	.130	.071	.119	.074	.127	-.022	.122
2:30-3:00	.046	.121	.070	.120	.073	.128	-.026	.120

Table 2.3. The intraday pattern of manipulation opportunity and price impacts. Each trading day is stratified into 9 time ranges, each of which corresponds to 30 minutes. The bins from one to four, and five to nine are from morning and afternoon sessions, respectively. For each time range, $M_t = E[PPI_t - IPI_{t+1}|t] - IPI_t$ are averaged over stocks and time.

In sum, the manipulation opportunity is more likely during the middle of a day, and less likely during the first and last 30 minutes.

2.4.2.3. Risk aversion and profitability of manipulation opportunity

I observe that the manipulation measure is high enough to create manipulation profits, but I also would like to evaluate the risk associated with the manipulation strategy. I consider two risks: the price fluctuation risk indicated by Eq. (2.2.5) and the estimation error. To quantify the risk that comes from estimation error, I calculate the lower two-sigma band from the estimation of $V_{t|t-1}$. I can see that the manipulation opportunity is likely to be well arbitraged when the risk is considered.

Figure 2.4.2 shows the distributions of the manipulation measure that takes the two risks into consideration. Both distributions exhibit that there is a clear cutoff between the manipulation opportunity region ($M_t > 0$) and the no-manipulation region ($M_t < 0$). The observation in $M_t > 0$ is very small. This indicates that the

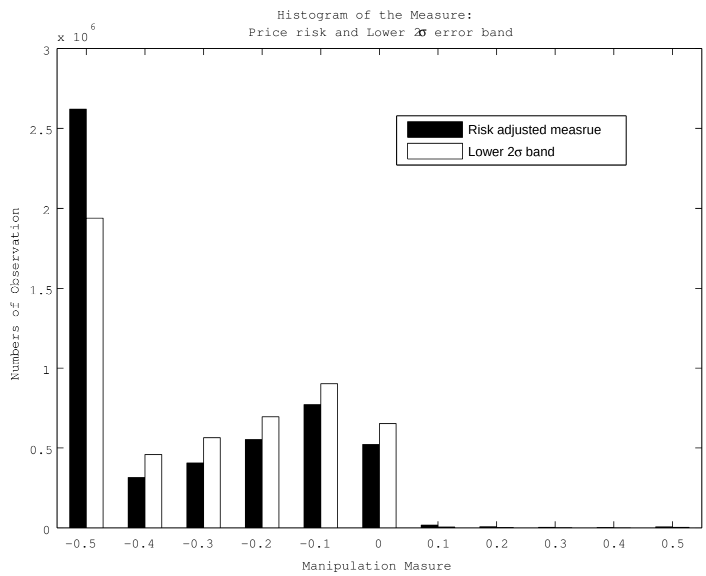

Figure 2.4.2. Overall frequency of the manipulation opportunity measures that consider risks: risk adjusted uninformed manipulation measure, and the measure subtracted by the two sigma of the standard error of the coefficients. The horizontal axis denotes the value of each measure, and the vertical axis the density. The leftmost bar express the observation (< -0.55). The risk aversion is set to one to derive the measure.

risk of the manipulation strategies is sufficiently high, and the opportunity to earn profit can be well arbitraged.

To evaluate the risk, I need to fix the risk aversion parameter. Figure 2.4.3 shows the relationship between the frequency of manipulation opportunity and the risk aversion to more detail. In this graph, the horizontal axis is the risk aversion γ and the vertical axis is the frequency. It shows how the manipulation opportunity decreases with an increase in the manipulator's risk aversion. The plot for the five-minutes interval shows the highest manipulation opportunity to begin with, but it decays quickly. Only 2% of the cases can be profitable for nearly risk neutral manipulator ($\gamma = 0.5$). This result implies that uninformed manipulation could be risky for most traders with moderate risk aversion.

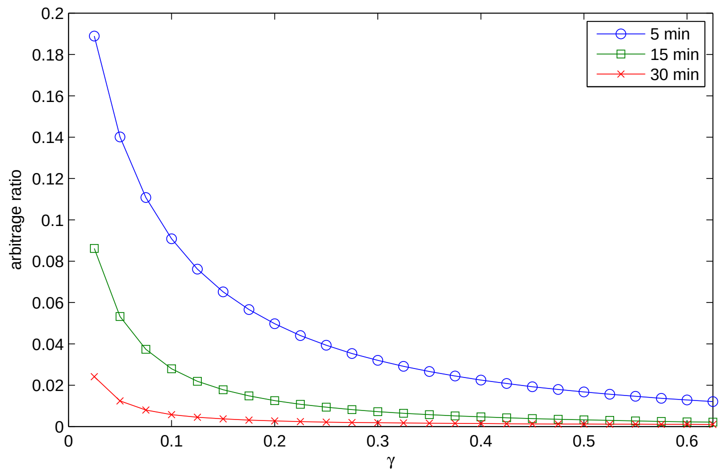

Figure 2.4.3. The uninformed manipulation opportunity and the manipulator's risk aversion. The vertical line denotes the frequency of manipulation opportunity.

2.4.3. Cross Sectional Analysis

For a cross-sectional analysis, I regress the frequency of the manipulation opportunity measure on the log of the market capitalization ($log(mrktcap)$), mean price range ($meanPrice$) in yen, the frequency of noise trading ($Noise$) estimated by the PIN model, [10] standard deviation of the short-term price changes ($Std(\Delta P)$, 5, 15 and 30 minute intervals), mean volume in share ($meanVol$), and mean trade frequency ($meanTrade\#$).

The dependent variable is the frequency of the positive uninformed manipulation measure ($M_t > 0$). For a robustness check, I also employe the mean manipulation measure as a dependent variable. The empirical results for the average manipulation measure are largely consistent with the results of the frequency measure. My

[10] The derivation for noise trading is based on the PIN model by Easley, Kiefer, O'Hara (1996) . The model is presented in the Appendix.

	Cross Section							
	M_freq(5min)	s.e.	M_freq(15min)	s.e.	M_freq(30min)	s.e.	M_mean(5min)	s.e
$std.log(mrktcap)$	-.021***	.003	-.020***	.003	-.017***	.004	-.005***	.002
$std.meanPrice$	.008***	.002	-.008**	.003	-.018***	.004	-.013***	.001
$std.Noise$	-.005	.004	-.004	.004	-.003	.006	-.001	.002
$std.Sd(\Delta P)$	-.018***	.002	-.015***	.003	-.003	.004	-.008***	.001
$std.meanVvolume$	-.003	.003	.005	.004	.009*	.005	-.008***	.002
$std.meanTtrade\#$	.014***	.005	.022***	.006	.029***	.008	.023***	.003
constant	.322***	.002	.286***	.003	.254***	.003	-.026***	.001
# of observations	432		431		445		432	

Table 2.4. Cross-sectional regression analysis for the mean frequency/absolute value of the uninformed price manipulation opportunity. For each column, dependent variables are the manipulation opportunity frequency/mean absolute values that are derived for 5, 15 and 30-minute interval price impacts. Independent variables are the standard deviations of 5, 15 and 30 minutes price changes corresponding to the sampling frequency of the dependent variables, the frequency of noise trading (based on the PIN model), log market capitalization, mean price range, and constant. Note: *** denotes p < .01, ** denotes p < .05, * denotes p < .1

regression specification is as follows:

$$\begin{aligned}\frac{\#(M_i > 0)}{Observations} &= constant + \beta_1 log(mrktcap) + \beta_2 meanPrice \\ &\quad + \beta_3 Noise + Std(\Delta P) + \beta_4 meanVol + \beta_5 meanTrade\# + error\end{aligned}$$

Each independent variable is standardized to ascertain the relative strength of the effect to the dependent variables.

The regression results are shown in Table 2.4. Market capitalization, mean price range, standard deviation of price changes, and number of daily trades are significantly different from zero. For such influential independent variables, first, market capitalization has a negative effect on the manipulation opportunity; the regression coefficient is -0.021. This means that there is less opportunity for price manipulation in larger stocks. Another standard deviation of log market capitalization reduces the frequency of uninformed manipulation opportunity by 2.1%. This confirms the empirical result of Aggarwal and Wu (2006) that manipulation is likely to happen for small and middle size of stocks.

For second, mean price range has mixed sign of coefficient dependent on the sampling intervals[11]. The absolute value is smaller than the other coefficients. When the price range is high (or minimum tick size is small), trader can influence the price more easily. However, the result indicates that it is not a big issue in manipulation.

Third, the coefficient of $sd(\Delta \mathrm{P})$ is -0.018, lower price volatility implies a higher possibility of price manipulation. This result may not be intuitive, because Aggarwal and Wu (2006) found that manipulated stocks usually showed high price volatility. I look at the ex-ante opportunity of manipulation, and not the ex-post consequence of manipulation. Different from market capitalization, volatility of price is determined in a market and not easily comparable to the result in Aggarwal and Wu (2006).

Lastly, mean trade numbers have positive coefficient (0.014), but the coefficients on mean volume and noise trading are not significant. Because high trade numbers with the same trade volume implies that each execution has small volume, this implies manipulation opportunity is likely when there are many small investors.

2.4.4. Time Series Analysis

I confirm that the manipulation opportunities are likely to be exploited (or arbitraged) during a day. I also examine how past returns, order imbalances, and changes in trading volume (measured in shares) affect the manipulation measure.

[11] Mean price can also seen as the inverse of relative minimum tick size. In this empirical study, I choose the stock with minimum tick size equal to one yen, but the relative tick size differs from the absolute price of the stock.

The independent variables are lagged manipulation measure, lagged manipulation measure times manipulation opportunity dummy ($1_{M_{i,t-j}>0}$), lagged return r_t, lagged order imbalances (in shares divided by shares outstanding, scaled by basis points) OIB_t, and lagged volume difference (in shares divided by shares outstanding, scaled by basis points) ΔVol_t. When the coefficients of lagged interaction variable (θ_j) are negative, the measure are less autocorrelated, and the probability that the measure goes to no-arbitrage region increases. The regression specification for time series analysis is as follows.

$$
\begin{aligned}
M_{i,t} = constant &+ \sum_j \left(\beta_{1,j} M_{i,t-j} + \theta_j M_{i,t-j} 1_{M_{i,t-j}>0}\right) \\
&+ \sum_j \beta_{2,j} r_{i,t-j} + \sum_j \beta_{3,j} OIB_{i,t-j} + \sum_j \beta_{4,j} \Delta Vol_{i,t-j} \\
&+ control_{i,t} + error_{i,t}
\end{aligned}
$$

For controls, I use a time range dummy, deviation of daily volume from its mean ($(daily\ volume - mean\ volume)/mean\ volume$), and deviation of number of daily trades from its mean defined in the same way. I take five lags: $j = 1, 2, \cdots 5$. The estimation method is OLS with robust clustered standard errors. I group stock codes to calculate the clustered standard error, but the results do not change much when I take two-way (time and code) clusters.

Table 2.5 shows the quantitative result. Because the scale of independent variables is not aligned, comparison of the magnitude of coefficients is not meaningful. The qualitative results are as follows. There are positive auto-correlations, but the interaction term $M \cdot 1_{M_{i,t-j}>0}$ can be negatively significant. This means that the manipulation opportunity tends to be arbitraged. The lagged return has a positive significant effect, but it has reversals in later lags. The one-period lagged order imbalance has a positive significant coefficient, but the later lags are insignificant.

The abnormal volume has long lasting negative effects. In sum, the manipulation opportunity could be driven by positive returns and order imbalances, which implies presence of momentum traders. However, this occurs only over short periods of time.

Comparing the results from different time ranges, I find the interaction term is negatively significant between 10 minutes and 75 minutes; the coefficients of $M * 1_{M_{i,t-j}>0}$ for five minutes intervals are negative significant from the second lag, those of 15 minutes lags are all negative significant, and those of thirty minutes lags are only significant at the first lag. The manipulation opportunity can be found during this time period but tend to be exploited. I can also find lagged variables (return, order imbalances, and volume) are less significant for longer interval estimations. The manipulation opportunity, which is inferred to be driven by rule of thumb traders, is not influenced by long-past variables. Rather, it is affected by recent changes in the market (for a time period of perhaps less than 60 minutes).

2.4.5. Robustness

In this section, I address robustness issues. My interest in doing so is two-fold—determining alternative specifications and an alternative estimation methodology.

For alternative specifications, I examine three cases: (1) inclusion of lagged IPIs as regressors, (2) separate estimations for different face value stocks, and (3) separate estimations for low volatility ranges. I can confirm most of the qualitative results still hold, though the magnitude of coefficients changes. For alternative methods, I change the estimation method of PPI to a rolling regression from the Kalman Filter. I also try to calculate the Fama-MacBeth standard error rather than

	M(5min)		M(15min)		M(30min)	
	coef	se	coef	se	coef	se
L.$M_{i,t}$	.452***	.026	.216***	.027	.237***	.034
L2.$M_{i,t}$	.070***	.006	.092***	.016	.076**	.033
L3.$M_{i,t}$	.046***	.005	.042***	.008	.106***	.021
L4.$M_{i,t}$	.027***	.005	.045***	.011	.018	.015
L5.$M_{i,t}$	.027***	.003	.041***	.004	-.025**	.012
L.$[M_{i,t} \cdot 1_{M_{i,t}>0}]$	.020	.013	-.075***	.020	-.155**	.072
L2.$[M_{i,t} \cdot 1_{M_{i,t}>0}]$	-.021*	.011	-.042***	.016	-.038	.028
L3.$[M_{i,t} \cdot 1_{M_{i,t}>0}]$	-.020***	.007	-.029***	.009	-.239	.181
L4.$[M_{i,t} \cdot 1_{M_{i,t}>0}]$	-.005	.007	-.038**	.017	.031	.045
L5.$[M_{i,t} \cdot 1_{M_{i,t}>0}]$	-.025***	.004	-.033***	.009	.024	.025
L.r_t	.541***	.175	.627***	.159	.294	.337
L2.r_t	-.195**	.088	.009	.122	.041	.221
L3.r_t	-.073	.064	.032	.104	-.176	.443
L4.r_t	.053	.058	.078	.074	.297**	.144
L5.r_t	-.012	.058	-.023	.063	-.094	.139
L.oib_t	.070***	.011	.012	.009	.013	.014
L2.oib_t	-.006	.005	.002	.008	.019**	.009
L3.oib_t	.003	.004	-.008	.005	.005	.025
L4.oib_t	.002	.004	.007	.006	-.021*	.011
L5.oib_t	.002	.005	.004	.006	.006	.012
L.D.vol_t	-.244***	.017	-.144***	.010	-.087***	.012
L2.D.vol_t	.003	.006	-.041***	.008	-.022**	.010
L3.D.vol_t	.006	.004	-.018***	.005	-.020	.015
L4.D.vol_t	.011***	.004	.002	.006	.011	.012
L5.D.vol_t	.012***	.004	-.001	.006	-.006	.023
cons	.030***	.010	.046**	.018	.062	.042
obs.	4,627,240		1,001,119		105,736	
Adjusted R^2	.303		.084		.093	
F	363.632		61.973		5.624	

Table 2.5. Intraday time series regression of the manipulation opportunity measure $M_{i,t}$. The regression is clustered over the code to calculate robust standard errors. Independent variables are own lags, lagged returns, lagged order imbalances, lagged abnormal volume, and lagged interaction variables $1_{PPI_t - IPI_t - IPI_{t+1} > 0} * (PPI_t - IPI_t - IPI_{t+1})$. They have up to 5 lags. The fixed control variables are the time range dummy, deviation of volume from its mean, and deviation of number of trades from its mean, but they are not reported here. Each column corresponds to the different time intervals to calculate the PPI: 5, 15, or 30 minutes. Note: *** denotes p < .01, ** denotes p < .05, * denotes p < .1

clustered OLS standard errors, and experiment with data from different years for the estimation. The result do not change much.

2.4.5.1. Different specification

In this section, I examine variants of the original five-minute interval time-series estimation. The difference from the original model is that I added IPIs into the regression analysis. In stock price manipulation, manipulators sometimes submit "spoofing" limit orders, intending a disguise as if there is buying (or selling pressures). In this case, the changes in limit order book may affect the manipulation measure itself. Including IPI as independent variables can be a simple way to examine how plausible the manipulation technique is.

Because the manipulation measure itself is defined by IPI and IPI is highly autocorrelated, I take the differences for IPI as independent variables. The definition of other independent variables are the same as those of previous section.

$$
\begin{aligned}
M_{i,t} = constant &+ \sum_j \beta_{1,j}\left(M_{i,t-j} + \theta_j M_{i,t-j}\cdot 1_{M_{i,t-j}>0}\right) \\
&+ \sum_j \beta_{2,j} t_{i,t-j} + \sum_j \beta_{3,j} OIB_{i,t-j} + \sum_j \beta_{4,j}\Delta Vol_{i,t-j} \\
&+ \sum_j \beta_{5,j}\Delta IPI(ask)_{i,t-j} + \sum_j \beta_{6,j}\Delta IPI(bid)_{i,t-j} + control_{i,t} + error_{i,t}
\end{aligned}
$$

I take up to five lags but present only up to three lags, so as to avoid confusion in the interpretation of the result. Based on this different formulation, I further examined two different datasets: the dataset restricted to different face values of the stocks, and the dataset when the price change is less than the minimum tick size. The regression result is shown in Table 2.6.

First, I examine the influence of lagged changes of the ΔIPI. The inclusion of the additional regressor does not change the other estimation by much, nor does it improve the adjusted R^2. The bid-side change positively affects the manipulation measure, and it is persistently significant. This implies that order cancellation to the bid-side book (i.e., increase in IPI (bid)) increases the likelihood of profitable manipulation. In contrast, the negative coefficient in IPI-ask implies that of order submission to the ask-side book (decrease in IPI (ask)) increases the manipulation opportunity. The influence from the bid-side book is significant over longer lags than the ask-side. .

Second, as a robustness check, I examine separate estimations for stocks of different face values. The results are presented in the second and third column of Table 2.6. Because I scale the volume by the minimum trading unit that in turn is determined by the face value, it might affect the result. The difference in the face value, whether it is 50 yen or 500 yen, determines the minimum unit to trade: 1000 shares for 50 yen face value, and 100 shares for 500 yen face value. The estimation result shows that the qualitative result does not change much. Also, the relative frequency of manipulation opportunity is .329 for the 100 shares per unit stock, and .321 for the 1000 shares. Thus, the changes in face value have little effect on the analysis.

Lastly, I examined the case when the price change is small. Because I used the weighted average price to calculate permanent price impacts, the estimated PPI may not be accurate when the price bounces between the bid and ask. I added interaction terms to differentiate whether the recent price change is less than the minimum tick size ($1_{\Delta P<minimum\ tick}$) or not. Here, the minimum tick size is always 1 by data construction. The values in the right column are the coefficients for the interaction variables. The regression results when the price change is small can be obtained by the sum of these coefficients.

The result shows that many interaction terms are significant.The manipulation opportunity still tends to follow a self-exciting process, but the influence of lagged return and order imbalance becomes significantly weaker when the price change is small. For example, the sum of the first lag of return becomes -0.18, which are much less than the original regression results (0.541). This implies a non-linear effect; the attention traders are more attracted by a jump or a dramatic change. The relative frequency of manipulation opportunity is .320 for the $\Delta P < minimum\ tick$ case, and .329 for the rest.

2.4.5.2. Fama-MacBeth Standard Error

Finally, I examine the methodological robustness. Here I examine the method used to calculate the PPI, and the method used to calculate the time series regression. The estimation results presented here all depend on five minute interval dataset. First, I consider a different way to calculate PPI. Second, I employ the Fama-MacBeth method to calculate the regression coefficients and standard errors. For an alternative way to calculate PPI, I use a rolling regression instead of the Kalman Filter. I took a one-day lag as the rolling window. This typically smoothes out the time series of the PPI when the Kalman Filter finds high volatility in the transition equation.

The first estimation column of 2.7 show the result. The auto-correlation is stronger than the Kalman Filter result, and the self-exciting process $M_{i,t} \cdot 1_{M_{i,t}>0}$ needs more lags to become negatively significant. For example, the original setup by Kalman filter presents 0.452 and 0.70 as coefficients of first and second lag of dependent variables, while the OLS setup shows 0.504 and 0.149, respectively. The interaction variable was negative significant at the second lag, but now it is not significant. Despite such subtle differences, the overall qualitative result remains the same.

	all		1 unit=100		1 unit=1000		$\Delta P < 1$			
	coef	s.e.	coef	s.e.	coef	s.e.	coef	s.e.	interaction	s.e.
L.$M_{i,t}$	.457***	.030	.343***	.054	.504***	.025	.271***	.028	.394***	.016
L2.$M_{i,t}$	.073***	.006	.085***	.019	.059***	.006	.061***	.008	.009	.009
L3.$M_{i,t}$	.046***	.006	.068***	.011	.036***	.005	.057***	.008	-.016**	.007
L.$[M_{i,t} \cdot 1_{M_{i,t}>0}]$	.017	.013	.037	.027	.005	.013	.130***	.016	-.269***	.025
L2.$[M_{i,t} \cdot 1_{M_{i,t}>0}]$	-.023**	.011	-.010	.019	-.023*	.013	-.021*	.012	.006	.009
L3.$[M_{i,t} \cdot 1_{M_{i,t}>0}]$	-.019**	.008	-.033**	.016	-.010*	.006	-.043***	.012	.036***	.012
L.D.IPI(ask)	-.204**	.088	-.328**	.166	-.145**	.072	-.644***	.095	.791***	.066
L2.D.IPI(ask)	.042	.076	-.231	.198	.114*	.058	-.076	.073	.242***	.044
L3.D.IPI(ask)	.111*	.065	-.006	.116	.129*	.075	.099	.063	.100	.065
L.D.IPI(bid)	.339***	.088	.000	.161	.457***	.061	.309***	.086	-.091*	.051
L2.D.IPI(bid)	.250***	.077	.077	.198	.287***	.063	.208***	.071	-.031	.045
L3.D.IPI(bid)	.225***	.054	.068	.125	.255***	.050	.200***	.037	-.014	.042
L.r_t	.559***	.178	.612**	.309	.597***	.212	.517**	.219	-.535**	.211
L2.r_t	-.222***	.074	-.024	.198	-.266***	.081	-.265***	.093	.129	.109
L3.r_t	-.101	.069	-.136	.140	-.082	.081	-.047	.083	.037	.108
L.oib_t	.075***	.011	.097***	.020	.067***	.013	.108***	.019	-.069***	.018
L2.oib_t	.001	.005	-.011	.013	.005	.005	-.006	.009	.008	.010
L3.oib_t	.003	.004	.001	.011	.003	.005	-.005	.009	.014	.010
L.vol_t	-.232***	.016	-.352***	.041	-.204***	.017	-.188***	.022	-.256***	.028
L2.vol_t	-.014***	.004	-.049***	.014	-.010**	.004	-.003	.009	-.027**	.013
L3.vol_t	-.002	.004	-.027**	.012	.003	.004	.013*	.007	-.014*	.008
cons	.029***	.010	.026	.040	-.022***	.008	.031***	.012		
obs	4,627,240		908,877		3,696,449		4,829,487			
Adjusted R2	.303		.232		.333		.336			
F	338.134		362.314		393.130		57.214			

Table 2.6. Intraday time series regression of the manipulation opportunity measure $M_{i,t} = E[PPI_t - IPI_{t+1}] - IPI_t$. The regression is clustered over the code to calculate robust standard errors. Independent variables are own lags, lagged returns, lagged order imbalances, lagged abnormal volume, lagged IPI for both ask and bid, and lagged interaction variables $1_{PPI_t - IPI_t - IPI_{t+1} > 0} * (PPI_t - IPI_t - IPI_{t+1})$. I take up to 5 five lags, but report up to 3three lags. The fixed control variables are the time range dummy, deviation of volume from its mean, and deviation of number of trades from its mean, but they are not reported here. From Starting with left the column on the left: regression with all observations, with stock of 100 shares per unit, with stock of 1,000 shares per unit, and with interaction variables $1_{\Delta P<1} * Independent$ variables. Note: *** denotes p < .01, ** denotes p < .05, * denotes p < .1

For the estimation of robust standard error, the Fama-MacBeth method is often employed in the literature on empirical finance. To implement the Fama-MacBeth method, I first calculate the time series regression stock-by-stock, and then take the average over the coefficients. I also present a result of different year estimations (for the years 2005 and 2006). The estimation results are shown in the second and third column of Table 2.7. The qualitative results are the same, indicating methodological robustness.

2.5. Conclusion

I study the intraday opportunity of stock price manipulation. My model suggests two conditions for price manipulation that are obtained as restrictions on the variation of liquidity. The model views price manipulation as an arbitrage opportunity regarding expected liquidity changes. While it is easier for informed manipulation to take place (given that it concerns payment of one-way slippage only), it nevertheless requires private information about the fundamentals. The model suggests how the risk of price fluctuation may be considered during manipulation.

Each manipulation condition that is described by price impacts (PPI and IPI), is tested by using intraday data at TSE. I use the LOB data to identify the IPI. The PPI is identified as a Kyle's lambda. I find that while the opportunity for uninformed price manipulation may exist, the transactions cannot be profitable enough if the manipulators are risk averse.

My empirical investigation implies that the manipulation opportunity is more likely for stocks with small market capitalization, low mean price (high minimum tick size), low price volatility, and large trade number. The measure of noise trading implied by the PIN model does not have a significant effect on the manipulation opportunity.

	OLS vs Kalman		M_t (2005)		M_t (2006)	
	coef	se	coef	se	coef	se
L.$M_{i,t}$	.504***	.011	.456***	.008	.399***	.007
L2.$M_{i,t}$	.149***	.004	.051***	.003	.059***	.003
L3.$M_{i,t}$	.077***	.003	.022***	.002	.027***	.002
L4.$M_{i,t}$	.060***	.003	.014***	.001	.019***	.001
L5.$M_{i,t}$	.065***	.003	.012***	.001	.011***	.001
L.$[M_{i,t} \cdot 1_{M_{i,t}>0}]$	.272***	.052	.049***	.006	.076***	.006
L2.$[M_{i,t} \cdot 1_{M_{i,t}>0}]$	-.041	.028	-.023***	.004	-.028***	.005
L3.$[M_{i,t} \cdot 1_{M_{i,t}>0}]$	-.053***	.015	-.013***	.003	-.011***	.003
L4.$[M_{i,t} \cdot 1_{M_{i,t}>0}]$	-.060***	.006	-.011***	.002	-.016***	.002
L5.$[M_{i,t} \cdot 1_{M_{i,t}>0}]$	-.069***	.010	-.006***	.002	-.008**	.002
L.r_t	.644***	.094	.406***	.145	.392	.390
L2.r_t	-.279***	.042	-.226**	.083	-.174	.198
L3.r_t	-.031	.029	-.068	.075	-.293**	.131
L4.r_t	-.045*	.025	.030	.060	.079	.213
L5.r_t	-.064***	.022	.096	.081	.057	.110
L.oib_t	.097***	.008	.077***	.009	.108***	.035
L2.oib_t	.003	.002	-.012*	.006	-.008	.028
L3.oib_t	-.004**	.002	.002	.008	.022	.022
L4.oib_t	.002	.002	.003	.006	.019	.022
L5.oib_t	-.001	.002	-.001	.006	-.040	.029
L.D.vol_t	-.174***	.011	-.317***	.021	-.473***	.038
L2.D.vol_t	-.016***	.002	-.012**	.005	.019	.015
L3.D.vol_t	-.003**	.002	-.012**	.004	.013*	.018
L4.D.vol_t	.004***	.001	-.010**	.005	.059***	.013
L5.D.vol_t	.012***	.001	.000	.005	.048***	.013
cons	.002***	.000	-.004***	.000	-.010***	.001
obs	4,626,552					

Table 2.7. Intraday time series regression of the manipulation opportunity measure $M_{i,t} = E[PPI_t - IPI_{t+1}] - IPI_t$. The difference between this table and Table 6 lies in the methodology employed. Starting with the column on the left: rolling OLS to obtain PPI, Fama-MacBeth regression for the year 2005, Fama-MacBeth regression for the year 2006. Note: *** denotes p < .01, ** denotes p < .05, * denotes p < .1

For the intraday analysis, I find that the manipulation opportunity is likely when the lagged returns and order imbalances are high, and the abnormal volume is low. The manipulation measure follows a self-exciting process. The estimation implies that the opportunity starts to be exploited after 10 minutes. Various robustness checks confirm the results.

In this study, I look at only single stocks for manipulation. It is possible to consider the price impact across multiple stocks. In reality, a portfolio manager can make a position of index future in advance, and they can mitigate the price impact of individual stocks. Thus, the study on cross price impact may be practically useful. I leave it to future research.

Chapter 3

The Informational Channel of Financial Contagion: An Empirical Analysis with Market Microstructure Data

with Marco Cipriani[1]

3.1. Introduction

Motivation of this research Contagion during a financial crisis has been the topic of scholarly discussion for a long time, but identifying the existence of financial contagion and its characteristics is not straightforward. To measure contagion, we focus on the informational channel in a stock market. Individual stocks are influenced by different motivations as a result of idiosyncratic or common information shocks, and stock transactions reflect this information through the trading of informed traders. In this study, we build a structural framework to distinguish these differently motivated trades caused by informed traders. Our framework is applied to stocks in the New York Stock Exchange (NYSE), where cross-country stocks are listed as American Depositary Receipts (ADRs). We look for the indication that common information influences emerging-market ADRs that are hit by a financial crisis.

Our methodology shows how much informed trades are motivated by common shocks. We found that for emerging country ADRs, correlated informed trades were dominant during the Asian financial crisis of 1997. In this research, we

[1] Federal Reserve Bank of New York and the George Washington University.

define contagion as the exposure to common information and the high probability of informed trading motivated by this common information.

The majority of research on financial contagion has focused on increased correlation during financial crises. A simple statistical test gives an evidence of financial contagion (King and Wadhwani (1990)). However, Forbes (2002) points out that this estimation is biased, because the conditional variance is influenced by the regressor's variance. After correcting this bias, the evidence of contagion disappears.

Our research aims to identify contagion in a different way from these previous studies, on at least two points. First, our research deals with the sequence of trades rather than prices. Our structural model detects informed trades on the basis of trade frequency and order imbalance (OIB)[2]. Second, we estimate the model's structural parameters directly by using maximum-likelihood estimation. This gives us a different identification method from reduced-form regression models.

Methodology Our methodology is an extension of that in Easley, Kiefer, and O'Hara (1997; hereafter, EKO). Based on the paper by Glosten and Milgrom (1985), these authors develop an empirical framework to estimate the frequency of informed trades, noise traders, and the probability and direction of information events. They assume only one risky stock to trade, while our model allows multiple stocks. We assume that informed traders receive information about the fundamental and whether it is common or idiosyncratic. Their trades contribute to the correlation of trade imbalance among stocks. Based on the probability structure of traders' arrival, our theoretical model gives a likelihood function for

[2] The relation between the probability of informed trading (PIN) and liquidity is further studied by Duarte and Young (2008).

the number of buyer- and seller-initiated trades observed in one day. From the trade-and-quote (TAQ) data, we can recover the buyer- and seller-initiated trade numbers using the Lee–Ready Algorithm. Then we can estimate the structural parameters by maximizing the likelihood function.

In our model, there are two major new advances. The first is that our model identifies the occurrence of common information events and their probability among the targeted group of stocks.

The second is that our model provides further details on the individual stocks. The original PIN model does not identify what factors drive stock movement: common or idiosyncratic events. Our framework can identify them, and the result tells whether the stock is driven by common or idiosyncratic events.

To find financial contagion, we focus on ADRs listed in the NYSE. Intraday data are obtained from the TAQ database . We calculate the number of buys and sells by using the Lee–Ready algorithm. We constitute three groups of stocks to which apply our methodology. The first is ADRs from emerging countries, which include Asian and South American countries . The second is blue chip stocks, which are listed as Dow industrial components. The last group is ADRs from developed countries, which include the U.S., Japan, and European countries. (See Table 3.4 for details.) We choose the stocks based on the number of trades per day.

Related Literature Aside from EKO (1997), our model can also be compared to Kodres and Pritsker (2002). Based on the classic model of Grossman and Stiglitz (1980), these authors studied contagion in the informational channel. In our model, in contrast, informed traders are assumed to know rather than infer the correlation of fundamentals. The uninformed market maker does not know the information, and makes an inference regarding the fundamentals of a stock group;

then, his inference is reflected into multiple stock prices at the same time. His behavior is much like that assumed by Kodres and Pritsker (2002).

The empirical literature on financial contagion is plentiful. The most straightforward approach to test contagion is to use cross-market correlation coefficients. Examples can be found in King and Wadhwani (1990), Forbes and Rigomon (2002), Baig and Goldfajn (1999), and Chung (2005), for the use of ADR . But the results are mixed and controversial.

Empirical Results In order to evaluate the statistical properties of the model, we first conducted an artificial simulation. The result shows unbiasedness and consistency. The nested structure of the model contributes to the unbiasedness. Otherwise, the model does not work well when the stock group includes unrelated stocks.

Our main interest in this model is its application to financial crises. We expect that there was a common information event that influenced contagious stocks. In order to test this hypothesis, we took ADRs from the NYSE. We take three groups of stock: emerging country ADRs, developed country ADRs, and U.S. blue chip stocks.

We found that the emerging country ADRs during 1997 were mostly driven by a common information event during 1997. This is especially true for Asian stocks. This was not observed in the other groups. This implies that information for common events was important for the price efficiency of these emerging ADRs but not for developed ADRs or U.S. blue chips. For developed ADRs and blue chips, we didn't see as much evidence of contagion as for emerging ADRs. We can observe common events, but they didn't necessarily have wide influence among stocks.

The organization of this research is as follows. In section 2, we demonstrate the model. In section 3, we examine the identification by running a simulation. In section 4, we apply the method and obtain empirical results. Section 5 concludes.

3.2. The Model

The model extends the Easley, Kiefer, and O'Hara (EKO; 1997) model to an economy with many risky assets. EKO builds a sequential trading model based on Glosten and Milgrom (1985), where agents trade one asset strategically in a market. The behavior of informed and uninformed traders generates specific patterns in trade submissions, and they estimate economic structural parameters based on the model.

An important simplification of the EKO's model is that it assumes only one risky asset. However, there are many risky assets in the real economy, and private information can easily affect not only one asset but also other assets that have similar characterizations. Also, some traders may project stock values based on news from other stocks. As a result, a single piece of news may propagate contagiously, as Kodres and Pritsker (2002) proposed. In this section, we present a framework to extend the original single-asset EKO model to a multiple-asset model.

EKO's model is characterized by its market structure, assets, traders, and market makers. The behavior of traders resulting from it introduces a likelihood function that is characterized by the number of buys and sells.

Market Structure There are three types of agents: informed traders, market makers, and noise traders. Individuals trade risky assets with a market maker over $d = 1, 2, \cdots D$ trading days. For each intraday trading, time is continuous but trading opportunity is indexed by $t = 1, 2, \cdots T$. A market maker determines a price by observing order imbalances. Each trade consists of a trade of one unit of the asset for cash. The trader's action space is defined as $A = buy, sell, notrade$. Here we assume that the asset is indivisible and that agents are restricted to hold only one asset. We denote the history of day d until time $t \downarrow$ as H_t^d. The history is the sequences of trades, which can be buyer- or seller-initiated until time t for each day d.

Fundamental Value of Assets Figure 3.2.1 shows the process of events in this model. Before each day's opening bell, nature determines whether a *common* informational event occurs. It is independently distributed and occurs with probability ω. When the common shock occurs, the fundamental value of all assets V_d^i, $i = 1, 2, \cdots N$ changes in the same direction. The shock is bad with probability δ, and good with probability $1-\delta$. Even when there is a common event, individual stock may not be influenced, with probability $1-\theta^i$. Even if an individual stock is not influenced by the common shock, it may be influenced by idiosyncratic events. Idiosyncratic events after common events take the same form as those that are not after common events.

In the case where there is no common event, nature also determines whether idiosyncratic informational events occur. Each idiosyncratic shock is independently distributed across days and cross-sections. As a result of the idiosyncratic shock, the fundamental changes with probability α^i, or doesn't change ($V_d^i = V_{d-1}^i$) with probability $1-\alpha^i$. Again, each shock fundamental is bad with probability δ^i, and good with probability $1-\delta^i$. We assume that changes in the fundamental value are the same across common and idiosyncratic shocks. That is, the fundamental value of i at day d only takes $\left\{\bar{V}_d^i, V_d^{*i}, \underline{V}_d^i\right\} = \{V_{d-1}^i + \lambda_i^H,\ V_{d-1}^i,\ V_{d-1}^i + \lambda_i^L\}$. Note that we can allow λ_i^H and λ_i^L to be different when the info event is common as opposed to idiosyncratic, but nothing will change. The value of the fundamental does not change during a day, but is revealed after the closing bell every day.

Traders There are countable number of traders of two types: informed and noise. Both informed and noise traders arrive in the market following Poisson processes. We assume the arrival rate of informed traders in stock i is μ^i and the arrival rate of noise is ε^i for each day. On a day with no common or idiosyncratic events, only noise traders arrive. In contrast, on a day with events, informed traders also arrive. We assume the arrival rates do not change depending on the common or idiosyncratic events; the traders specialize in a stock and don't trade others[3].

Informed traders are assumed to know the true state of the economy, whether the information involved is idiosyncratic or common and whether good or bad. In other words, the precision of the signal they get on the informational event is infinite. They are risk neutral and competitive. If they get good signals, they buy the stock, as a profit-maximizing behavior. If they get bad signals, they sell the stock. These arrival process are assumed to be independent. We do not assume a short-sale constraint here.

Noise traders are motivated to trade solely by a liquidity reason independent of any of the events described in our model. In order to justify the behavior of these traders, they are assumed to have a payoff function $U : \{\underline{V}_d^i, \bar{V}_d^i\} \times \mathscr{A} \times [\underline{V}_d^i, \bar{V}_d^i]^2 \rightarrow \mathbb{R}^+$:

$$U(V_d, X_t^d, a_t^d, b_t^d) = \begin{cases} V_d - a_t^d & \text{if } X_t^d = buy. \\ 0 & \text{if } X_t^d = no\ trade \\ b_t^d - V_d & \text{if } X_t^d = sell. \end{cases}$$

[3] We tried the model with changing arrival rates, but the identification was not good enough.

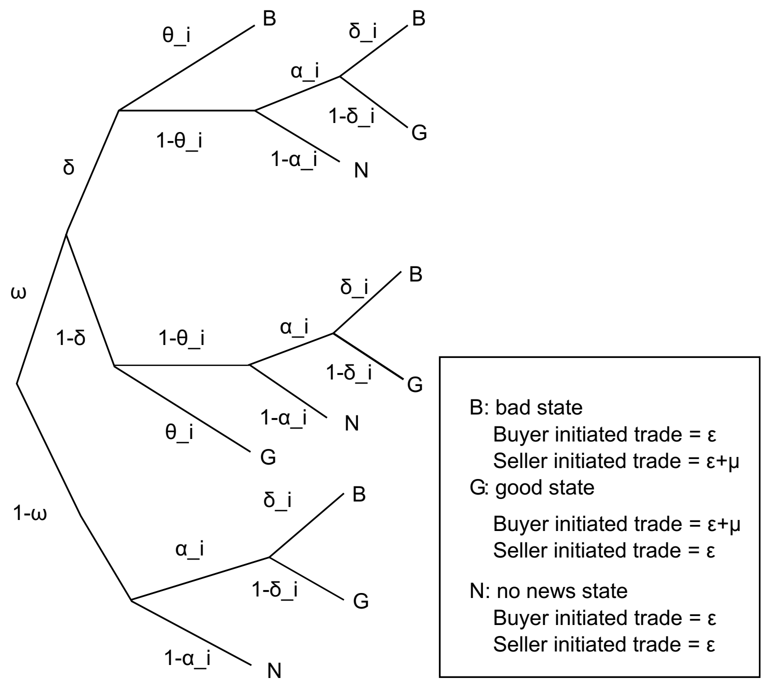

Figure 3.2.1. Tree of benchmark multiple-asset trading model. There is a common shock in probability ω at the beginning of each day. The common shock is bad in probability δ and good in $1-\delta$. Each stock i is influenced by this shock in probability θ_i. When the stock is not affected by the common event, it draws an idiosyncratic event in probability α_i. Also, in the case of no common event, stocks also have an idiosyncratic event in the same probability, α_i . Informed traders arrive in the market with a Poisson distribution μ and submit orders according to the information. Uninformed traders arrive with ε and submit orders as noise.

An informed trader chooses X_t^d to maximize the expected utility. Therefore, she finds it optimal to buy whenever $E(V_d|H_t^d, S_t^d) \geq a_t^d$, and sell whenever $E(V_d|H_t^d, B_t^d) \leq b_t^d$. She chooses not to trade when $b_t^d \leq E(V_d|H_t^d, s_t^d) \leq a_t^d$.

Figure 3.2.1 shows the diagram of the trading process. At the first node of the tree, the nature determines there is a common event or not. If there is a common event, the nature then decides whether it is bad or good. After that, the nature further decides whether each firms is influenced by this event or not. When a firm is not influenced by the event, they follow the case when there is no common event. In this sense, the model is nested.

Without a common event, the tree is the same as the original PIN model. Nature choose whether there is a idiosyncratic event and whether it is bad or good. Here, we assumed that the idiosyncratic parameters are same between cases with and without common events.

The market maker and price process The market maker observes the number of buys and sells, setting different prices for buying and selling. The *ask price* is a price conditional on the number of buys, and the *bid price* is contingent on the number of sells. In order to simulate price easily, here we present the price of a stock at each end of fixed period t.

Let the belief of the market maker at t as $P(t) = \{P_h(t), P_b(t), P_n(t)\}$. $P_h(t)$ represents the probability of a good event at time t, $P_l(t)$ represents the probability of a bad event, and $P_n(t)$ represents the probability of no event. At time zero, the initial belief is defined as

$$P(0) = \{(1-\omega)\alpha(1-\delta_i) + \omega\theta(1-\delta) + \omega(1-\theta)\alpha(1-\delta_i)$$
$$,(1-\omega)\alpha\delta_i + \omega\theta\delta + \omega(1-\theta)\alpha\delta_i, \omega(1-\theta)(1-\alpha) + (1-\omega)(1-\alpha)\}$$

Every time the market maker receives an order submission, she repeatedly updates her belief for each probability, in the manner of Bayesian updates. Let B_t and S_t be the number of buy and sell orders which the market maker receives between $t-1$ and t, and we define the posterior probability $P_h(t|B_t, S_t)$ as follows:

$$P_h(t|B_t,S_t) = \frac{P_h(t) \cdot Pr(B_t,S_t|\Psi = H)}{P_h(t) \cdot Pr(B_t,S_t|\Psi = H) + P_l(t) \cdot Pr(B_t,S_t|\Psi = L) + P_n(t) \cdot Pr(B_t,S_t|\Psi = 0)},$$

Here the label of individual stock i is suppressed. Ψ represents the state of the stock; it is either high, low or no event. $P_l(t|B_t,S_t)$ and $P_n(t|B_t,S_t)$ can be defined similarly. The probability of the history follows a Poisson distribution, and its explicit form is described as follows.

$$Pr(B_t, S_t|\Psi = 0) = e^{-\frac{\varepsilon}{\tau}} \frac{(\frac{\varepsilon}{\tau})^B}{B!} e^{-\frac{\varepsilon}{\tau}} \frac{(\frac{\varepsilon}{\tau})^S}{S!} \tag{3.2.1}$$

$$Pr(B_t, S_t|\Psi = H) = e^{-\frac{\mu+\varepsilon}{\tau}} \frac{(\frac{\mu+\varepsilon}{\tau})^B}{B!} e^{-\frac{\varepsilon}{\tau}} \frac{(\frac{\varepsilon}{\tau})^S}{S!} \tag{3.2.2}$$

$$Pr(B_t, S_t|\Psi = L) = e^{-\frac{\mu+\varepsilon}{\tau}} \frac{(\frac{\varepsilon}{\tau})^B}{B!} e^{-\frac{\mu+\varepsilon}{\tau}} \frac{(\frac{\mu+\varepsilon}{\tau})^S}{S!} \tag{3.2.3}$$

The parameterτ is exogenously fixed to match the time length. For example, $\tau = 390$ means we take one minute interval to calculate prices, because each day has 390 trading minutes. The true fundamental is assumed to be $\bar{V}_i$ when there is a good event, $\underline{\mathrm{V}}_i$ when there is a bad event, and V_i^* when there is no events. The market maker prices the stock according to his/her belief:

$$Price_i(t) = \bar{V}_i P_h(t) + \underline{\mathrm{V}}_i P_l(t) + V_i^* P_n(t). \tag{3.2.4}$$

The market maker is assumed to be risk neutral and competitive; then we can derive the martingale condition on the market prices:

$$((1-\omega)(1-\delta_i) + \omega\theta(1-\delta) + \omega(1-\theta)(1-\delta_i))\overline{V}^i + ((1-\omega)\delta_i + \omega\theta\delta + \omega(1-\theta)\delta_i)\underline{V^i} \tag{3.2.5}$$

$$= \omega(1-\theta)(1-\alpha) + (1-\omega)(1-\alpha)V_i^*.$$

Given $\bar{V}_i$ and $\underline{\mathrm{V}}_i$, we can use V_i^* to pin down (3.2.5).

The Probability of Informational Trade (PIN), Revised PIN measures the probability of informational trade. In the standard environment of EKO (1997), it is computed as

$$PIN = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon}$$

In contrast, PIN in the multi-asset model is computed as

$$MPIN_i = \frac{\left((1-\omega\theta^i)\alpha^i + \omega\theta^i\right)\mu^i}{\left((1-\omega\theta^i)\alpha^i + \omega\theta^i\right)\mu^i + 2\varepsilon^i}.$$

where we suppressed i subscript. Thus, given the same set of parameters, the condition that $MPIN > PIN$ always holds. This is because informed traders are assumed to be aware of not only idiosyncratic events but also common events. Obviously, $\omega = 0$, $\theta = 0$ and $N = 1$ imply the standard single-asset formulation. Also, MPIN is increasing in ω and θ. Thus, with the assumption of an informed trader, more highly correlated stocks are likely to undergo more informed trades. When PIN is seen as a measure of liquidity, as Duarte and Young (2009) suggested, increase of probability of a common event implies global illiquidity commonality among stocks.

As we will confirm by simulation in the next section, each parameter $\hat{\alpha}'$ and $\hat{\delta}'$ estimated by single PIN model could be biased if a common event is more likely. However, estimated PINs for these parameters are the same as MPIN. That is, denoting the parameters estimated by the multi-asset PIN model as $\hat{\alpha}$, $\hat{\omega}$, $\hat{\theta}$, $\hat{\alpha}' = (1-\hat{\omega}\hat{\theta}^i)\hat{\alpha}^i + \hat{\omega}\hat{\theta}^i$ holds.

We can divide MPIN into two parts: probability of trading based on idiosyncratic event (IPIN) and common event (CPIN):

$$IPIN = \frac{(1-\omega\theta^i)\alpha^i\mu^i}{((1-\omega\theta^i)\alpha^i + \omega\theta^i)\,\mu^i + 2\varepsilon^i},\; CPIN = \frac{\omega\theta^i\mu^i}{((1-\omega\theta^i)\alpha^i + \omega\theta^i)\,\mu^i + 2\varepsilon^i}.$$

IPIN represents trade driven by an idiosyncratic event, and CPIN represents trade driven by a common event. We will define the ratio of common event–driven trades to the overall informed trades $CPIN/MPIN$. This ratio plays a central role of our analysis. We consider it to be evidence of contagion.

Total Number of Trade, Order imbalances The expected value of the total trade is

$$E[TT_i] = 2\varepsilon^i + (1-\omega)\alpha^i\mu^i + \left(\theta^i + (1-\theta^i)\alpha^i\right)\omega\mu^i.$$

$\omega = 0$ or $\theta^i = 0$, reduced to the standard single asset case. Because α^i, θ^i, ω are between zero and one, expected total trade is supposed to be larger than in the no common event case. The larger θ leads the larger total trade, because informed traders trade on not only idiosyncratic information but also common informational events.

Order imbalance is defined as, $OIB = number\ of\ buys - number\ of\ sells$. The expected value of the order imbalance is

$$E[OIB_i] = \omega\theta^i\mu^i(1-2\delta) + (1-\omega\theta^i)\alpha^i\mu^i(1-2\delta^i).$$

Thus, the order imbalances of one stock may affect the estimation of common event direction δ as well as idiosyncratic event direction δ^i. Positive order imbalance, meaning more buyer-initiated than seller-initiated trades, pushes δ towards zero, which implies good (positive) information events, while negative order imbalance pushes δ towards one, which implies bad (negative) information events. The cutoff point is $\delta = 1/2$ and $\delta_i = 1/2$. The expected value of OIB is a weighted sum of the deviation from 1/2 for each δ. The numerator of the ratio $CPIN/MPIN$ is the weight.

Price Efficiency We are interested in the efficiency of price determination according to the market maker's information set. In other words, we wish to answer the question, to what extent does the price approaches the true fundamental price if the market maker knows the occurrence of common information event? We address this question by conducting a following simulation, based on O'Hara (1997).

1. The market maker may know of the occurrence of a common information event (full information case), or she may not know it (limited information case). We also assume she knows the probability structure: $(\omega, \delta, \{\delta_i, \alpha_i, \theta_i\mu_i, \varepsilon_i\}_{i\in I}) \in \mathscr{F}_0$. The initial belief, $Prob(\Psi_i|\mathscr{F}_0)$, is calculated as follows. For the limited information case, for every state in $3^{\#I}$ probability space,

$$
\begin{aligned}
Prob(state|\mathscr{F}_0) = \sum_{state} \{\ & \omega\delta \cdot Prob(state|\Psi_i = bad) \\
& + \omega(1-\delta) \cdot Prob(state|\Psi_i = good) \\
& + (1-\omega) \cdot Prob(state|\Psi_i = noEvent)\ \}\ ,
\end{aligned}
$$

$$
Prob(\Psi_i|\mathscr{F}_0) = \sum_{state \in \Psi_i} Prob(state|\mathscr{F}_0).
$$

   Note that we replace ω with 0 or 1 in case of full information.

2. The market maker observes the number of buy and sell orders $\{buy_i, sell_i\}_{i\in I}$ for every fixed time interval τ, which follows the Poisson distribution.

3. Dependent on her initial belief and the observed buy and sell orders, the market maker updates the occurrence of event Ψ_i using Bayesian updating.

$$Prob(state|\mathscr{F}_{t-1},\{H_t^i\}_i) = \frac{Prob(\{H_t^i\}_i) \cdot Prob(state|\mathscr{F}_{t-1})}{\sum_{state} Prob(\{H_t^i\}_i|state) \cdot Prob(state|\mathscr{F}_{t-1})},$$

$$Prob(\Psi_i|\mathscr{F}_{t-1},\{H_t^i\}_i)) = \sum_{state \in \Psi_i} Prob(state|\mathscr{F}_{t-1},\{H_t^i\}_i)).$$

4. The price is determined according to (3.2.4):

$$\begin{aligned} Price_t = {} & P(\Psi_i = good|\mathscr{F}_{t-1},\{H_t^i\}_i) \cdot 1 + P(\Psi_i = noEvent|\mathscr{F}_{t-1},\{H_t^i\}_i) \cdot V_{0,i} \\ & + P(\Psi_i = bad|\mathscr{F}_{t-1},\{H_t^i\}_i) \cdot 0. \end{aligned}$$

Note that the market maker updates belief by using order information for multiple stocks. The probability of history $Prob(H_{t\,i}^i|state)$ follows a Poisson p.d.f and is a function of the realization of orders $buy_i, sell_{i\,i\in I}$ and the Poisson parameters $\{\mu_i, \varepsilon_i\}_{i\in I}$ given the state. The numerator of the equation at 3. ends up with $P(H_t, state|F_{t-1})$. This state is defined as a set of possible occurrences of events, and there are $3^{\#I}$ possibilities depending on whether each stock is good, bad, or no event. The value $V_{0,i}$, where no events happen, is determined by the martingale condition (3.2.5): $V_{0,i} = (P(\Psi_i = good) \cdot 1 + P(\Psi_i = bad) \cdot 0)./(1 - P(\Psi_i = noEvent))$.

We randomly generate the occurrence of events 1000 times, and for each event, we simulate intraday price sequence calculated by this algorithm. Efficiency is defined as the distance between the full information price and the limited information price.[4]

$$\text{Efficiency}_i = \sum_{t=1}^{T} |p_{t,i,ful-info} - p_{t,i,limited-info}| \tag{3.2.6}$$

3.2.1. The Likelihood Function

In order to estimate the structural parameters $\Theta = (\omega, \delta, \{\alpha\}_{i\in I}, \{\delta\}_{i\in I}, \{\mu\}_{i\in I}, \{\varepsilon\}_{i\in I}, \{\theta\}_{i\in I}))$, we build a maximum likelihood function. We estimate the PIN for each firm-year.

Let us demonstrate the likelihood function for a generic day d. We denote by B^i and S^i, the number of buys and sells for asset i on a given day. The history, H^i, is a sequence of buy and sell transactions. Let us denote by $\Psi^i = 0, H, L$ the fact there is either a no-information event, a high-information event or a low-information event in market i. Note that the event may be idiosyncratic, common, or both. Now we can compute the probability of the history of the day, conditional on each informational event

$$Pr(H^i|\Psi^i = 0) \equiv Pr(B^i, S^i, N^i|\Psi^i = 0) = e^{-\varepsilon^i} \frac{(\varepsilon^i)^{B^i}}{B^i!} e^{-\varepsilon^i} \frac{(\varepsilon^i)^{S^i}}{S^i!} \tag{3.2.7}$$

$$Pr(H^i|\Psi^i = H) \equiv Pr(B^i, S^i, N^i|\Psi^i = H) = e^{-(\mu^i+\varepsilon^i)} \frac{(\mu^i + \varepsilon^i)^{B^i}}{B^i!} e^{-\varepsilon^i} \frac{(\varepsilon^i)^{S^i}}{S^i!} \tag{3.2.8}$$

[4] The three matlab programs `Efficiency_simulation.m`, `Efficiency_Bayesian_multi.m`, `Efficiency_Bayesian_initial.m` provide the computation.

$$Pr(H^i|\Psi^i = L) \equiv Pr(B^i, S^i, N^i|\Psi^i = L) = e^{-\varepsilon^i}\frac{(\varepsilon^i)^{B^i}}{B^i!}e^{-(\mu^i+\varepsilon^i)}\frac{(\mu^i+\varepsilon^i)^{S^i}}{S^i!}. \quad (3.2.9)$$

Next, we calculate the probability of a common high event, common low event, and no common event using Bayes' law. Let us denote by I^θ the set of assets affected by common events at each day. $I^{\backslash\theta}$ is the set of assets that is not affeced by the common events. Then the probability of each state given common shock is

$$Pr_{CS} \equiv Pr(I^\theta, I^{\backslash\theta} I^H, I^L, I^0) = \prod_{I^\theta}\theta^i \times \prod_{I^{\backslash\theta}}(1-\theta^i) \times \prod_{I^H\cap I^{\backslash\theta}}\alpha^i(1-\delta^i) \times \prod_{I^L\cap I^{\backslash\theta}}\alpha^i\delta^i \times \prod_{I^0\cap I^{\backslash\theta}}(1-\alpha^i).$$

Let us denote by I^H, I^L, I^0 the set of assets with a high, low and no idiosyncratic event. Obviously the number of assets in I^H, I^L, I^0 has to be equal to the number of assets N: $\#I^H + \#I^L + \#I^0 = N$. Then, given no common shocks, the probability of each state characterized by idiosyncratic informational events is,

$$Pr_{NCS} \equiv Pr(I^H, I^L, I^0) = \prod_{I^H}\alpha^i(1-\delta^i) \times \prod_{I^L}\alpha^i\delta^i \times \prod_{I^0}(1-\alpha^i)$$

Here we omit the notation that Pr_{CS} and Pr_{NCS} is a function of the realization of the combination of stock. Now we are ready to describe the day likelihood function. The probability of the history of trades in a day d will be given by the sum of the following terms.

1. Probability in case of common high event (L1):

$$\omega(1-\delta)\sum_{all\ I}\left[Pr_{CS} \times \prod_{I^\theta}\Pr(H^i|\Psi^i = H)\left\{\prod_{I^H\cap I^{\backslash\theta}}\Pr(H^i|\Psi^i = H) \times \prod_{I^L\cap I^{\backslash\theta}}\Pr(H^i|\Psi^i = L) \times \prod_{I^o\cap I^{\backslash\theta}}\Pr(H^i|\Psi^i = 0)\right\}\right]$$

2. Probability in case of common low event (L2):

$$\omega\delta\sum_{all\ I}\left[Pr_{CS} \times \prod_{I^\theta}\Pr(H^i|\Psi^i = L)\left\{\prod_{I^H\cap I^{\backslash\theta}}\Pr(H^i|\Psi^i = H) \times \prod_{I^L\cap I^{\backslash\theta}}\Pr(H^i|\Psi^i = L) \times \prod_{I^o\cap I^{\backslash\theta}}\Pr(H^i|\Psi^i = 0)\right\}\right]$$

3. Probability in case no common event (L3):

$$(1-\omega)\sum_{all\ I}\left[Pr_{NCS}\times\prod_{I^H}\Pr(H^i|\Psi^i=H)\times\prod_{I^L}\Pr(H^i|\Psi^i=L)\times\prod_{I^o}\Pr(H^i|\Psi^i=0)\right]$$

$\sum_{all\ I}$ describes the summation of all possible (the number of $3^{\#I}$) realization of I. The likelihood function for the whole history of trading is simply the product of the likelihood of each single day, because the information events are independently distributed. The standard errors of the estimated parameters are calculated from the asymptotic distribution using the delta method.

The Curse of Dimensionality Problem Estimating this likelihood function is a challenging task due to the "curse of dimensionality." The number of states needed to evaluate the likelihood function grows exponentially, because we have to evaluate the probability of every event that can occur. The number of evaluations thus skyrockets according to the number of assets. With Matlab and Pentium dual-core processor computers, it takes about five seconds to calculate the likelihood function of a case with eight assets with 500 observations. The minimization of likelihood function usually needs at least 2000 evaluations, and it takes more than three hours to finish one estimation. Adding one stock requires about six times more calculation. Therefore, we limit the number of stocks to 9 and run the estimation on various mixes of stocks.

In order to speed up the algorithm, we can estimate in two steps. The Poisson parameters μ and ε are unbiasedly estimated by stock-by-stock PIN calculations. Therefore we first conduct single-asset PIN calculations for each stock to estimate

μ and ε, and then calculate other parameters simultaneously by using the first-step results.[5]

Computational Overflow Furthermore, there is a well known computational difficulty in implementing the PIN model: the a problem of computational overflow. This overflow occurs because the likelihood function is composed of high-powered values, which are too large for computers to evaluate. This problem often occurs when a stock has large order imbalances. In order to deal with this problem, we transform the likelihood function.

After factoring out $\prod_i (\frac{\varepsilon^i}{\mu^i+\varepsilon^i})^{2M^i}$, $\prod_i e^{-2\varepsilon^i}$,$\prod_i \frac{1}{B^i!S^i!}$, and $\prod_i (\mu^i+\varepsilon^i)^{B^i+S^i}$ from the log-likelihood function $\ln \mathscr{L}(B,S|\Theta) = \ln((L1)+(L2)+(L3))$, we finally obtain

$$\begin{aligned}
\ln \mathscr{L}(B,S|\Theta) = & \sum_{d\in D}\sum_{all\ I}\sum_{i\in I}\left[-2\varepsilon^i + 2M^{i,d}ln(x^i) + \left(B^{i,d}+S^{i,d}\right)ln(\mu^i+\varepsilon^i)\right] \\
& + \sum_{d\in D} ln\left[\omega(1-\delta)\sum_{all\ I}\left\{Pr_{CS}\left(\prod_{i\in I^\theta} e^{-\mu^i} x_i^{S^{i,d}-2M^{i,d}}\right)\left(\prod_{i\in I^H\cap I\backslash\theta} e^{-\mu^i} x_i^{B^{i,d}-2M^{i,d}} \prod_{i\in I^L\cap I\backslash\theta} e^{-\mu^i} x_i^{S^{i,d}-2M^{i,d}} \prod_{i\in I^0\cap I\backslash\theta} x_i^{S^{i,d}+B^{i,d}-2M^{i,d}}\right)\right\}\right. \\
& + \omega\delta\sum_{all\ I}\left\{Pr_{CS}\left(\prod_{i\in I^\theta} e^{-\mu^i} x_i^{B^{i,d}-2M^{i,d}}\right)\left(\prod_{i\in I^H\cap I\backslash\theta} e^{-\mu^i} x_i^{B^{i,d}-2M^{i,d}} \prod_{i\in I^L\cap I\backslash\theta} e^{-\mu^i} x_i^{S^{i,d}-2M^{i,d}} \prod_{i\in I^0\cap I\backslash\theta} x_i^{S^{i,d}+B^{i,d}-2M^{i,d}}\right)\right\} \\
& \left. + (1-\omega)\sum_{all\ I}\left\{Pr_{NCS}\left(\prod_{i\in I^H} e^{-\mu^i} x_i^{B^{i,d}-2M^{i,d}} \prod_{i\in I^L} e^{-\mu^i} x_i^{S^{i,d}-2M^{i,d}} \prod_{i\in I^0} x_i^{S^{i,d}+B^{i,d}-2M^{i,d}}\right)\right\}\right].
\end{aligned} \tag{3.2.10}$$

We define $x_i \equiv \frac{\varepsilon_i}{\mu+\varepsilon_i}$ and $M^{i,d}$ are arbitrary chosen to improve the computational efficiency. Easley, Hvidkjaer, and O'hara (2002) suggests $M^{i,d} = min(S^{i,d},B^{i,d}) + \frac{max(S^{i,d},B^{i,d})}{2}$. We searched optimal $M^{i,d}$ according to the choice of stocks.

Even after this transformation, sometimes it is still difficult to avoid overflow, especially when we estimate the multiple-asset model on blue chips. This is because the order imbalance tends to incline in one direction after earning reports or remarkable events, and when it is imbalanced, the blue chips sometimes record more than 500 imbalances. This messes up the likelihood function, and a systematic treatment is difficult to obtain.

[5] We can confirm that the estimation results without this shortcut return the same result.

For the computation to minimize the log-likelihood function, we employed the Matlab built-in optimization function "fmincon." Probability parameters are restricted to take a value between zero and one. The Poisson arrival parameters μ and ε, are restricted to take a value between zero and $\max\{B_t + S_t\}_{t=1,\cdots,T}$ because μ and ε are the average number of informed and uninformed trades, which will never be bigger than the max trade number. The initial value is set randomly between the lower and upper bounds.

3.2.2. Simulation Results

In this section, we check the robustness and identification of the multiple-asset model by simulation. We intend to recover the original parameters by estimating the parameters for data generated by the simulation.

Table 3.1 We first show the unbiasedness and consistency of the estimation.

Given certain sets of parameters, we generate data simulated by the structure assumptions. Then we conduct the maximum-likelihood estimation to recover the original parameters. We set the number of observations to 253 and 505, the yearly and biannual numbers of trading days, and use five stocks for simultaneous estimation. We carry out six different fixed-parameter experiments. For each experiment, we calculate the error, defined as the distance between the original parameters and the estimated parameters, and the standard deviation of the error.

Table 3.1 shows the estimation result for the multiple-asset specification; the estimated values are largely unbiased and consistent. For every parameter, the error and standard deviation are reduced when many observation is available. The common probability of bad δ has little effect on the efficiency: the standard deviations are not affected by the value of δ.

M3	N=5										
		$\delta = .25$					$\delta = .75$				
obs	ω	$\omega - \hat{\omega}$	$\delta - \hat{\delta}$	$\frac{\sum \alpha - \hat{\alpha}}{N}$	$\frac{\sum \delta - \hat{\delta}}{N}$	$\frac{\sum \theta - \hat{\theta}}{N}$	$\omega - \hat{\omega}$	$\delta - \hat{\delta}$	$\frac{\sum \alpha - \hat{\alpha}}{N}$	$\frac{\sum \delta - \hat{\delta}}{N}$	$\frac{\sum \theta - \hat{\theta}}{N}$
	.3	-.004	-.0006	.0038	.0023	-.007	.0046	-.0113	.0012	.0113	-.0132
	S.D.	.0698	.0827	.0383	.0759	.118	.1125	.0837	.0424	.0812	.1349
253	.5	-.0037	-.0033	.0079	.0012	.0031	.009	.0122	.0053	0	-.0038
	S.D.	.0615	.0559	.0601	.0948	.0848	.0977	.0635	.0518	.0895	.0988
	.7	.0032	0	.003	-.0008	.0022	-.0063	.0078	.0087	.0114	-.0009
	S.D.	.0651	.0455	.0599	.1077	.0687	.0803	.0457	.056	.1269	.0686
	.3	.0079	.0064	.0025	.0024	-.0012	-.0007	-.0011	.0036	.0036	-.011
	S.D.	.0566	.0642	.0314	.0529	.089	.062	.061	.0276	.0507	.0828
506	.5	.001	-.0021	.0024	.0028	-.0045	-.0018	.0092	.005	.0054	.0045
	S.D.	.0463	.0482	.0285	.06	.0558	.0777	.0509	.0444	.0679	.0673
	.7	-.0052	.0018	.0052	.0006	-.0026	.0091	-.0004	.002	.0075	-.001
	S.D.	.0367	.0312	.0324	.0768	.0448	.0622	.0408	.039	.0911	.0494

Table 3.1. M3 simulation and estimate result. ω is fixed at .3, .5, or .7. We simulate the data generation ten times for each parameter set and estimated the parameters on that data. All the estimated values presented are means of the ten simulation-estimations. The standard deviation is calculated from the ten estimated values. The estimated values should go to zero if the estimator is unbiased. The standard deviation should be reduced if many observations are available. The other parameters are set as $\alpha = [0.2, 0.2, 0.5, 0.5, 0.8]$, $\delta_i = [0.3, 0.8, 0.3, 0.8, 0.3]$, $\mu = [20, 150, 20, 150, 20]$, $\varepsilon = [15, 120, 15, 120, 15]$, $\theta = [0.3, 0.8, 0.3, 0.8, 0.1]$.

	Random				Fixed			
	$\omega-\hat{\omega}$	$\delta-\hat{\delta}$	$\frac{\sum\alpha-\hat{\alpha}}{N}$	$\frac{\sum\delta-\hat{\delta}}{N}$	$\omega-\hat{\omega}$	$\delta-\hat{\delta}$	$\frac{\sum\alpha-\hat{\alpha}}{N}$	$\frac{\sum\delta-\hat{\delta}}{N}$
	.0121	.0071	.022	.0148	.0002	-.0009	.0008	-.0011
SD	.1326	.12	.0903	.1082	.0482	.0438	.0368	.0753

Table 3.2. The benchmark model's simulation result with a irrelevant stock. The left panel is an experiment for randomly generated parameters, and the right panel is for fixed parameters. The fixed parameters are the same as the last estimations, but δ is always .25 and ω is .3 or .5 or .7. The simulation is generated to allow one stock that is totally irrelevant with common events. Each value is the mean of estimated value over 30 simulations. Standard deviations are associated.

In contrast, the common parameters δ and ω, as well as θ_i are slightly better estimated when the probability of common event ω is high. However, idiosyncratic parameters are less efficient when ω is high. Thus, the efficiency of common event-related parameters ω, δ, θ and the efficiency of idiosyncratic parameters is a tradeoff. This is because the shock for each stock is either idiosyncratic or correlated, and more observations for one shock means less observations for the other.

Table 3.2 In order to check robustness, we test the multiple-asset specification under different data-generation processes. The last test deals with the case in which the data generation process is assumed to match the likelihood function. However, deviation from this assumption is likely and can devastate the estimation results.

We conduct the following robustness check. First, we generate 30 simulations based on fixed parameters for five stocks. Each simulation follows the data-generation process of the benchmark model, but only one stock is totally irrelevant, and it is assumed to follow the single-asset PIN model. In other words, $\theta = 0$ for one stock. As a supplemental result, we provide estimation results where the parameters are totally randomized rather than fixed.

Table 3.2 show the simulation results for this experiment. For both fixed and random experiments, the benchmark model does a good job in terms of unbiasedness and efficiency. This is because the model is nested and immune to this kind of misspecification. When the model is not nested, the estimation result is not robust and becomes sensitive to the choice of stock. Nevertheless, the estimation efficiency is worse in the case of randomly assigned parameters.

Identification We address the identification of each structural parameter. Trades can occur many times in a day, and μ and ε can be identified even by one-day data. This is because μ and ε are parameters of the Poisson process, and the frequency of occurrence is many times throughout the day.

We assume that informational events occur only once in a day, however, and the idiosyncratic parameters α_i and δ_i cannot be identified from that one draw. Multiple days are needed to α_i and δ_i.

Similarly, parameters related to common event ω , δ, and θ_i are assumed to be drawn only once a day; therefore, they cannot be identified from the data of only one stock. They can be identified only when we have multiple stocks.

When the number of observations is limited, there is a tradeoff between identifying idiosyncratic and common parameters. Suppose every stock is independent of every other—then we cannot identify the common event parameters. Thus, common parameters can only be weakly identified when stocks are not affected by a common event (low θ_i). On the contrary, when θ_i is too high, it becomes hard to identify idiosyncratic parameters because we cannot obtain as many observations on the idiosyncratic case. Regardless of this potential identification problem, as we have seen in the simulation, the estimation works well as long as the parameters are not at the extreme.

3.3. Data

In order to estimate the structural parameters, we need to calculate the number of buys and sells day by day and stock by stock. Our data, however, does not identify whether the transaction is buyer- or seller-initiated. We employ the Lee–Ready (1991) algorithm to differentiate trade transactions. That is, we attach a timestamp to each quote transaction every five seconds ; then we decide the trade is buyer-initiated if the price is higher than the mid-point of the last quote, and vice versa. If the price is same as the last mid-quote, it is compared with the second-last transaction price, and so on. If the current transaction price had decreased (increased) with respect to the last transaction price, it is considered a seller- (buyer-) initiated trade. The Lee–Ready algorithm is found to be reasonable, because the quote records are sometimes delayed compared to real trade time, especially during the 1990s. Our dataset covers only the 1990s, and a five-second delay therefore seems reasonable.

We collect cross-sectional intraday trade and quote data from the TAQ database. After obtaining the data, we conduct the following data-cleaning procedures: (1) keep the transaction only if it is from the New York stock exchange; (2) drop all the trade observations where the "corr" sign is not equal to zero; (3) drop all the quote observations if the ask price is 1.5 times higher than the bid price or the bid price is higher than the ask; (4) drop all the trade transactions before any quote is recorded at the beginning of the day; and (5) drop all the first opening call trades. This follows standard data cleaning approaches, but some studies don't truncate the trade from regional stock exchange markets, and because of this the estimations don't necessarily exactly match.

When we conduct the multiple-asset estimation, sometimes the total trading-day data doesn't match perfectly. Some stocks lack transaction after the data cleaning described above; we take an intersection of the data in these cases. As a result, we miss some data, but it is for less than six trading days in all, and this doesn't change the qualitative result of the estimation.

Our data set spans from 1995/Jan/03 to 1998/Dec/3. There is total 1011 trading days. We choose the sample stocks as follows. First, we choose all the ADR stocks that had been listed in the NYSE before 1995/Nov/21 ; in total 41 ADR stocks from developed and emerging countries. Second, we choose 30 stocks from the Dow Jones Industrial Average. This means that in the end we have 71 sample stocks in our dataset.

Some stocks can show extreme order imbalance. DIS and PT are examples. When we conduct an estimation for many stocks, like eight or nine, the presence of these stocks not only pushes the estimation towards an extreme but also makes for a severe overflow problem. Therefore, we didn't include these stocks in our estimations of many stocks. Also, some stocks were delisted during the period of the study, like WX, TLK, AWC, and IRE ; we exclude these stocks as candidates.

Up-tick Rule for Short Sales The uptick rule for short sales was effective during the sample period. According to Asquith, Oman, and Safaya (2010) and Diether, et al. , this regulation biases trade classification using Lee–Ready. Short sales in NYSE stocks are recognized as buyer-initiated trade at 70 %. Because the order imbalance tends to be positive, with a lot of buyer-initiated trades, it implies lower δ: a good information event. However, short sales are more likely to be associated with bad economic conditions, and the result of δ will therefore be severely downwardly biased.

In contrast, the other parameter estimations are less likely to be biased. This is because the bias mainly affects order imbalance and doesn't much influence the other structural parameters.

3.4. Estimation

In this section, we first show the descriptive statistics and single-asset PIN. Then we move to estimate the multiple-stock model.

3.4.1. Descriptive Statistics and Standard PIN

First, we applied the EKO method to calculate standard individual PIN. The results are summarized in Table e 3.3. As mentioned, stocks with large order imbalances are hard to make converge, but the transformation of the likelihood function works well. We obtained convergent result for all firm-years.

As documented in Easley, Hvidkjaer and O'hara (2010), the liquid blue-chip stocks usually show low PIN while the illiquid ADR stocks show high PIN.

Also we note that the order imbalance of each stock is mostly positive during the period. This is because of the Uptick-rule to restrict short sell as mentioned in Asquith, Oman, and Safaya (2010) . As a result, the probability of bad event, δ is very low. But this doesn't necessarily imply the business condition was good during the period. On the contrary, bad business conditions may lead to short sales, which implies a low δ. Without adjustment for the uptick rule, δ results may mislead.

In order to investigate the near-zero δ, we also looked into the price changes and order imbalances. Table 3.4 summarizes the result of descriptive statistics. There are two hypotheses which could be related to the near zero δ (high likelihood of positive fundamental news). The first is the hypothesis of highly frequent negative public news[6]. If negative public news is common, traders may be more attracted to contrarian behavior, and this may generate pressure for buyer-initiated trade.

[6] We thank Prof.O'Hara for this point.

Second, sell orders may be larger than buy orders, since the PIN calculation ignores volume data. If sell orders are biased upward, OIB based on trade numbers may yield confusing results.

In order to capture the arrival of public news, we calculated price jumps for each stock. A jump is defined as a price change beyond two sigmas of the stock price. The descriptive statistics shows that the jumps are mostly balanced between positive and negative[7].

The order imbalance is usually positive, regardless of the way it is measured. This is because short sales are restricted by the uptick rule. We report OIB based on volume as well as trade numbers. It is largely proportional to the imbalance in trade numbers. A simple regression analysis shows that the relationships are usually positive and rarely become negative. This is the opposite of the previous hypothesis.

3.4.2. Estimation result of Multi-asset PIN model

As we have noted, this multiple-asset PIN model suffers from the "curse of dimension" problem. The computational burden grows on the order of 3^N. For tractability, we limit the number of stocks to six. Therefore, we need to select sets of stocks to be estimated.

Our model assumes only one common event per stock group. Because of this restriction, expanding the stock pool isn't necessarily the right specification. The more stocks are included, the more common shocks will be involved. This causes potential misspecification. Our choice of stocks is as follows.

[7] The descriptive statistics for price changes imply that the effect of time-zone. For Asian stocks, where the openings of the stock markets don't overlap, we observe more frequent large price change between days. This indicates that public information which change the price often occur while markets open.

— First, we take ADRs listed on the NYSE. We focus on emerging-market ADRs to capture contagion among countries stemming from the Asian currency crisis in 1997. The stocks used are YPF (Argentina), CCU (Chile), TMX (Mexico), IIT (Indonesia), PKX (Korea), and SHI (China). The choice is based on total trades per day for the country's ADRs.

— Second, for blue chips, we take six stocks that have different first-digit SIC codes. When there are more than one stocks where the first-digit SIC code is the same, we pick the one with the highest individual PIN. The list is BS, DIS, IP, JPM, T, and Z.

— Third, we pick developed-country ADRs and one blue chip stocks . The list is STM, BS, HIT, TOT, and BT. The choice is based on total trades per day among the country's ADRs.

The choice of stock is based on the PIN and the total number of trades. For ADR stocks, high-PIN stocks are usually very illiquid stocks, so we prefer to use the total number of trades as a criterion. For U.S. stocks, high-trade stocks usually cause overflow problems due to high order imbalance. We take PIN for the criterion.

In this experiment, we would like to focus on the following economic parameters: common event probability ω, probability of informational trade based on idiosyncratic or common events (IPIN and WPIN respectively), their ratio, and the efficiency of the price.

Table 3.5 First, for cross-country ADR samples, we conducted a whole-year estimation during 1995/Jan/4 to 1998/Dec/30 using single-asset and multiple-asset models.

The estimation results differ in α_i and δ_i. The multiple-asset model estimates a lower α_i than the single-asset model does. This is natural, because the multiple-asset model identifies some informational events as common events which are identified as idiosyncratic events in the single-asset model. Also, each δ_i in the multiple-asset model is higher. This means that idiosyncratic news was usually worse than common news. During the study period, these stocks usually recorded positive order imbalances, which pushes δ and δ_i downwards, but the multiple-asset model separates out these good common events and finds the true value of δ_i. However, again, we have to be careful in interpreting the result, because this estimation doesn't consider the uptick rule.

The result of θ is only available for the multiple-asset model. This probability implies that roughly half of the common events influence each stock.

The estimated PIN results are almost identical. This indicates that, while each economic parameter is biased, the single-asset model can be as accurate as the multiple-asset model to estimate the probability of information trade. Thus, the advantage of the multiple-asset model is not to provide more accurate estimates for probability of information trade, but to separate information trade into common and idiosyncratic components.

Rolling Estimation for Emerging ADRs In order to check the time-series continuity of the estimated parameters, we conducted a rolling estimation spanning the period from 1995/Jan/4 to 1998/Dec/3 . We take a rolling window for 253 days, and apply the multiple-asset PIN model for every other 30-day period. Each figure describes the time-series of ω, δ, MPIN, and the ratio of common to idiosyncratic event-driven trades (WPIN/MPIN).

In Figure 3.5.1 and 3.5.2, we can see that ω is largely continuous. The sudden spike in δ at 271 days, which is a period during 1996, is led by the order imbalance of TMX. If we omit TMX, we do not observe this spike any more. During 1997, ω keeps steady and high, while δ stays near zero. However, this result doesn't necessarily show evidence of contagion. As a more direct measure of contagion, we can look at the ratio of common event-driven trade.

Figure 3.5.3 shows the ratio of trades based on common events against overall informed trades. The top, middle, and bottom graphs shows the emerging ADRs, developed ADRs, and U.S. blue chips, respectively.

The emerging ADRs apparently show highly correlated common informational trades during 1997. The blue chips and developed ADRs do not show a similar pattern. This indicates that during 1997, many of the emerging ADR stocks were driven by common information events but the other ADR stocks and U.S. stocks were not. While we cannot evaluate the direction of the information, the uptick rule bias lets us infer that there was a large amount of short selling during this period. Thus, our model suggests that there was financial contagion among emerging countries, but that it did not spread into developed countries.

Comparison between Tranquil and Crisis Period, Table 3.6, 3.7, 3.8 In these tables, we estimated the parameters for two periods: 1996 (tranquil period) and 1997 (crisis period). We conducted the estimation for cross -country ADRs, developed-country ADRs, and cross-industry blue chips. The choice of ADRs was the same as in the last estimation. We sorted the 30 stocks from the Dow Industrial average by single-asset PIN. Then we picked the highest-PIN stock among each industry.

In these tables, we also report the efficiency gain from knowledge of common information events. When market makers know of a common information event, they can price stocks more accurately. Compared to the case when the market maker does not know of the occurrence of a common event, the distance to the true price should be shorter. Formally, the efficiency gain is calculated as the 3.2.6. Here S is the number of simulation, set as 1000, and the calculation of prices p

are shown in the section 2. We confirmed that price efficiency of informed case is always higher than the no information case.

In general, high θ and low α_i are associated with high efficiency gain, because the price is mainly driven by common information even in this case. We can also say that efficiency gain is high when WPIN/MPIN ratio is high.

Table 3.6 shows the estimation results for emerging-country ADRs in 1996 and 1997. The ratio of common-informed trading is uniformly higher in 1997 than in 1996, which indicates contagion. The MPIN is slightly higher in 1997, but the biggest difference is in θ. In 1997, θ is uniformly high, which implies a significant influence of a common informed event. In 1996, only YPF shows high θ. This implies that YPF played a central role in the common informed event for 1996, but that this event was not as influential as the common event for 1997. The low δ in 1997 implies massive short sales rather than a good event. Because the common event in 1996 is not influential, knowing about its occurrence is not efficiency-improving for most stocks. This shows a sharp contrast to 1997.

Table 3.7 shows the estimation results for developed-country ADRs in 1996 and 1997. Unlike emerging ADRs, developed ADRs don't change much in terms of common/idiosyncratic ratio, efficiency, and δ. While the center of the common informed event shifts from STM-BS to HIT-TOT, the overall level of the estimated values stays the same.

Table 3.8 shows the estimation results for U.S stocks in 1996 and 1997. Again, the common/idiosyncratic ratio is relatively unchanged. BS, T, and Z are less affected by the common event. The generally low δ for blue chips is mostly driven by DIS and JPM, which have huge positive order imbalances. Their θ_i is also high, which means that the common event is strongly affected by these two companies.

3.4.3. Robustness Check

In this section, we propose a robustness check for the previous result. We propose two sets of the check. The first is for choice of stock, as demonstrated above, and the other is to address the concern regarding time difference between countries.

Choice of Stock So far, our estimation highlights only specific subsets of securities. Here, we repeat the estimation by looking at many possible combinations of securities.

First, we illustrate how to generate a combination of securities. We again divide the whole set of stocks into emerging-country ADRs, developed-country ADR, and U.S. blue chips. For emerging ADRs, we maintain the diversity of countries and rotate stocks within countries listing more than one stock as ADR. We rotate the stock of Argentina, Chile, and Mexico. The other countries, mostly located in Asia, have only one stock listed as ADR. Using this method, we can generate 24 alternative combinations. For developed-country ADRs and U.S. blue chips, we don't care about diversity. We choose the five most-traded stocks and the four highest-PIN stocks from the blue chips, and for the developed ADRs, we choose the nine most-traded stocks and the blue chip with the code BS [8]. We tried all six possible combinations within these sets. The total number of combination is (9, 6) = 84.

[8] High PIN developed ADRs sometimes show very low liquidity and less than 1000 trading days. Therefore we choose 9 most traded stocks. Blue chips show no such problem. Finally, our choice set is 'GE','IBM','T','MRK','MO','BS','Z','IP','BA' for blue chips, and 'BT','PHG','ELN','STM','SNE','REP','BS','TOT' for developed ADRs.

In Table 3.9, the results shows estimated average and standard deviation of ω, ratio of common-information trade, and price efficiency. Emerging-country ADR shows high CPIN/MPIN ratio, which indicates that common-information trade is not a special case but a common situation.

3.5. Conclusion

We studied a multiple-asset market microstructure model as an extension of Easley, Kiefer, and O'Hara's (1997) model to studying financial contagion. We find that the multiple-asset model performed well with respect to unbiasedness, efficiency, and robustness. The estimation based on this model differentiates common information events from idiosyncratic events.

We applied the model to NYSE-listed stocks from 1995 to 1998. The results show that trades are motivated mostly by common information shocks among emerging-country ADRs in 1997, which implies financial contagion between these countries. However, we didn't observe correlated informed trades of this sort among developed-country ADRs and U.S. blue chip stocks.

The estimation results of δ, unlike our expectations, are usually negative (showing good information events) during the financial crisis. Some hypotheses are tested regarding the reason for this result, but they don't give clear evidence. Uptick rule for short sales may contribute to this result, but the model cannot identify short sales.

Symbol	Nationality	days	Total	mean B	mean S	α	δ	μ	ε	PIN
CCU	Chile	1011	124.8	68.5	56.3	.282	.212	61.0	53.3	.171
IIT	Indonesia	1010	32.4	17.4	15.0	.236	.332	34.6	12.5	.235
PKX	Korea	1004	57.2	31.7	25.4	.295	.213	42.0	22.3	.239
SHI	Indonesia	1010	29.3	15.4	14.0	.188	.387	37.8	2.0	.230
TMX	Mexico	1011	495.5	236.9	258.6	.334	.393	226.9	21.4	.151
YPF	Argentina	1011	188.6	2.0	87.6	.334	.320	84.9	79.9	.152
BS	U.S.A	1011	155.0	81.9	73.0	.385	.307	65.0	65.4	.161
DIS	U.S.A	1011	728.5	424.0	304.5	.423	.080	265.9	306.3	.150
IP	U.S.A	1011	439.4	247.3	192.1	.434	.123	137.5	189.8	.143
JPM	U.S.A	1011	436.6	24.3	196.3	.440	.136	125.2	19.6	.124
T	U.S.A	1011	1028.8	52.2	508.6	.377	.444	284.0	461.8	.106
Z	U.S.A	1011	145.3	7.2	75.2	.358	.535	61.1	61.7	.152
STM	Italy	1011	139.4	77.9	61.5	.268	.192	87.91	57.74	.182
BS	U.S.A	1011	155.0	81.9	73.0	.385	.307	65.0	65.4	.161
HIT	Japan	1010	45.1	28.1	17.0	.571	.134	23.67	15.80	.309
TOT	French	1010	48.3	27.4	21.0	.361	.158	22.55	2.33	.166
BT	U.K.	1011	289.4	157.2	132.2	.350	.169	143.61	122.56	.145

Table 3.3. Standard calculation of PIN. The list of stocks is from different three groups: emergent-country ADRs, U.S. blue chips, and developed-country ADRs. The data covers 1995 to 1998.

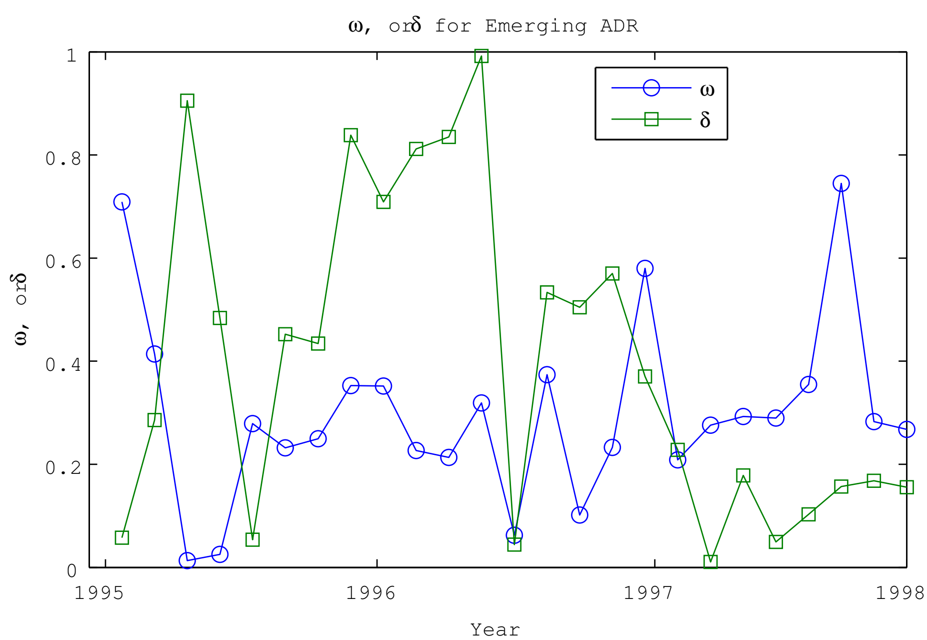

Figure 3.5.1. Rolling estimation of ω and δ. The window size is 253-days.The list of stock is YPF, TMX, CCU, SHI, IIT, PKX.

Symbol	Nationality	OIB (#)	OIB(vol)/VOL	iner/intra PC	# PC	mean PC	std PC
CCU	Chile	12.231	.064	.222	44	-.054	1.534
IIT	Indonesia	2.401	.097	.824	135	-.030	.422
PKX	Korea	6.326	.104	1.057	109	-.039	.439
SHI	Indonesia	1.393	.032	4.313	85	-.009	.570
TMX	Mexico	-21.776	-.045	.227	119	-.015	.734
YPF	Argentina	13.345	-.011	.288	103	.010	.394
BS	U.S.A	8.89	.025	.167	126	.011	.213
DIS	U.S.A	119.54	.144	.337	115	-.018	.819
IP	U.S.A	55.17	.107	.163	121	.018	.652
JPM	U.S.A	44.01	.093	.144	135	.055	1.275
T	U.S.A	11.53	.048	.198	97	.003	.661
Z	U.S.A	-4.96	-.007	.124	127	-.020	.300
STM	Italy	16.4	.049	.446	133	.089	1.340
BS	U.S.A	8.89	.025	.167	126	.011	.213
HIT	Japan	11.1	.280	3.207	122	-.254	1.050
TOT	French	6.4	.141	1.848	131	-.036	.622
BT	U.K.	25.0	.080	.279	110	.018	1.180

Table 3.4. Descriptive statistics for order imbalance and price changes. Daily order imbalance (OIB) with respect to the number and volume of trades is reported. Price change, or large intraday and interday price change (PC), is also reported. “Large” price change is defined as that larger than two sigmas. The stocks are is from three different groups: emerging-country ADRs, U.S. blue chips, and developed-country ADRs. The data covers 1995 to 1998.

		YPF	TMX	CCU	SHI	IIT	PKX
ω	.240						
δ	.122						
α	Single	.365	.278	.281	.144	.158	.321
	Multiple	.303	.243	.169	.074	.081	.208
δ	Single	.245	.394	.203	.337	.284	.364
	Multiple	.268	.462	.284	.591	.489	.546
θ	Single	-	-	-	-	-	-
	Multiple	.377	.195	.566	.313	.354	.592
μ		88.4	28.7	124.4	5.1	44.4	55.5
ε		78.3	208.8	45.2	11.1	12.7	19.8
PIN	Single	.171	.157	.279	.245	.216	.311
MPIN	Multiple	.171	.157	.279	.245	.217	.310

Table 3.5. Whole-year estimation. The list of stocks is YPF, TMX, CCU, SHI, IIT, PKX. Each row shows the estimation results from M0 (original single-asset model) and multiple-asset benchmark models. For μ and ε, the estimated values are the same between the single- and multi-asset models.

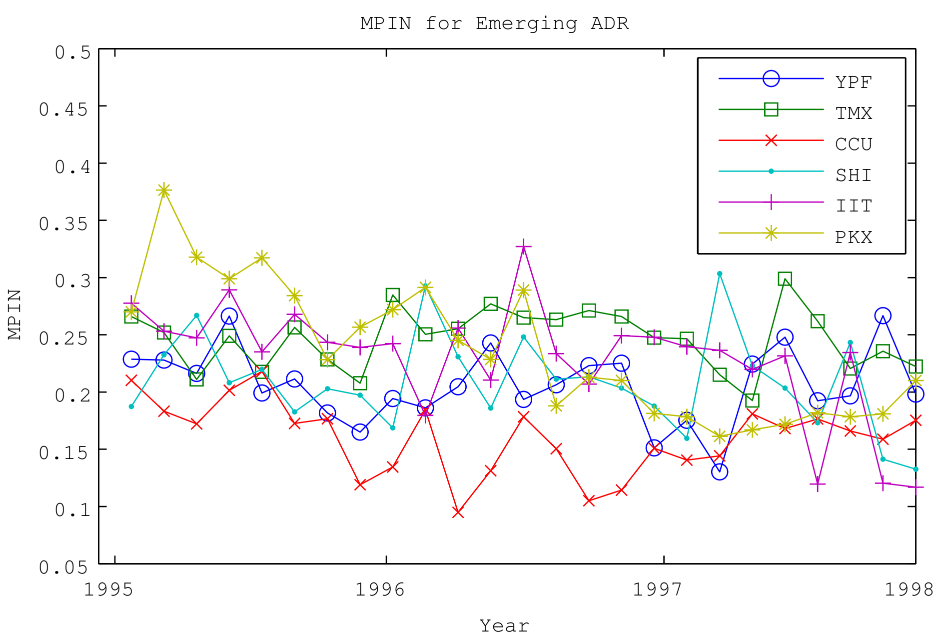

Figure 3.5.2. Rolling estimation of PIN. 253-days window size. List of stock is YPF, TMX, CCU, SHI, IIT, PKX.

1996	α	S.E.	δ	S.E.	θ	S.E.	MPIN	Ratio	Eff. Gain			S.E.
YPF	.4616	.2289	.7627	.0989	.8977	.117	.1552	.2827	.0188	ω	.1715	.0152
TMX	.9178	.0261	.9493	.0287	.5843	.0621	.2228	.1082	.0051	δ	.4200	.1705
CCU	.4524	.0781	.485	.0251	.2412	.1518	.1467	.0871	.0248			
SHI	.3902	.0462	.429	.0449	.0444	.0173	.2309	.0193	.0138			
IIT	.2563	.0029	.5188	.1222	.5887	.0092	.2532	.3047	.0132			
PKX	.4176	.0881	.1171	.1846	.2069	.0863	.2103	.081	.0248			
1997	α	S.E.	δ	S.E.	θ	S.E.	MPIN	Ratio	Eff. Gain			S.E.
YPF	.7827	.0342	.6181	.0879	.4973	.0341	.216	.1235	.0244	ω	.1997	.0616
TMX	.8019	.0152	.7062	.0408	.7004	.0478	.2212	.1686	.0617	δ	.1119	.0432
CCU	.4939	.0314	.2113	.08	.7824	.0688	.1651	.2727	.0349			
SHI	.2647	.0588	.4544	.0007	.5817	.04	.2948	.3318	.0236			
IIT	.0909	.0021	.3081	.0037	.9428	.0439	.1798	.7186	.0122			
PKX	.4543	.0385	.3481	.046	.4338	.0504	.2279	.1728	.045			

Table 3.6. Emerging-country ADRs. The list of stocks is YPF, TMX, CCU, SHI, IIT, and PKX. Each row shows the estimation result from a multiple-asset benchmark model. MPIN, or of informed trade, is defined as $MPIN_i = \frac{\left((1-\omega\theta^i)\alpha+\omega\theta^i\right)\mu^i}{((1-\omega\theta^i)\alpha^i+\omega\theta^i)\mu^i+2\varepsilon^i}$. The ratio of common-informed trade to overall informed trade is defined as $CPIN/MPIN$. We also report the marginal efficiency improvement by obtaining a common information event.

1996	α	S.E.	δ	S.E.	θ	S.E.	MPIN	Ratio	Eff. Gain			S.E.
STM	.3115	.1268	.1224	.115	.7817	.0171	.1654	.579	.0271	ω	.3837	.0111
BS	.5939	.004	.4816	.0041	.212	.0365	.1942	.1298	.0427	δ	.2002	.0793
HIT	.5732	.0489	.0451	.102	.1639	.0599	.2598	.1048	.0933			
TOT	.4266	.0172	.2471	.2487	.6664	.0831	.2103	.4461	.0557			
BT	.6045	.1906	.223	.2549	.3513	.075	.1547	.2049	.0612			
1997	α	S.E.	δ	S.E.	θ	S.E.	MPIN	Ratio	Eff. Gain			S.E.
STM	.4288	.0166	.1992	.0549	.5505	.0202	.1542	.4602	.0564	ω	.4863	.0517
BS	.5277	.0306	.601	.0043	.4495	.0322	.1664	.3465	.0222	δ	.232	.0039
HIT	.44	.028	.159	.0062	.4507	.0715	.1789	.3895	.026			
TOT	.49	.0259	.242	.0075	.3273	.0073	.1438	.2786	.037			
BT	.8222	.0072	.2624	.042	.4483	.0003	.2161	.2532	.0334			

Table 3.7. Developed-country ADRs with one U.S. stock (BS). The list of stocks is STM, BS, HIT, TOT, and BT. Each row shows an estimation result from the multiple-asset benchmark model. MPIN, or probability of informed trade, is defined as $MPIN_i = \frac{\left((1-\omega\theta^i)\alpha+\omega\theta^i\right)\mu^i}{((1-\omega\theta^i)\alpha^i+\omega\theta^i)\mu^i+2\varepsilon^i}$. The ratio of common-informed trade to overall informed trade is defined as $CPIN/MPIN$. We also report the marginal efficiency improvement by obtaining a common information event.

1996	α	SE	δ	SE	θ	SE	MPIN	Ratio	Eff. Gain			SE
IP	.9974	.1089	.0069	.0022	.4011	.0465	.2408	.263	.0466	ω	.6545	.079
BS	.5866	.0553	.3937	.2715	.0372	.1261	.17	.0408	.0022	δ	.1463	.1873
T	.9855	.0678	.4465	.0556	.1895	.0205	.235	.1256	.0057			
Z	.8537	.0619	.7244	.0417	.1196	.0826	.2919	.0905	.0108			
DIS	.9671	.1026	.1794	.0312	.4459	.0993	.2668	.2988	.0093			
JPM	.9713	.0494	.435	.0745	.5587	.0647	.271	.3724	.0272			
1997	α	SE	δ	SE	θ	SE	MPIN	Ratio	Eff. Gain			SE
IP	.9356	.051	.5027	.001	.6137	.0181	.2432	.4822	.0168	ω	.7588	.0622
BS	.4201	.0591	.6743	.0299	.4753	.0098	.1949	.5731	.0317	δ	.3495	.0009
T	.971	.0244	.4268	.0257	.1502	.0259	.2609	.1169	.0047			
Z	.7318	.0446	.7458	.058	.4259	.0579	.2212	.3949	.0419			
DIS	.961	.04	.2492	.0239	.4619	.0128	.2236	.3596	.015			
JPM	.892	.0031	.1488	.0302	.3682	.0073	.2516	.303	.0156			

Table 3.8. U.S. stocks. The list of stocks is IP, BS, T, Z, DIS, and JPM, which are chosen from NYSE blue chips. Each row shows the estimation result from the multiple-asset benchmark model. MPIN, or probability of informed trade, is defined as $MPIN_i = \frac{\left((1-\omega\theta^i)\alpha+\omega\theta^i\right)\mu^i}{((1-\omega\theta^i)\alpha^i+\omega\theta^i)\mu^i+2\varepsilon^i}$. The ratio of common informed trade to overall informed trade is defined as $CPIN/MPIN$. We also report the marginal efficiency improvement by obtaining common information event.

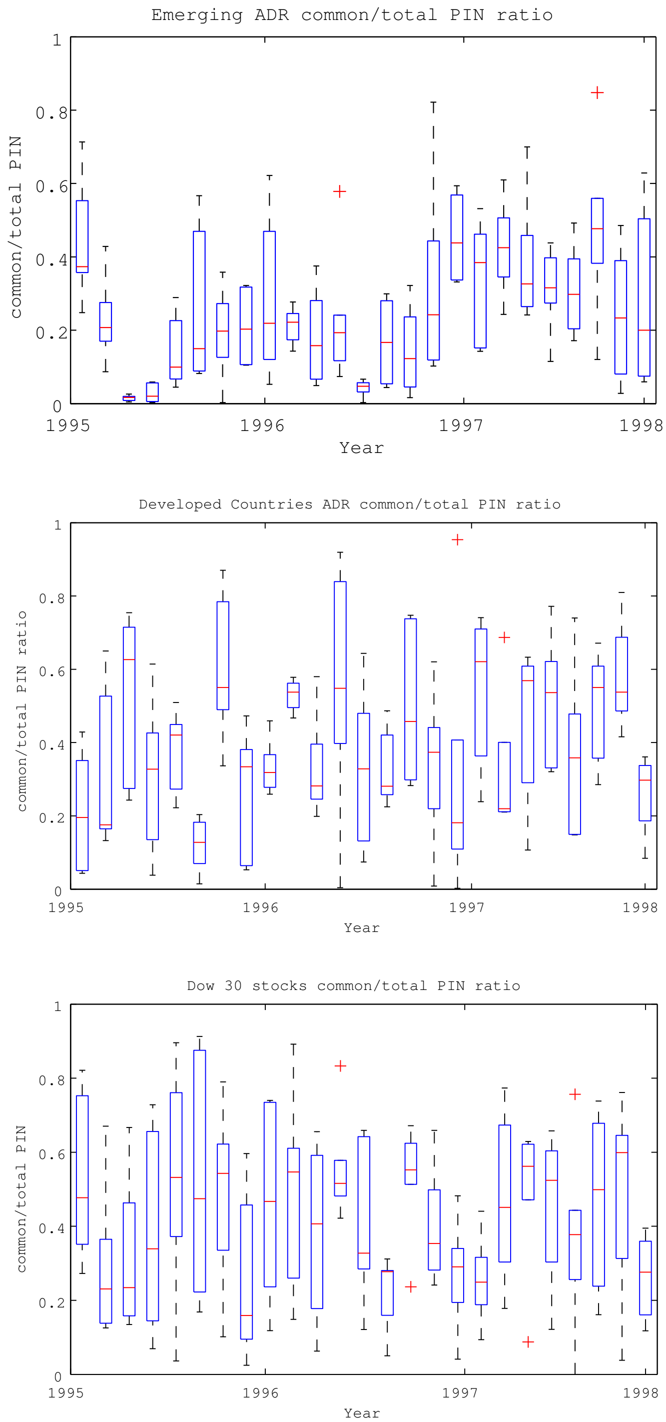

Figure 3.5.3. Rolling estimation of $CPIN/MPIN$. Top: Emergin country's ADRs, Middle:Developped's ADRs, Bottom: U.S. bluechips. This shows whether the private informed trade is driven by common event or idiosyncratic event. The window size is 253-days. The list of stock is YPF, TMX, CCU, SHI, IIT, PKX. Here, YPF, ENI, TMX are South America ADRs, and PKX, SHI, IIT are Asia ADRs. The central mark represents the median, the edges of the box are 25th and 75th percentiles, the whiskers are the most extreme data points that is not considered as outliers, and outliers are plotted individually as "+".

		Emg ADR	U.S.	Dev ADR
1996	ω	.261	.746	.418
	S.D	.138	.241	.243
	PIN	.202	.23	.207
	S.D	.052	.035	.056
	Ratio	.228	.363	.296
	S.D	.173	.222	.230
	Eff. Gain	.031	.016	.03
	S.D	.018	.014	.019
1997	ω	.351	.796	.448
	S.D	.15	.213	.247
	PIN	.199	.231	.18
	S.D	.051	.035	.034
	Ratio	.375	.446	.322
	S.D	.17	.24	.197
	Eff. Gain	.032	.017	.032
	S.D	.017	.016	.021

Table 3.9. Robustness check.

Appendix A

Appendix for Chapter 1

A.1. Characterization of Equilibrium

I now describe how to characterize a linear equilibrium. I solve it by backward induction. I note that uninformed traders solve a static problem at $t = 1$ non-strategically: they do not expect the arrival of informed traders[1]. I summarize the variables that are used in this model at Table 1.1. I solve for the endogenous variables for the linear conjecture.

Step 1: Conditional expectation of $\tilde{v}$ and its variance.

Between $t = 1$ and $t = 2$, the uninformed traders make an projection to the fundamental value of the asset conditional on their available information. Our conjecture (1.2.7) and the market clearing condition imply that, for uninformed traders,

$$\tilde{P}_1 = \frac{1}{\lambda_1 + \zeta_1} \left(\mu_1 + (\alpha_1 + \beta_1 \tilde{v}) + \tilde{z}_1 \right). \tag{A.1.1}$$

[1] The informed traders' awareness of uninformed traders appears in their conditional volatility of the fundamental. As in Kyle (1985), this conditional volatility does not depend on the endogenous variables, and it is determined only by exogenous volatility. To simplify the calculation, I omit this first stage projection. Also, I do not assume that the uninformed trader considered the price fluctuation induced by noise trading. This assumption is a consequence of the assumption of uninformed traders as price takers.

Thus, the fundamental value $\tilde{v}$ and the price $\tilde{P}_1$ are jointly normally distributed. I apply the projection theorem to calculate $\hat{v}_U \equiv E[\tilde{v}|P_1]$ and $\hat{\sigma}_U^2 \equiv Var(\tilde{v}|P_1)$:

$$\hat{v}_U = E[\tilde{v}] + \frac{\frac{\beta_1}{\lambda_1+\zeta_1}\sigma_v^2}{\left(\frac{\beta_1}{\lambda_1+\zeta_1}\right)^2\sigma_v^2 + \left(\frac{1}{\lambda_1+\zeta_1}\right)^2\sigma_z^2}(P_1 - E[\tilde{P}_1])$$

$$\hat{\sigma}_U^2 = \sigma_v^2 - \frac{\left(\beta_1\sigma_v^2\right)^2}{\beta_1^2\sigma_v^2 + \sigma_z^2}.$$

Note that $\frac{\frac{\beta_1}{\lambda_1+\zeta_1}\sigma_v^2}{\left(\frac{\beta_1}{\lambda_1+\zeta_1}\right)^2\sigma_v^2+\left(\frac{1}{\lambda_1+\zeta_1}\right)^2\sigma_z^2} = \frac{Cov(P_1,v)}{Var(P_1)}$ and $\sigma_v^2 - \frac{\left(\beta_1\sigma_v^2\right)^2}{\beta_1^2\sigma_v^2+\sigma_z^2} = (1-\rho_{P_1,v}^2)\sigma_v^2$. I abbreviate the expression above as $\hat{v}_U = m_0 + m_1 P_1$. That is,

$$m_0 = v_0(1-m_1),\ m_1 = \frac{\beta_1\sigma_v^2(\lambda_1+\zeta_1)}{\beta_1^2\sigma_v^2+\sigma_z^2}. \tag{A.1.2}$$

This conditional expectation is the same for uninformed traders who enter the market at different times.

Step2: $t = 2$ **problems**

Uninformed trader's problem Next, I solve the optimization for uninformed traders. Their maximization problem is

$$max_{x_{2,i}}\, E\left[-exp(-\gamma_i\left\{(\tilde{v}-p_2)x_{2,i} + (\tilde{v}-P_1)x_{1,i}\right\})|\mathscr{F}_{2,U}\right].$$

Because they have a negative exponential utility with a parameter $\gamma_i,\ i = A,B$ and the terminal wealth is normally distributed (because the fundamental value follows a normal distribution), their demand function is now calculated as

$$x_{2,i}^{*} = \frac{\hat{v}_U - p_2}{\gamma_i \hat{\sigma}_U^2} - x_{1,i} \quad i = A, B.$$

I note that they are assumed to be a price taker. If the uninformed traders are new entrants B, $x_{1,B} = 0$. Thus I can define $\mu_{2,i}, \lambda_{2,i}, \delta_i$,which are strategic variables for new entrants, as a function of m_0, m_1 as follows:

$$\mu_{2,i} = \frac{m_0}{\gamma_i \hat{\sigma}_U^2}, \lambda_{2,i} = \frac{1}{\gamma_i \hat{\sigma}_U^2}, \delta_i = \frac{m_1}{\gamma_2 \hat{\sigma}_U^2}. \tag{A.1.3}$$

The aggregated demand of both uninformed traders ($x_{2,U} = x_{2,B} + x_{2,A}$) is

$$\begin{aligned} x_{2,B} + x_{2,A} &= (\mu_{2,B} + \theta \mu_{2,A}) + (\delta_B + \theta \delta_A) P_1 - (\lambda_{2,B} + \theta \lambda_{2,B}) p_2, \\ &= (1 + \frac{\theta \gamma_B}{\gamma_A}) \mu_{2,B} + (1 + \frac{\theta \gamma_B}{\gamma_A}) \delta_B P_1 - (1 + \frac{\theta \gamma_B}{\gamma_A}) \lambda_{2,B} p_2. \end{aligned} \tag{A.1.4}$$

Remember, only a fraction θ of uninformed traders at $t = 1$ trade at $t = 2$. I denote $\mu_{2,B} = \mu_2$ and so on, in order to omit the subscript. Here, λ_2 is strictly positive because γ_i is assumed to be positive and $\hat{\sigma}_U^2$ is squared. Therefore, Equation (A.1.3) obviously clears the second order condition for the maximization problem. Intuitively, a positive λ_2 assures a downward sloping curve of the demand function of uninformed traders at $t = 2$.

Informed trader's problem An informed trader solves following problem.

$$max_{x_{2,I}} \, E\left[(v - \tilde{P}_2(x_{2,I}))x_{2,I} | \mathscr{F}_{2,I}\right]$$

$$\tilde{P}_2 = \frac{1}{(1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi}\left((1+\frac{\theta\gamma_B}{\gamma_A})\mu_2-\theta\mu_1+\left((1+\frac{\theta\gamma_B}{\gamma_A})\delta+\theta\lambda_1+\phi\kappa\right)P_1+x_{2,I}+\tilde{z}_2\right). \tag{A.1.5}$$

Note that, in period $t=2$, a fraction of the initial old θ arrive at the market, and unwind the position they make at period $t=1$. I can determine $\tilde{P}_2$ from $x_{2,U,o}+x_{2,U,n}+x_{2,R}=0$, which is the sum of uninformed traders and rule of thumb traders. I can also interpret $\tilde{P}_2$ is a transaction price for the informed trader. The first order and second order conditions are

$$\frac{x_{2,I}}{(1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi}-\left(v-E[\tilde{P}_2|\mathscr{F}_{2,I}]\right)=0,\ \frac{-2}{(1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi}<0. \tag{A.1.6}$$

The second order condition, or a strictly positive λ_2, makes a trader's demand function agree with their private information. That is, there is no motivation to manipulate at this period. Arranging terms, I obtain the following expression for $x^*_{2,I}$. Writing $E[\tilde{P}_2|\mathscr{F}_{2,I}]=p_2$, I obtain

$$x^*_{2,I}=\left((1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi\right)(v-p_2)$$

Then the coefficients of a trader's decision rule is

$$\alpha_2=0,\ \beta_2=(1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi,\ \zeta_2=(1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi,\ \xi_2=0 \tag{A.1.7}$$

Thus, positive λ_2 necessarily implies positive β_2 and ζ_2. The p_2 can be substituted for by $E[\tilde{P}_2|\mathscr{F}_{2,I}]$, but for tractability I leave it as is.

Proof of Remark 1: The price change at the limit order book I define the mid-price change as a difference of quotes *before* the informed trader trades. At the second period, the mid-quote is a market clearing price for $x_{2,U}+x_{2,RT}=0$[2].

The mid-price change from $t=1$ is $\hat{v}-v_0$, and it can be rearranged as

$$\begin{aligned}
\Delta P_2 &\equiv \frac{1}{(1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi}\left((1+\frac{\theta\gamma_B}{\gamma_A})\mu_2-\theta\mu_1+\left((1+\frac{\theta\gamma_B}{\gamma_A})\delta+\theta\lambda_1+\phi\kappa\right)P_1\right)-v_0 \qquad \text{(A.1.8)}\\
&= \frac{1}{(1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi}\left((1+\frac{\theta\gamma_B}{\gamma_A})\mu_2-\theta\mu_1+\left((1+\frac{\theta\gamma_B}{\gamma_A})\delta+\theta\lambda_1+\phi\kappa\right)\left(\lambda_1^{-1}(x_{1,I}+z_1)-v_0\right)\right)-v_0\\
&= \frac{1}{(1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi}\left(\left((1+\frac{\theta\gamma_B}{\gamma_A})\delta+\theta\lambda_1+\phi\kappa\right)\lambda_1^{-1}(x_{1,I}+z_1)+\left((1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi\right)v_0\right)-v_0\\
&= \frac{(1+\frac{\theta\gamma_B}{\gamma_A})\delta+\theta\lambda_1+\phi\kappa}{\lambda_1\left((1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi\right)}(x_{1,I}+z_1)\,.
\end{aligned}$$

To the first equation, I applied the market clearing condition at $t=1$: $P_1-v_0=\lambda_1^{-1}(x_{1,I}+z_1)$. From the second to third equation, I used the results for μ. The left hand side is the mid-price change (P_2-v_0), and the right hand side is order imbalance at the end of $t=1$ multiplied by a coefficient. Because $E[x_{1,I}+z_1|\mathscr{F}_{1,U}]=0$, the mid-price follows a Martingale.

This result confirms the findings of Kyle (1985). I use this coefficient as a definition of the permanent price impact, or Kyle's lambda.

[2] Here I implicitly assume the rule of thumb traders can advance to the informed trader, because they can execute a part of their order against the uninformed traders. The informed trader delays the trade, but the noise traders come last. This exogenous timing doesn't influence the equilibrium much, because of the price taking behavior or uninformed traders and risk neutrality of the informed trader, but it does matters when the informed trader is risk averse (potential settlement risk).

The intentional delay in double auction markets and the role of rule of thumb traders are also documented in Rust,Miller, and Palmerf (1993).

Step 3: $t = 1$ **problems**

Uninformed trader's problem The uninformed trader A's problem is

$$max_{x_{1,A}} \, E\left[-exp(-\gamma_A(\tilde{v}-p_1)x_{1,A})|\mathscr{F}_{1,A}\right]$$

Here, an informed entrant is not expected. This problem is solved as follows.

$$x^*_{1,U} = \frac{E[\tilde{v}]-p_1}{\gamma_A \sigma_v^2},$$

$$\mu_1 = \frac{v_0}{\gamma_A \sigma_v^2}, \quad \lambda_1 = \frac{1}{\gamma_A \sigma_v^2}. \tag{A.1.9}$$

$E[\tilde{v}] = v_0.\lambda_1$is assumed to be positive to obtain a downward sloping curve.

Informed trader's problem The problem for the informed trader is

$$max_{x_{1,I}} \, E\left[(v-P_1)x_{1,I} + (v-\tilde{P}_2)x^*_{2,I}|\mathscr{F}_{1,I}\right].$$

Substituting $x^*_{2,I} = ((1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi)(v-P_2)$ by (A.1.6), I obtain

$$max_{x_{1,I}} \, E\left[(v-P_1)x_{1,I} + \left((1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi\right)(v-\tilde{P}_2)^2|\mathscr{F}_{1,I}\right].$$

The first order condition is

$$\left(v-P_1-\frac{\partial P_1}{\partial x_{1,I}}x_{1,I}\right) - \left[2\left((1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi\right)(v-E[P_2|\mathscr{F}_{1,I}])\cdot\frac{1}{2}\frac{\partial P_2}{\partial P_1}\frac{\partial P_1}{\partial x_{1,I}}\right] = 0. \tag{A.1.10}$$

The first term shows the profit from period one deals, and the second shows the profit from the second period.

The second order derivative is

$$-2\frac{\partial P_1}{\partial x_{1,I}}+\frac{1}{2}\left((1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi\right)\left(\frac{\partial P_2}{\partial P_1}\frac{\partial P_1}{\partial x_{1,I}}\right)^2.$$

Our conjecture suggests $\frac{\partial P_1}{\partial x_{1,I}}=\frac{1}{\lambda_1}$, $\frac{\partial P_2}{\partial P_1}=\frac{(1+\frac{\theta\gamma_B}{\gamma_A})\delta+\theta\lambda_1+\phi\kappa}{\left((1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi\right)}$. Then the F.O.C. and S.O.C. become

$$\begin{aligned}
x^*_{1,I} &= \lambda_1(v-P_1)-\frac{1}{2}\frac{(1+\frac{\theta\gamma_B}{\gamma_A})\delta+\theta\lambda_1+\phi\kappa}{\left((1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi\right)}\left[\left((1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi\right)\lambda_2 v-\left((1+\frac{\theta\gamma_B}{\gamma_A})\mu_2-\theta\mu_1+((1+\frac{\theta\gamma_B}{\gamma_A})\delta+\theta\lambda_1+\phi\kappa)P_1\right)\right],\\
& \frac{1}{4}\left((1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi\right)\left(\frac{(1+\frac{\theta\gamma_B}{\gamma_A})\delta+\theta\lambda_1+\phi\kappa}{\left((1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi\right)\lambda_1}\right)^2-\frac{1}{\lambda_1}<0
\end{aligned}$$

The second order condition may not necessarily hold. Finally I obtain

$$\alpha_1=\frac{1}{2}\frac{(1+\frac{\theta\gamma_B}{\gamma_A})\delta+\theta\lambda_1+\phi\kappa}{(1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi}\cdot(\theta\mu_1-(1+\frac{\theta\gamma_B}{\gamma_A})\mu_2),\ \beta_1=\lambda_1-\frac{1}{2}((1+\frac{\theta\gamma_B}{\gamma_A})\delta+\theta\lambda_1+\phi\kappa), \tag{A.1.11}$$

$$\zeta_1=\lambda_1-\frac{1}{2}\frac{\left((1+\frac{\theta\gamma_B}{\gamma_A})\delta+\theta\lambda_1+\phi\kappa\right)^2}{(1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2+\phi}.$$

The sign of ζ_1 is the same as the S.O.C. This means that the informed trader must have upward sloping curve with respect to prices.

The equations (A.1.2), (A.1.3), (A.1.7), (A.1.9), (A.1.11) with the informed trader's $t=1$ second order condition pin down the equilibrium.

A.2. Derivation of Uninformed Manipulation Condition

The uninformed manipulation condition is derived from the profitability condition of a round trip trade. I check whether the informed trader (i.e., manipulator) has an incentive to holding the round trip trade. Let $x_{1,I} = x \in \mathbb{R}$ and $x_{2,I} = -x$, the trader's expected profit is

$$\max_x \; E\left[x \cdot \{P_2(-x) - P_1(x)\}\right].$$

Without the loss of generality, I let $v_0 = 0$. I use the market clearing conditions at $t = 1$ and $t = 2$. We can find the solution is either $x = 0$ or $x = \pm\infty$. When the second order condition holds, I obtain $x = 0$. Namely

$$\frac{(1+\frac{\theta\gamma_B}{\gamma_A})\delta + \theta\lambda_1 + \phi\kappa}{\left((1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2 + \phi\right)\lambda_1} - \frac{1}{(1+\frac{\theta\gamma_B}{\gamma_A})\lambda_2 + \phi} - \frac{1}{\lambda_1} < 0.$$

This is the condition that the informed trader does not deviate to taking the round trip position. When the equality holds, the expected profit is equal to zero regardless of the value of x. Thus, I can derive the condition that describes the profitability of uninformed manipulation.

Appendix B

Appendix for Chapter 2

B.1. Immediate Price Impact

The model sets a uniform price double auction, and does not induce any bid and ask spread. Further, the market-clearing price for the model is not the same as the transaction price at the LOB market. Fortunately, the linear demand function gives us a simple relationship between them. The IPI in the model is half the linear price impact inferred from the LOB; $IPI = IPI_{from\ LOB}/2$.

Proof. Consider the case of buying $\bar{q}$ shares in an LOB market, and we define a linear price impact coefficient $IPI_{from\ LOB}$ to satisfy the total amount of payment $p\bar{q} = \int_0^{\bar{q}} \left(\underline{\mathrm{p}} + IPI_{from\ LOB}q\right) dq$. Here, p is the average purchasing price (considering uniform pricing), and $\underline{\mathrm{p}}$ is also the lowest execution price, or the best ask price. We define the bid and ask spread as $bas = 2(\underline{\mathrm{p}} - \tilde{p})$, where $\tilde{p}$ is the mid quote. Substituting for $\underline{\mathrm{p}}$ and calculating the integration, we get the expression $p - \tilde{p} = bas/2 + IPI_{from\ LOB}\bar{q}/2$. The left hand side of the equation is the price change in the uniform pricing market, and the right hand side is the linear price impact in the LOB market. Since the bid and ask spread appears as a first order term, we can ignore it because the uninformed manipulation gives a profit, which is a square of the amount of traded volume. Thus, we can find a direct relationship exists between empirical price impact $IPI_{from\ LOB}$ and theoretical IPI as $IPI = IPI_{from\ LOB}/2$. □

B.2. Details of Data Cleaning

Data Cleaning The raw data dates back to two years, and includes 1,000 most traded stocks listed on the TSE. The 1,000 stocks were chosen by the trade volume in January 2005. I first performed a cleaning process on the raw data in the following manner.

1. I truncated data for the whole day for stock where it hits the upper or lower limit of one-day price change.
2. I interpolated the observation with missing order book entries with very small numbers (less than .0001% of the observation).
3. When the number of ask side LOB does not match the number of bid side of the book, I omitted data corresponding to the whole day of that stock.
4. Lastly, I picked stocks with observations for more than 200 trading days.

These omissions did not reduce the data by much.

Then, I created a sampling or snapshot of the LOB, cumulative volume, number of trades, and order imbalances. I employed a sampling frequency of one minute. The volume and order imbalances were an accumulation of this sampling frequency. Figure B.2.1 explains the sampling timing. For each snapshot of the LOB, the depth-weighted price and price impacts were calculated.

Thus, I obtained the one-minute sequence of volume, number of trades, order imbalances, weighted price, and IPIs.

Then, I calculated the prediction for PPI and IPI using the Kalman Filter for 5, 15, and 30-minute intervals. The Kalman Filter was applied to whole the sequence once. The overnight factor remained, but I omitted the first and last observations of one day anyway.

After performing the Kalman filtering to obtain the predicted PPI and IPI, I truncated (1) the first and the last observation of each day (because they were supposed to be priced by the opening and closing auctions), (2) stock with tick size bigger than 1, and (3) the data between November 2, 2004 and November 2, 2005.

Unlike stocks listed on the NYSE, stock prices in the TSE have different face values, tick size, and minimum unit of shares to trade. The changes in the minimum tick size are dependent on the price range. Comparing the stock liquidity among different face value, unit of shares, and the tick size is often complicated. Fortunately, around 70% of the stocks have a tick size of 1 yen, so I focused on tick size stocks of this value.

One minute interval data I made minute-by-minute data from the original data. I took a sample of price and price impact that were last recorded within each minute. I added up the signed trade volume over one minute, and constructed the order imbalance. The number of transactions was also calculated in the same way. In this manner, I could compress the data volume. The raw data of each day had a volume of around 2GB, and was difficult to deal with. Since my data did not have a second-by-second time stamp, it was reasonable to focus on minute-by-minute records. Whenever I could not observe any records for some fixed time ranges, the order imbalance and number of trades were set zero, while the price was set the same as that in the last minute.

Although I picked the most liquid 1,000 stocks in the TSE, some stocks did not have any trade transactions for more than 10 minutes. This could have led to a

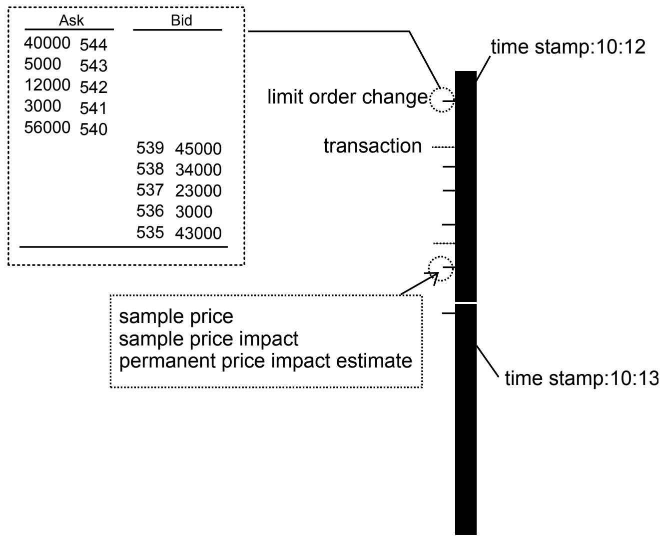

Figure B.2.1. Sampling timing of the data and the LOB snapshot. The price and the price impact were picked up from the bid and ask price of the last LOB record within a minute. The order imbalance at t , v_t, is a summation of order imbalances between the time between $t-1$ and t. At the end of time t, the LOB is revealed and the values for slippage IPI and the mid-price change $\Delta\tilde{p}_t$ become known. Based on this information, it is possible to estimate the PPI and IPI

bid and ask bounce problem, which I mitigated by employing the depth-weighted average price.

Scaling I summarize how I scaled the variables.

— All the volume and order imbalances were scaled by the unit rather than the raw sequence, because the minimum number of trading units depended on the face value of the stock.

— In the regression models, the order imbalance and volume (as independent variables) were scaled by the total volume of the day.

— In the regression models, the price impacts (as independent variables) were scaled by the price, and denoted as a percentage.

Measure of Noise trading In order to calculate the measure of noise trading, I resorted to the framework of Easley, Kiefer, O'Hara, and Paperman (1996).

They assumed the Poisson distribution for incoming informed noise trade, with each realized trade being dependent on whether the informational event happens or not on the given day. The informational event drives informed traders, who buy or sell at the bid or ask price, and it induces positive or negative order imbalances. The likelihood function of the Easley, Kiefer, O'Hara and Paperman (1996) model is

$$L(\theta|B,S) = (1-\alpha)e^{-2\varepsilon}\frac{\varepsilon^{B+S}}{B!S!} + \alpha\delta e^{-(\mu+\varepsilon)}\frac{(\varepsilon+\mu)^B\varepsilon^S}{B!S!} + \alpha(1-\delta)e^{-(\mu+\varepsilon)}\frac{\varepsilon^B(\varepsilon+\mu)^S}{B!S!}.$$

where $\theta = (\alpha, \delta, \mu, \varepsilon)$, and α is the probability that the information event occurs, δ is the probability that the event is a bad news, μ is the Poisson parameter according to which informed traders arrive at the market, and ε is the Poisson parameter according to which noise traders arrive at the market. B and S are the number of buys and sells for a given day. We can estimate these parameters year-by-year by maximizing the likelihood.

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