THE CHINESE EQUITY MARKET: CHARACTERISTICS, MICROSTRUCTURE AND EFFICIENCY

by

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The candidate confirms that the work submitted is his own and that appropriate credit has been given where reference has been made to the work of others.

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ABSTRACT

The purpose of this research is to examine various issues about market efficiency and market microstructure in the Chinese equity market, where, to date, there has been relatively little attention. Specifically, this thesis intends to answer the following questions. Is the Chinese equity market efficient? If not, has it been evolving towards efficiency over the years? What are the intraday patterns of price behaviour? Which trades move prices? Finally, does Chinese investors' psychology have effects on prices? In order to answer these questions, four sets of empirical analysis have been undertaken.

The first study investigates the evolution of China's stock market via analysing the ongoing predictive ability and profitability of simple, well known technical trading rules. The results suggest that while technical trading rules had short term predictive ability and profitability in the Chinese stock markets during the 1990's, this lessened as the markets evolved.

The second research study documents the intraday variation in bid-ask spreads, trading volumes and volatility. The findings suggest that the existence of the intraday anomalies is not due to the peculiarities of the US markets. However, the shape of the intraday patterns in order-driven markets is different from those in quote-driven markets, which suggests a need for new theoretical models.

The third area of work examines which trades move prices by testing three hypotheses: stealth trading, public information and price manipulation hypotheses. The results show that while medium and large-size trades are associated with disproportionately cumulative price changes, it is the large-size trades which have the largest effect on cumulative price increases. Aligned with the concerns noted by some eminent individuals in China, there seems to be price manipulation in China's stock market.

The final research area studies the influence of Chinese cultural factors on price clustering and resistance. The results show a higher propensity of clustering on the digit 8 and lower propensity on digits 4 and 7, which is consistent with the preference for number 8 and the avoidance of numbers 4 and 7 in Chinese culture. The results suggest that investors' psychology does have effects on prices.

This research hopes to help academics and practitioners understand better the market efficiency and the trading behaviour in the Chinese equity market. Especially, it has implications for policy makers and regulators who involve in the design of an efficiency market.

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LIST OF ABBREVIATIONS

ADB	Asian Development Bank
AIM	Alternative Investment Market
AMS	Automatic Order Matching and Execution System
CCER	China Centre for Economics Research
CORES	Computer Assisted Order Routing and Execution System
CRSP	Centre for Research in Security Prices
CSD	Clearance, Settlement, and Depository
CSRC	China Securities Regulatory Commission
DJIA	Dow Jones Industrial Average
ECN	Electronic Communication Networks
EMH	Efficient Market Hypothesis
FDI	Foreign Direct Investment
FORES	Floor Order Routing and Execution System
GDP	Gross Domestic Product
GMM	Generalized Method of Moment
HK	Hong Kong
IIBFS	International Institute of Banking and Financial Services
IPO	Initial Public Offering
LSE	London Stock Exchange
MOF	Ministry of Finance
NASDAQ	National Association of Securities Dealers Automated Quotation
NBS	National Bureau of Statistics
NETS	National Electronic Trading System
NPC	National People's Congress
NYSE	New York Stock Exchange
PBOC	People's Bank of China
QFII	Qualified Foreign Institutional Investors
RMB	Renminbi
SCSC	State Council Securities Commission
SEAQ	Stock Exchange Automated Quotation
SEHK	Stock Exchange of Hong Kong
SES	Stock Exchange of Singapore
SETS	Stock Exchange Electronic Trading Service
SETS PLUS	Stock Exchange Alternative Trading Service
SETC	State Economic and Trade Commission
SHSE	Shanghai Stock Exchange
SOE	State-Owned Enterprise
STAQS	Securities Trading Automated Quotations System
SZSE	Shenzhen Stock Exchange
TSE	Tokyo Stock Exchange
UN	United Nations
WTO	World Trade Organization

CHAPTER 1

INTRODUCTION

1.1 Introduction

Ever since Fama (1970) introduced the idea of the Efficient Market Hypothesis (EMH) there has been a long debate about whether the stock market is efficient. In Fama's work the market is said to be 'efficient' if stock prices fully reflect all available information. Based on different information sets, he defined three types of market efficiency: weak-form efficiency, semi-strong-form efficiency and strong-form efficiency. The weak-form efficiency assumes that the current prices of stocks instantly and fully reflect all past information. The semi-strong-form efficiency assumes that the current prices of stocks reflect all publicly available information. The strong-form efficiency assumes that the current prices of stocks reflect all information, including public and private.

The EMH sets up a platform for testing and comparing the efficiency of asset markets. It assumes that the market is competitive, trading is frictionless, information is costless, and investors are rational. However, the equity markets do not behave like the perfectly competitive markets of frictionless economics. In addition, investors are not fully rational in general. For all equity markets, friction exists in the forms of; for example, taxes and commissions, order handling and clearance costs, trading halts, and other trading restrictions. Therefore, the institutional design of a market matters, and it affects market efficiency.

Market microstructure research emerged to examine how specific trading mechanisms affect the price formation process. The purpose of market microstructure research is to reveal the relative efficiency of a market, to identify the source of such and to inform on better market design. Previous studies in testing the EMH focus on the realized efficiency of a market, while market microstructure researchers try to explore the underlying mechanisms of the market which lead to market efficiency or inefficiency. Microstructure studies try to analyse how demand and supply turn into individual transactions which causing the short-run fluctuation in asset markets. This is achieved by relaxing some of the key assumptions in EMH and studying the trading frictions (trading costs), informational efficiency (information diffusion) and the irrationality of investors' behaviour in the markets.

Over the past decades there has been growing interest in the microstructure of stock markets. The research is concerned with investors' trading behaviour at the level of individual transactions. O'Hara (1997) stated that market microstructure is the study of the process and outcomes of exchanging assets under explicit trading rules. Madhavan (2000) argued that market microstructure is concerned with the process by which investors' latent demands are ultimately translated into transactions. Early work focused on the stochastic nature of demand and supply, while later research interests were those from the viewpoint of informational economics, which focused on the information-aggregation properties of the markets. These theories and models have evolved from focusing on inventory-based problems to those issues associated with information economics. More recently, behavioural finance has emerged as an alternative view of financial markets. A number of recent papers in the finance literature have argued that behavioural and psychological factors account for asset pricing anomalies (see Coval and Shumway, 2005, Barberis et al., 1998, Daniel et al., 1998, Odean, 1998, Benartzi and Thaler, 1995, Shumway, 1998, Barberis and Huang, 2001, and Barberis et al., 2001). The research of investors' psychology would provide further insights.

China is an economy undergoing rapid transformation. Its rapid growth has brought great business opportunities for the rest of the world. Its dynamism makes it increasingly important for global economic growth. Although China's stock market emerged only about 14 years ago, it has become the eighth largest market in the world and Asia's second largest. The total market capitalization reached some RMB 3,800 billion at the end of 2002, which accounts for 37 percent of GDP. The development of China's stock market is so impressive that it has made foreign investors begin to take the market more seriously as an investment proposition, especially after China entered the World Trade Organization (WTO) in 2001. Moreover, the institutional and regulatory structure of China's stock market are different from those of the more mature markets and are able to provide insights into a number of aspects of financial markets. The findings will have important implications for academics, practitioners and regulators.

The rest of the chapter is organized as follows. Section 1.2 discusses the theoretical motivations of this thesis, while section 1.3 discusses the objectives. Section 1.4 gives a general overview of the results. Section 1.5 discusses the contributions and possible implications. The structure of the thesis is presented in the last section.

1.2 Theoretical Motivations

1.2.1 Market Efficiency

One of the most important concepts in the financial economics literature is efficiency. It concerns the way a market allocates resources. The efficiency of the equity market is essential not only to firms for fundraising but also to individuals who invest their savings in shares. Schwartz (1988) argued that the efficiency allocation of plant, equipment and working capital across firms in the economy depends on the efficiency with which financial capital is distributed across firms. A firm will seek to raise funds by the sale of a security, and it costs. If the capital costs of the firm are inaccurately assessed, the distribution of funds and of real investment across firms will be distorted. The price it receives for its newly issued shares will affect the firm's capital costs. Therefore, it is important for the primary market to be efficient. The primary market, in turn, requires an efficient secondary market for the following reasons: the marketablility of shares and the accuracy of share valuation. The efficiency discussed in this research refers mainly to the efficiency of the secondary market.

Investors are also affected by the efficiency of equity market for the reasons relating to the informational efficiency and the operational efficiency, as discussed by Schwartz (1988). In the dynamic market, prices continuously adjust to the arrival of news. The dynamic adjustment of prices to new information enables some investors to profit at the expense of others. These profits are reward for information gathering activities, which give those investors an advantageous position over the information flow. However, if informational imbalances endure too long, those who are at the informational disadvantage may be driven from the market. This would decrease the aggregate demand of shares and lower the prices for all.

Copeland and Weston (1988) stated that operational efficiency deals with the cost of transferring funds. In an idealized world, the perfect capital markets are operationally efficient because the transaction costs are assumed to be zero.

However, transaction costs do exist in the real world. The market can only become relatively more operationally efficient with lower transaction costs. Moreover, Schwartz (1988) argued that operational efficiency concerns the stability of a market. Prices are more volatile if the quality of the price discovery process is poor, with price volatility being attributable to operational inefficiency. It will have a similar effect to the informational inefficiency: investors reduce the demand to hold shares, and the shared prices are lowered for all.

To conclude, the informational efficiency and operational efficiency of the equity markets affects both the firms and share owners. The efficient operation of the equity market is a matter of importance to a sizable proportion of the financial fortunes. Many of the issues related to the efficiency of price discovery have been examined at the microstructure level, which will be discussed in the next section.

1.2.2 Market Microstructure

The equity markets do not behave like the perfectly competitive markets of frictionless economics. Market participants have to take various trading costs into account, when they make their strategic decisions to trade. These decisions depend upon the market's institutional structure: the rules that determine how orders are handled and translated into trades. Since the equity market is not a frictionless environment, the institutional design of a market does affect the market efficiency.

Standard microeconomic decision models and market equilibrium models take demand and supply as market forces. If demand exceeds supply, competition between buyers will cause prices to rise and, if supply exceeds demand, competition between sellers will cause prices to fall. To an extent share prices are determined by demand and supply. However, if the equilibrium cannot be actually attained, how could the economy coordinate the desires of demanders and suppliers to find out a price to trade? Since few economists provide the answer to this question, the market microstructure research emerged.

Madhavan (2000) argued that market microstructure is concerned with the process by which investors' latent demands are ultimately translated into transactions. Microstructure analysis focuses on the details of the trading process, and is concerned with investors' trading behaviour at the level of individual transactions. O'Hara (1997) stated that market microstructure is the study of the process and outcomes of exchanging assets under explicit trading rules. The major elements of this process include; for example, the generation and dissemination of information, the arrival of orders, and the rules, institutions, and other design features of a market that determine how orders are transformed into trades. Microstructure analysis could, in principle, be applied to any market. Thus far, it has been developed almost exclusively in relation to securities markets, and will be the approach adopted in this research.

The trading process varies in many ways. Buyers can trade directly with sellers. Or, there might be an intermediary who arranges every trade and sets prices. No matter what the setting, there are rules that govern the trading mechanism and result in the price formation. O'Hara (1997) viewed trading mechanism as 'a type of trading game in which players meet at some venue and act according to some rules.' There are three dimensions of a trading mechanism, which are the market participants, the exchange, and the trading rules.

The institutional structure of equity markets differs widely among the various markets throughout the world. While most previous research has focused mainly on the US markets, there are very few empirical studies examining the Chinese equity market at the micro level. Although there has been considerable change, innovation, and experimentation with market design during the years of stock market development, much still remains to be learned, and many issues remain unresolved.

1.3 Objectives

This thesis covers a wide range of topics focusing on the Chinese equity market. The development of the Chinese equity market is impressive. However, what does development actually mean? Obviously, the market has been developing in terms of the number of listed companies and market capitalisation, etc. However, what does this actually tell us about the efficiency of the stock market?

Since market efficiency is of interest to financial economists, the first empirical chapter of this thesis therefore examines the evolution of market efficiency in China. The chapter considers whether the Chinese equity market is efficient, or if has it been evolving towards an efficient state over time. It intends to provide a general picture of what level of efficiency exists in the Chinese equity market by testing changes in the predictability and profitability of technical trading rules.

The analysis will then consider price behaviours in more detail using high-frequency intraday data. This is particularly important for practitioners who make their investment decisions by observing tick-by-tick data. The intraday patterns of price behaviours will provide practical applications for market participants. Therefore, the second empirical chapter examines the intraday patterns of the bid-ask spread, volume and volatility.

The third empirical chapter will further the analysis by examining the relationship between variables such as price and trade size. It will focus on the informed traders' trade size choice, and show which trades move prices. This is important in the Chinese stock market where price manipulation is a serious problem and this will be specifically examined.

After the analysis of how trading mechanisms affect the price discovery process, the last empirical study examines the influence of the investors' behaviour and psychology on prices. Since market participants are one of the dimensions of a trading mechanism, it is important to investigate whether their behaviour or psychology affects the price discovery process beyond the influence of the institutional structure of the stock market. Therefore, the fourth empirical chapter examines how behavioural and psychological factors affect the price discovery process. In the case of the Chinese stock market, cultural factors will provide unique and interesting insights.

Specifically, this thesis intends to answer the following questions. Is the Chinese equity market efficient? If not, has it been evolving towards an efficient state? What are the intraday patterns of the price behaviours? Which trades move prices? Finally, does Chinese investors' psychology have an effect on prices?

1.3.1 Market Efficiency and Evolution

Much of finance theory depends, explicitly or implicitly, on the notion of market efficiency and, therefore, not surprisingly, there has been extensive testing as to whether financial markets are efficient (for example, Fama, 1970, 1991 and 1998, Baillie, 1989, and Campbell, Lo and MacKinley, 1997). However, the vast majority of the professional traders do not believe the market to be efficient, and they use technical analysis to predict stock prices and make excess return. Most academics had not recognized the validity of these methods until recently. Brock et al. (1992) tested two of the simplest technical trading rules, moving average and trading range breakout, and found them to have predictive ability in terms of the Dow Jones Index over the period 1897 to 1986. Hudson et al. (1996) conducted a similar type of analysis on the UK FTSE 30 index and found the rules to have predictive ability. More recently, Gencay and Stengos (1997 and 1998), Gencay (1998a, 1998b and 1999), LeBaron (1998 and 1999) and Fernandez-Rodriguez et al (2000) have all found evidence to support the predictive ability of technical trading rules.

In contrast to this extensive literature on market efficiency and the testing thereof, there has been little discussion of the mechanisms which might lead to its achievement. If markets are not efficient, and in the absence of an alternative mechanism, the theory of financial market efficiency seems to have to rely on an evolutionary mechanism. There is an implicit assumption in finance theory that natural selection will favour strategies that are more rational and effective in investments, capital budgeting, etc. This eventually leads to an efficient market, since only the most effective strategies can survive in the marketplace.

Although China's stock market emerged only about 14 years ago, the growth has been impressive. To reach its potential China will need to develop an efficient market. However, as an emerging market it seems more likely that markets will initially be inefficient but, hopefully, evolve towards efficiency. Chapter 4 of this thesis investigates market efficiency and evolution of China's stock market via analyzing the ongoing predictive ability and profitability of simple, well know technical trading rules.

1.3.2 Intraday Patterns

Researchers found other evidence against market efficiency, such as calendar anomalies. The major calendar anomalies include: the turn of the year effect and/or January effect (Keim, 1983, and Thaler, 1987), the turn of month effect (Ariel, 1987, and Lakonishok and Smidt, 1988), the day of the week effect (French, 1980, Gibbons and Hess, 1981, and Keim and Stambaugh, 1984), the holiday anomalies (Ariel, 1990, and Lakonishok and Smidt, 1988) and the intraday anomalies (Harris, 1986). The regularity that the returns vary across months, weekdays and time intervals suggests the possibility that the use of past price information might yield potential excess profits.

Due to the data constraints early research could only examine the calendar anomalies at a low frequency base, while the availability of high frequency data has provided finance researchers with the enviable opportunity of being able to explore intraday variables, such as bid-ask spread, trading volumes and volatility (see McInish and Wood, 1985, Wood et al., 1985, Harris, 1986, Jain and Joh, 1988, and McInish and Wood, 1990b). For example, returns and its volatility tend to be greater at the open and close than at other times during the trading day and exhibit a U-shaped pattern (see McInish and Wood, 1985, Wood et al., 1985, Harris, 1986, Jain and Joh, 1988, and McInish and Wood, 1990b). The U-shaped intraday patterns have also been documented in bid-ask spreads (McInish and Wood, 1985, and Abhyankar et al., 1997), and trading volume (Jain and Joh, 1988, McInish and Wood, 1990a, and Atkins and Basu, 1995). Previous studies consider the possible explanations for the intraday patterns by considering the market with specialists or market makers (See Brock and Kleidon, 1992, Admati and Pfleiderer, 1988, and Foster and Viswanathan, 1990).

However, Brockman and Michayluk (1997) suggested that the calendar anomalies might be attributed to market microstructure-related underlying causes. Since the intraday variation of stock market activities has been well documented in the literature with the evidence band on US data, the study of China's stock market is important for the following reasons. First, the institutional setting of China's stock market is different from the US market in at least three ways. They include the use of a fully centralized and computerized screen based dealer system, the used of order-driven system without any market makers or specialists, and a 90-minute lunch time. Second, it would be useful to examine whether the intraday regularities are consistent with the predictions of theoretical models, such as those of Brock and Kleidon (1992) or Admati and Pfleiderer (1988). It is important that predictions of theoretical models are tested in a variety of institutional settings so as to examine their robustness.

By examining the intraday patterns in China's stock market, chapter 5 has the following exploratory objectives. First, it shows the intraday trading activity patterns and documents a wide range of market characteristics. Second, it compares the patterns in China's stock market to those in other markets, and tries to explain the similarities and differences by considering the theoretical models and different market structures.

1.3.3 Price Manipulation

Huebner (1934) argued that stock-price manipulation is the most widely discussed aspect of stock markets. There are a large number of studies that examine theoretically and empirically price manipulation in a number of different settings (see Jarrow, 1992, Vila, 1989, Felixson and Pelli, 1999, and Vitale, 2000, etc.). At the National People's Congress (NPC) in spring 2000, Premier Zhu Rongji remarked that China's stock markets had developed quickly, achieved much, but was still not well regulated. His concerns are about the rampant speculation, poor-quality listed firms, defective regulation and widespread corruption. Zhu (1996) argued that the fraudulent behaviours have become significant problems in China. Gilley (2001) also pointed out that the wrongdoings in China's stock market include insider trading, false disclosure and market manipulation. Insider trading and price manipulations are not exceptional in China's stock market with Kang et al. (2002) pointing out that investment companies team up with large investors to manipulate share prices, and about 30% of stocks are being manipulated at any given time.

Allen and Gale (1992) found that it is the larger trades that move prices, which is associated with 'trade-based manipulation'. In contrast, Barclay and Warner (1993) introduced stealth trading hypothesis, which predicts that privately informed traders use medium sized trades so as not to reveal their information. They found most of the cumulative stock-price change is due to medium-size trades. Similarly, Chakravarty (2001) found that medium-size trades are associated with a disproportionately large cumulative stock price change relative to their proportion of all trades and volume. In addition, they found that the source of the disproportionately large cumulative price impact of medium-size trades is trades initiated by institutions.

Given the presence of price manipulation it is unclear whether there would be the same need for privately informed investors to adopt stealth trading in China's stock market. Moreover, it is interesting to examine traders' trading strategy in a less developed regulatory regime. Chapter 6 of this thesis intends to test price manipulation hypothesis in addition to the stealth trading and public information hypotheses by investigating which trades move prices in China's stock market.

1.3.4 Investor Psychology

Market microstructure research examines how prices are set under specific trading mechanisms. O'Hara (1997) viewed trading mechanisms as 'a type of trading game in which players meet at some venue and act according to some rules.' There are three dimensions of a trading mechanism, which are the market participants, the exchange and the trading rules. Therefore, is a market participant's behaviour or psychology going to have an effect on prices? Behavioural finance has then emerged as an alternative view of financial markets. Behavioural finance theory rests on two major foundations: investor sentiment and limited arbitrage. Shleifer (2000) argued that investors are not fully rational in general. Many investors react to irrelevant information in forming their demand for securities and act as noise traders in the market because of their irrationality. Black (1986) confirmed that they trade on noise rather than information. If the theory of efficient markets relied entirely on the rationality of individual investors, the theory is questionable because investors' psychology has great influence.

One of the fascinating subjects that should receive more attention from investors is the psychology of numbers. According to the EMH, share prices should follow a simple random walk process. However, prices tend to be observed more frequently at some numbers than other. Psychological experiments demonstrate more generally that clustering of outcomes at round numbers is a fundamental attribute of human behaviour. Most research on price clustering has been conducted in western financial markets, where there is manifest preference for trading at round numbers. The number preferences under Chinese culture might provide interesting insights.

Brown et al. (2002) analysed the effect of Chinese cultural factors, such as preferences for specific numbers, on price clustering for six Asia-Pacific stock markets (Australia, Hong Kong, Indonesia, Philippines, Singapore and Taiwan). They found that Chinese try to avoid the 'unlucky' number 4 because the pronunciation of 4 is similar to the phrase 'to die'. Chapter 7 of this thesis has a primary purpose of extending the work of Brown et al. (2002) testing whether cultural factors help explain price clustering in China's stock market.

1.4 Overview of Findings

The major findings are summarized in this section. Firstly, Chapter 4 investigates the evolution of China's stock market via analysing the ongoing predictive ability and profitability of simple, well known technical trading rules. It extends the analysis of Brock et al. (1992) and Tian et al. (2002) in two ways. It examines if the conclusions extend to other markets – namely, the U.K., Hong Kong and Japan. It also investigates that in the case of China whether the predictability and profitability of technical trading rules changed across the 1990's. The results suggest that while technical trading rules had short term predictive ability and profitability in the Chinese stock markets during the 1990's. this lessened as the decade progressed and the markets evolved. The notion of stock markets evolving is supported by results for a number of the main developed markets where the technical trading rules had predictive ability during the 1970's that disappeared by the 1990's.

Secondly, Chapter 5 examines the intraday variation in the bid-ask spread, trading volume and volatility in China's stock market. The results are different from previous research. It documents an L-shaped pattern of bid-ask spread and volatility. The volume pattern is relatively flat in the morning session with a marginal increase at the open and marginal decrease at the close; while it shows a J-shaped pattern in the afternoon session. The evidence in support of the two main theoretical models of intraday behavior, information models (Admati and Pfleiderer, 1989, and Foster and Viswanathan, 1990) and market closure model (Brock and Kleidon, 1992), is very mixed. Moreover, as the theoretical models have been developed in the context of quote-drive markets, it is felt that there is a room for a theoretical model to explain the intraday behavior in an order-driven market.

Thirdly, chapter 6 extends Barclay and Warner's (1993) original work on stealth trading by analysing which trades move price for the emerging China stock market. China is an emerging market with a developing regulatory framework and lack of sophistication of the general investing public. Given the nature of

China's stock market, the price manipulation hypothesis is proposed in addition to the stealth trading and public information hypotheses examined by Barclay and Warner. Using high-frequency data the results show that while medium and large-size trades are associated with disproportionately large, overall, cumulative stock price changes, it is the large-size trades which have the largest effect on cumulative price increases. Thus, while there is some support for stealth trading in the Chinese market, there are other effects in operation such as price manipulation. The results add to the current literature on stealth trading and would also be of interest to regulators in China to strengthen the regulation.

Finally, Chapter 7 extends the work of Brown et al. (2002) on the impact of cultural factors on price clustering to the China's stock market and to an analysis of price resistance. The results support the presence of cultural factors impacting on price clustering with the digit 8 showing a higher propensity for clustering and the digits 4 and 7 showing a lower propensity. These results are further supported by an analysis of limit order prices. However, a range of measures for price resistance shows only the digit 0 as a significant resistance point. The theoretical contribution of this study is the addition of a new explanation for price clustering, namely cultural preference. This is broadly consistent with the proposition of behavioural finance theory that investors are not fully rational in general and they react to irrelevant information in forming their demand for securities; for example, the preference of the lucky number 8 among Chinese investors. This study also enriches the market microstructure literature that not only the trading mechanism affects prices but the psychology of investors does so as well.

1.5 Contributions and Implications

Generally, this thesis is a further contribution to a better understanding of the characteristics, the microstructure and market efficiency of the Chinese equity market. It is expected to contribute to the existing literature in the following areas. First, it contributes to the existing studies of market efficiency by investigating the informational and operational efficiency, using both low-frequency and high-frequency data. Second, it provides further evidences of the market microstructure research by examining various issues in the Chinese equity market. Third, it extends the existing understanding of investors' irrationality from evidence of the Chinese cultural effects.

Compared to extensive empirical work of the US market, the Chinese equity market has received relatively little attention. Jaffe and Westerfield (1985) suggested that the evidence of international markets other than the US may provide support for or against the proposition that the stock market anomalies are a world-wide phenomenon and not due to specific institutional arrangement in the United States. Since China is becoming an emerging global power, investors from the rest of the world will want to understand China's stock market better.

The results of this research will have implications for practical investment strategies. Particularly, with China's entry into WTO, the Chinese equity market attracts more and more foreign investors' attention. Thus, understanding the characteristics, the microstructure and market efficiency becomes increasingly important, in particular, for global institutional investors.

This research could also serve as a reference for regulators and policy makers who are involved in the design of an efficient trading system. Despite the shortcomings of the regulatory framework in China, government has played an important role in the evolution of the equity markets. Efforts have been made in order to assure an honest and fair market, to enhance market efficiency with regard to the provision and pricing of broker/dealer services, and to enhance market efficiency with regard to the pricing of shares traded. Because of the tremendous importance of the equity market to the economy and the complexity of its microstructure, the equity has received analysis in depth and breadth. There is a further reason to the extensive research of the equity market: the designer of the trading systems and the regulators of the market do in fact have the power to improve the efficiency of the market's operations. Therefore, this research hopes to provide implications to the regulatory body to improve the market design and regulation.

1.6 Structure of the Thesis

This thesis includes 8 chapters. The remainder of this thesis is organized as follows. Chapter 2 describes the background to China's stock market, including the brief overview of China's economy, the background to the stock market, and the institutional structure of the market as compared to other international markets. Chapter 3 generally describes the data used in this research. The rest of the thesis comprises four empirical studies. Chapter 4 investigates the evolution of market efficiency of China's stock market via analysing the ongoing predictive ability and profitability of technical trading rules. Chapter 5 studies the intraday regularities of the volatility, volume and spread. Chapter 6 examines which trades move prices by testing the stealth trading, public information and price manipulation hypotheses. Chapter 7 is dedicated to studying the influence of cultural factors on price clustering and price resistance in China's stock market. Finally, chapter 8 summarizes the findings and discusses the possible implications. The limitations of the thesis and future research directions are also discussed in the final chapter.

CHAPTER 2

BACKGROUND TO CHINA'S STOCK MARKET

2.1 Introduction

No matter what the measure, the growth of China's economy has been impressive. However, although the potential scale of its markets is huge, it is often difficult for westerners to fully comprehend. Particularly, since the stock markets in China emerged over a decade ago, several important issues remain unaddressed. This chapter, therefore, describes the background to China's stock market. Section 2.2 briefly reviews China's economy. Section 2.3 discusses the major characteristics of China's stock market. Section 2.4 reviews the institutional structure of China's stock market and compares it with developed markets. Finally, section 2.5 concludes.

2.2 Overview of China's Economy

China has adopted the planned economy system since 1949. It embarked on its reform and open policy in 1979, and entered the era of the socialist market economy. China's role is increasingly important in the world economy. It is widely acknowledged that one of the most important changes in the world is the rapid development of China. Using statistics from the World Bank, the Asian Development Bank (ADB) and the Chinese National Bureau of Statistics (NBS), the position of China's economy in the world is summarized briefly as follows.

Firstly, China is the largest country in terms of population, which has a population of 1.3 billion. It has the biggest market potential in the world. The real GDP (Gross Domestic Product) grew by 9.7 percent a year on average from 1990 to 2003 (from ADB). It is important to remember that this was an economy starting from a very low base. Such a high growth resulted from exports, surging foreign direct investment (FDI), buoyant domestic demand, and expansionary fiscal and monetary policies. World Trade Organization (WTO) accession brought a significant increase in FDI. Out of the top 500 companies in the world, over 400 have set up offices in China. China attracted FDI of over USD 53 billion in 2003, exceeding the United States for the first time and becoming the largest FDI recipient (from World Bank).

Secondly, China has the second largest foreign currency reserve which exceeded USD 510 billion. The UN (United Nations) Conference on Trade and Development concluded that China is the second largest engine for world economic growth, after the United States. Measured at purchasing power parity (PPP), China's contribution rate to the world economic growth in 1980-2000 was 14 percent, ranking second in the world after the United States (from World Bank).

Thirdly, China is the third largest importing country in the world. The volume of total amount of imports in 2003 reached over USD 410 billion. The contribution rate of China to world trade ranks third behind the United States and Japan (from NBS).

Fourthly, China is the fourth largest exporting country with the volume of total exports reaching USD 438 billion in 2003 (from NBS).

Fifthly, China is the fifth biggest investing country. By the end of year 2003, there are more than 7400 Chinese enterprises investing in over 160 countries and regions with a total investment of USD 33 billion (from NBS).

Finally, China is the sixth largest economy in the world in terms of its economic size. China's GDP reached USD 1.4 trillion in 2003. China's economy is deeply integrated into the world economy. It makes 40 percent of the air-conditioners, 50 percent of the televisions and refrigerators, 60 percent of the garments, and 80 percent of the toys (from ADB).

To conclude, China is an economy undergoing rapid transformation. The size of China's economy is likely to climb to the second largest by 2030. Its rapid growth has brought great business opportunities for the rest of the world. All of the world's economic fortunes are now linked with those of China. Its dynamism makes it increasingly important for global economic growth.

2.3 Background to China's Stock Market

2.3.1 Fact and Figures

China has been developing its stock markets for more than 14 years. Officials hoped the stock market would put household savings to use as financing for listed companies, most of which were state-owned enterprises (SOEs). Although the stock market is not large compared to those foreign markets, the growth has been impressive. Stock markets have played an important role in China's economy. Table 2.1 shows the total market capitalization and its percentage over the GDP from year 1992 to 2002. The total market capitalization reached some RMB 3,800 billion at the end of 2002, which accounts for 37 percent of GDP. By 2001, China's stock market has become the eighth largest market in the world and Asia's second largest, as Table 2.2 shows.

Table 2.1 Stock Market Capitalizations and National Economy, 1992-2002 (RMB bn)

Year	Market Capitalization	Market Capitalization as % of GDP
1992	104.8	3.9
1993	353.3	10.2
1994	369.1	7.9
1995	347.4	5.9
1996	984.2	14.5
1997	1752.9	23.4
1998	1950.6	24.5
1999	2647.1	31.8
2000	4809.1	53.8
2001	4352.2	45.4
2002	3832.9	37

(Source: China Securities Regulatory Commission, CSRC)

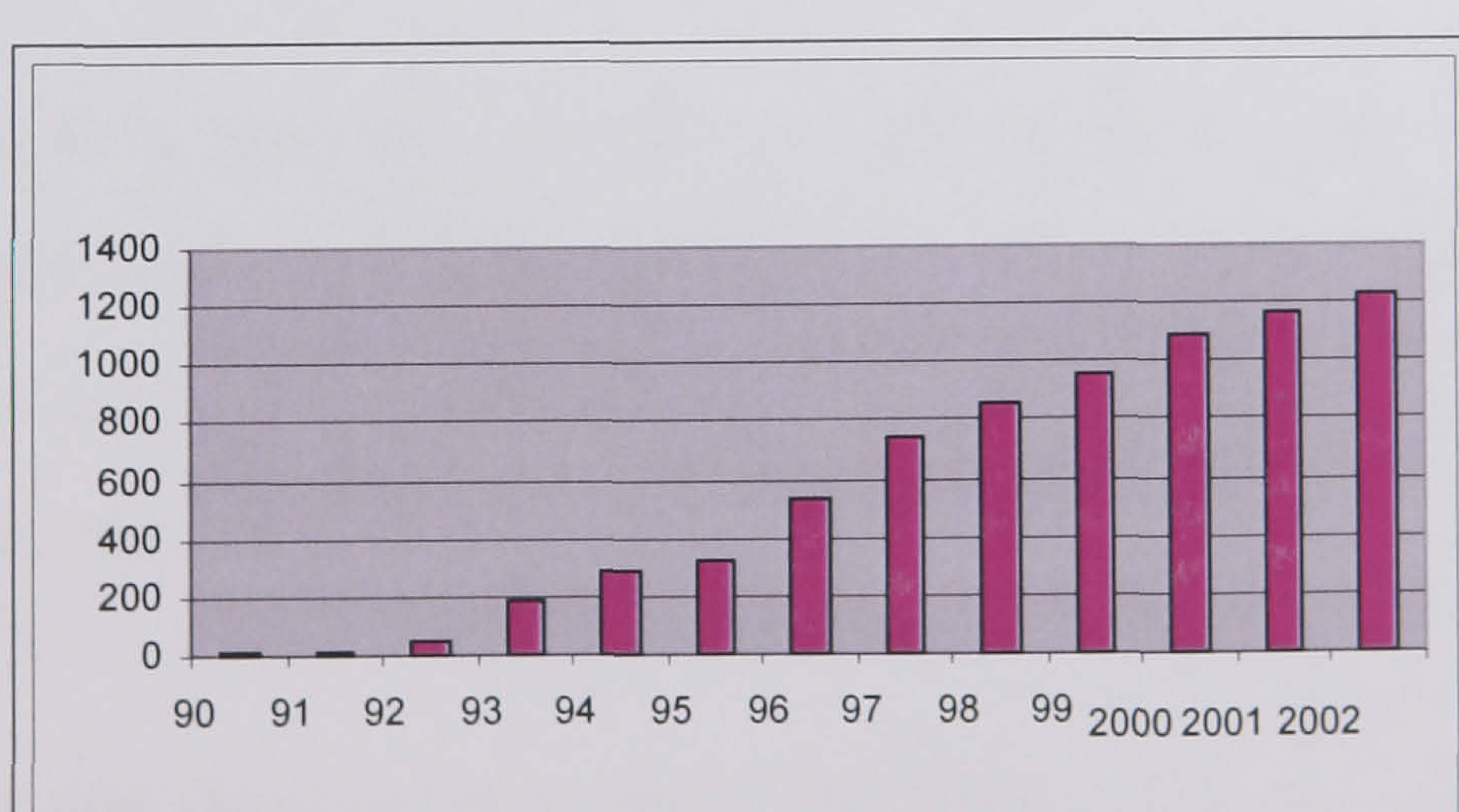
Table 2.2 World Largest Stock Markets at Year-End 2001

Country	Market Capitalization $bn
United States	13,810
Japan	2,252
United Kingdom	2,217
France	1,174
Germany	1,072
Canada	701
Italy	527
China	***524***
Switzerland	521
Hong Kong	506

(Source: Standard and Poor's)

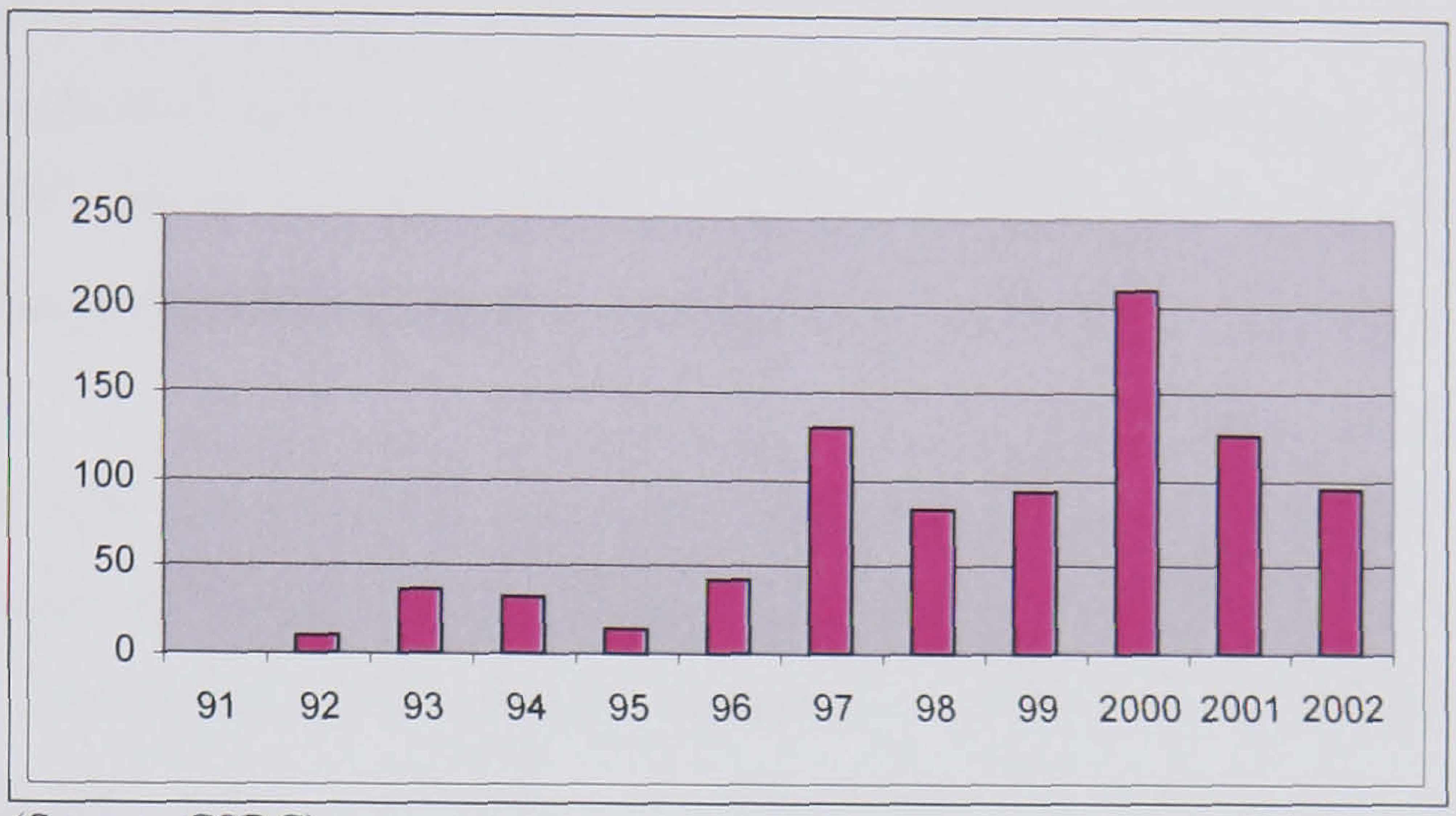
There are two stock exchanges: Shanghai Stock Exchange (SHSE), which is located in the coast city of Shanghai, and Shenzhen Stock Exchange (SZSE) located in the Special Economic Zone city of Shenzhen. The SHSE and SZSE were formally established respectively on December 19, 1990 and on July 3, 1991. The number of listed companies has increased from 10 in 1992 to 1,224 in 2002, as Figure 2.1 shows. Figure 2.2 shows that the amount of funds raised has increased steadily over years, and it reached a peak of RMB 210.3 bn in 2000. In China, shares are classified as domestic (A shares) and foreign (B shares and H shares) by holders' residency. The B share is a special type of share only for trading by foreign investors. The B share market is separated from the A share market. The B share markets of SHSE and SZSE are denominated in US dollars and in Hong Kong dollars respectively. Since China's currency (Renminbi, RMB) is not freely convertible, foreigners cannot trade A shares, and Chinese citizens cannot use their home currency to buy B shares and overseas equities. H shares are issued by Chinese companies and traded on the Stock Exchange of Hong Kong.

Figure 2.1 Domestic Listed Companies, 1990-2002



(Source: CSRC)

Figure 2.2 Total Raised Capital, 1991-2002



(Source: CSRC)

The development of China's stock market is so impressive that it has made foreign investors begin to take the market more seriously as an investment proposition. Despite the official statistics of the market, there appears a need for a more objective treatment to the market. The next section attempts to provide a more realistic picture of what China's stock market is really like.

2.3.2 Ownership Structure

In China, the A shares are classified as tradable and non-tradable shares. The non-tradable shares include: the state shares, the legal person shares, and the employee shares. The tradable shares are those A shares traded on the stock exchanges. The definitions of these shares are clarified as follows.

> *The state shares are those held by the central government, local government, or entirely government-owned enterprises. Ultimately,*

the owner of state shares is the State Council of China. State shares are not allowed to be traded at the stock exchanges, but are transferable among domestic institutions upon approval of the CSRC. In most of the listed companies, the state is the largest or the majority shareholder.

The legal person shares are shares owned by domestic institutions. A legal person in China is defined as a non-individual legal entity or institution. In official documents, domestic institutions, including stock companies, non-bank financial institutions, and State Owned Enterprises (SOEs), have at least one non-state owner. Securities companies, trust & investment companies, finance companies, and mutual funds are major non-bank financial institutions. There is a subcategory called 'state-owned legal person shares'. It refers to shares held by institutions in which the state is the majority owner but has less than 100% shareholding. Like state shares, legal person shares are not tradable at stock exchanges, but can be transferred to domestic institutions upon approval from the CSRC.

The employee shares are offered to workers and managers of a listed company, usually at a substantial discount. These shares offerings are designed more like a benefit to employees than as an incentive scheme. Employee shares are registered under the title of the labour union of the company which also represents shareholding employees to exercise their rights. After a holding period of 6 to 12 months, the company may file with CSRC for allowing its employees to sell the shares in the open market.
(Source: CSRC)

Therefore, a typical Chinese listed company has a mixed ownership structure with the state, legal person, and domestic individual investors as the three predominant groups of shareholders. Each of the three holds about 30% of total outstanding shares. It indicates that only about 30% of total outstanding shares are traded in the open market. Many listed companies do not issue employee and foreign shares. In those that do offer employee and foreign shares, they account less than 10% of total outstanding shares.

2.3.3 Market Size

One of the myths that is often propagated about China's stock market is that China's stock market has grown extremely large and quickly. By 2001 China's had become Asia's second largest market and the eighth in the world. However, the official figure is questionable. The reason is that the official market capitalization figure includes all the non-tradable shares. It seems only reasonable that 'market capitalization' should only include shares traded 'in the market'. So the market capitalization should be calculated excluding those non-tradable shares. Table 2.3 shows the capital structure of listed companies at year-end 2001.

Table 2.3 The Capital Structure of Listed Companies at Year-End 2001

Type of share	Proportion of total share capital (%)
State shares	37
Legal person shares	26
Others	2
Individual A-shares	26
Individual B-shares	5
Individual H-shares	4

(Source: CSRC)

If the market capitalization is recalculated using only the tradable share, China's stock market had a value of only about RMB 1.4 trillion ($170bn) at year-end 2001. It then ranked at 20th place among the world's market in 2001 after Brazil, Finland, and Argentina.

Another common misperception is that China's stock market plays a vital role of the economy like the banks. However, the truth is that the stock market is still small relative to the size of the domestic economy. Although the stock market has been developing rapidly over the last decade, enterprises in China still rely heavily on banks. Table 2.4 shows the market capitalization compared to the size of their domestic economy of Asia's major stock markets.

Table 2.4 The Market Capitalization Compared to GDP of Asia's Major Stock Markets at Year-End 2001

Markets	Market capitalization, $bn	Proportion of GDP, %
Japan	2,252	54
Hong Kong	506	312
Korea	220	52
China (non-tradable shares excluded)	***170***	***17***
Malaysia	120	136
Singapore	117	136

(Source: Standard and Poor's)

To conclude, although China's stock market has been developing very fast, it is still small, relative both to other markets and to the size of its economy. Claessens (1995) argued that successful stock market development is strongly correlated with low inflation, a legal framework that protects minority shareholders' rights, and the existence of sizeable institutional investors. The next section will discuss the regulatory framework of China's stock market and the associated problems.

2.3.4 Regulatory Framework

The development of stock markets inevitably leads to the establishment of a complete legal system. La Porta et al. (1997, 1998, 1999, 2000, and 2002) argued that the laws and the quality of their enforcement by the regulators and courts are essential elements of investor protection and finance of firms. When investors' rights are protected by law and well enforced by regulators or courts, investors are willing to finance firms. In contrast, when investors are not protected by the legal system, firms have difficulties in getting finance from investors. However, in China the establishment of relevant laws have been after the set-up of the stock markets, and they have been weak.

The current legal framework of the stock markets is based primarily on the following national laws and regulations: the Certified Accountant Law issues in 1993, Audit Law in 1994, Company Law in 1994, People's Bank of China Law in 1995, Commercial Bank Law in 1995, Securities Law in 1998, and Accounting Law 1999. The key regulatory bodies involved in the lawmaking process are the China Securities Regulatory Commission (CSRC), the State Economic and Trade Commission (SETC), the Ministry of Finance (MOF), and the People's Bank of China (PBOC).

The establishment of the State Council Securities Commission (SCSC) and the CSRC in October 1992 marked the formation of the regulatory body in China. The SCSC is the State authority responsible for exercising centralised market regulation. The CSRC is the SCSC's executive branch responsible for conducting supervision and regulation of the securities markets in accordance with the law. In April 1998, pursuant to the State Council Reform Plan, the SCSC and the CSRC were merged to form one ministry rank unit directly under the State Council. Both the power and the functions of the CSRC have been strengthened after the reform. A centralised securities supervisory system was thus established.

In September 1998, the State Council approved the Provisions regarding the CSRC's functions, internal structure and personnel, further confirming CSRC to be one of the enterprise units directly under the State Council and the authorised department governing the securities and futures markets of China. This strengthened and clarified the CSRC's functions, and made the CSRC the only centralised market regulatory body.

2.3.5 Problems – Price Manipulation

Despite its development, the weak legal framework has been causing problems in China's stock market. At the National People's Congress (NPC) in spring 2000, Premier Zhu Rongji remarked that China's stock markets had developed quickly, achieved much, but was still not well regulated. His concerns are about the rampant speculation, poor-quality listed firms, defective regulation and widespread corruption. One of the most famous economists, Professor Wu Jinglian (2001), condemned that 'China's stock market is no better than a casino. At least in a casino there are rules.'

Zhu (1996) argued that fraudulent behaviour has become a significant problem in China. Gilley (2001) also pointed out that the wrongdoings in China's stock market include insider trading, false disclosure and market manipulation. The insider trading and price manipulations are not exceptional in China's stock market. Kang, Yu and Jin (2002) pointed out that investment companies team up with large investors to manipulate share prices, and about 30% of stocks are being manipulated at any give time. The well-known scandal of the century of Zhongke Chuangye (otherwise known as China Venture Capital) revealed much about who is involved in insider trading and price manipulation and how the game is played (for detail see Kang, Yu and Jin, 2002)[1]. Surprisingly, it is widely accepted by the individual investors that the market is full of institutional manipulation. The individual investors have no choices but to play against the manipulators by following their moves, for they believe that the manipulators have informational advantage and will always make the right decision. The only thing the manipulators need to think about is how to fool the individual investors and trap them to buy when they are selling. One reason of these wrongdoings is that the rewards far outrun the punishment. Usually those breaking regulations receive no more that a warning issued by the CSRC. Only in serious cases are fines and bans used. However, the fines rarely exceed a few thousand renminbi and are no threat compared to the several million that can be gained from a typical scam.

As cited in Green's (2003a), there is a favourite saying among China's investors: 'Seven lose, two even, one wins.' It means that out of every ten of them, seven lose money, two break even and one makes money, the latter of whom is an institutional investor with inside information. Institutional investors dominate China's stock market. The individual investors are those who have always been

[1] There are two high-quality magazines as recommended by Green (2003a), *Caijing* (Finance and Economics) magazine and *Xin Caifu* (New Fortune) magazine, that have campaigned for better regulation and have covered a series of major events that have forced the CSRC to strengthen the regulation and enforcement.

sacrificed by institutional investors' manipulative schemes. The only way for the small investors to make money is to follow the manipulator's move, or even beat them, hopefully.

The price manipulation is associated with another myth about China's stock market; Green (2003b) argued that China's stock market is often seen as being dominated by small individual investors. However, the truth is that individual investors account for only a small proportion of the market. The majority of individual share accounts are empty, disused or have been opened fraudulently by institutional investors. Officially, individual investors have opened some 68.7m share accounts by the end of 2002. However, the truth is that individual investors are far fewer than the official figures with institutions. Investors travel to rural areas to rent farmers' ID cards with which they illegally opened individual accounts. It allowed them to engage in complex schemes to manipulate share prices. A recent survey by the SHSE found that only 20m of its 35m accounts have shares in them, and that only 8m of them are actively traded. Furthermore, there are many *simu jijin* (privately raised funds) that act as an institutional investor without formal registration with the government. A senior official at PBOC, Xia (2001) stated that there were more than 7,000 *simu jijin* operating around the country by year-end 2000, and they were worth some 40% of the total tradable market capitalization. Because the funds of *simu jijin* are from rich individual, SOEs and other sources that are often influential and have inside information, the *simu jijin* often act as manipulators, profiting from individual investors.

The weak regulation and enforcement is common in all emerging markets because of officials' lack of expertise in regulation and the limited resources available. In China there have been improvements since mid-2001 that the CSRC announced 2001 was to be 'regulatory year' and launched its most aggressive enforcement campaign. Progress has been made which includes the capacity building at the CSRC and expanding the role of the courts in regulation.

2.3.6 Opening Up to Foreign Investors

After 15 years of hard work and negotiation, China became a member of the World Trade Organization (WTO) on December 11, 2001. China made serious commitments in its WTO accession package to open its stock markets to foreign investors.

> *First, upon accession China agreed it would allow representative offices of foreign investors to become special members of two Chinese stock exchanges.*
>
> *Second, the SHSE and SZSE issued rules in June and July 2002 allowing foreign securities institutions to apply for a B share transaction seat.*

> *Third, the regulations on the establishment of foreign-invested fund management companies, effective from July 2002, allow foreign investors to establish fund management joint ventures with 33% ownership upon accession, and 49% ownership 3 years after accession.*
>
> *Fourth, the regulations on the establishment of foreign-invested securities companies, effective from July 2002, allow foreign investors to establish securities companies with up to 1/3 equity share to underwrite A shares, and to underwrite and trade B shares and H shares.*
> *(Source: CSRC)*

The Qualified Foreign Institutional Investors (QFII) scheme was promulgated by the CSRC and the PBOC on November 5, 2002. The introduction of the QFII scheme could be seen as the milestone of the opening of the Chinese stock markets, for it opens the A share and domestic bond markets to foreign investment for the first time. It is also a positive sign of a wider reform of the Chinese stock markets. There are more than 25 leading foreign financial institutions that have been qualified since then, including Goldman Sachs, Morgan Stanley, and some other institutions. The opening-up to foreign investors would be beneficial in a number of ways. It could increase the capital available to domestic issuers, as well as introducing international expertise and experience into the market. It would undoubtedly deepen and improve the efficiency of China's stock market.

2.3.7 Summary

This section has introduced the background to China's stock markets and several special characteristics have been highlighted. Obviously, as an emerging market China's stock market is less developed than those well developed ones. China's stock market is still small, compared to that of other markets and to its own economy. The market is dominated not by individuals but by institutional investors, most of whom are not formally registered with some involve in price manipulation. However, there is still cause for optimism. The government is working hard in improving the quality of regulation. There is good reason to believe that China's stock market will grow in size and quality, and become a market worth investing in.

Despite the growing interest in understanding the markets, the institutional structure of China's stock markets has seldom been studied. Section 2.4 will mainly examine the institutional structure of China's stock markets with a special focus on comparing it to that of the developed markets.

2.4 Institutional Structure and International Comparison

Recent research suggests that market microstructure, such as the trading systems, has important effects on price discovery. With the innovations in communications technology, stock markets are in the process of rapid structural changes, and so it is important to understand the relationship between market structure and price formation, in order to evaluate the impact of these changes and to guide policy making.

Therefore, this section compares the market microstructure of China's stock market to that of the developed markets. First, section 2.4.1 discusses the institutional structure of China's stock markets. Second, section 2.4.2 offers international comparison of market microstructure among other five developed markets.

2.4.1 Institutional Structure of China's Stock Market

Although there is growing research interest about China's stock market, the key elements about the market microstructure, such as market design in terms of its clearance, settlement, and depository (CSD) facilities, and the trading process have not been documented systematically. These issues are fundamental for understanding China's stock market, and will be studied in detail in this section.

The adoption of modern technology and a computerized automated order matching trading system, along with China's rapid economic growth have contributed to China's promising stock market development. In China, there are two trading systems: Securities Trading Automated Quotations System (STAQS) and National Electronic Trading System (NETS). Currently, most stocks on both exchanges are traded through the NETS, which is a centralized, computerized order-driven system.

Both stock exchanges are open from Monday to Friday except on holidays. Both exchanges officially open at 9:30 and close at 15:00, with a lunch break from 11:30 to 13:00. There are, therefore, a total of four trading hours each day. In addition to this, there is a pre-trading session from 9:15 to 9:25 each trading day. Two trading methods are used by the order matching system: a periodic auction and a continuous auction. The morning opening prices are generated by the periodic auction during the pre-trading session. In this type of auction, all orders are submitted during the morning pre-trading session and are batched for execution at a single equilibrium price. It should be noted that the periodic auction is used only once per day. After the morning opening, unmatched buy orders constitute a downward schedule while unmatched sell orders constitute an upward schedule. The trading mechanism stays the same for the rest of the day and so there is a continuous market until closing. Further despite the lunch break, the afternoon session is a continuation of the morning session.

In the continuous and discriminating auction, orders are matched with a price and time priority scheme. In this type of auction, buy and sell orders are submitted and auctioned off continuously. Matched orders are executed and then dispatched from the system, whereas unmatched orders remain in the system until they are executed or cancelled. The transaction prices of a particular auction are generated contingent upon the bid/ask prices and time of order submissions. At present, the best three bid/ask prices and the according aggregate volumes are revealed continuously to investors. Market orders and limit orders are the only two order types allowed. A big market order will be split up by the system once they have been submitted, and will be transacted at the best bid/ask prices till the order has been filled. In addition, a traders' identity will not be disclosed to public.

The automated order matching system can instantaneously execute orders that have accumulated during the lunch break. This operation is different from the Tokyo Stock Exchange where the periodic auction is used twice per day. This is also different from the Hong Kong market where the morning and afternoon sessions open as a continuous market.

All orders are valid for one day only. The smallest trading unit is 100 shares. The SHSE and SZSE use a single tick size, which is RMB 0.01 Yuan. Floor trading among member brokers and short selling are strictly prohibited. Any legally recognized transaction has to be carried out through the automated order matching system. There is no market maker to stabilize stock prices by trading for his own accounts. Settlement takes place on the next day (T+1) between a broker and his customer.

In order to subscribe to and trade A shares, an individual investor must open an account with a broker. The broker issues the potential investor an account number that will be quoted on all exchange settlements. The broker channels each order to his member broker on the floor of the exchanges. The member broker then records the order in the stock exchanges' centralized order matching system.

2.4.2 International Comparison of Market Microstructure

While most of previous market microstructure research has been focusing on the US markets, this study not only analyzes the institutional structure of China's stock market but also pays attention to other developed markets. This section compares the market microstructure of five of the largest stock markets in the world. The differences of the institutional structure might ultimately affect the price discovery process.

2.4.2.1 New York Stock Exchange

The New York Stock Exchange (NYSE) is a centralised exchange. The NYSE adopts the order-driven system. Every security listed on the NYSE is assigned to a NYSE-assigned dealer, known as specialists, who is responsible for maintaining a fair and orderly market. The specialist sets the opening price after observing the limit order book in a single-price call auction. Most trading is conducted by brokers acting on behalf of customers, rather than by dealers trading for their own account. For this reason, the NYSE is often described as a specialist auction market. The normal trading hours of the NYSE are from 09:30 to 16:30. Before

1995, the settlement on stocks on the NYSE took place five business days after trading. In 1995, the three-day settlement period was introduced into the NYSE. The NYSE uses a single absolute tick size of US$ 1/16 that applies to most stocks.

2.4.2.2 NASDAQ

The NASDAQ (National Association of Securities Dealers Automated Quotation) market is a dealer market. In contrast to NYSE, NASDAQ has no single specialist. The NASDAQ adopts quote-driven system before 1997. The NASDAQ's market structure allows multiple market participants to trade stocks through a sophisticated computer network linking buyers and sellers from around the world. In 1997, the NASDAQ implemented new order handling rules, and introduced a new trading system ECN (Electronic Communication Networks). The new rules required certain customer limit orders to be displayed in both market maker and the ECN. Therefore, the NASDAQ is a hybrid market now and adopts both quote-driven and order-driven system. Essential to the NASDAQ's market structure, market makers are independent dealers who actively compete for investor orders by displaying quotations representing their buy and sell interest, plus customer limit orders. Each market maker has equal access to NASDAQ's trading system to all market participants. In contrast to the NYSE, trading on NASDAQ opens with competing dealers' posting quotes. The regular trading hours on the NASDAQ are from 09:30 to 16:30. The NASDAQ uses the same tick size as that of the NYSE, which is US$ 1/16, for most stocks.

2.4.2.3 London Stock Exchange

In terms of market capitalization, the London Stock Exchange (LSE) is the third largest stock market in the world behind NYSE, NASDAQ. Currently, there are three trading systems for the UK domestic equities: the SETS (Stock Exchange Electronic Trading Service) order book, the SEAQ (Stock Exchange Automated Quotation), and the SEATS PLUS (Stock Exchange Alternative Trading Service).

SEAQ is a continuously updated database, which distributes market makers' bid and ask prices digitally to the market. Specifically, the market makers quote the best price at which they are willing to buy (bid price) or sell (ask price) shares of a given stock on SEAQ electronic bulletin board, while actual trades are generally negotiated on the telephone. The market makers compensate for the risks they undertake in quoting constant bids and offers by adjusting the width of the bid-ask spread.

The LSE introduced SETS, an electronic order book initially trading for the FTSE 100, on October 20th, 1997. Unlike past quote-driven market makers system, the order book is based on the order matching system in which member firms display their bid and offer orders to the market on electronic order book, which makes it an order-driven system. A member firm shall only use the following types of order when entering orders to the order book: limit order, at best order, execute and eliminate order, or fill or kill order. The tick size for securities is 0.25p, 0.5p or 1p depending on the price of securities. Other non-SETS stocks are traded on either SEAQ or SEATS PLUS.

The LSE launched SEATS in October 1992. Where a stock attracts less than two competing market makers, or is listed on the Alternative Investment Market (AIM), it is traded on SEATS PLUS. SEATS PLUS is a combination of competing quote-driven system and order-driven system. A market maker is appointed for illiquid stocks and will be obliged to make continuous two-way quotes. Meanwhile, investors can post buy and sell orders at limit prices.

From September 20th, 1999, the LSE advanced its opening hour to 08:00, which was 09:00 before, as part of the European Alliance market harmonisation. The closing time is 16:30. There are eight and a half trading hours in total without a lunch break. There is a 10-minute opening auction period from 07:50 to 08:00. Participants may add/delete new limit or market orders during the opening action period.

In order to reduce risk by shortening the period of credit between brokers and clients, the settlement period was reduced from T+10 to T+5 in June 1995. The LSE further reduced the settlement to T+3 with effect form February 5th, 2001.

2.4.2.4 Tokyo Stock Exchange

The Tokyo Stock Exchange (TSE) is the fourth largest stock market in the world and the largest in Asia, in terms of market capitalisation. The trading on the TSE is order driven, and there are no market makers as in the NYSE. Stocks on the TSE are traded either in the First Section or the Second Section. The First Section handles active stocks while the Second Section is for inactive stocks. The most heavily traded First Section stocks were traded on the trading floor under the system called the Floor Order Routing and Execution System (FORES). The remaining First Section stocks and all of the Second Section stocks were traded electronically on the Computer Assisted Order Routing and Execution System (CORES). For stocks traded under CORES, all orders are submitted electronically.

The closest counterpart to the NYSE specialist on the TSE is the *saitori*. The *saitori* plays a central role both in trades transacted through CORES and those transacted manually. Orders, which may be market or limit orders, are entered into the CORES by exchange members via their terminals. However, they are not matched automatically but through the manual intervention of *saitori* seated in front of screens on which the orders are displayed. The *saitori* members do not trade on their own account or make markets in the stocks. Their function is purely to match the orders received from the other members.

TSE trading takes place in two different trading sessions. The morning session begins at 9:00 and ends at 11:00, while the afternoon session begins at 12:30 and ends at 15:00. Trade at the beginning of each session is initiated through a single-price auction called the *itayose*. This is followed by the continuous market called the *zaraba*. Virtually all trades occurring under the *zaraba* mechanisms are the result of market orders hitting limit orders or limit orders crossing. The TSE uses a tick size that is a step function of share prices, which is from 1 to 10,000 Yen.

2.4.2.5 Stock Exchange of Hong Kong

The Stock Exchange of Hong Kong (SEHK) is a limited company owned by its member brokers. In terms of market capitalization, it is the seventh largest equity market in the world and is the second largest in Asia after the TSE. The SEHK relies solely on an order-driven system. There are no market makers or floor traders with special obligations.

Trading is carried out on the exchange floor in two sessions each day, from 10:00 to 12:30, and from 14:30 to 16:00 on weekdays. Trading is conducted through terminals in the Exchange's trading hall, and also through terminals at the members' offices. Investors place orders in the computerized market through brokers. Share trading originates from an investor order in the form of either a market order or limit order, but the trading system only accepts limit orders.

Orders are executed through an automated trading system, known as the Automatic Order Matching and Execution System (AMS), which is a computerized limit-order driven trading system. All brokers are directly connected to the AMS system. The AMS displays the five best bid and ask prices, along with the broker identity (broker code) of those who submit orders at the respective bid/ask prices being shown, and the number of shares demanded or offered at each of the five bid/ask queues. The AMS currently supports both automatic order matching and the manual execution method. Under this dual operational mode, all securities are traded through the AMS and are divided into two categories: auto-match stocks and non-auto-match stocks. Orders in auto-match stocks are executed on a strict price and time priority basis. Orders are matched in those entered into the AMS, based on the best price. The queue position in the system is maintained until the orders are either completely filled or cancelled, or the end of the trading day, whichever comes first. At the end of the trading day, all orders are purged from the AMS.

The SEHK maintains a finer tick size schedule than any other major stock exchange in the world. The SEHK tick size is a step function of the stock price. The SEHK has probably the most extreme version of a step function, with ten different tick sizes, whose ranges are from HK$0.001 to HK$2.50.

To conclude, the SEHK is basically a continuous double auction market operated on a pure order driven system. Trades are done through a computer-assisted system. Unlike the China and Japan markets where trading is facilitated by two trading mechanisms (a call market and a continuous double auction market) in a trading day, the SEHK trading mechanism stays the same for the whole trading day.

2.4.2.6 Summary

To summarise this section, the comparisons of the market microstructure between China's stock market and other markets are shown in Table 2.5. Since China's stock market has a different institutional structure to the developed markets, it may have different price discovery process. However, being an emerging market, China's stock markets have received relatively little attention in literature due to the lack of data in the past. The recent advent of high-frequency data from China's stock market has given researchers the chance to examine this emerging market empirically.

Table 2.5 International Comparisons of Market Microstructure

	Trading System	Type	Trading Hours	Lunch Break	Opening Mechanism	Settlement	Tick Size
NYSE	Specialist	Order-driven Specialist-Auction	09:30—16:00	No	Specialist sets opening price	T+3[2]	US$ 1/16
NASDAQ	ECN	Hybrid ((both quote- and order-driven) Multiple-dealership	09:30—16:00	No	Multiple dealers' posting quotes	T+3	US$ 1/16
LSE	SETS	Order-driven	08:00—16:30[3]	No	Dealers' posting quotes and periodic auction	T+3[4]	0.25p
	SEAQ	Quote-drive with market maker					0.5p
	SEAT PLUS	Hybrid (both quote- and order-driven)					1p
TSE	FORES and CORES	Order-driven	09:00—11:00, 12:30—15:00	1.5 Hours	Periodic auction is used twice per day	T+3	Yen 1-10,000
SEHK	AMS	Order-driven	10:00—12:30 14:30—16:00	2 Hours	Continuous market for the whole day	T+2	HK$ 0.001-2,500
SHSE& SZSE	STAQS and NETS	Order-driven	09:30—11:30 13:00—15:00	1.5 Hours	Periodic auction in the morning; continuous market in the afternoon	T+1[5]	RMB 0.01 Yuan

[2] It was T+5 before 1995.
[3] It was 09:00 to 16:30 before September 20, 1999.
[4] It was T+5 since June, 1995 to February 7, 2001.
[5] It was T+0 before January 1, 1995.

2.5 Conclusions

This chapter first provides general descriptions about the background to China's stock market. Obviously, as an emerging market China's stock market is less developed than those well developed ones. However, since China's economy has been growing so rapidly, and the stock markets are opening to the world, Chinese stock markets may become one of the largest stock markets in the world in the near future. Therefore, the understanding of the nature of the markets is important not only to academics but also investors. Although China's stock market has been developing very rapidly, it is still small relative both to other markets and to the size of its economy. The regulatory framework is relatively weak, which has caused some problems; for example, price manipulation. However, Chinese government is working hard in strengthening the regulation, and the opening-up to the foreign investors would bring international expertise into the market, hence improving the quality of the market.

In addition, since this study is about the market microstructure, it is necessary to examine the institutional structure of the stock markets. Unlike most North American stock markets that adopt quote-driven system, China's stock market is a fully centralized and computerized order-driven market. Most Asian markets, like SEHK and TSE, also depend on the order-driven system. In an order-driven market investors submit their orders for execution through an auction process. In contrast, the quote-driven system depends on market makers to post prices. While most of previous market microstructure research has been undertaken in quote-driven markets, the different institutional structure of China's stock market might provide further insight about how the price discovery process is affected by the trading mechanism.

In order to better examine the microstructure issue, high-frequency data is employed in this research. With the financial support from the International Institute of Banking and Financial Services (IIBFS), a comprehensive high-frequency data set has been constructed. The next chapter will describe the data used in this research.

CHAPTER 3

DATA DESCRIPTION

3.1 Introduction

The availability of high-frequency data has provided finance researchers with the enviable opportunity of being able to explore the market microstructure issue at the finest level of data. This is particularly important for some practitioners who make their investment decisions by observing tick-by-tick data. Low-frequency data, such as the daily prices, do not provide enough accuracy required by such traders in the increasing competitive and risky environment of today's financial markets.

Compared to low-frequency data (e.g. daily or weekly data), high-frequency data offers further insights into the price discovery process, especially for market microstructure models. The market microstructure research examines the detailed operation of the markets: bid-ask spread, tick size, information diffusion and investor behaviour, etc. High-frequency data and market microstructure theory are natural complements. With the development of information technology, high-frequency data became available for researchers to find out how prices are formed related to the 'black box' of economics.

This chapter briefly describes the high-frequency data used in this research. The structure of this chapter is as follows. Section 3.2 describes the data generally. Section 3.3 discusses the data filtering criteria. Section 3.4 examines the relation between SHSE and SZSE. Finally, section 3.5 offers conclusions.

3.2 Overview of Data

3.2.1 Data Source

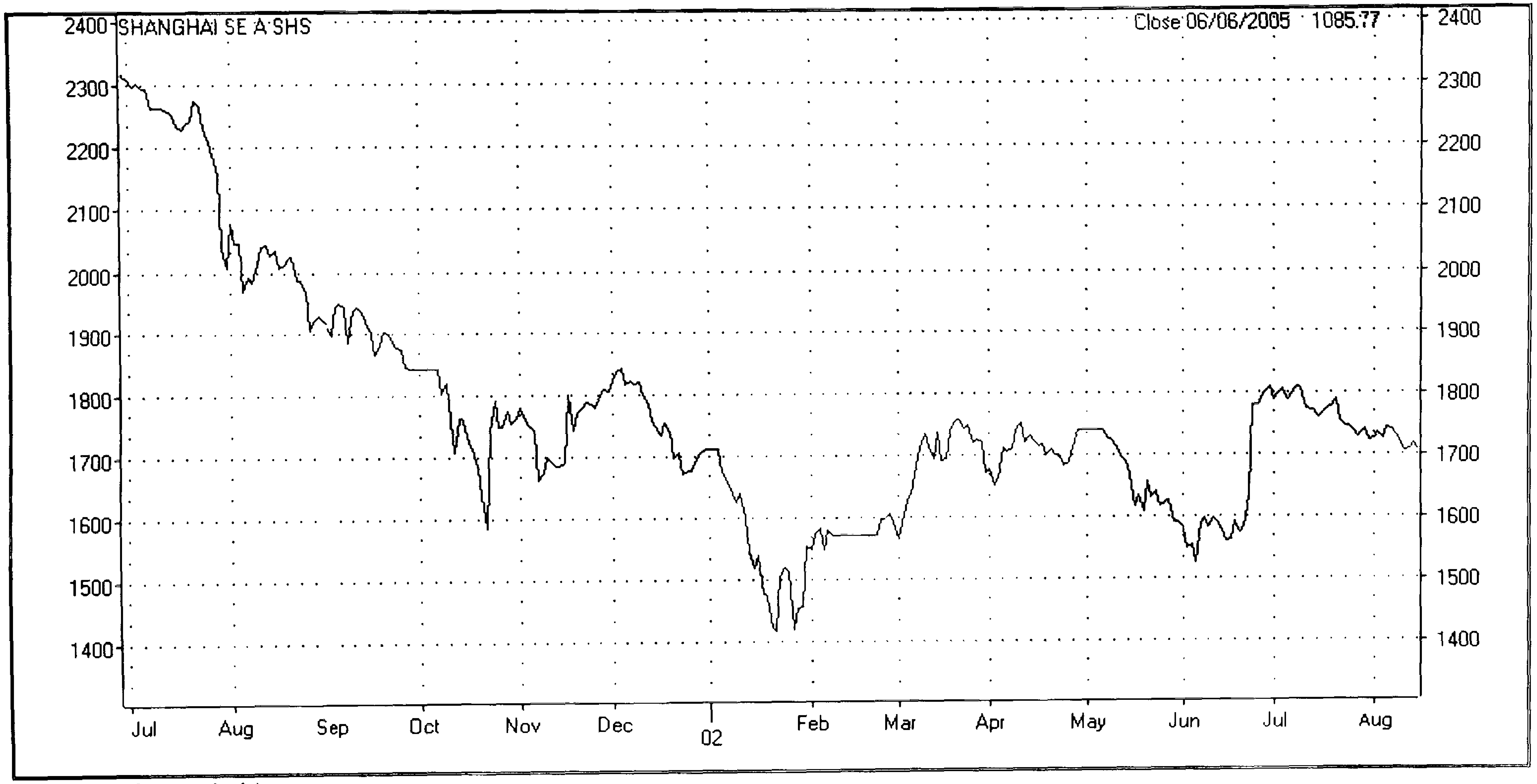
The high-frequency data used in this research is from *SinoFin Information Services* within the China Centre for Economics Research (CCER) at Beijing University. In terms of the history of empirical finance, the success of modern financial study stems from the CRSP (Centre for Research in Security Prices) database at the University of Chicago. In order to push forward the academic study of emerging markets, especially the Chinese financial markets, the data platform needed to be established. As a member of one of the most leading economics and finance research institution in China, *Sinofin Information Services* provides the domestic and international academe with a comprehensive and research-oriented standard database.

3.2.2 Data Description

As has been discussed in chapter 2, Chinese companies issue three main types of shares: A shares, B shares and H shares. The A shares are exclusively sold to Chinese nationals. The B shares are traded and purchased in foreign currency exclusively by foreigners. The H shares are issued by Chinese companies and traded on the SEHK. Moreover, the A shares are classified as tradable and non-tradable shares, and only the tradable A shares are those traded on the stock exchanges. Given the objective of this research, the data employed in this research is tick-by-tick data of 1,140 stocks' tradable A shares trading on Shanghai and Shenzhen Stock Exchanges.

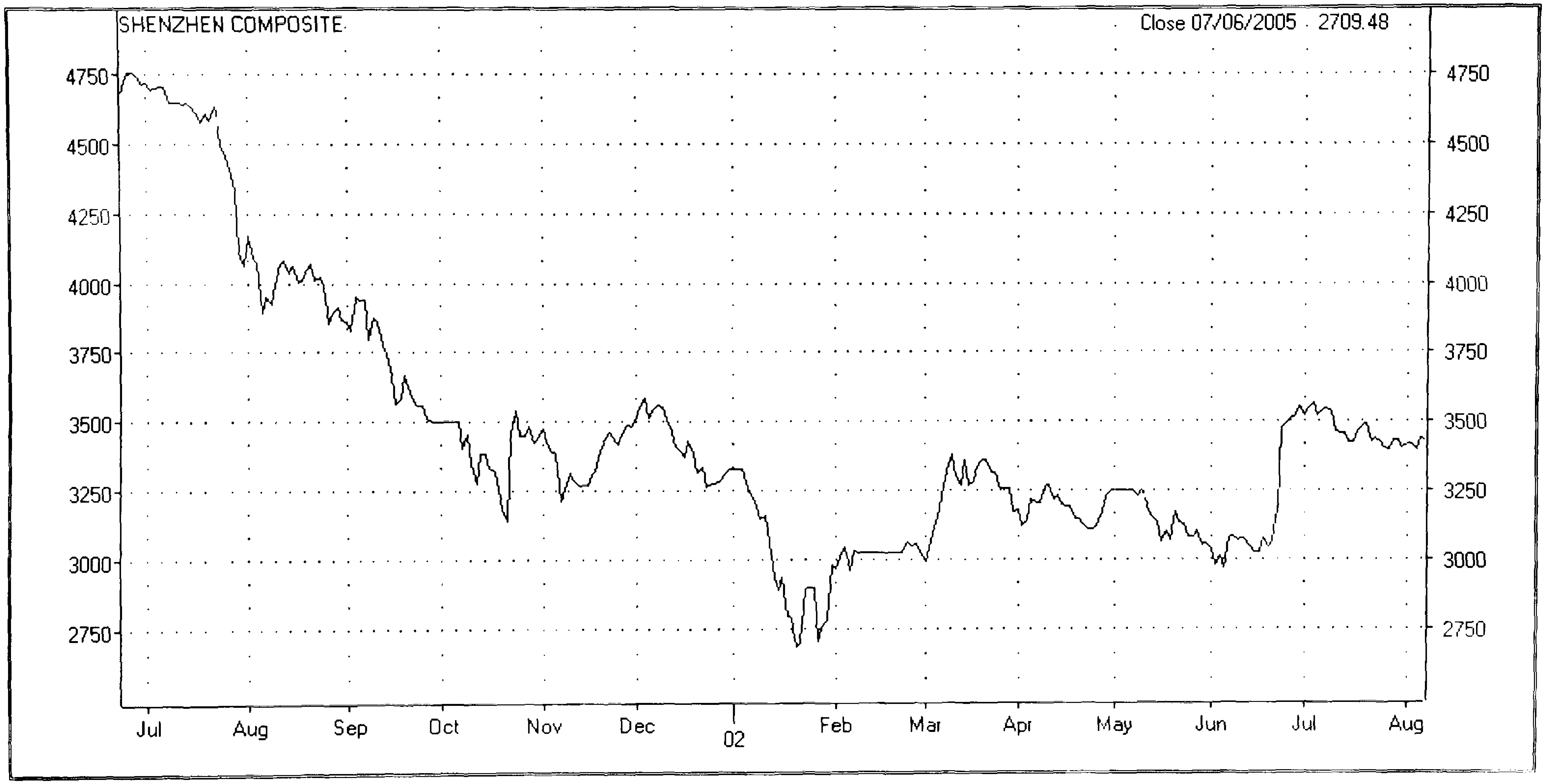
The sample period is from 1st August, 2001 to 31st July, 2002 for the period of twelve months. The Shanghai Stock Exchange Composite Index for the sample period is shown in Figure 3.1, and the Shenzhen Stock Exchange Composite Index for the sample period is shown in Figure 3.2.

Figure 3.1 Shanghai Stock Exchange Composite Index between August 2001 and July 2002



(Source: Perfect Analysis)

Figure 3.2 Shenzhen Stock Exchange Composite Index between August 2001 and July 2002



(Source: Perfect Analysis)

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The data consists of share codes, trading times, transaction prices and volumes, trading amounts, opening and closing prices, the highest and lowest prices on each trading day, the best three bid and ask prices and the according volume. The data fields for the data file are summarized in Table 3.1 as follows.

Table 3.1 Data File Description

Data	Type	Length	Description
Code	Char	6	The code of listed companies in Shanghai or Shenzhen Stock Exchange
Time	Bigint	8	Time of transactions in a day
Close	Numeric	9	Close Price of the stock on that day
Open	Numeric	9	Open Price of the stock on that day
High	Numeric	9	Highest Price of the stock on that day
Low	Numeric	9	Lowest Price of the stock on that day
New	Numeric	9	Transaction price of the stock at the time
Amount	Numeric	9	Trading amount of the transaction
Volume	Numeric	9	Trading Volume of the transaction
Buyprice1	Numeric	9	The highest bid price
Buyprice2	Numeric	9	The second highest bid price
Buyprice3	Numeric	9	The third highest bid price
SellPrice1	Numeric	9	The lowest ask price
Sellprice2	Numeric	9	The second lowest ask price
Sellprice3	Numeric	9	The third lowest ask price
Buyvol1	Numeric	9	Volume at Buyprice1
Buyvol2	Numeric	9	Volume at Buyprice2
Buyvol3	Numeric	9	Volume at Buyprice3
Sellvol1	Numeric	9	Volume at Sellprice1
Sellvol2	Numeric	9	Volume at Sellprice2
Sellvol3	Numeric	9	Volume at Sellprice3

The data sample contains exactly the same information as what traders are able to observe from the trading system. The code of stocks differs across exchanges: for example, code for stocks in SHSE are 600***, and 000*** for SZSE. The format transaction time is displayed as 'year/month/date/hour/minute/second': for example, if a trade is transacted at 11:23:35 on 4th August 2001, the transaction time will be 20010804112335. The transaction amount equals to the transaction price multiplied by volume.

3.3 Data Filtering Criteria

A total of 1,140 different companies were listed on the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE) during the sample. However, only 1,050 stocks (566 on the SHSE and 484 on the SZSE) were listed on both markets at all times throughout the entire sample periods and had a complete set of price data available. Three types of stocks' transactions are deleted from the data sample: the newly listed stocks, the de-listed stocks and the ST (Special Treatment) and PT (Particular Transfer) stocks.

The newly listed stocks and the de-listed stocks that do not have a full twelve-month record are excluded. Another reason for excluding new listings is because Chinese IPOs (Initial Public Offering) are notoriously underpriced. For example, Su (1998) reported an average A-share IPO initial return of 136.4% in China. This unusual IPO underpriceing is likely to affect the results given the objectives of this research.

The transactions of ST and PT shares are also deleted. In China when a listed company has experienced two years of net loss, it will be classified as a Special

Treatment share, and its daily price fluctuation is restricted within 5% (10% for normal shares). If the income loss extends to a third year, the stock will be classified as a Particular Transfer stock which will only be traded every Friday. These stocks are usually subject to heavy manipulation and have quite abnormal price behavior, so they are deleted from the data sample.

Moreover, further actions have been taken to clean the transaction data. Transaction data occurring outside the normal trading hours are deleted. Only regular trades transacted within the four hours of normal trading hours are considered which is from 09:00 to 11:30 and 13:00 to 15:00. Other abnormal and incorrect data have also been deleted from the data sample, which account for no more than 0.1% of the total observations.

3.4 Relation between SHSE and SZSE

This thesis includes four empirical studies, and each of them contains a descriptive analysis of the data used in that particular study. Since each empirical study has its own objectives, the descriptive analysis of data is undertaken for each study, respectively. Thus, replicative analysis of data will not be undertaken in this chapter.

However, because the data are from two stock exchanges, it is important to discuss whether the two exchanges will generate different results or not. This section intends to test the differences of price behaviour between SHSE and SZSE. People sometimes expect different results between the two exchanges: however, the difference is slight. Both exchanges are national exchanges, not local ones. They are the only legal organized exchanges recognized in China. Not only the listed companies but also the investors are from all over the country. Both stock exchanges adopt exactly the same trading system, as has been discussed in chapter 2. The two stock exchanges are treated as ONE market when talking about China's stock market. The only difference is that the size of SHSE is bigger than SZSE, in terms of the number of listed companies, and this is due to a government policy shift.

There has been research about trading and location (Feng and Seasholes, 2004, and Chan et al., 2003). Feng and Seasholes (2004) analyzed investors' trading behaviour, and found that individual investors engage in correlated trading behaviour in China. They showed that purchases and sales are highly correlated when investors are divided geographically. Investors who live near a firm's headquarters react in a similar manner to releases of public information. In China, brokerage rules require that an individual place all of his or her trades through the branch office where he or she opens the account. The data set employed in their study is the account-level data from brokers, and the data allow them to pinpoint an investor's location at the time he or she places a trade. The location of the stock exchanges does not provide any insights in their study. Therefore, it is the trading location, not the location of the stock exchanges, that may affect investor's trading behaviour. Moreover, Girardin and Liu (2005) found the evidence of very similar movements in seasonality between the two stock exchanges whatever the frequency, and confirmed that there is no difference between the behaviour of prices in SHSE and SZSE.

As shown in Figure 3.1 and 3.2, the shape of the movement of the two indices for both exchanges is almost identical. Together with the same institutional structure, both exchanges should give the same empirical results. Moreover, further tests have been undertaken to examine the correlation between the two exchanges.

Table 3.2 Descriptive Analysis of the Daily Returns in SHSE and SZSE

Table 3.2 reports the descriptive analysis of the daily return in SHSE and SZSE for the sample period from 1 August 2001 to 31 July 2002.

	SHSE	SZSE
Mean	-0.00030877	-0.000339553
Standard Error	0.00047702	0.00048773
Median	0	0
Mode	0	0
Standard Deviation	0.007691718	0.007864411
Sample Variance	5.92E-05	6.18E-05
Kurtosis	6.910925201	6.851856003
Skewness	1.213655458	1.052588633
Range	0.069242972	0.071485556
Minimum	-0.028415872	-0.030097593
Maximum	0.0408271	0.041387963
Sum	-0.080280322	-0.08828376
Count	260	260
Correlation	0.949721	

Table 3.2 reports the descriptive statistics and the correlation of the daily returns in the SHSE and SZSE for the sample period from 1st August 2001 to 31st July

2002. From Table 3.2, almost identical results are found between two exchanges, and the return correlation between SHSE and SZSE is about 0.95. It further confirms that although SHSE and SZSE are located in different cities, they are virtually the same markets.

3.5 Conclusions

This chapter has given general descriptions of the data used in this thesis. This comprehensive high-frequency database provides a platform for studying various important issues of China's stock market.

This chapter also describes the relation between SHSE and SZSE. Although located in different locations, the two exchanges are virtually the same markets. Both exchanges are national exchanges, and adopt exactly the same trading mechanism. The price behaviour is found to be identical between the two exchanges. The empirical results should not be expected to be different across exchanges.

The rest of this thesis includes four empirical studies organised on a subject by subject basis. The first empirical study starts with the investigations of low-frequency data across years, in order to provide a more general picture of the efficiency level of China's stock market. The next three empirical chapters will further the analysis by using the high-frequency data. They will focus on the areas of the intraday patterns, the trade size effects and investors' psychology, respectively.

The first empirical study, chapter 4, intends to examine the evolution of market efficiency via the ongoing predictive ability and profitability of well known technical trading rules. Given the formation of the Chinese equity market in the early 1990's, chapter 4 tries to understand whether trading behaviours have changed across years, and whether markets evolve towards efficiency generally.

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CHAPTER 4

THE EVOLUTION OF MARKET EFFICIENCY IN CHINA

4.1 Introduction

China is increasingly being seen as a major economic force and one that is likely to be a key global player over the coming decades. A key part of the transformation of the Chinese economy into a global economic player is the development of efficient financial markets. Despite the impressive growth over the years, the emerging nature has led some to question whether China's stock market is as informationally efficient as its U.S. or European counterparts.

In general terms, market efficiency implies that prices fully reflect available information. When prices are informationally efficient, no investor can consistently realize above normal returns by trading on the basis of existing information. However, there is much empirical evidence of predictability in recent financial research. For example, Campbell (1987), Fama and French (1989) and Lewellen (2001), among others, found that the dividend yield, interest rates and financial ratios appear to forecast stock returns. Fama (1991) offered an excellent summary of the empirical studies on return predictability.

Since stock returns can be predicted, technical analysts attempt to forecast prices by using a wide range of techniques. Almost all major brokerage firms all over the world publish technical commentary based on technical analysis on the markets and individual securities. Brock et al. (1992) investigated two of the simplest and most popular trading rules, moving average and trading range break, in the Dow Jones Industrial Average (DJIA) over a long sample period. They concluded that the technical trading rules possess significant forecast power. Their results have been further tested with the bootstrap methodology, and thus, are robust. Since then many studies in the finance literature have investigated technical analysis to determine its validity as an investment tool (e.g., Bessembinder and Chan, 1995, and Hudson et al., 1996). All the results confirmed that technical trading rules possess significant forecast power for equity returns. However, Bessembinder and Chan (1998) argued that although the technical trading rules do have predictive ability in U.S. data, their use would not allow investors to make excess returns in the presence of transaction costs.

More recently, Tian et al. (2002) explored the predictability and profitability of technical trading rules in markets with different efficiency levels; namely, the U.S. and China. In the case of the U.S. they found rules to have no predictability after

1975, whereas their results give support to technical trading rules having both predictability and profitability for the Chinese markets across the 1990's. This empirical evidence of predictability suggests that stock markets tend to be inefficient at their early stages.

To reach its potential China will need to be able to harness investment capital from its own people and overseas' investors, and to achieve this it will need efficient security markets. Many decisions need to be made in the creation of new financial markets (for example, the type of trading system, the forms of trading and the structure of regulation) and it is not a foregone conclusion they will be efficient from inception. In fact, in new markets where trading is still thin, disclosure practices of firms are limited and there are institutional barriers to trade, it seems more likely that markets will initially be inefficient but, hopefully, evolve towards efficiency.

The purpose of this chapter is twofold. First, it is to extend Brock et al.'s and Tian et al.'s analysis of technical trading rules to see if the conclusions extend to other developed markets – namely, the U.K., Hong Kong and Japan. Second, this chapter is to add to the limited, albeit expanding, literature on China's stock market (for example, see Bessembinder and Chan, 1995, and Tian et al., 2002) by examining the evolution of the China's stock market via the ongoing predictive ability and profitability of well known technical trading rules.

Tian et al's results for the U.S. market are supported by the results for a number of the main developed markets where the technical trading rules had predictive ability during the 1970's that had disappeared by the 1990's. The results of this chapter suggest that while technical trading rules had short term predictive ability and profitability in China's stock market during the 1990's, this lessened as the decade progressed. This indicates that while short term speculation may have been a dominant force in the past, the markets seem to be becoming more sophisticated and this has positive implications for the future role of the markets as a means of underpinning the development of the Chinese economy. Particularly, the results have implications for practitioners that the technical analysis has decreasing predictability and profitability in China's stock market. Practitioners might need to carry out more fundamental analysis when investing.

This chapter is organised as follows. Section 4.2 reviews briefly the literature concerned with technical trading rules and market evolution. Section 4.3 presents the sample, the trading rules and methods of analysis. The empirical results are presented in section 4.4 and the final section offers conclusions.

4.2 Technical Trading Rules and Market Evolution

4.2.1 Technical Trading Rules

Given the support for the predictability of stock returns (for example, Fama, 1991, and Pesaran and Timmerman, 1995), it is, perhaps, not surprising that authors have sought to identify the sources of predictability. Brock et al. (1992) tested two of the simplest technical trading rules, moving average and trading range breakout, and found them to have predictive ability in terms of the Dow Jones Index over the period 1897 to 1986. Hudson et al. (1996) conducted a similar type of analysis on the UK FTSE 30 index and found the rules to have predictive ability. More recently, Gencay and Stengos (1997 and 1998), Gencay (1998a, 1998b and 1999), LeBaron (1998 and 1999) and Fernandez-Rodriguez et al. (2000) have all found evidence to support the predictive ability of technical trading rules. In terms of the objective of the current chapter it is worth noting that Bessembinder and Chan (1995) found simple technical trading rules to have predictive ability in the emerging markets of Malaysia, Thailand and Taiwan but had less explanatory power in the more developed markets of Hong Kong and Japan.

More importantly, however, given the purposes of the current chapter, Tian et al. (2002) found a wide range of technical trading rules to have no predictive ability for the US after 1975 but in the case of the Chinese markets during the 1990's they had both predictability and profitability. In examining the predictability and profitability of technical trading rules Tian et al. expanded the variants of the rules from the 26 examined by Brock et al. (1992) to 412.

4.2.2 Market Evolution

Much of finance theory depends, explicitly or implicitly, on the notion of market efficiency and, therefore, not surprisingly, there has been extensive testing as to whether financial markets are efficient (for example, Fama, 1970, 1991 and 1998, Baillie, 1989, and Campbell, Lo and MacKinley, 1997). In contrast to this extensive literature on market efficiency and the testing thereof, there has been little discussion of the mechanisms which might lead to its achievement. If markets are not efficient, and in the absence of an alternative mechanism, the theory of financial market efficiency seems to have to rely on an evolutionary mechanism. There is an implicit assumption in finance theory that natural selection will favour strategies that are more rational and effective in investments, capital budgeting, etc. This eventually leads to an efficient market, since only the most effective strategies can survive in the marketplace.

Friedman (1953) argued that irrational agents will disappear from the marketplace since they should receive systematically lower than average returns and losses. Miller (1977) used the concept of evolution to reconcile the difference between financial theory and the actual decision procedures used by financial professionals within a corporation. According to Miller evolutionary mechanisms are at work to give survival value to those heuristics that are compatible with rational market equilibrium, however far from rational they may appear to be when examined up close and in isolation. Miller argues that it is not necessary that these efficient investors use highly sophisticated statistical and mathematical techniques to arrive at the efficient investment strategy. Evolution ensures that only the heuristics with survival value will continue to exist. Zingales (1998) summarises the position of modern financial theory very well by concluding that most economic theories are either implicitly or explicitly based on an evolutionary argument.

Despite its widespread use in finance as an implicit mechanism for the achievement of market efficiency, the term evolution has not been rigorously defined nor described. One consequence of this state of affairs is that different approaches have been/might be used to explore the evolution of financial markets. A number of authors (for example, Bekaert and Harvey, 1995 and 1997, Classens, Dasgupta and Glen, 1995, and Campbell, 1996) have examined the ongoing correlations between the returns of emerging and developed markets. As an approach to testing the evolution of emerging markets it has the weakness that it needs to assume that as a market emerges it will become more correlated with developed markets. Another approach might be to examine changing market efficiency via testing predictability with a time varying parameter model. While this approach examines the predictability of returns, it does not examine the equally important, from an evolution of market standpoint, notion of profitability.

In contrast to these approaches, and following a well developed literature on testing market efficiency, this chapter examines the evolution of the China's stock market via the ongoing predictability and profitability of simple, technical trading rules.

4.3 Technical Trading Rules and Methods of Analysis

4.3.1 Technical Trading Rules

In analysing the efficiency of markets, standard statistical tests and the auto-correlation of one-day returns are used. Because the primary purpose of the current chapter is to extend the analysis of Tian at al. (2002) across the two important dimensions of markets and sub periods in the case of China, for ease of exposition we only present results for the two technical trading rules (moving average and trading range breakout rules with a range of variants for each rule) used by Brock et al. (1992) and Hudson et al. (1996). With moving average rules, buy (sell) signals are generated when the short run moving average is above (below) the long run moving average. For the sake of conciseness, only variable moving average rules, as compared to fixed rules, are considered. The trading range breakout rule triggers a buy (sell) signal if the stock price moves above (below) a 'resistance' (support) level defined as the maximum (minimum) price achieved by the stock over the previous period. Variants of both types of rule are considered by defining the rules over different period lengths and with different band widths[6].

4.3.2 Data

These technical trading rules are analysed using daily stock indices data from a range of markets – the Shanghai and Shenzhen indices in China, the Hang Seng index in Hong Kong, the Nikki 225 index in Japan, the FTSE All Share index for the UK and the Dow Jones Industrial Index for the US. However, it is worth noting that there are currently no tradable index assets to exploit any market inefficiencies in the Chinese stock markets. Due to the unavailability of the data of individual stocks, this study can only use daily stock indices for the analysis. With the development of the Chinese stock markets, it is believed that there will be tradable index assets in the future. Therefore, this research could be treated as a forward-looking study, and has implications for future usage.

The technical trading rules are analysed using two different samples. Given the formation of the Chinese markets in the early 1990's, sample I consists of data for all the indices (US, UK, Japan, Hong Kong and China) for the period 21 May 1992 to 31 October 2003. To understand whether trading behaviours have changed in the Chinese markets, results for four equal sub-periods across the 1990's are presented for the Chinese markets. In addition, to understand whether

[6] We have extensively examined hundreds of variants of the technical trading rules and the results are not significantly different from those reported.

market efficiency changes more generally. analysis is undertaken on a similar sized second sample (sample II) which consists of data for the period 21 November 1969 to 21 November 1980 for the indices other than China's. This period has been chosen to form a distinctive but still comparable benchmark to that of sample I.

4.3.3 Methodology

In examining whether the predictive ability could be put to profitable use in a costly trading environment, a "double or out" trading strategy is simulated (see, Bessembinder and Chan, 1995). Under this strategy investors double their investment in a stock index when there is a buy signal and liquidate their stock holding when there is a sell signal. The risk free interest rate is assumed to be zero in the current calculation. In the absence of transactions costs, the additional return (E) earned by technical trading relative to a buy and hold strategy is given as:

$$E = \sum_{i=1}^{N_b} (BR_i - R_i) + \sum_{j=1}^{N_s} (SR_j - R_j) \quad \text{Equation 4.1}$$

$$= \sum_{i=1}^{N_b} (2 * R_i - R_i) + \sum_{j=1}^{N_s} (0 - R_j) \quad \text{Equation 4.1.1}$$

$$= \sum_{i=1}^{N_b} (R_i) - \sum_{j=1}^{N_s} (R_j) \quad \text{Equation 4.1.2}$$

Where

BR_i is the trading returns on buy days;

SR_j is the trading returns on sell days;

N_b is the number of days the doubled (buy) position is held;

N_s is the number of days the out (sell) position is held;

R_i is the index return on day i;

Therefore to breakeven the transaction cost for each transaction should be equal to:

$$C = \frac{E}{N_b + N_s}$$ Equation 4.2

This estimate of breakeven cost is then compared with the estimated transaction cost, to examine the profitability of the trading rules cross different time period.

Following the approach of Tian et al. (2002), the analysis corrects for the possibility of nonsynchronous trading. Scholes and Williams (1977) showed that the nonsynchronous trading of component securities induces spurious positive serial dependence in measured portfolio or index returns. Since the technical rules rely on positive serial dependence, their apparent success may reflect return measurement errors. Bessembinder and Chan (1995) evaluated this possibility by investigating the sensitivity of all results to the implementation of a one-day lag. Technical trading returns are measured beginning with the closing index value one day after the technical signal is initiated. Omitting the first-day return eliminates the bias in measured returns attributable to nonsynchronous trading if each security trades during the intervening day.

Furthermore, a bootstrap procedure is used (see Brock et al., 1992, and Bessembinder and Chan, 1995) to accommodate dependencies across rules. The actual return data are scrambled by randomly drawing from the original series with replacement to construct simulated indices. The trading rules are applied to the simulated indices, and the returns for each trading rule and the mean return across trading rules are computed. This procedure is repeated 500 times to generate an empirical distribution of returns. The fraction of the simulations, which generate a return larger than that observed in the actual series, is recorded. This fraction is interpreted as a simulated p-value.

4.4 Empirical Results

4.4.1 Sample Statistics

Table 4.1 contains summary statistics for one-day returns for the six indices. The mean daily returns for the various indices largely confirm common perceptions of these markets. The Chinese markets have shown returns that compare well with the developed markets. The Nikkie index has shown negative returns across the 90's but showed very strong returns across the 70's; the Hang Seng index showed exceptional daily returns during the 70's. The FTSE All Share has shown fairly consistent returns across the two sample periods, while the Dow Jones index showed poor returns across the 70's (reflecting both the oil crisis and the competition from the Far East) and very good returns across the 90's (reflecting the strong bull market and the technology bubble).

Table 4.1 Summary Statistics

This table reports the summary statistics for the daily returns of all market indices. Sample I contains data in the period of 21 May 1992 -- 31 Oct 2003 and Sample II contains data in the period of 21 Nov 1969 - 21 Nov 1980. Estimated autocorrelations up to lag 5 for each series are reported. Numbers marked with * (**) are significant at the 5% (1%) levels for a two-tailed test.

	Sample I						Sample II			
	Shanghai	**Shenzhen**	**HangSeng**	**Nikkie225**	**FTALL**	**Djindus**	**HangSeng**	**Nikkie226**	**FTALL**	**Djindus**
N	2986	2986	2987	2987	2987	2987	2705	2705	2705	2705
Mean	0.0004	0.0003	0.0004	-0.0001	0.0002	0.0004	0.0008	0.0005	0.0003	0.0000
Std Deviation	0.0269	0.0240	0.0174	0.0145	0.0098	0.0105	0.0212	0.0091	0.0121	0.0091
Skewness	2.2548	1.5220	0.3360	0.2078	-0.1386	-0.1561	0.4942	-1.1264	0.4099	0.3140
Kurtosis	26.2812	21.6975	9.9977	2.4061	3.1371	4.5956	6.8890	11.6747	5.6856	1.9843
Autocorr										
1	0.0223	0.0185	0.0217	-0.0391	0.0370 *	-0.0053	0.1117 **	0.0656 **	0.2231 **	0.1907 **
2	0.0251	0.0325	-0.0278	-0.0255	-0.0279	-0.0248	-0.0238	0.0654 **	0.0146	-0.0100
3	0.0667 **	0.0170	0.0817 **	0.0000	-0.0650	-0.0232	0.0273	0.0344	0.0364	-0.0197
4	0.0548 **	0.0852 **	-0.0320	0.0032	0.0288	-0.0030	0.0975 **	-0.0060	0.0473 *	-0.0254
5	0.0367 *	0.0077	-0.0329	0.0037	-0.0331	-0.0171	-0.0120	-0.0100	0.0210	-0.0058

All the indices show signs of skewness and kurtosis, with the Chinese markets showing relatively high levels of positive skewness and kurtosis. In addition, the Shanghai market shows higher levels of significant autocorrelation than the other markets during the 1990's. Interestingly and relevant to the purposes of this paper, all the developed markets showed positive and significant first order autocorrelation during the 1970's.

4.4.2 Price Predictability

The results for the technical trading rules (VMA and TRB) for samples I and II are shown in panels A and B of Table 4.2. The three sections of each panel refer to different variants of each rule. For example, the first section of panel a reports results for the VMA (1, 50, 0) rule where the short run moving average is defined over one day, the long run moving average is defined over 50 days and the percentage bandwidth is zero percent. Whereas the first section of panel b refers to the TRB rule where the breakout range is defined for the maximum/minimum values for the 5 days previous to the signal, there is a 0 percentage band value and the buy or sell decision would be held for 5 days. The significance of the trading rules is generated by comparing the observed buy-sell returns to the bootstrap returns. The fraction of the bootstrap simulations which generate a return larger than that observed in the actual series is interpreted as a P-value. Clearly only positive values of the buy/sell average are relevant. Therefore, one tail tests of significance are used. (Tables 4.2 and 4.3 report standard levels of statistical significance with *** equalling 99%, ** 95% and * 90%).

Table 4.2 Results for Whole Period

This table reports the results for two trading rules on different market indices. It reports both the results for sample I (21 May 1992 to 31 October 2003) for all market indices and sample II (21 November 1969 to 21 November 1980) which are only available for non-Chinese market indices. Panel A reports the results for the variable-length moving average (VMA) rules. Rules are identified as (short, long, band) where short and long are the short and long moving averages respectively, and band is the percentage difference that is needed to generate a signal. "N(Buy)" and "N(Sell)" are the number of buy and sell signals reported during the sample. "Buy-Sell" is the mean of buy returns minus sell returns which are generated by the trading rules. Bootstrap p-values test for the difference between buy and sell returns. Panel B reports the results for the trading range breakout (TRB) rules. The "Buy-Sell" is the mean of buy return minus sell return for a fixed holding period of 5and 20 days.

Panel A VMA

			Sample I						Sample II			
	Rules	**Market**	**Shanghai**	**Shenzhen**	**HangSeng**	**Nikkie225**	**FTALL**	**Djindus**	**HangSeng**	**Nikkie226**	**FTALL**	**Djindus**
Panel A.1		N(Buy)	1432	1408	1576	1465	1644	1675	1444	1535	1396	1375
		N(Sell)	1474	1488	1411	1519	1343	1311	1260	1157	1310	1330
		Buy-Sell	0.001969	0.00178	0.001416	-0.00056	0.000259	0.000255	0.002341	0.000896	0.001803	0.001017
	(1,5,0)	p-value	0.001996	<0.0001	<0.0001	0.98004	0.139721	0.175649	<0.0001	<0.0001	<0.0001	<0.0001
			***	***	***				***	***	***	***
Panel A.2		N(Buy)	1611	1506	1799	1399	1961	2141	1697	1899	1533	1353
		N(Sell)	1372	1477	1184	1584	1022	842	1005	803	1169	1349
		Buy-Sell	-0.00026	-4.5E-06	0.000202	0.000351	0.000225	-1.1E-05	0.000834	0.000268	0.000611	-8.5E-05
	(5,120,0)	p-value	0.796407	0.704591	0.387226	0.113772	0.441118	0.894212	0.187625	0.07984	0.417166	0.810379
										**		
Panel A.3		N(Buy)	1706	1412	1795	1375	1951	2209	1841	2000	1747	1553
		N(Sell)	1277	1571	1188	1608	1032	774	861	702	955	1149
		Buy-Sell	-0.00046	-5.5E-05	0.000513	0.00027	0.000231	7.68E-05	0.00117	0.000247	0.00048	0.000104
	(5,200,0)	p-value	0.874251	0.738523	0.125749	0.181637	0.459082	0.836327	0.087824	0.41517	0.700599	0.487026
									*			

Table 4.2 *Continued*

			Panel B TRB									
			Sample I						Sample II			
	Rules	Market	Shanghai	Shenzhen	HangSeng	Nikkie225	FTALL	Djindus	HangSeng	Nikkie226	FTALL	Djindus
Panel B.1		N(Buy)	342	315	380	369	401	426	317	359	299	334
		N(Sell)	358	364	353	392	343	336	266	285	303	307
	(1,5,0) Holding	Buy-Sell	0.001854	0.001261	0.000388	-0.00048	-4.8E-05	-0.0003	0.002622	0.000243	0.000851	0.000307
	5 days	p-value	<0.0001	0.003992	0.117764	0.974052	0.718563	0.98004	<0.0001	0.10978	0.003992	0.037924
			***	***					***		***	***
Panel B.2		N(Buy)	86	72	109	83	131	153	124	159	86	83
		N(Sell)	71	81	59	95	57	33	33	34	56	78
	(1,120,0) Holding	Buy-Sell	-0.00075	2.17E-05	-1E-04	-0.00022	0.000269	2.73E-05	0.002989	0.000474	0.001058	-0.00019
	20 days	p-value	0.868263	0.714571	0.656687	0.700599	0.483034	0.842315	<0.0001	0.209581	0.219561	0.838323
									***			
Panel B.3		N(Buy)	69	63	95	64	117	146	106	146	72	66
		N(Sell)	52	50	46	79	39	19	29	15	45	69
	(1,200,0) Holding	Buy-Sell	-0.00132	0.000212	0.000113	-0.00066	6.8E-05	-1.4E-05	0.003118	0.00056	0.000955	-6.4E-05
	20 days	p-value	0.916168	0.644711	0.493014	0.914172	0.806387	0.886228	<0.0001	0.191617	0.345309	0.686627
									***			

A simple conclusion emerges from the results for sample period I (the 90's) reported in panels A and B of the left hand columns of Table 4.2. In terms of both Chinese markets, only the short term variants of both technical trading rules are positive and significant. This implies that speculative forces are evident in the Chinese markets during the 1990's. For the rest of the markets during period I (the 90's), the picture is somewhat different if allowance is made for the signs of the coefficients and their significance. In terms of both the VMA and TRB rules only the Hong Kong market has a significant result (this is for the short term VMA rule) with a positive coefficient; perhaps, this is not surprising given the relationship between Hong Kong and China. However, in terms of the other developed markets, the short term rules do show significance during the earlier period of the 1970's (sample II in Table 4.2) for the FTSE and the Dow Jones. Therefore, these current results largely confirm the thrust of those presented by Bessembinder and Chan (1995) and Tian et al. (2002) with the Chinese markets showing significant results for the short term rules during the 1990's but the developed markets only showing significant results for the 1970's and even here, this is again only the case for short term rules.

Given the results for the developed markets show that market efficiency tends to change across periods, results for four equal sub-periods across the 1990's are presented for the Chinese markets in Table 4.3.

Not surprisingly, given the results for the whole period, the results of Table 4.3 show only the short term variants of the VMA and TRB rules to be significant, at traditional confidence levels, in the separate sub periods. In general, the returns from the short term VMA and TRB rules and their significance, as compared to bootstrap returns, decline across the four sub periods of the 1990's. This conclusion is supported by the significance, at the 10% level, of the Jonckheere-Terpstra test[7] for ordered alternatives. Therefore, while it is not possible to draw completely unequivocal conclusions from Table 4.3, the results, when taking in their entirety, tend to suggest that the efficiency, as measured by the predictive power of technical trading rules, of the Chinese markets is improving across the 1990's.

[7] The Jonckheere-Terpstra test is used to test for ordered differences among returns in different sub-periods. It tests the null hypothesis that the samples are ordered in a specific a-priori sequence. For the purpose of studying the change of the trading rules' predictability over time, the Jonckheere-Terpstra test for ordered alternatives is preferable to tests of more general class difference alternatives such as Kruskal-Wallis tests. One sided p-values for the Jonckheere-Terpstra test are reported. A small left-sight p-value supports the alternative hypothesis of decreasing order in returns across more recent timed periods, and vice versa.

Table 4.3 Results for Sub Periods

This table reports the results for sub-periods for the two Chinese indices. The definitions of rows are same as those in table 4.2. Panel A reports the results for the variable-length moving average (VMA) rules. Rules are identified as (short, long, band) where short and long are the short and long moving averages respectively, and band is the percentage difference that is needed to generate a signal. "N(Buy)" and "N(Sell)" are the number of buy and sell signals reported during the sample. "Buy-Sell" is the daily mean of buy returns minus sell returns which are generated buy the trading rules. Bootstrap p-values test for the difference between buy and sell returns. Panel B reports the results for the trading range breakout (TRB) rules. The "Buy-Sell" is the daily mean of buy return minus sell return for a fixed holding period of 5, 20, and 20 days. PL_JT and PR_JT are the left-sided and right-sided p-value of Jonckheere-Terpstra test.

Panel A VMA

		(1,5,0)		(5,120,0)		(5,200,0)	
Period		**Shanghai**	**Shenzhen**	**Shanghai**	**Shenzhen**	**Shanghai**	**Shenzhen**
Sub-period 1	N(Buy)	331	303	353	306	398	300
	N(Sell)	447	465	425	472	380	478
	Buy-Sell	0.005285	0.00257	-0.00183	-0.00071	-0.00143	-0.0014
	p-value	<0.0001	0.00998	0.894212	0.744511	0.824351	0.868263
		***	***				
Sub-period 2	N(Buy)	425	438	535	503	575	437
	N(Sell)	336	323	247	279	207	345
	Buy-Sell	0.000657	0.002421	0.000506	0.000218	-0.00029	0.001176
	p-value	0.251497	0.00998	0.359281	0.618762	0.752495	0.281437
			***				
Sub-period 3	N(Buy)	414	414	473	461	545	533
	N(Sell)	337	337	310	322	238	250
	Buy-Sell	0.001201	0.000999	0.000253	0.000335	3.81E-05	7.01E-05
	p-value	0.011976	0.033932	0.447106	0.443114	0.616766	0.634731
		**	**				
Sub-period 4	N(Buy)	262	253	250	236	188	142
	N(Sell)	354	363	390	404	452	498
	Buy-Sell	0.00034	0.000956	8.41E-05	0.00017	-0.0001	-7.4E-05
	p-value	0.383234	0.159681	0.608782	0.518962	0.620758	0.612774
PL_JT		0.067339	0.099706	0.488091	0.068444		0.054388
PR_JT						0.197425	

Table 4.3 *Continued*

		Panel B TRB					
		(1,5,0) holding 5 days		(1,120,0) holding 20 days		(1,200,0) holding 20 days	
Period		**Shanghai**	**Shenzhen**	**Shanghai**	**Shenzhen**	**Shanghai**	**Shenzhen**
Sub-period 1	N(Buy)	74	73	11	9	4	4
	N(Sell)	103	105	33	34	26	22
	Buy-Sell	0.005542	0.002158	-0.00302	-0.00307	-0.00501	-0.00232
	p-value	<0.0001 ***	0.027944 **	0.874251	0.94012	0.942116	0.866267
Sub-period 2	N(Buy)	108	96	31	31	29	30
	N(Sell)	83	74	7	11	5	6
	Buy-Sell	0.001166	0.002266	0.000227	0.002034	0.000344	0.002283
	p-value	0.085828 *	0.001996 ***	0.506986	0.229541	0.477046	0.209581
Sub-period 3	N(Buy)	97	86	38	29	34	27
	N(Sell)	83	92	7	7	4	4
	Buy-Sell	0.000308	0.000153	6.56E-06	2.95E-05	-0.0006	-0.00051
	p-value	0.259481	0.39521	0.542914	0.355289	0.798403	0.756487
Sub-period 4	N(Buy)	63	60	6	3	2	2
	N(Sell)	89	93	24	29	17	18
	Buy-Sell	0.000253	0.000389	3.67E-05	0.000898	0.000103	0.000885
	p-value	0.41517	0.343313	0.477046	0.237525	0.40519	0.237525
PL_JT		0.0003	0.007029	0.146272		0.114178	
PR_JT					0.100793		0.442623

4.4.3 Trading Profits

As been discussed by Brock et al. (2002), since technical trading strategies require frequent transactions, transaction costs should be carefully considered before such strategies can be implemented. The profitability of the rules for the Chinese markets is analysed in the presence of trading costs in the current section. Table 4.4 reports the breakeven costs for each trading rule under the "double or out" strategy. Investors in China face the following trading costs: stock-broking buy and sell commissions, Chinese government stamp duty and bid-offer spreads. The estimation of the transaction costs in different periods is reported in panel C of Table 4.4. The government stamp-duty is levied on both the seller and buyer for each transaction and it has been changing across the 1990s ranging from 0.2 to 0.5% (Shi et al, 2002). In terms of the buying and selling commissions, after Oct 1996, the commission charges for A-share trading in both the Shenzhen and Shanghai exchanges were fixed at 0.35% by the authorities. This has been changed to a maximum of 0.3% from May 2001. The bid-offer spreads are considered to be the smallest transaction components in the Chinese stock markets and are often ignored by investors in practice. A typical effective spread in the Chinese stock markets is about 0.088% (Sun et al., 2002). This is partly due to a small tick size relative to the price level. The tick size is 0.01 Chinese Yuan and the average price is at a level of about 15 Yuan[8]. It is not unusual to find that the

[8] As Sun et al. (2002) point out, this fixed tick size is too small for high priced stocks and affects their market depth. They recommend a variable tick size system which would be similar to the Hong Kong and London markets to improve overall market liquidity.

price difference between the best sell and best buy is only one tick size. Therefore, the relative spread is very low. In summary, the overall one way transaction costs estimated for the whole period is about 0.75%[9]. For the VMA trading rules, only one-way transaction costs are involved as each transaction is closed by another new transaction when a new signal is generated. For the TRB trading rules with different holding periods, two-way transaction costs are needed for each signal to open and close a position.

The results in Table 4.4 strengthen the findings noted in the previous section. First, the breakeven transaction costs are found to be lower as the market changed across the 1990s for both markets. In panels A and B of Table 4.4 the over all breakeven costs have declined from period one to four. Second, comparing the breakeven costs with the estimated transaction costs, weak-form market efficiency is achieved for both markets as they changed across the whole period.

[9] This estimation of 0.75% for one-way transaction costs (1.5% for a two-way transaction cost) is similar to that is used in the study of Tian et al. (2002).

Table 4.4 Breakeven Cost for Double and Out Strategy

This table reports the mean breakeven costs for the double and out strategy relative to the buy and hold strategy. Buy and sell signals are generated from variable length moving average rules (VMA) in panel A and trading range breakout rules (TRB) with 5, 20 holding days in panel B. It reports the results for both the Shenzhen Stock Exchange and Shanghai Stock Exchange for all periods and the 4 sub-periods. Panel C reports the estimated one-way and two-way transaction costs. The information on commissions and stamp duty are from Shi et al, (2002). and the bid-ask spread information is from Sun et al. (2002).

Panel A VMA

	(1,5,0)		(5,120,0)		(5,200,0)		
Sub-periods	Shanghai	Shenzhen	Shanghai	Shenzhen	Shanghai	Shenzhen	estimated costs
1	0.025858	0.011215	-0.109670	-0.032610	-0.08532	-0.109090	0.0074
2	0.002658	0.011517	0.032961	0.007734	-0.01420	0.054100	0.0084
3	0.005531	0.004549	0.016539	0.018730	0.00213	0.004571	0.0074
4	0.001327	0.004090	0.004138	0.009864	-0.00589	-0.003662	0.0069
All	0.008566	0.007994	-0.015560	-0.000210	-0.02539	-0.003154	0.0075

Panel B TRB

	(1,5,0) holding 5 days		(1,120,0) holding 20 days		(1,200,0) holding 20 days		
Sub-periods	Shanghai	Shenzhen	Shanghai	Shenzhen	Shanghai	Shenzhen	estimated costs
1	0.027711	0.010791	-0.060423	-0.061437	-0.100287	-0.046312	0.0148
2	0.005829	0.011331	0.004542	0.040689	0.006871	0.045656	0.0168
3	0.001542	0.000766	0.002626	0.011786	-0.012084	-0.010139	0.0148
4	0.001267	0.001944	0.000734	0.017965	0.002064	0.017707	0.0138
All	0.009269	0.006305	-0.014943	0.000433	-0.026423	0.004246	0.0151

Panel C Estimated Transaction Costs

		Components			Total	
	Sub-periods	Commissions	Stamp duty	Spread	One-Way	Two-Way
1	21 May 1992 - 19 May 1995	0.0035	0.003	0.0009	0.0074	0.0148
2	20 May 1995 - 19 May 1999	0.0035	0.004	0.0009	0.0084	0.0168
3	20 May 1999 - 28 Jun 2000	0.0035	0.003	0.0009	0.0074	0.0148
4	29 Jun 2000 - 31 Oct 2003	0.0035	0.0025	0.0009	0.0069	0.0138
All		0.0035	0.0031	0.0009	0.0075	0.0151

4.5 Conclusions

Equity market can be informationally efficient or operationally efficient. In an informationally efficient market, prices fully reflect all available relevant information. In a perfect operationally efficient market, transaction costs are assumed to be zero. The results of this chapter show that China's stock market is neither informationally efficient nor operationally efficient. Stock returns could be predicted through technical trading rules. However, investors cannot make excess returns because of transaction costs.

As a means of adding to the literature on China's stock market, this chapter has a further contribution that it has analysed the evolution of China's stock market. It extends the work of Brock et al. (1992) and Tian et al. (2002) analysing a wider range of developed stock markets and sub periods across the 1990's in the case of China's stock market. The results for a number of the main developed markets support those of Tian et al. for the U.S., in that though technical trading rules had predictive ability during the 1970's, this had largely disappeared by the 1990's. Similarly, the results suggest that while technical trading rules had short term predictive ability and profitability in the China's stock market during the 90's, this has generally lessened as the decade progressed. The evolution of markets is supported by the results for both the main developed markets and Chinese markets. Overall, the results for the evolution of both the developed and Chinese markets bode well for China having stock markets that will underpin its development over the coming years.

This chapter examines the efficiency of China's stock market adopting low-frequency data over the years. However, some practitioners make their investment decisions by observing tick-by-tick data. Therefore, it is important to explore the microstructure issues at finer levels of data with high-frequency data. In the next chapter, high-frequency data will be used to further examine the market efficiency by investigating the intraday patterns of price behaviours.

CHAPTER 5

INTRADAY PATTERNS

5.1 Introduction

The intraday variation of stock market activities has been well documented in the literature with the evidence of US data. Most stock markets in North America depend on market makers to set price and provide liquidity. For example, every security listed on the New York Stock Exchange (NYSE) is assigned to a NYSE-assigned dealer, known as a specialist, who sets the opening price and is responsible for maintaining a fair and orderly market. In contrast to NYSE, the National Association of Securities Dealers Automated Quotation system (NASDAQ) has no single specialist but multiple dealers. Previous research has been focusing on the intraday variables, such as bid-ask spreads, trading volumes and volatility. For example, returns and its volatility tend to be greater at the open and close than at other time during the trading day and exhibit a U-shaped pattern (see McInish and Wood, 1985, Wood et al., 1985, Harris, 1986, Jain and Joh, 1988, and McInish and Wood, 1990b). The U-shaped intraday patterns have also been documented in bid-ask spreads (McInish and Wood, 1985, and Abhyankar, et al., 1997), and trading volume (Jain and Joh, 1988, McInish and Wood, 1990a, and Atkins and Basu, 1995). Previous studies consider the possible explanations for the intraday patterns by considering the market with specialists or market makers (Brock and Kleidon, 1992, Admati and Pfleiderer, 1988, and Foster and Viswanathan, 1990).

However, most stock exchanges outside North America, such as those in continental Europe and Asia, rely on the order-driven mechanism without designated market makers. Although there is relatively sparse research on the markets under the order-drive system, other markets are being increasingly researched, in addition to the US literature. The intraday variation has been documented for the London Stock Exchange (LSE) (Cai et al., 2004, Abhyankar, et al., 1997, Yadav and Pope, 1992, Kleidon and Werner, 1993, Naik and Yadav, 1999, Taylor, et al., 2000, Ellul, 2001, and Ellul, et al., 2002), the Tokyo Stock Exchange (TSE) (Hamao and Hasbrouck, 1995), the Stock Exchange of Hong Kong (SEHK) (Ho and Cheung, 1994, and Cheung, 1995), and the Stock Exchange of Singapore (SES) (Ding and Lau, 2001). These findings suggest that the intraday anomalies are not due to the peculiarities of the US markets.

The recent availability of intraday data from China's stock market has spurred investigations of intraday regularities in a different institutional setting. Research of China's stock market is important for the following reasons. First, the institutional setting of China's stock market is different from the US market in at least three ways. They include the use of a fully centralized & computerized screen based dealer system, the used of order-driven system without any market makers or specialists, and a 90-minute lunch time. Second, it would be useful to examine whether the intraday regularities are consistent with the predictions of theoretical models, such as those of Brock and Kleidon (1992) or Admati and Pfleiderer (1988). It is important that predictions of theoretical models are tested in a variety of institutional settings so as to examine their robustness. Finally, the results would be of interest to market participants as well as regulators and policy makers who are involved in the design of an efficient trading system.

By examining the intraday patterns in China's stock market, this chapter has a number of exploratory objectives. First, it shows the intraday trading activity patterns and documents a wide range of market characteristics. Second, it compares the patterns in China's stock market to those in other markets, and tries to explain the similarity and difference by considering the theoretical models and different market structure.

The results can be summarized as follows. First, the bid-ask spread has an L-shaped pattern. The spread opens wide and narrows down in the first trading hour and is relatively stable for the rest time of the trading day. It shows only a marginal increase at the end of the trading day. The 90-minute lunch break does not change the spread. Second, the volume pattern is relatively flat in the morning session with a marginal increase at the open and marginal decrease at the close;

while it shows a J-shaped pattern in the afternoon session. Moreover, both the numbers of trades and trade size contribute to the volume pattern. Third, the pattern of volatility is similar to the spread pattern in that it exhibits an L-shaped pattern. The findings have implications for market participants who have discretion to time their trades to make profits. It also helps investors minimize risks to trade when bid-ask spread and volatility are low.

This chapter is organised as follows. Section 5.2 reviews the empirical evidence and Section 5.3 discusses the theoretical predictions of intraday patterns. Section 5.4 discusses the data and methodology. Section 5.5 provides the empirical results and interpretations. Finally, section 5.6 concludes.

5.2 Empirical Evidence

5.2.1 Empirical Evidence from US Markets

Brock and Kleidon (1992) and Lee, Mucklow and Ready (1993) found that the intraday width of bid-ask spreads for NYSE stocks display a U-shaped pattern. Madhavan, Richardson and Roomans (1997) documented that the bid-ask spread of NYSE stocks follow a U-shaped pattern by developing a structural model of intraday price formation. Moreover, the U-shaped pattern of bid-ask spread is also observed in the LSE by Abhyanhar et al. (1997) and in the SEHK by Ahn and Cheung (1999).

Wood et al. (1985), Jain and Joh (1988), Foster and Viswanathan (1990). McInish and Wood (1990a) and Gerety and Mulherin (1992) documented that the trading volume (measured as the number of shares traded) follows a U-shaped pattern in NYSE and NASDAQ during the trading day. Gerety and Mulherin (1992) argued that overnight volatility causes increased volume at the open and close of the stock market. Atkins and Basu (1995)'s work indicated that the large volume at the beginning of the trading day could be the result of the aggregate amount of new information that becomes known overnight.

French and Roll (1986) argued that return volatility is a direct measure of risk and an indirect measure of the level of information. Wood et al. (1985), Jain and John (1988), McInish and Wood (1990a) and Lockwood and Linn (1999) found a U-shaped pattern of volatility in the NYSE. Similarly, Abhyankar et al. (1997) found the volatility follows a U-shaped pattern in the LSE.

Block et al. (2000) investigated institutional investor buy and sell decisions as a cause of the intraday patterns of common stock returns and trading volume. They found that buy decisions tend to be concentrated during the market opening and closing hours. In addition, the volume of portfolio manager decisions tends to be concentrated during the opening and closing hours as well. The results are consistent with not only the previous evidence but also the notion that the actions of portfolio managers contribute to the intraday patterns of volume. Their findings support the contention of Brock and Kleidon (1992) that the demand or supply imbalances that could lead to observed daily trading patterns.

Chung and Zhao (2003) showed that intraday variation in spreads for NASDAQ-listed stocks has converged to intraday variation in spreads for NYSE-listed stocks after the implementation of the new order-handling rules. They attributed this convergence to the Limit Order Display Rule, which requires that limit orders be displayed in NASDAQ best bid and offer when they are better than quotes posted by market makers. They suggested that the different patterns of intraday spreads between NYSE and NASDAQ stocks reported in prior studies can largely be attributed to the different treatment of limit orders before the market reform in 1997. They documented that after the market reform, the intraday pattern of NASDAQ spreads follows the familiar U-shaped pattern, which has been observed for stocks traded on the NYSE.

5.2.2 Recent Evidence from Other Markets

Bildik (2001) examined the intraday seasonalities of the stock returns in the emerging Turkish Stock Market which is an order-driven market using electronic trading without market maker. He showed that the stock returns follow a U-shaped or more precisely a W-shaped pattern over the trading day at the Istanbul Stock Exchange since there are two separate trading sessions in a day. Volatility is higher at the openings and follows an L-shaped pattern during the both sessions.

They concluded that the intraday seasonalities exist significantly in the Turkish Stock Market as consistent with those of the international stock markets.

Ding and Lau (2001) examined the intraday patterns in the Stock Exchange of Singapore by employing transactions data. They documented that the presence of a trading halt in the midday results in a double U-shaped return pattern. However, the 90-minute trading halt does not cause volume to be unusually high just before or after the trading halt. The patterns observed in the volume and bid-ask spreads are distinctively similar to those of the US, and have a U-shaped pattern. Trading activity (measured by the number of transactions) is not high at the beginning of the day but rises dramatically towards the market closing.

Copeland and Jones (2002) extended the research on intraday patterns in stock and futures exchanges into the Korean market. Similar pattern to those found previously in the heavily investigated Western markets are observed, despite the differing microstructures, institutional framework and time zones between the East and West. The results are consistent with the hypothesis that the observed patterns reflect at least to some extent features of underlying investor behaviour.

Ke et al. (2004) examined the impact of tick size on intraday stock price behaviour for stocks listed on the Taiwan Stock Exchange. They found that the intraday patterns of bid-ask spread, return volatility, and trading volume are U-shaped. The U-shaped patterns are consistent with the information asymmetry hypothesis in that the degree of information asymmetry between informed trader and uninformed traders is higher near market open and close. Moreover, Wang et al. (1999) found higher volatilities of the Nikkei index futures at the opening and closing of the market. However, Chang et al. (1993) found a double U-shaped return pattern for the Tokyo Stock Exchange, one in the morning session and the other in the afternoon session. Andersen et al. (2000) documented that the intraday volatility exhibits a double U-shaped pattern by examining the 5-minute Nikkei 225 index returns from 1994 to 1997. Similarly, Cheung et al. (1994) documented a double U-shaped intraday market return volatility pattern for the Stock Exchange of Hong Kong. The double U-shaped pattern of Tokyo and Hong Kong market might be because of the lunch break between morning and afternoon trading session.

5.3 Theoretical Framework

There are currently two major microstructure models for intraday variations in volatility, bid-ask spread and volumes to explain these patterns, which are the Admati and Pfleiderer's (1988) information model and Brock and Kleidon's (1992) market closure model. The former relies on the behaviour of some uninformed (liquidity) traders who strategically execute their trades in order to minimize their trading costs. The latter, on the other hand, relies on portfolio rebalancing at trading halts based on the idea that the optimal portfolio is a function of the ability to trade. These alternate models explain the concentrated trading and the different patterns in spreads, volume and volatility. Admati and Pfleiderer's (1988) information model suggests that volume will be concentrated during the day, and volume and volatility are positively correlated due to the presence of informed traders. Brock and Kleidon's (1992) market closure model predicts that volume and spread will be U-shaped during the day, volatility is independent of volume and spreads because information arrival is constant and thus follows no intraday pattern.

5.3.1 Market Closure Model

Brock and Kleidon (1992) examined the implications of periodic closure on the dynamics of volume and the bid-ask spreads in the dealership market. They argued that liquidity demand is more inelastic at the open and close of the market than the rest of the day, which is because of the following two reasons. First, the accumulation of overnight information in the absence of an opportunity to trade means that portfolios at the open have in general deviated form optimal holdings, resulting in opening trade to re-establish optimal portfolios. Second, in preparation for an overnight non-trading period, the optimal portfolios at the close will differ from those that are optimal during the continuous trading interval. More specifically, the market makers or specialists will be able to charge a larger spread at market open and close by exploiting these differentials liquidity demand elasticity when many traders will prefer to close their position without carrying overnight risks. They predicted that volume is concentrated at the open and close, and there exists wider bid-ask spreads at the same periods of time. thus a U-shaped pattern. In addition, their model implies that volatility is independent of volume and bid-ask spread because information arrival is constant and thus no intraday pattern will be found in volatility. The prediction is supported by the evidence from the NYSE.

5.3.2 Information-based Models

The intraday patterns are broadly consistent with information-based models of market microstructure (Copeland and Galai, 1983, Glosten and Milgrom, 1985, Easley and O'Hara, 1987, Foster and Viswanathan, 1990, among others]. These models predicted that greater information asymmetry between informed traders and uninformed traders leads to wider spreads as uninformed traders attempt to minimize losses from trading with informed traders. The information models are based on the strategic interaction of informed traders and uninformed traders (liquidity traders or noise traders). The traditional information asymmetry model, presented by Copeland and Galai (1983), Glosten and Milgrom (1985) among others, assumed that in a stock market there exists two types of traders: informed traders who trade for superior private information and uninformed liquidity traders who trade for better liquidity.

Copeland and Galai (1983) suggested that the spread will exist independent of risk aversion, market maker's market power, or the inventory effects. However, it does not incorporate the dynamic considerations. Glosten and Milgrom (1985) extended the previous model and develop a model to provide the insight of the market maker's pricing strategy. They addressed the market maker's learning problem, which sets a new direction in microstructure research. The ability of the market maker to learn from the market suggests that information plays a role between price setting and underlying asset value, hence affecting prices. The market microstructure research thus moves to analyzing how the market maker learns from the market and how information affects the prices. Glosten and Milgrom (1985) demonstrated several important results in their model. First, a spread will exist independent of any transaction or inventory costs. Second, one could not predict future price by using current price. This finding is consistent with the efficient market hypothesis.

After research about market makers, many researchers have addressed the uninformed traders' strategic behaviour in a variety of contexts (see Admati and Pfleiderer, 1988, 1989, Foster and Viswanathan, 1990, and Seppi, 1990). Admati and Pfleiderer (1988) using a game-theoretic model posited that trading costs are the lowest in the periods when volume is highest because market makers compete to lower spreads in view of concentrated liquidity. They argued that volume will be concentrated during the day and explain that the concentration of trading and volatility at the open and close is because that these periods fall just after and just before the exchange is closed, which will cause an increase in discretionary liquidity traders and informed traders. This implies that prices are more informative in periods of concentrated trading and that the volatility in the period when trading is not heavy is lower than that during periods of concentrated trading.

Foster and Viswanathan (1990) predicted that information heterogeneity among market participants generates patterns in volume, trading costs and volatility. Their model predicts that in equilibrium, both the market marker's sensitivity to changes in the order flow and the variance of price changes decline over the week. In addition, volume is the lowest when the information asymmetry is the largest. Foster and Viswanathan (1990) analyzed the interday trading patterns when informed traders take their informational advantage across time. The most important finding of the model is the imbalance of information at the start of the trading week. The informed trader begins to trade with greater informational advantages at the start of the week, for they have more information on Monday. It results in a large price effects on Monday. It makes the market maker know that the order flow is information related. It also makes it optimal for the uninformed to delay their trade, and not to trade on Monday.

If there is no information on weekends, the informational imbalance would not occur, which makes the trade patterns stay the same across days. However, given that there is more private information on Mondays, the uninformed traders might prefer to delay their trades. As in Admati and Pfleiderer (1988), the model also assumes that there are both discretionary and nondiscretionary uninformed traders.

Discretionary traders are only allowed to delay their trades for at most one trading day, which means they might only be able to postpone trading from Monday to Tuesday. It is also true in Admati and Pfleiderer (1988) that the discretionary uninformed traders act competitively in choosing when to trade. If there is no public information, the single informed trader chooses his order quantity only in order to offset the discretionary effects. Consequently, the behaviour of the uninformed traders only affects the profit gained by the informed traders, and there will be no pattern in security prices and variances with no entry of informed traders.

When there is public information, the informed trader cannot offset the uninformed traders' trading behaviour, and trade patterns emerge. Moreover, the most interesting and important contribution of Foster and Viswanathan's (1990) model is that it allows for multiple equilibriums with single or dual periods of trade concentration being feasible outcomes. They demonstrate that in each equilibrium Monday volume is always lowest because the uninformed delay trading to avoid the informed trader's information advantage. The variance of returns on Mondays also differs from other days. In both Foster and Viswanathan's (1990) and Admati and Pfleiderer's (1988) models, the ability of uninformed traders to delay trading introduces patterns in trade behaviour.

5.3.3 Predictions for China's Stock Market

To summarize the theoretical models, information models predict that greater information asymmetry between informed traders and uninformed traders leads to wider spreads as uninformed traders attempt to minimize losses from informed trading. Admati and Pfleiderer (1988) predicted that in equilibrium low bid-ask spreads and high volatility are associated with the period when volume is higher. However, Foster and Viswanathan (1990) predicted low bid-ask spreads and low volatility exist in the period when volume is higher. Differently, the market closure model proposed by Brock and Kleidon (1992) predicted that a U-shaped pattern should be observed in bid-ask spread and volume, but volatility is independent of volume and spread and follows no intraday pattern.

However, all the theoretical models discussed are based on the US market, a quote-driven system with market makers or specialists. Since China's stock market adopts order-driven system, the difference of the trading mechanisms might make the intraday patterns different from what the theoretical models have predicted.

Madhavan (1992) argued that the crucial function of a trading mechanism is to transform the latent demands of investors into realized transactions. The key to this transformation is price discovery, which is the process of finding market clearing prices. There are different ways to classify the trading mechanisms. One distinction is made between continuous and periodic mechanisms. In a continuous market an investor's order is executed immediately upon submission. In a periodic system, however, investors' orders are accumulated for simultaneous execution at a pre-determined time. Another important distinction is often made between quote-driven and order-driven trading mechanisms.

The quote-driven system depends on market makers to post prices. In a quote-driven market, investors can obtain price quotations from market makers prior to order submission. This mechanism is also known as a continuous dealer market because an investor need not wait for order execution, but instead trades immediately with a market maker. Almost all North American stock markets and a few exchanges in Europe operate under the trading system based on market makers for price-setting. By contrast, in an order-driven system investors submit their orders for execution through an auction process. Order-driven mechanism can operate either as continuous systems or as a periodic system. When the order-driven system operates as a periodic auction, the orders are stored for execution at a single market clearing price. While, in the continuous auction investors submit orders for immediate execution by dealers on the exchange floor or against existing limit orders submitted by public investors or dealers. The system is continuous, since orders are executed upon arrival, but operates as an auction because the price is determined multilaterally. Most stock exchanges outside North America operate under the order-driven mechanism without market makers. In addition, there is no exchange in Asia that depends on market makers.

There have been studies of order-driven markets (e.g., Ho and Cheung, 1994, Bildik, 2001, and Ding and Lau, 2001), and the results from these markets are not entirely consistent with the theoretical models. Therefore, the evidence from the order-driven markets might be more appropriate to predict the intraday patterns in China's stock market.

For example, the institutional structure of the SES (Stock Exchange of Singapore) is quite similar to that of China's stock market: including a fully computerized screen-based dealer system, the use of good-till-day limit orders, and a 90-minute lunch break. Therefore, the evidence found in the SES should also be the case of the Chinese markets. As discussed in section 5.2.2, the predictions of the intraday patterns for China's stock market should be similar to Ding and Lau's (2001) results. However, there is only one difference between the Chinese markets and the SES that SES does not have a batch trade at the open, which might provide further insights.

5.4 Data and Methodology

5.4.1 Data

The data used in this study consist of time-stamped (to the second) intraday best bid and ask prices and volumes, and transaction prices and volumes. The sample period is from the April to June, 2002. The results are shown for a sample consisting of 566 stocks trading on the Shanghai Stock Exchange (SHSE).[10] Only regular trades transacted in the four hours of normal trading hours are considered in this study, which is from 09:30 to 11:30 and 13:00 to 15:00. Opening trades are excluded, because they are traded under a different mechanism. Each regular trade's price and volume, and the best bid and ask price and volume are extracted, and additional variables are derived from the existing database. The tick-by-tick data are then averaged into 5-minute observations, for it is manageable and easily interpreted to create dummy variables. Moreover, it allows comparison of the results with prior studies.

5.4.2 Empirical Methods

Variables, including return volatility (*absR*), volume (*V*), bid-ask spread (*BAS*), number of trades (*NT*) and trade size (*TS*), are defined as follows:

Return Volatility (*abs*R) – in terms of return, the logarithmic returns of each trade are summed to construct 5-minute returns. Volatility is measured by the absolute returns, as in Abhyankar's et al. (1997) and Cai et al. (2004).

Volume (*Vol*) – volume is measured as the volume that shares are traded at transaction price. The 5-minute volume is the sum of the volume for each

[10] The analysis was conducted for both sets of stocks on SHSE and SZSE but as both samples gave very similar results, only the results for the 566 stocks listed on the SHSE during April to June, 2002 are reported are here.

transaction within the 5 minutes.

Bid-ask Spread (*BAS*) – following Abhyankar et al. (1997) and Cai et al. (2004) amongst others, the proportional spread rather than the absolute spread is used in this study.

$$BAS_t = \frac{Ask_t - Bid_t}{Mid_t} \times 100 \qquad \text{Equation 5.1}$$

Moreover, the proportional bid-ask spreads are standardized by dividing them by the mean of the series for that day. Standardization equally weighting the influence of the companies with larger bid-ask spreads, and also helps reducing heteroscedasticity. The number of trades (*NT*) is the number of trades in a 5-minute interval. Trade size (*TS*) is the average of volume of stocks traded per transaction.

This study carries out simple descriptive statistics; for example, the graphical results. Plots are used to show the intraday patterns. Moreover, the statistical significance of each variable was tested by running three separate regressions.

$$V_{i,t} = \sum_{i=1}^{23} \alpha_i D_i + \alpha_0 + \sum_{j=25}^{48} \alpha_j D_j + e_{i,t} \qquad \text{Equation 5.2}$$

Where V = the dependent variables (return volatility, volume and bid-ask spread) at time t; Ds are the ith explanatory dummy variables at time t. D=1 if the observation lies in the ith 5-minute of the trading day, and D=0 otherwise. There are 48 5-minute observations in total.

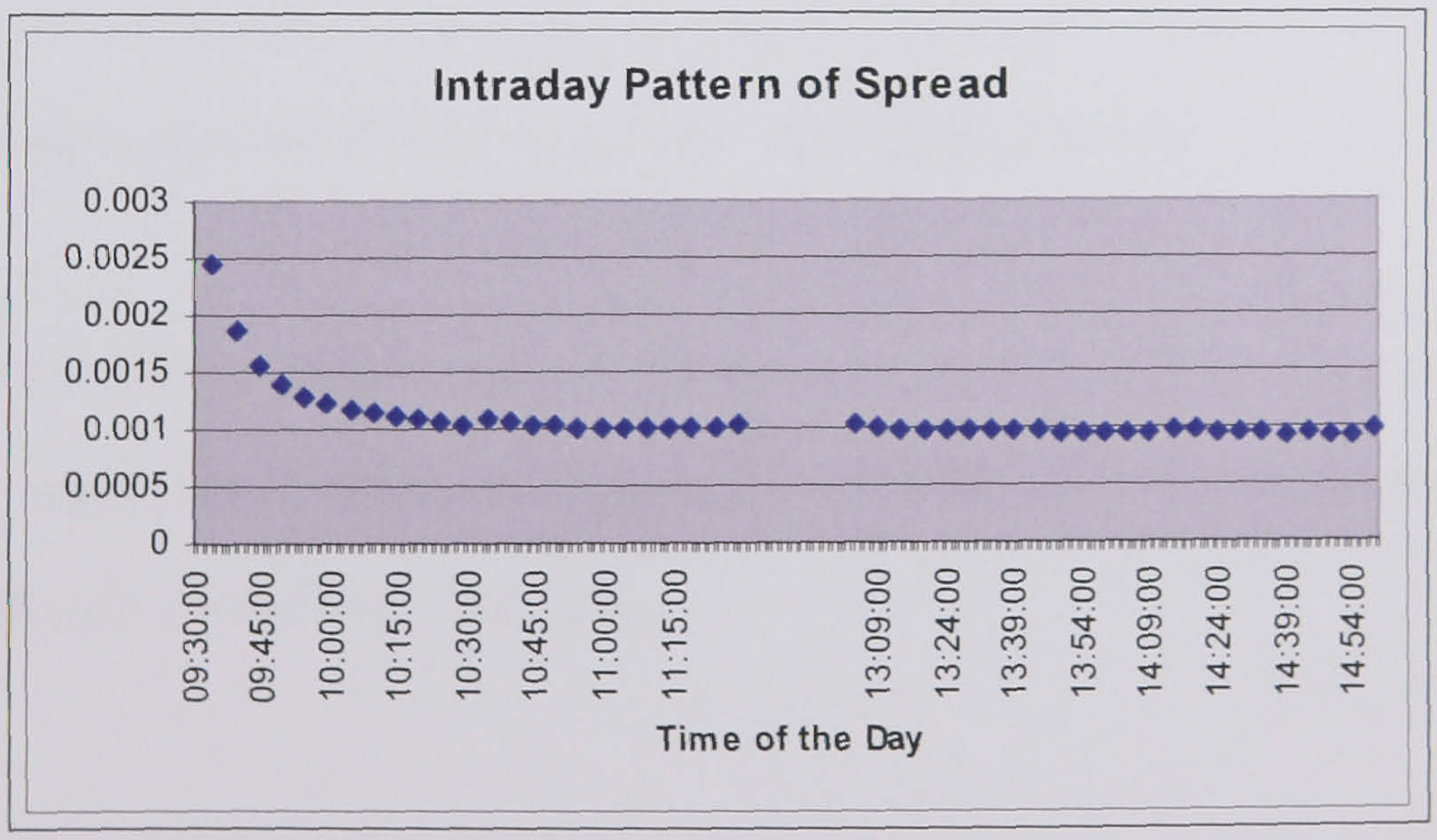
This study adopts Hansen's (1982) Generalized Method of Moment (GMM) estimation to examine the statistical significance for the following reasons. Firstly, GMM estimates are robust to the presence of autocorrelation and heteroscedasticity, both of which we would expect to find in this type of data. In addition, autocorrelation and heteroscedasticity will also be fixed by using Newey and West's (1987) correction for serial correlation. Secondly, the regression reports whether each of the dummy variables has a coefficient that is significantly different from zero. The size of the coefficient also indicates the relative importance of that time-interval with reference to the average importance over the intervals used in the estimation. Particularly, as has been discussed by Abhyankar (1997), each regression could also provide more insight to the changes in the dependent variable at the beginning and close of the market relative to activity during the middle of the day.

5.5 Empirical Results

5.5.1 Intraday Pattern of Spread

The information models predict that greater information asymmetry between informed traders and uninformed traders leads to wider spreads at market open as uninformed traders attempts to minimize losses from informed trading. The evidence from China's stock market shows wider spreads at market open, which is broadly consistent with the predictions of information models. In Figure 5.1, the bid-ask spread has an L-shaped pattern, which is also consistent with the predictions and is similar to the reversed J-shaped findings of Cai et al. (2004), Ding and Lau (2001), McInish and Wood (1992) and Kleidon and Werner (1993).

Figure 5.1 Intraday Pattern of Spread



The spread opens wide and narrows down in the first trading hour and is relatively stable for the rest of the trading day. It shows only a marginal increase at the end of the trading day. Even with a 90-minute lunch break the spread does not change too much before and after the break, which is consistent with the findings of the SES by Ding and Lau (2001). However, the market closure model predicts that the re-establishment of optimal portfolio makes the market makers charge a larger spread at market open and close, which helps explain the findings of NYSE (Brock and Kleidon, 1992, and Lee et al., 1993), LSE (Abhyankar et al., 1997), Taiwan Stock Exchange (Ke et al., 2004) and SEHK (Ahn and Cheung, 1999), where U-shaped patterns of spread are documented.

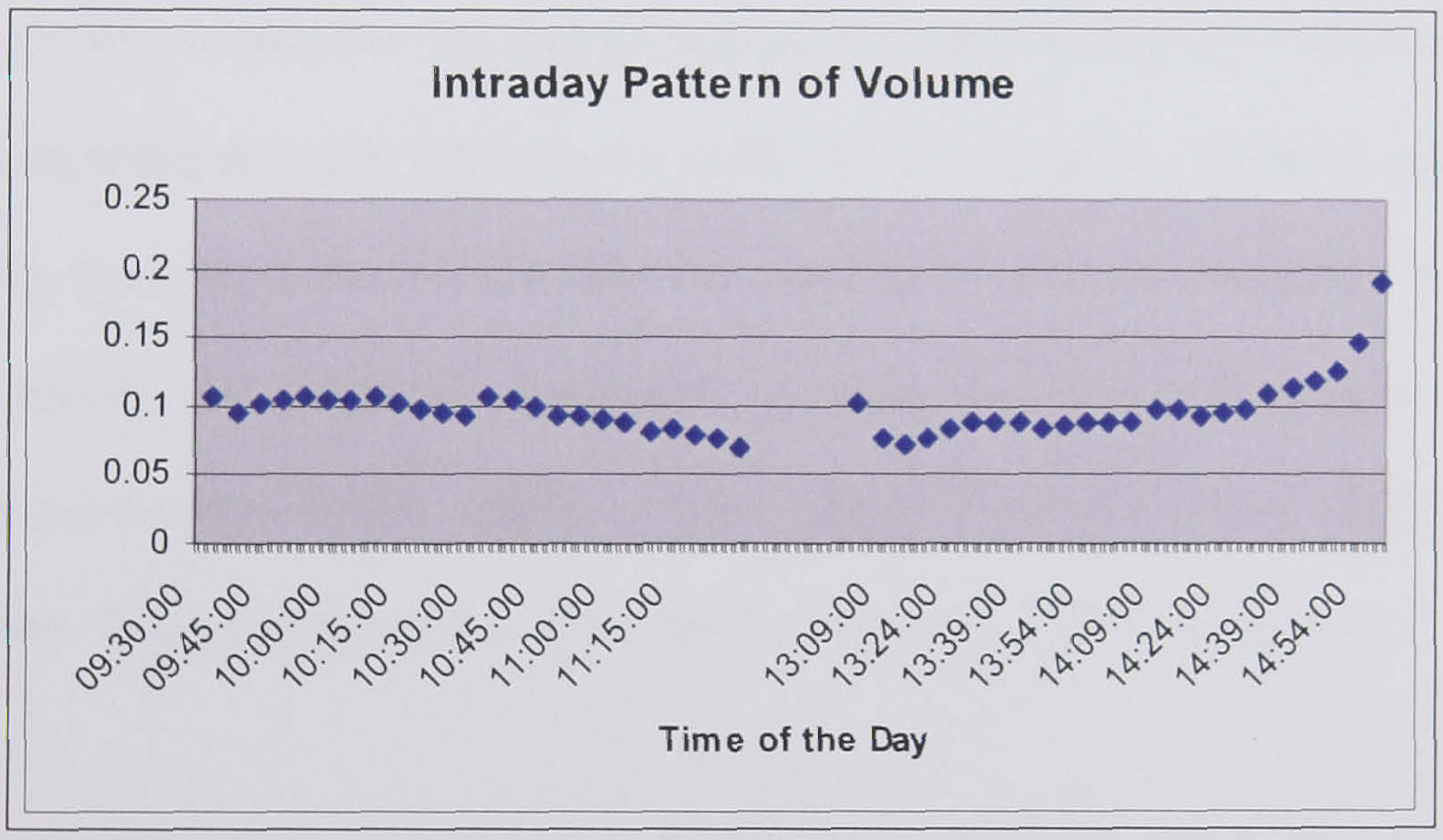
China's stock market is a pure limit-order market without market makers. The L-shaped intraday spread pattern can be explained by information models. In addition, the findings are consistent with most empirical evidence found in other order-driven markets. The wide spread at market open might be due to the information asymmetry between informed and informed traders.

The results of the GMM estimation in Panel A of Table 5.1 confirm the validity of the L-shaped pattern that the coefficients of the dummy variables decrease and are significant for most of the trading day.

5.5.2 Intraday Pattern of Volume

Brock and Kleidon's (1992) market closure model predicted that much of the trading at the open and close are due to the inability to trade when the market is closed. This prediction is supported by the U-shaped volume patterns found in the NYSE (Jain and Joh, 1988), NASDAQ (Chan et al., 1995), SES (Ding and Lau, 2001), Taiwan Stock Exchange (Ke at al., 2004), and the Toronto Stock Exchange (McInish and Wood, 1990b).

Figure 5.2 Intraday Pattern of Volume



However, the intraday volume pattern of China's stock market as shown in Figure 5.2 is different from all the prior studies. Especially, it is not consistent with what is predicted from the SES evidence. It is relatively flat in the morning session with a marginal increase at the open and marginal decrease at the close; while it shows a J-shaped pattern in the afternoon session. In fact, the volume is marginally higher at the morning open and decreases towards the morning close. Moreover, volume is lowest at the close of the morning session. The overall and average volume of the afternoon session is higher than that in the morning, and the volume is highest at the afternoon close.

The relatively flat volume pattern at the open could be explained by the effect of the batch pre-trading session used in China's stock market. China's stock market adopts a batch pre-trading session from 09:15 to 09:25, which is not within the normal trading time. As has been discussed in chapter 3 of this thesis, all orders are submitted during the pre-trading session and are batched for execution at a single equilibrium price, which is the morning opening price. After the morning opening, the trading mechanism stays the same at a continuous market in the rest of the trading day. Since this research does not include the transactions occurring in the pre-trading session, much of the 'actual' opening volume will not be observed. Thus, it makes the volume pattern relatively flat in the morning.

While the lunch break causes two U-shaped volume pattern of the TSE (Chang et al., 1993, Hamao and Hasbrouck, 1995), it does not have the same level of significance of the effects in China's stock market. It only makes the volume higher in the afternoon session, which is after the lunch break. More interestingly, the presence of a higher volume at the open and close of the afternoon session is consistent with Brock and Kleidon (1992). Therefore, apart from the effect of the different opening mechanism, the results are broadly consistent with the market closure model and evidence from other order-driven markets (Ding and Lau, 2001, and Chang et al., 1993).

This study further analyses the components of volume: the number of trades (Figure 5.3) and trade size (Figure 5.4). As has been discussed by Cai et al. (2004), both of the numbers of trades and trade size contribute to the volume pattern. Furthermore, the GMM estimations in Panel B, C and D of Table 5.1 confirm the patterns observed in the plots.

Figure 5.3 Intraday Pattern of Number of Trades

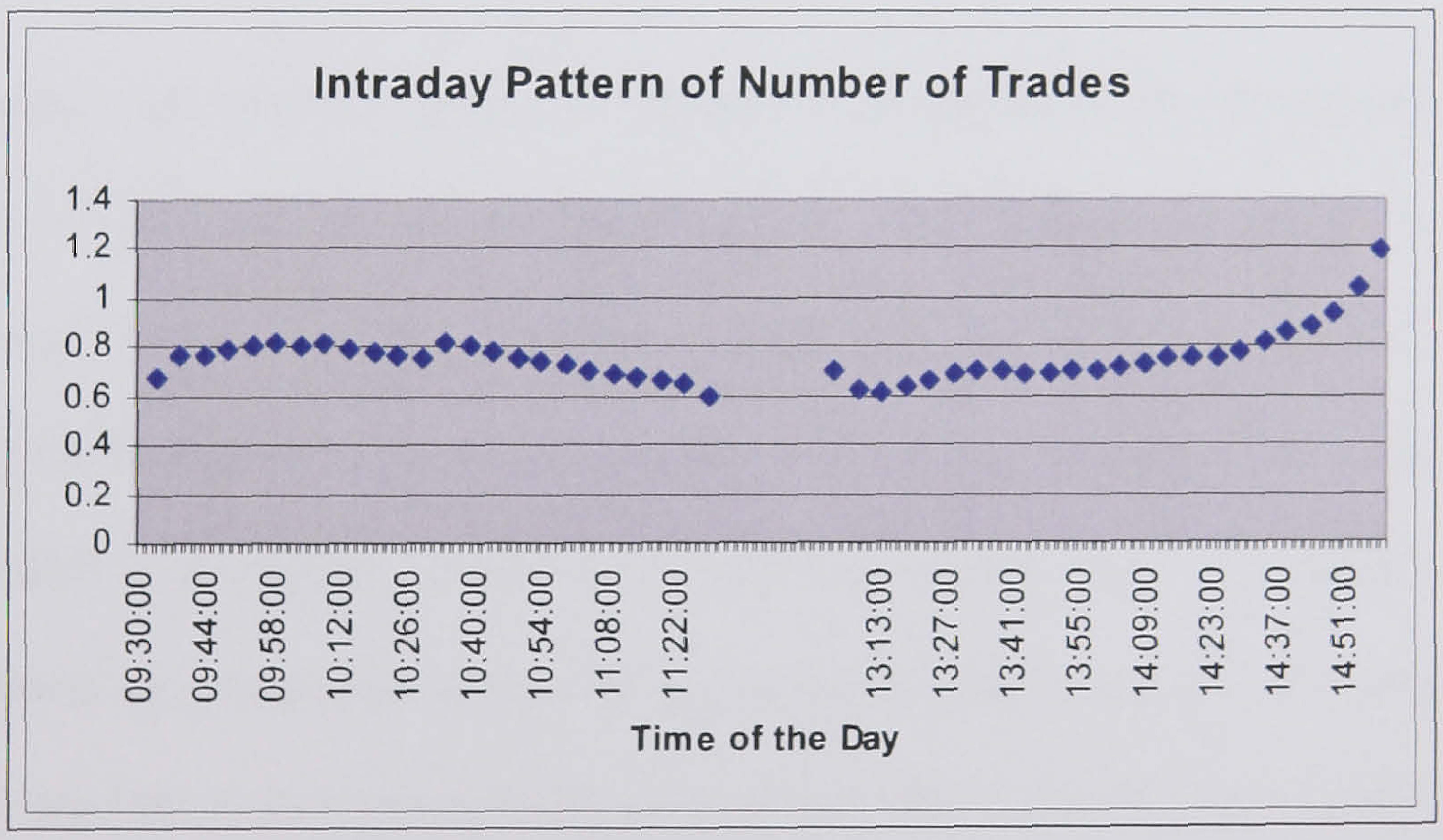
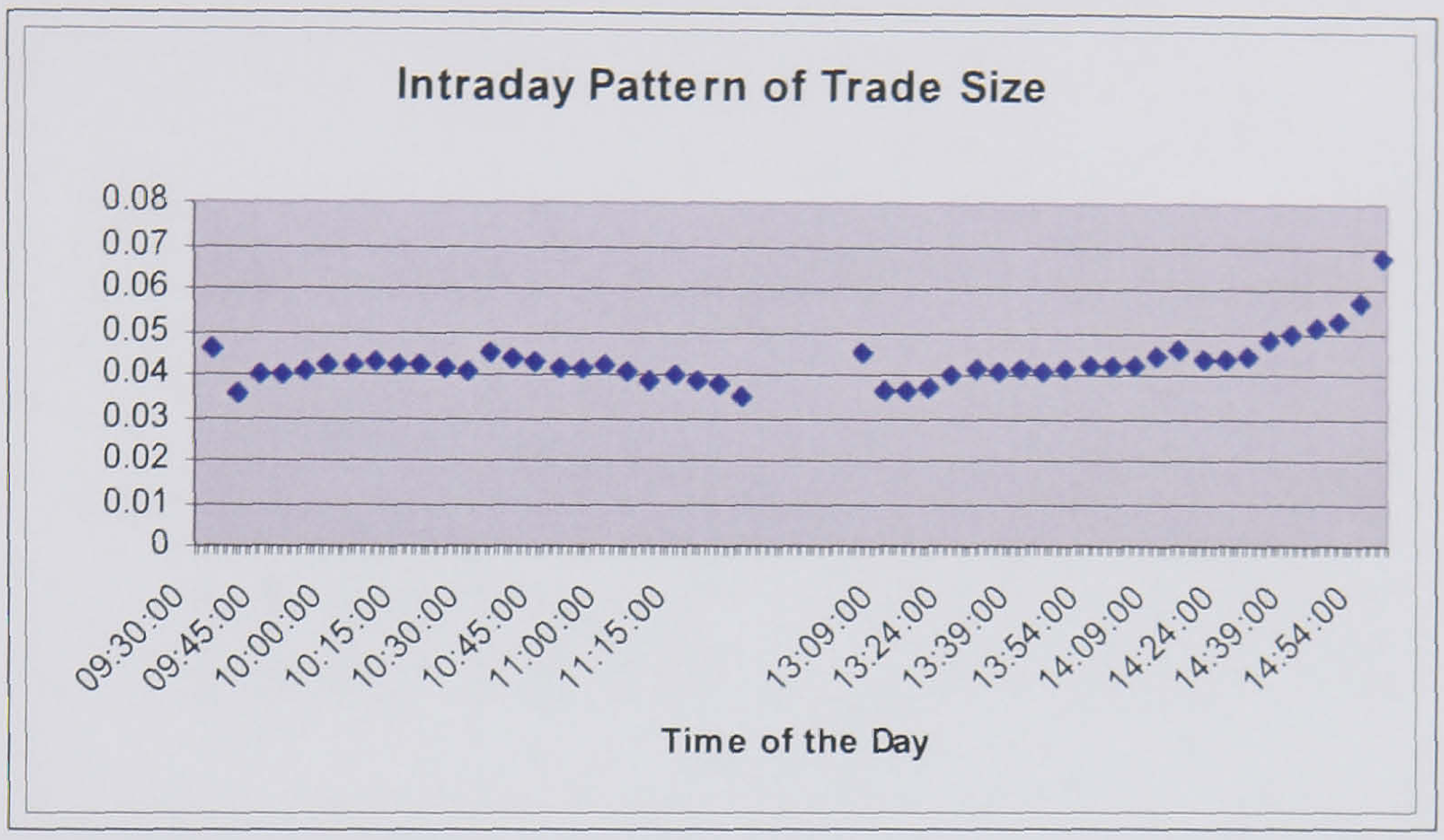


Figure 5.4 Intraday Pattern of Trade Size



5.5.3 Intraday Pattern of Volatility

The pattern of volatility shown in Figure 5.5 is similar to the spread pattern in Figure 5.1 that exhibits an L-shaped pattern. The finding for volatility is not consistent with Admati and Pfleiderer (1998) who predict the variability of price changes to be higher in periods of concentrated trading because more information is revealed in this period by actions of informed traders. However, together with the pattern of spread and volume it is consistent with Foster and Viswanathan's (1990) prediction that low bid-ask spreads and low volatility exist in the period when volume is higher. It is also consistent with the prediction from the evidence of the SES by Ding and Lau (2001).

Figure 5.5 Intraday Pattern of Volatility

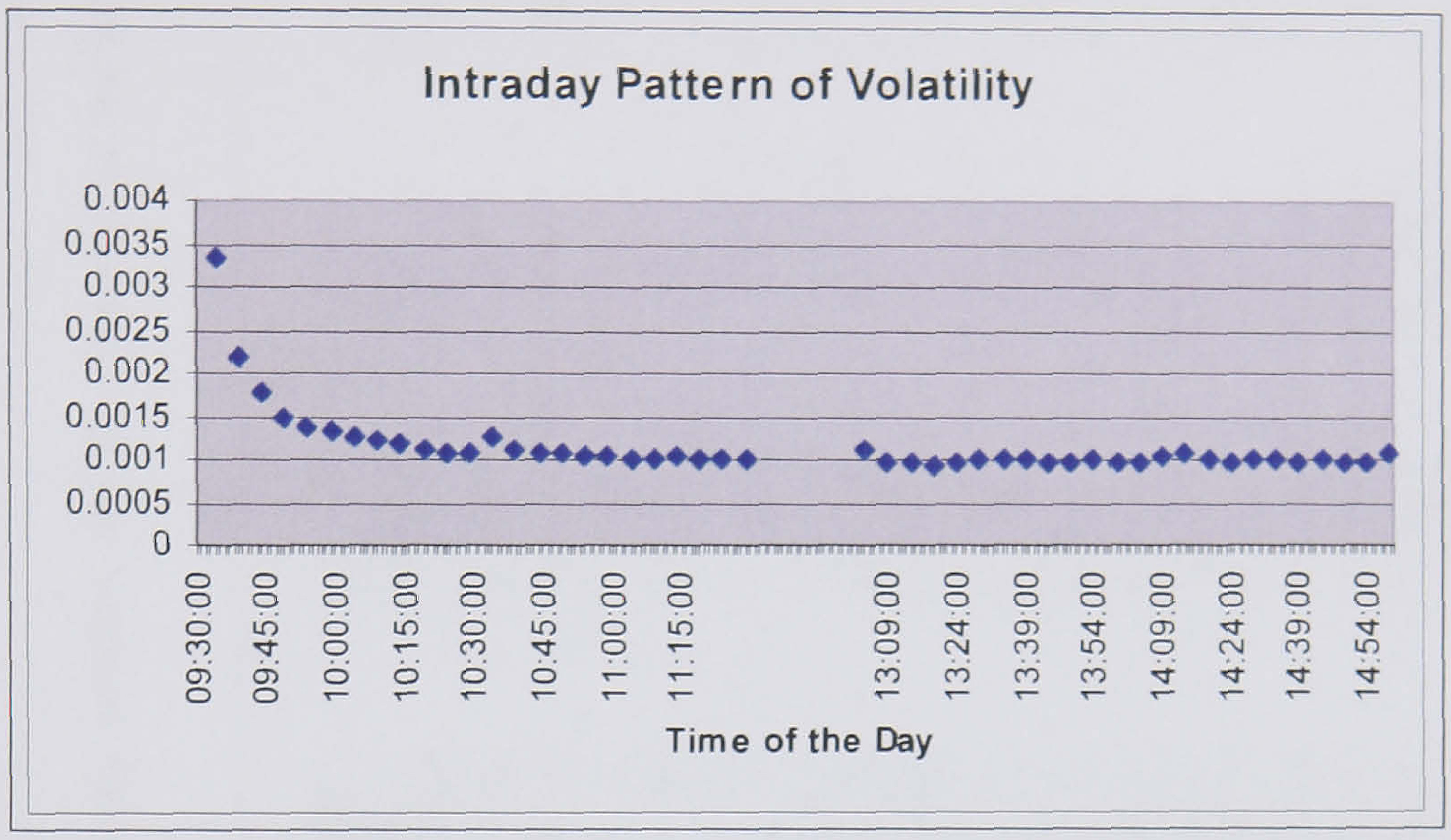


Figure 5.5 shows that volatility is higher at the openings and follows an L-shaped pattern for the rest of the trading day. The lunch break at the midday does not appear to affect the return volatility. The finding is not consistent with the findings of most other studies. It is neither a U-shaped pattern as found in the NYSE (Wood et al., 1985, Jain and John, 1988, McInish and Wood, 1990a, and Lockwood and Linn, 1999) and the LSE (Cai et al., 2004 and Abhyankar et al., 1997), nor a double U-shaped pattern as found for the TSE (Chang et al., 1993) and SEHK (Cheung et al., 1994).

It suggests that investors in China prefer not to trade (low volume) at the market opening because there is higher risk (high volatility) and larger trading costs (high spread). The GMM estimations in Panel E of Table 5.1 confirm the results.

Table 5.1 GMM Estimations of Intraday Patterns

This table reports the results of the GMM estimations. It reports the coefficients of the dummy variables and the *t*-statistics of the following intraday variables: spread, volume, number of trades, trade size and volatility.

	Panel A Spread		Panel B Volume		Panel C Number of Trades		Panel D Trade Size		Panel E Volatility	
Parameter	Estimate	tValue	Estimate	tValue	Estimate	tValue	Estimate	tValue	Estimate	tValue
a1	0.002711	135.2881	0.409184	31.1751	1.622053	189.3048	0.235044	26.78506	0.031112	37.12606
a2	0.00253	169.0586	0.794186	45.56161	7.328843	142.0412	0.104799	54.1079	0.007441	35.44485
a3	0.002062	174.2296	0.975912	68.63693	7.709764	156.041	0.116408	92.26818	0.004779	44.77439
a4	0.001735	172.947	1.073969	71.05954	7.935189	160.6222	0.128001	77.37279	0.003855	71.95229
a5	0.00156	175.0013	1.141607	78.32908	8.374608	165.0429	0.128786	100.0414	0.00295	112.238
a6	0.001425	178.2873	1.157769	89.58719	8.76335	175.4154	0.131078	100.7478	0.002708	103.1982
a7	0.001342	180.7357	1.183498	98.04394	8.997037	184.0568	0.138462	78.50861	0.002813	104.5171
a8	0.001282	186.0305	1.195645	99.02002	9.137543	187.5871	0.136972	112.0987	0.002582	137.9952
a9	0.001251	184.3946	1.204093	99.83586	9.373514	191.3923	0.139291	90.14877	0.002547	108.4197
a10	0.00121	190.4458	1.178588	104.2002	9.26126	193.1609	0.139289	108.272	0.002313	144.4988
a11	0.001178	192.1649	1.145429	109.0541	9.141319	194.571	0.141795	104.5188	0.00221	151.0345
a12	0.001153	192.9453	1.109918	112.4699	8.982942	196.622	0.140199	114.2288	0.002101	148.9835
a13	0.001159	189.6234	1.098968	103.5679	8.882277	198.3248	0.152637	81.63856	0.002657	33.23038
a14	0.001155	192.4036	1.140822	96.80862	8.84896	191.4825	0.141666	103.1215	0.002289	78.49111
a15	0.001124	203.0794	1.137162	101.964	8.659987	188.5867	0.144311	100.9442	0.002208	145.0779
a16	0.00111	201.3531	1.08966	99.13682	8.351969	185.0867	0.141715	101.1459	0.002167	148.2916
a17	0.001089	205.8283	1.031855	99.10415	7.899325	178.7348	0.140442	103.169	0.002002	144.6727
a18	0.001078	205.4074	1.005637	100.5763	7.677655	177.3051	0.139262	101.3568	0.001963	148.9618
a19	0.001069	210.2296	0.997424	99.56804	7.355998	173.9446	0.142433	105.2888	0.00205	146.3142
a20	0.00107	205.1725	0.927596	100.6668	6.914433	168.1398	0.138662	94.83575	0.001908	149.7219
a21	0.001059	205.0038	0.862751	91.6187	6.527892	163.5815	0.135946	98.06416	0.001865	153.6368
a22	0.001065	205.8803	0.856242	89.33658	6.215535	156.2213	0.137768	99.48053	0.001955	141.1971

a23	0.001055	207.0529	0.803091	89.41395	5.869652	148.7061	0.13228	98.04658	0.001814	146.7207
a24	0.00104	197.5316	0.727366	80.09812	5.540295	143.4232	0.13141	81.73003	0.001789	141.9428
a25	0.001018	188.8519	0.408814	83.6285	2.28131	279.9334	0.190201	91.21929	0.001427	124.9141
a26	0.001041	209.1369	0.804113	73.64401	5.640019	136.6102	0.135333	90.24748	0.001668	142.5566
a27	0.001033	216.0748	0.786944	70.31082	5.756994	144.3813	0.13227	81.09647	0.00164	142.9181
a28	0.001024	213.1982	0.766156	83.10326	5.938606	152.4841	0.130931	86.18228	0.001662	144.5738
a29	0.001015	205.1205	0.836812	82.24219	6.367053	158.8476	0.134235	89.63858	0.001583	140.1732
a30	0.001015	212.5824	0.943347	89.04274	6.919507	168.9426	0.14125	97.64215	0.001697	142.3682
a31	0.001021	211.4351	0.987557	98.57046	7.340025	178.2765	0.143162	93.55424	0.001873	144.1879
a32	0.001028	219.6858	1.000544	76.10221	7.683279	186.5042	0.142884	90.79019	0.001858	146.8156
a33	0.001027	217.1158	0.997237	92.5806	7.877895	190.6345	0.141911	98.08713	0.001819	153.9733
a34	0.001026	219.8181	0.982343	104.5161	7.783221	194.0108	0.145683	102.0474	0.001814	149.9863
a35	0.001013	223.0373	0.99504	95.61468	7.921803	194.6931	0.146218	80.70557	0.001744	147.1607
a36	0.001022	215.0781	1.012743	105.7151	7.998117	197.9307	0.146303	99.04782	0.0019	146.3145
a37	0.001017	219.2244	1.013347	102.1684	8.067437	196.6854	0.144995	99.41851	0.001792	149.2799
a38	0.001014	220.6483	1.031515	107.5309	8.164403	198.9451	0.144319	111.1766	0.001832	147.0203
a39	0.00102	217.7277	1.115925	105.9267	8.36025	196.2127	0.149899	111.8066	0.002049	138.1765
a40	0.001011	221.3204	1.084782	109.7457	8.225251	195.5068	0.150542	109.1205	0.002155	127.682
a41	0.001009	220.374	1.020461	105.4963	8.013762	189.3936	0.144691	101.3379	0.001965	132.8774
a42	0.000995	227.2945	1.014455	97.025	7.804794	188.0528	0.143053	110.258	0.001813	138.9031
a43	0.000993	224.9915	1.034904	104.2615	7.738913	182.5365	0.146251	110.1026	0.001851	131.792
a44	0.000969	228.5112	1.134391	97.84828	7.8227	183.4483	0.152872	100.8045	0.002077	148.77
a45	0.000964	230.5447	1.092776	97.69194	7.779858	180.4849	0.147075	121.3063	0.001916	155.1056
a46	0.000951	218.2826	1.090814	102.7207	7.819261	183.42	0.150659	107.112	0.001939	153.7196
a47	0.000947	223.4558	1.064183	95.35864	7.930583	182.5381	0.14971	109.4656	0.001844	154.7996
a48	0.000926	214.1969	1.144017	91.34577	8.643796	193.8132	0.153999	106.7317	0.001738	147.5938
DF	1321256		1321256		1321256		1321256		1321253	
AdjRSq	0.01972		-0.01566		-0.04015		-0.01432		0.040489	

5.6 Conclusions

This chapter examines the intraday variation in the bid-ask spreads, trading volumes and volatility in China's stock market. The results can be summarized as follows. First, the bid-ask spread has an L-shaped pattern. The spread opens wide and narrows down in the first trading hour and is relatively stable for the rest time of the trading day. It shows only a marginal increase at the end of the trading day. The 90-minute lunch break does not change the spread. Second, the volume pattern is relatively flat in the morning session with a marginal increase at the open and marginal decrease at the close; while it shows a J-shaped pattern in the afternoon session. Moreover, both the numbers of trades and trade size contribute to the volume pattern. Third, the pattern of volatility is similar to the spread pattern in that it exhibits an L-shaped pattern.

The evidence in support of the two main theoretical models of intraday behavior is very mixed. Information models (Glosten and Milgrom, 1985; Admati and Pfleiderer, 1988; Foster and Viswanathan, 1990) predict that greater information asymmetry between informed and uninformed traders leads to wider spreads as uninformed traders attempt to minimize losses from trading with those who are informed. Admati and Pfleiderer (1988) predict that in equilibrium, low bid-ask spreads and high volatility are associated with the period when volume is higher. Foster and Viswanathan (1990) predict low bid-ask spreads and low volatility exist in the period when volume is higher. Differently, the market closure model proposed by Brock and Kleidon (1992) predicts that a U-shaped pattern should be observed in bid-ask spreads and volume, but volatility is independent of volume and spread and follows no intraday pattern. However, none of the above models could explain the intraday patterns of all three variables in China's stock market. In contrast, the empirical evidence from other order-driven markets has offered better predictions. Moreover, as these models have been developed in the context of quote-drive market, it is felt that there is a room for a theoretical model to explain the intraday behavior in an order-driven market.

To conclude, the intraday seasonality is closely related to the unique institutional features of the market being studied. The behaviour of the market variables especially at the open and close appears to be closely linked to the market institutional structure. The design of efficient trading systems should emphasize the price discovery process at market open and close. Future research will be needed to consider the theoretical explanation of the intraday behaviour in order-drive system.

While the institutional structure of a stock market (e.g., order-driven or quote-driven) affects the price discovery process, the specific characteristics might also have effects as well. As has been discussed in chapter 2, one of the characteristics in the emerging Chinese equity market is price manipulation. The next chapter will examine this issue by investigating which trades move prices.

CHAPTER 6

WHICH TRADES MOVE PRICES

6.1 Introduction

This chapter analyses the price discovery process in the emerging Chinese stock market by examining which sizes of trades move price. The chapter examines the stealth, public information and large block trade/price manipulation hypotheses and concludes that while stealth trading has explanatory power for overall price changes, it is large block trades/price manipulation which best explain prices increases.

The stealth trading hypothesis has a simple premise at its core; informed traders will try to hide their information by fragmenting their orders and this means they will, on average, use medium sized trades because small trades are too expensive and large trades run counter to their objectives. This literature has its roots in Kyle (1985) who argued that informed investors attempt to camouflage their trades by spreading them over time, while Admati and Pfleiderer (1988) found that informed traders like to trade when liquidity volume is high. Barclay and

Warner (1993), however, were the first to focus on the informed traders' choice of trade size. Effectively, informed traders are unlikely to use small sized trades because the profit potential from these positions is small. Equally, large trades are unlikely to be used because of the issue of revealing too much information to the market. In addition, large trades are likely to suffer from the need to give price concessions. From both of these perspectives, informed traders will use medium-size trades to maximize their profits.

The central predictions of the stealth-trading hypothesis concern the proportion of cumulative price movement across all trades of a given size rather than the price impact on a given trade. Because privately informed traders concentrate use on medium sized trades, and stock price movements are argued to be due mainly to private information, most of a stock's cumulative price change over a given period should result from medium-size trades. For a sample of all NYSE firms that were tender-offer targets between 1981 and 1984, which consists of 105 different target firms with 108 tender offers, Barclay and Warner found most of the cumulative stock-price change is due to medium-size trades. The evidence is consistent with their hypothesis that informed trades are concentrated in the medium-size category, and the price movements are due mainly to informed traders' private information.

Using audit trail data for a sample of NYSE firms, Chakravarty (2001) found that medium-size trades are associated with a disproportionately large cumulative stock price change relative to their proportion of all trades and volume, which is consistent with the predictions of Barclay and Warner (1993). Moreover, since their data provided the identities of the traders, they found that the source of the disproportionately large cumulative price impact of medium-size trades is trades initiated by institutions.

Anand and Chakravarty (2003) investigated and found support for stealth trading in the options markets. They found that informed traders tend to operate in medium sized trades of high leverage and high volume options, whereas they fragment their trades into small trades for high leverage and low volume. These results suggest the strategies of informed traders are not static and to accommodate this possibility, the analysis here is conducted for all prices, price decreases and price increases.

In addition to the stealth trading hypothesis, Barclay and Warner (1993) argued that stock price changes might be caused by the release of public information. This public information hypothesis provides different empirical implications as compared to the stealth-trading hypothesis. As long as public announcements do not affect the distribution of trade sizes, the likelihood that the stock price change associated with a release of public information release will occur on a trade of a given size is directly proportional to the relative frequency of that trade size. Thus, under the public information hypothesis, the percentage of the cumulative price change occurring in a given trade-size category is directly proportional to the percentage of transactions in that category. In contrast. the stealth-trading hypothesis implies that the proportion of the cumulative price changes occurring on medium-size trades should be higher than the proportion of transactions in the small and large trade categories.

A second alternative hypothesis is the large block trade/price manipulation hypothesis. Stock-price manipulation has a long history (see for example. Huebner, 1934) with the Securities Exchange Act of 1934 outlawing manipulation arising from two perspectives. First, is 'action-based manipulation', which is based on actions that change the actual or perceived value of assets. Second, is 'information-based manipulation' which is based on releasing false information or spreading false rumours. However, Allen and Gale (1992) discuss a third category - 'trade-based manipulation' – which occurs when a trader attempts to manipulate a stock simply by buying and selling, without taking any publicly observable actions to alter the value of the firm or releasing false information to change the price. Allen and Gale (1992) confirmed that it is possible for an uninformed speculator to make profits from the 'trade-based manipulation' with large traders frequently buying and then selling substantial blocks of stock.

Aggarwal and Wu (2003) extended Allen and Gale's (1992) model to a setting where active information seekers try to ferret out information about the firm's prospects. In general, information seekers improve market efficiency and manipulators reduce market efficiency. Surprisingly, they found that increasing the number of information seekers may worsen market efficiency when there are manipulators present. Because the information seekers compete for shares, increasing the number of information seekers will increase the manipulators' profit, thereby making manipulation more likely. Moreover, Aggarwal and Wu (2003) found that stock prices rise throughout the manipulation period and then fall in the post-manipulation period. The implication of their findings that there will be more large-size trades during periods of price increases will be further tested here.

In the case of the large block trade/manipulation hypothesis, large-size trades should be associated with a disproportionately large cumulative stock price because of manipulation. This hypothesis is formalized as follows:

> large-size trades should be associated with a disproportionately large cumulative stock price increase relative to their proportion of all trades and volume.

Given the hypotheses described above this study examines the price discovery process by analysing the relationship between cumulative price change and trade size and volumes. To take account of previous results, the analysis also considers the relationship between cumulative price changes and trade size for sub samples of price decreases and price increases.

While the results reject the public information hypothesis and give some support for the stealth trading hypothesis, large cumulative stock price changes are found to be related to large-size trades and there is a strong relationship between these variables during periods of price increase. The results confirm that price manipulation does exist in China's stock market, as many have argued (e.g., Wu, 2001, and Gilley, 2001). This study has particular implications for the regulatory bodies, such as the CSRC, that laws and regulations should be reinforced to improve the quality of the market and to protect investors.

The structure of this chapter is as follows. Section 6.2 reviews the literature. Section 6.3 discusses the data and methodology, while section 6.4 presents the results. Section 6.5 offers conclusions and suggestions for further research.

6.2 Literature Review

6.2.1 Stealth-trading Hypothesis

Kyle (1985) argued that informed investors attempt to camouflage their trades by spreading them over time. Furthermore, Admati and Pfleiderer (1988) found that informed traders like to trade when liquidity volume is high. However, the trade size issue has not been addressed in most of these models. Barclay and Warner (1993) first focused on the informed traders' trade-size choice. They argued that if informed investors' trades are the main cause of stock-price movements, this procedure should allow people to infer the size of their trades.

First, the informed traders are unlikely to trade with small-sizes, for the profit potential from these positions is small. The large institutional investors will take larger share positions to maximize profits. Thus, informed investors' share positions consist of medium and large size trades. Second, whether an informed trader spreads his trades or not depends on the expected price impact of the trades; for example, price concessions. Medium share positions are likely to be achieved in a single trade because the price concession for a medium-size trade is small, which finds support from the NYSE Fact Book (1991, p. 20). It reported that the average stock showed no change or a 1/8 point price change in 3,000 shares of volume 84.4% of the time. To conclude, informed traders break their trades into medium-size trades to maximize their profits.

Empirical research shows that cumulative stock price movements are due largely to private information revealed through trading, rather than to public information releases (e.g. French and Roll, 1986, Barclay et al., 1990). Moreover, Barclay and Warner (1993) first proposed the stealth trading hypothesis, which finds support from empirical evidence. The central predictions of the stealth trading hypothesis concern the proportion of cumulative price movement across all trades of a given size rather than the price impact on a given trade. Because privately informed traders concentrate their trades in medium sizes, and stock price movements are due mainly to private information, so most of a stock's cumulative price change over a given period should take place on medium-size trades.

Using audit trail data for a sample of NYSE firms Chakravarty (2001) found that medium-size trades are associated with a disproportionately large cumulative stock price change relative to their proportion of all trades and volume, which is consistent with the predictions of Barclay and Warner (1993). Moreover, since the data provide the identities of the traders, they found that the source of the disproportionately large cumulative price impact of medium-size trades is trades initiated by institutions.

Although Barclay and Warner's (1993) focus on trade size, institutional features are also relevant to understanding both informed traders' trading strategy and which trades move prices. They have not examined the differing implications of market and limit orders, of which informed traders appear to use both (Cornell and Sirri, 1992). Since China adopts a pure limit-order mechanism, the study of Chinese markets could enrich the understanding of informed traders' behaviour.

6.2.2 Public Information Hypothesis

If volatility is caused by private information revealed through trading, the distribution of informed trades could be inferred. However, there are plausible alternative hypotheses about the cause of volatility. Barclay and Warner (1993) argued that stock price changes might be cased by the release of public information, which is the public information hypothesis. The alternative hypothesis provides different empirical implications to the prediction of stealth-trading hypothesis. As long as public announcements do not affect the distribution of trade sizes, the likelihood that the stock price change associated with a public information release will occur on a trade of a given size is directly proportional to the relative frequency of that trade size. Thus, under the public information hypothesis, the percentage of the cumulative price change occurring in a given trade-size category is directly proportional to the percentage of transactions in that category. In contrast, the stealth-trading hypothesis implies that the proportion of the cumulative price changes occurring on medium-size trades should be higher than the proportion of transactions in that category.

6.2.3 Large Block Trades/Manipulation Hypothesis

Stock-price manipulation is the most widely discussed aspect of stock markets (Huebner, 1934). There were many ways for speculator to manipulate share prices; for example, the speculators could generally make profits from insider trading or from the release of false information. The Securities Exchange Act of 1934 outlawed manipulation into two categories. The first is 'action-based manipulation', which is based on actions that change the actual or perceived value of the assets. The second category is 'information-based manipulation', which is based on releasing false information or spreading false rumours. However, there is a third category of manipulation, 'trade-based manipulation', as discussed by Allen and Gale (1992). It occurs when a trader attempts to manipulate a stock simply by buying and selling, without taking any publicly observable actions to alter the value of the firm or releasing false information to change the price. Allen and Gale (1992) confirmed that it is possible for an uninformed speculator to make profits from the 'trade-based manipulation', which is consistent with rational utility-maximizing behaviour. Large traders frequently buy and then sell substantial blocks of stock, even though they are apparently not interested in taking over the firms.

Aggarwal and Wu (2003) extended Allen and Gale's (1992) model in a setting in which there are active information seekers trying to ferret out information about the firm's prospects. In general, information seekers improve market efficiency and manipulators reduce market efficiency. Surprisingly, they found that increasing the number of information seekers may worsen market efficiency when there are manipulators present. Because the information seekers compete for shares, increasing the number of information seekers will increase the manipulators' profit, thereby making manipulation more likely. So, the manipulation hypothesis in this study is formalized as follows: if there is manipulation, large-size trades should be associated with a disproportionately large cumulative stock price increase relative to their proportion of all trades and volume.

Moreover, Aggarwal and Wu's (2003) found that stock prices rise throughout the manipulation period and then fall in the post-manipulation period. The implication of their findings is that there will be more large-size trades during the price increase, which will be further tested in this study.

6.3 Data and Methodology

6.3.1 Data Description

The sample period is from the 1st to 30th September, 2001 and the sample consists of 566 stocks trading on the Shanghai Stock Exchange (SHSE).[11] Only regular trades transacted in the four hours of normal trading from 09:30 to 11:30 and 13:00 to 15:00hours are considered. The data consist of time-stamped (to the second) intraday best bid and ask prices and volumes, transaction prices and volumes. Additional variables such as percentage of volume and number of transactions are derived from the data.

[11] The analysis was conducted for 566 stocks on the SHSE and 484 stocks on the Shenzhen Stock Exchange (SZSE) for September 2001, May 2002 and June 2002 respectively. As all six samples gave similar results, however, only the results for the 566 stocks listed on the SHSE during September 2001 are reported here.

Table 6.1 Sample Statistics

The data sample used in this study consists of 566 shares trading on Shanghai Stock Exchange in September 2001. It provides the mean, minimum, 1st quartile, median, 4th quartile and maximum of the returns (%), number of trades (in thousands), volume (in millions) and average trade size (in thousands) over the sample period.

	Mean	Min	Q1	Median	Q3	Max
Return %	-2.09	-25.05	-6.55	-2.10	2.00	29.28
Number of Trades '000	4.02	0.50	2.59	3.45	5.18	11.94
Volume of Trades '000,000	9.36	0.42	3.34	5.48	11.39	89.72
Average Trade Size '000	1.96	0.52	1.24	1.64	2.28	10.33

Table 6.1 shows that the mean return is -2.09%, and the average trade size is 1,960 shares per trade. The first/last quartile with the lowest/highest returns will be further examined in the following sections.

Barclay and Warner (1993) initially restricted attention to a sample of tender-offer targets, which display abnormal price increases before the initial tender-offer announcement. Chakravarty (2001) also used a restricted sample, which consist of stocks displaying a significant price increase (5%) over the sample period, in order to maximize the probability of detecting stealth-trading. They stated that the intuition behind selecting stocks with significant price increases is that any stealth-trading activity is likely to be focused on one side of the market.

In order to provide more insights, this study examines the sample of all stocks over the sample period. Moreover, it examines stocks with significant price decreases and increases separately. No particular information event is conditioned on the sample.

6.3.2 Trade Size and Cumulative Stock Price Changes

Consistent with Barclay and Warner (1993) and Chakravarty (2001), the trade-size categories are defined as small, medium and large. While Barclay and Warner (1993) and Chakravarty (2001) defined 100 to 400 shares traded in a single transaction as the small trade-size category, this is inappropriate for China's stock market as trades of 100 to 400 shares account for less than 25% of the total transactions. Accordingly, trades of 0 – 999 shares are defined as small-size trades; trades of 1000 – 9,999 shares are defined as medium-size trades; and large-size trades are those of 10,000 shares or greater. Moreover, this study employs 23 subcategories[12] to provide more detailed analysis.

The method of calculating the cumulative stock price return follows Barclay and Warner (1993) and Chakravarty (2001). A price change that occurs on a given trade is defined as the difference between the trade's price and the price of the previous transaction. For each of the 566 stocks, all price changes that occur on trades in a given trade size category over the sample period are summed. The sum is then divided by the cumulative price changes for the stock over the sample.

[12] 0 - 99, 100 - 199, 200 – 299, 300 - 399, 400 - 499, 500 - 599, 600 - 699, 700 - 799, 800 - 899, 900 - 999, 1000 - 1999, 2000 - 2999, 3000 - 3999, 4000 - 4999, 5000 - 5999, 6000 - 6999, 7000 - 7999, 8000 - 8999, 9000 - 9999, 10000 - 14999, 15000 - 19999, 20000 – 24999, and 25000 and over

Finally, the weighted cross-sectional mean of the cumulative stock price change (over the 566 stocks) is estimated, where the weights are the absolute value of the cumulative price change in each stock over the sample. More specifically, the following equations apply.

Price Change

$$PC_i = P_i - P_{i-1}$$ Equation 6.1

where P_i is the transaction price

Percentage of cumulative price change

$$PDP = \frac{\sum_{i=1}^{t} PC_i}{P_t - P_0}$$ Equation 6.2

Weighted percentage of cumulative price change

$$WPDP = \frac{\sum_{j=1}^{556} PDP_j \times \left(P_{t,j} - P_{0,j}\right)}{\sum_{j=1}^{556} \left(P_{t,j} - P_{0,j}\right)}$$ Equation 6.3

6.3.3 Weighted Least Squares Regression

In order to test the above hypotheses Barclay and Warner's (1993) weighted least squares regression is used. The following two regression models examine the relation between the percentage of cumulative price change, the dummy variables and percentage of volume or number of transactions.

$$WPDP_i = \sum_{j=1}^{3} \alpha_j \times DUMMY_{i,j} + \beta \times POT_i + \varepsilon_i \qquad \text{Regression 6.1}$$

$$WPDP_i = \sum_{j=1}^{3} \alpha_j \times DUMMY_{i,j} + \beta \times POV_i + \varepsilon_i \qquad \text{Regression 6.2}$$

where j = 1, 2, 3 for categories small, medium and large, respectively, $WPDP_i$ is the weighted percentage of cumulative price change for firm i; $DUMMY_{i,j}$ represent the dummy variables for small, medium and large trade size, respectively. POT_i is the percentage of number of transactions for the *i-th* firm, while POV_i is the percentage of volume of for the *i-th* firm. Moreover, regression analysis is also carried out for the 23 subcategories as follows.

$$WPDP_i = \sum_{j=1}^{23} \alpha_j \times DUMMY_{i,j} + \beta \times POT_i + \varepsilon_i \qquad \text{Regression 6.3}$$

$$WPDP_i = \sum_{j=1}^{23} \alpha_j \times DUMMY_{i,j} + \beta \times POV_i + \varepsilon_i \qquad \text{Regression 6.4}$$

In terms of the above models, if the stealth-trading hypothesis holds, only medium-size trades should be associated with a disproportionately large cumulative stock price change relative to their proportion of all trades and volume. Whereas, if the public-information hypothesis holds, the percentage of the cumulative price change occurring in a given trade-size category will be directly proportional to the percentage of transactions in that category. Finally, if the large block/price manipulation hypothesis holds, large-size trades will be associated with a disproportionately large cumulative stock price changes relative to their proportion of all trades and volume and this is effect should be more noticeable for a sample of price increases.

6.4 Empirical Results

6.4.1 All Price Changes

For the cross-section of 566 stocks, Table 6.2 reports the mean percentage of the cumulative stock price changes (WPDP), the corresponding numbers (NOT) and percentages (POT%) of trades, the volume (VOT) and volume (POV%) percentages, and the ratio of percentage cumulative stock price change over the percentage of number of trades (WPDP/POT) and volume (WPDP/POV) in each of the three trade-size categories and twenty-three subcategories. A stock price change corresponding to a specific trade is defined as the difference between that trade's price and the price of the previous trade. For each stock, the percentage of cumulative price change for a trade of a given size is the sum of all stock price changes occurring on trades in that size category (subcategory) divided by the total cumulative price change in that stock over the sample. The weighted cross-sectional mean of the cumulative stock price change are then estimated and reported where the weights are the absolute value of the cumulative price change of each stock in the sample. The proportion of trades (volume) is the sum of all transactions (volume), in a given size category, divided by the total cumulative trades (volume) in the sample.

Table 6.2 Analysis of Whole Sample

For the cross-section of 566 stocks, Table 6.2 reports the mean percentage of the cumulative stock price changes (WPDP), the corresponding numbers (NOT) and percentages (POT%) of trades, the volume (VOT) and volume (POV%) percentages, and the ratio of percentage cumulative stock price change over the percentage of number of trades (WPDP/POT) and volume (WPDP/POV) in each of the three trade-size categories and twenty-three subcategories. A stock price change corresponding to a specific trade is defined as the difference between that trade's price and the price of the previous trade. For each stock, the percentage of cumulative price change for a trade of a given size is the sum of all stock price changes occurring on trades in that size category (subcategory) divided by the total cumulative price change in that stock over the sample. The weighted cross-sectional mean of the cumulative stock price change are then estimated and reported where the weights are the absolute value of the cumulative price change of each stock in the sample. The proportion of trades (volume) is the sum of all transactions (volume), in a given size category, divided by the total cumulative trades (volume) in the sample.

	WPDP	NOT	POT%	WPDP/POT	VOT	POV%	WPDP/POV
Small	**-57.33**	**1133.62**	**49.82**	**-1.15**	**456.65**	**8.62**	**-6.65**
0-99	2.41	19.1	0.84	2.87	0.99	0.02	120.50
100-199	-14.59	162.53	7.14	-2.04	16.89	0.32	-45.59
200-299	-12	190.44	8.37	-1.43	38.66	0.73	-16.44
300-399	-13.47	165.74	7.28	-1.85	50.24	0.95	-14.18
400-499	-4.16	107.29	4.72	-0.88	43.36	0.82	-5.07
500-599	-18.68	226.66	9.96	-1.88	113.74	2.15	-8.69
600-699	-0.81	81.62	3.59	-0.22	49.34	0.93	-0.87
700-799	-0.64	66.44	2.92	-0.22	46.87	0.89	-0.72
800-899	0.86	64.84	2.85	0.3	52.19	0.99	0.87
900-999	3.74	48.96	2.15	1.74	44.37	0.84	4.45
Medium	**116.7**	**1041.87**	**45.79**	**2.55**	**2792.18**	**52.73**	**2.21**
1000-1999	13.08	495.81	21.79	0.6	630	11.9	1.10
2000-2999	24.59	214.44	9.42	2.61	494.73	9.34	2.63
3000-3999	18.7	115.94	5.1	3.67	386.67	7.3	2.56
4000-4999	17.36	66.03	2.9	5.98	288.46	5.45	3.19
5000-5999	18.96	60.48	2.66	7.13	320.97	6.06	3.13
6000-6999	7.24	33.46	1.47	4.93	213.22	4.03	1.80
7000-7999	8	23.3	1.02	7.82	172.19	3.25	2.46
8000-8999	4.97	18.66	0.82	6.06	156.54	2.96	1.68
9000-10000	3.8	13.75	0.6	6.29	129.42	2.44	1.56
Large	**40.63**	**99.89**	**4.39**	**9.26**	**2046.62**	**38.65**	**1.05**
10000-14999	15.73	50.16	2.2	7.13	583.96	11.03	1.43
15000-19999	6.22	18.15	0.8	7.79	308	5.82	1.07
20000-24999	6.54	11.71	0.51	12.7	254.98	4.82	1.36
25000 +	12.15	19.87	0.87	13.92	899.68	16.99	0.72
Sum	**100**	**2275.37**	**100**	**1**	**5295.45**	**100**	**1**

From Table 6.2 it is clear that most of the cumulative price change (WPDP) occurs in medium-size and large-size trades. Trades in the medium-size category are responsible for about 117% of the cumulative price change, but only about 46% of transactions and about 53% of volume. The subcategory with the largest effect is that of 2000-2999 shares. These trades account for about 25% of the cumulative price change, but only about 9% of all transactions. Similarly, with only about 4% of the transactions the large-size trades cause about 41% of the cumulative price change. The small-size trades cause -57.33% of the cumulative price change and comprise about 50% of transactions and about 9% of the volume. The combination effects of medium- and large-size trades are consistent with the prediction of stealth and large block trades/price manipulation hypotheses. There appears to be little support for the public information hypothesis that the percentage of the cumulative price change occurring in a given trade-size category is directly proportional to the percentage of transactions in that category.

Table 6.3 Regression Results of Whole Sample

Table 6.3 reports the weighted-least-squares regressions of the percentage of the cumulative price change occurring in each trade-size category and subcategory on dummy variables for the trade-size categories and subcategories, the percentage of transactions (regression 6.1 and 6.3), and the percentage of volume (regression 6.2 and 6.4) occurring in that category. The weights are equal to the absolute cumulative price change over the sample period. It also reports the Wald tests for regressions 6.1 and 6.2, which test if all dummy variables are all equal to zero, if the coefficient for the percentage of transactions (or volume) is equal to one, and if all dummy variables are equal to each other. *, **, and *** denote significant at 10%, 5% and 1% level respectively.

	Regression 6.1			Regression 6.2		
Variable	Estimate	tValue		Estimate	tValue	
DummyS	-1.1627	-6.92	***	-1.2839	-8.38	***
DummyM	2.1861	12.69	***	1.0626	5.76	***
DummyL	1.9295	7.63	***	0.7073	2.66	***
POT	0.1520	2.14	**			
POV				1.0418	13.87	***
adjRsq	0.0235			0.0377		
	Wald tests			Wald tests		
Label	Statistics	ProbChiSq		Statistics	ProbChiSq	
S=0, M=0, L=0	295.7046	0.00	***	113.8708	0.00	***
POT=1	142.3747	0.00	***			
POV=1				0.3101	0.58	
S=M=L	238.1550	0.00	***	109.7935	0.00	***
M=L	0.7146	0.40		1.4234	0.23	
S=L	105.6517	0.00	***	43.6136	0.00	***
S=M	225.1376	0.00	***	102.0137	0.00	***

Continuing

Table 6.3 Continued

	Regression 6.3			Regression 6.4		
Variable	**Estimate**	**tValue**		**Estimate**	**tValue**	
Dummy 1	0.3650	0.76		0.4184	0.87	
Dummy 2	-3.1028	-6.20	***	-2.7151	-5.67	***
Dummy 3	-2.7085	-5.36	***	-2.4117	-5.03	***
Dummy 4	-2.8469	-5.74	***	-2.7148	-5.66	***
Dummy 5	-1.0272	-2.11	**	-1.0110	-2.11	**
Dummy 6	-3.8951	-7.71	***	-3.9836	-8.27	***
Dummy 7	-0.3526	-0.73		-0.4284	-0.89	
Dummy 8	-0.2828	-0.58		-0.3809	-0.79	
Dummy 9	-0.0114	-0.02		-0.1375	-0.29	
Dummy 10	0.5374	1.11		0.4141	0.86	
Dummy 11	1.1360	1.99	**	-0.8177	-1.53	
Dummy 12	3.8606	7.75	***	2.1327	4.21	***
Dummy 13	3.0452	6.26	***	1.6857	3.41	***
Dummy 14	2.9320	6.06	***	1.9468	4.00	***
Dummy 15	3.2193	6.66	***	2.1005	4.30	***
Dummy 16	1.2134	2.51	**	0.5325	1.10	
Dummy 17	1.3771	2.85	***	0.8404	1.74	*
Dummy 18	0.8491	1.75	*	0.3547	0.73	
Dummy 19	0.6729	1.37		0.2813	0.57	
Dummy 20	2.7039	5.58	***	1.0376	2.08	**
Dummy 21	1.1240	2.27	**	0.3046	0.61	
Dummy 22	1.2842	2.51	**	0.6126	1.20	
Dummy 23	2.4648	4.74	***	0.6451	1.21	
POT	0.3265	3.87	***			
POV				1.0852	13.30	***
adjRsq	0.0338			0.0459		

Table 6.3 reports the weighted-least-squares regressions of the percentage of the cumulative price change occurring in each trade-size category and subcategory on dummy variables for the trade-size categories and subcategories, the percentage of transactions (regression 6.1), and the percentage of volume (regression 6.2) occurring in that category. The weights are equal to the absolute cumulative price change over the sample period.

Under the public information hypothesis, the coefficient on each dummy variable in the regression should be zero, and the coefficient on the percentage of transactions in the trade-size category should equal one and for volume it should NOT equal one. If the public information hypothesis holds, the percentage of the cumulative price change occurring in a given trade-size is directly proportional to the percentage of transactions in that category, thus the coefficient on the percentage of transactions in the trade-size category should be one. Clearly, if this condition is to hold, the coefficient on the percentage of volume should NOT equal one.

The results in regression 6.1 are not consistent with the public information hypothesis. The hypothesis that the coefficient for the percentage of transactions is equal to one can be rejected at the 0.01 level of significance. The hypothesis that all of the dummy variables are equal to zero can also be rejected at the 0.01 level. The results in regression 6.2 show that the coefficient for the percentage of volume is equal to one cannot be rejected at the 0.01 level of significance. The dummy variables being equal to zero is also rejected at the 0.01 level.

The results indicate that the percentage of the stock-price change is smaller than predicted by the public information hypothesis in the small-size category, and larger than predicted in the medium- and large-size category. The coefficients are -1.1627, 2.1861 and 1.9295 respectively. The results reject the public information hypothesis but support the stealth and large block trades/manipulation hypotheses with the cumulative price changes occurring on medium- and large-size trades. Furthermore, all the results from twenty-three subcategories are consistent with those from the three categories.

For robustness purpose, stocks before the 1^{st} quartile and the 4^{th} quartile are separated from the whole sample. As shown in Table 6.1, stocks in the 1^{st} quartile have negative price changes between -25.05% to -6.55%, and stocks in the 4^{th} quartile have positive price change between 2.00% to 29.28%. The separation of the price-increase and price-decrease stocks provides more insights given Aggarwal and Wu's (2003) prediction that prices increase during manipulation period.

6.4.2 Cumulative Price Decreases

The results from Table 6.4 are consistent with those from Table 6.2 that most of the cumulative price decreases occur in the medium- and large-size trade categories. Trades in the medium-size category are responsible for about 144% of the cumulative price decrease, but with only about 45% of transactions and 56% of volume. The large-size trades cause about 52% of cumulative price decrease, but with only about 4% of transactions and 34% of volume. The subcategory with the largest effect is that of 10000-14999 shares. These trades account for about 27% of the cumulative price change, but only about 2% of all transactions. The small-size trades cause -96.26% of the cumulative price decrease and comprise about 52% of transactions and about 10% of the volume. Moreover, the ratio of percentage cumulative share price change over the percentage of number of trades for each category are -1.86, 3.22 and 14.25, which again confirms that large-size trades have a disproportionate impact on the cumulative price decreases.

Table 6.4 Analysis of Significant Price Decrease

For the cross-section of 141 stocks, this table reports the mean percentage of the cumulative stock price changes (WPDP), the corresponding numbers (NOT) and percentages of trades (POT%), the volume (VOT) and volume percentages (POV%), and the ratio of percentage cumulative stock price change over the percentage of number of trades (WPDP/POT) and volume (WPDP/POV) in each of the three trade-size categories and twenty-three subcategories.

	WPDP	NOT	POT%	WPDP/POT	VOT	POV%	WPDP/POV
Small	**-96.26**	**273.83**	**51.65**	**-1.86**	**110.54**	**10.04**	**-9.59**
0-99	7.72	4.53	0.85	9.05	0.23	0.02	386.00
100-199	-37.47	38.16	7.2	-5.21	3.96	0.36	-104.08
200-299	-17.39	45.75	8.63	-2.01	9.28	0.84	-20.70
300-399	-17.09	40.61	7.66	-2.23	12.3	1.12	-15.26
400-499	-3.12	25.97	4.9	-0.64	10.49	0.95	-3.28
500-599	-27.89	56.26	10.61	-2.63	28.22	2.56	-10.89
600-699	-3.03	19.33	3.65	-0.83	11.68	1.06	-2.86
700-799	-1.52	15.92	3	-0.51	11.22	1.02	-1.49
800-899	0.77	15.43	2.91	0.27	12.41	1.13	0.68
900-999	2.75	11.89	2.24	1.23	10.76	0.98	2.81
Medium	**144.01**	**236.91**	**44.68**	**3.22**	**615.78**	**55.92**	**2.58**
1000-1999	14.82	116.38	21.95	0.67	147.2	13.37	1.11
2000-2999	26.07	48.8	9.2	2.83	112.31	10.2	2.56
3000-3999	23.24	25.83	4.87	4.77	86.02	7.81	2.98
4000-4999	21.83	14.32	2.7	8.09	62.46	5.67	3.85
5000-5999	26.13	13.26	2.5	10.45	70.21	6.38	4.10
6000-6999	8.36	6.93	1.31	6.4	44.13	4.01	2.08
7000-7999	10.21	4.86	0.92	11.15	35.88	3.26	3.13
8000-8999	7.5	3.79	0.71	10.51	31.74	2.88	2.60
9000-10000	5.84	2.75	0.52	11.26	25.85	2.35	2.49
Large	**52.26**	**19.45**	**3.67**	**14.25**	**374.9**	**34.04**	**1.54**
10000-14999	27.06	10.15	1.91	14.14	117.55	10.67	2.54
15000-19999	8.43	3.43	0.65	13.05	57.85	5.25	1.61
20000-24999	7.54	2.35	0.44	17.02	50.93	4.63	1.63
25000 +	9.23	3.53	0.67	13.87	148.56	13.49	0.68
Sum	**100**	**530.18**	**100**	**1**	**1101.22**	**100**	**1**

Table 6.5 Regression Results of Significant Price Decrease

Table 6.5 reports the weighted-least-squares regressions of the percentage of the cumulative price change occurring in each trade-size category and subcategory on dummy variables for the trade-size categories and subcategories, the percentage of transactions (regression 6.1 and 6.3), and the percentage of volume (regression 6.2 and 6.4) occurring in that category. The weights are equal to the absolute cumulative price change over the sample period. It also reports the Wald tests for regression 6.1 and 6.2, which test if all dummy variables are all equal to zero, if the coefficient for the percentage of transactions (or volume) is equal to one, and if all dummy variables are equal to each other. *, **, and *** denote significant at 10%, 5% and 1% level respectively.

	Regression 6.1			Regression 6.2		
Variable	**Estimate**	**tValue**		**Estimate**	**tValue**	
DummyS	-5.9299	-6.85	***	-7.8789	-10.78	***
DummyM	12.0651	14.10	***	6.4655	6.55	***
DummyL	10.1668	8.49	***	5.6272	4.28	***
POT	-0.2129	-1.79	*			
POV				1.0083	7.81	***
adjRsq	0.1055			0.1214		
	Wald tests			**Wald tests**		
Label	**Statistics**	**ProbChiSq**		**Statistics**	**ProbChiSq**	
S=0, M=0, L=0	382.0200	0.00	***	189.3643	0.00	***
POT=1	104.2089	0.00	***			
POV=1				0.0041	0.95	
S=M=L	311.2163	0.00	***	179.1935	0.00	***
M=L	1.7021	0.19		0.3538	0.55	
S=L	122.1757	0.00	***	86.8670	0.00	***
S=M	289.0315	0.00	***	154.6332	0.00	***

Continuing

Table 6.5 Continued

	Regression 6.3			Regression 6.4		
Variable	Estimate	tValue		Estimate	tValue	
Dummy 1	5.0111	2.27	**	5.4040	2.47	**
Dummy 2	-29.7747	-12.00	***	-26.9451	-12.33	***
Dummy 3	-16.1791	-6.29	***	-13.5149	-6.17	***
Dummy 4	-15.2054	-6.21	***	-13.5281	-6.17	***
Dummy 5	-4.1605	-1.81	*	-3.4226	-1.56	
Dummy 6	-23.7624	-9.12	***	-22.7984	-10.25	***
Dummy 7	-3.5308	-1.57		-3.4016	-1.55	
Dummy 8	-2.2065	-0.99		-2.2717	-1.04	
Dummy 9	-0.5582	-0.25		-0.7689	-0.35	
Dummy 10	1.1006	0.50		0.8202	0.37	
Dummy 11	2.6736	0.78		-3.5473	-1.23	
Dummy 12	15.2466	6.25	***	8.6408	3.39	***
Dummy 13	14.7168	6.48	***	9.3348	3.92	***
Dummy 14	14.5894	6.55	***	10.6134	4.64	***
Dummy 15	17.5341	7.90	***	12.8998	5.59	***
Dummy 16	5.5178	2.49	**	2.7721	1.24	
Dummy 17	6.9617	3.15	***	4.8344	2.18	**
Dummy 18	5.2078	2.33	**	3.2416	1.45	
Dummy 19	4.1300	1.84	*	2.6129	1.16	
Dummy 20	18.5948	8.39	***	11.9998	5.01	***
Dummy 21	6.0014	2.67	***	2.8692	1.26	
Dummy 22	5.9340	2.52	**	3.2911	1.39	
Dummy 23	7.5445	3.14	***	0.7849	0.31	
POT	0.5383	2.95	***			
POV				1.1585	7.42	***
adjRsq	0.1735			0.1853		

The regression results from Table 6.5 confirm those from Table 6.3 in that whilst the public information hypothesis is rejected, stealth-trading and block trade/manipulation hypotheses are supported. The coefficients for each trade-size category are -5.9299 (-7.8789), 12.0651 (6.4655) and 10.1668 (5.6272) in regressions 6.1 (6.2), respectively. The results from the subcategories lead to the same conclusion.

6.4.3 Cumulative Price Increases

The results in Table 6.6 show that with about 48% of transactions the medium-size category causes only about 5% of the cumulative price increase. In contrast, the small-size trades cause about 76% of the cumulative price increase with about 46% of transactions and about 7% of the volume, and the large-size trades cause about 20% of cumulative price increase with only about 6% of transactions and about 45% of volume. The subcategory with the largest effect is that of 100-199 shares. These trades account for about 31% of the cumulative price change, but only about 7% of all transactions. However, the ratios of percentage cumulative share price change over the percentage of number of trades for each of the three categories (small, medium and large) are -1.65, 0.10 and 3.28, and this shows it is the large-size trades which have a disproportionate impact on price increases.

Table 6.6 Analysis of Significant Price Increase

For the cross-section of 141 stocks, this table reports the mean percentage of the cumulative stock price changes (WPDP), the corresponding numbers (NOT) and percentages of trades (POT%), the volume (VOT) and volume percentages (POV%), and the ratio of percentage cumulative stock price change over the percentage of number of trades (WPDP/POT) and volume (WPDP/POV) in each of the three trade-size categories and twenty-three subcategories.

	WPDP	NOT	POT%	WPDP/POT	VOT	POV%	WPDP/POV
Small	**75.8**	**307.23**	**46.06**	**1.65**	**123.88**	**6.56**	**11.55**
0-99	-9.76	4.96	0.74	-13.14	0.26	0.01	-976.00
100-199	30.96	45.51	6.82	4.54	4.73	0.25	123.84
200-299	23.01	52.17	7.82	2.94	10.6	0.56	41.09
300-399	14.37	43.73	6.56	2.19	13.27	0.7	20.53
400-499	1.81	28.73	4.31	0.42	11.62	0.61	2.97
500-599	12.33	59.32	8.89	1.39	29.78	1.58	7.80
600-699	2.37	22.53	3.38	0.7	13.63	0.72	3.29
700-799	1.38	18.63	2.79	0.49	13.15	0.7	1.97
800-899	0.18	17.98	2.7	0.07	14.48	0.77	0.23
900-999	-0.85	13.67	2.05	-0.41	12.39	0.66	-1.29
Medium	**4.6**	**319.94**	**47.97**	**0.1**	**912.05**	**48.28**	**0.10**
1000-1999	3.87	141.48	21.21	0.18	181.82	9.62	0.40
2000-2999	5.12	66.2	9.93	0.52	153.82	8.14	0.63
3000-3999	1.35	37.37	5.6	0.24	125.15	6.62	0.20
4000-4999	-2.52	22.04	3.3	-0.76	96.63	5.11	-0.49
5000-5999	-1.67	20.17	3.02	-0.55	107.47	5.69	-0.29
6000-6999	-1.12	11.98	1.8	-0.62	76.47	4.05	-0.28
7000-7999	0.34	8.56	1.28	0.27	63.41	3.36	0.10
8000-8999	1.4	7	1.05	1.33	58.83	3.11	0.45
9000-10000	-2.18	5.14	0.77	-2.83	48.44	2.56	-0.85
Large	**19.6**	**39.82**	**5.97**	**3.28**	**853.28**	**45.17**	**0.43**
10000-14999	-4.98	18.9	2.83	-1.76	221.8	11.74	-0.42
15000-19999	2.59	7.4	1.11	2.33	125.99	6.67	0.39
20000-24999	3.84	4.76	0.71	5.38	104.18	5.51	0.70
25000 +	18.14	8.75	1.31	13.82	401.31	21.24	0.85
Sum	**100**	**667**	**100**	**1**	**1889.21**	**100**	**1**

Table 6.7 Regression Results of Significant Price Increase

Table 6.7 reports the weighted-least-squares regressions of the percentage of the cumulative price change occurring in each trade-size category and subcategory on dummy variables for the trade-size categories and subcategories, the percentage of transactions (regression 6.1 and 6.3), and the percentage of volume (regression 6.2 and 6.4) occurring in that category. The weights are equal to the absolute cumulative price change over the sample period. It also reports the Wald tests for regressions 6.1 and 6.2, which test if all dummy variables are all equal to zero, if the coefficient for the percentage of transactions (or volume) is equal to one, and if all dummy variables are equal to each other. *, **, and *** denote significant at 10%, 5% and 1% level respectively.

	Regression 6.1			Regression 6.2		
Variable	**Estimate**	**tValue**		**Estimate**	**tValue**	
DummyS	3.0421	3.05	***	4.4358	4.88	***
DummyM	-1.8459	-1.78	*	-4.4239	-3.98	***
DummyL	3.1156	2.10	**	-2.0813	-1.28	
POT	0.6354	5.60	***			
POV				1.0424	8.44	***
adjRsq	0.0207			0.0326		
	Wald tests			**Wald tests**		
Label	**Statistics**	**ProbChiSq**		**Statistics**	**ProbChiSq**	
S=0, M=0, L=0	18.8085	0.00	***	42.5765	0.00	***
POT=1	10.3116	0.00	***			
POV=1				0.1179	0.73	
S=M=L	14.5324	0.00	***	42.1756	0.00	***
M=L	7.6934	0.01	***	1.7779	0.18	
S=L	0.0017	0.97		12.8493	0.00	***
S=M	13.6686	0.00	***	40.4956	0.00	***

Continuing

Table 6.7 Continued

	Regression 6.3			Regression 6.4		
Variable	Estimate	tValue		Estimate	tValue	
Dummy 1	-7.1787	-2.52	**	-6.8988	-2.45	**
Dummy 2	18.8739	6.35	***	21.2741	7.55	***
Dummy 3	13.1095	4.39	***	15.1767	5.38	***
Dummy 4	7.7658	2.65	***	8.9990	3.19	***
Dummy 5	-0.2359	-0.08		0.3299	0.12	
Dummy 6	5.7809	1.95	*	6.5283	2.31	**
Dummy 7	0.5399	0.19		0.6612	0.23	
Dummy 8	0.0495	0.02		0.0293	0.01	
Dummy 9	-0.7433	-0.26		-0.8660	-0.31	
Dummy 10	-1.2675	-0.44		-1.4634	-0.52	
Dummy 11	-3.8163	-1.11		-8.4306	-2.71	***
Dummy 12	0.6314	0.21		-4.8664	-1.63	
Dummy 13	-0.7087	-0.25		-5.4316	-1.86	*
Dummy 14	-2.7228	-0.95		-6.3430	-2.21	**
Dummy 15	-2.0385	-0.71		-6.1409	-2.13	**
Dummy 16	-1.2862	-0.45		-4.0195	-1.41	
Dummy 17	-0.1115	-0.04		-2.3505	-0.82	
Dummy 18	0.6989	0.24		-1.4092	-0.50	
Dummy 19	-1.8293	-0.63		-3.5112	-1.21	
Dummy 20	-4.3527	-1.51		-11.6906	-3.89	***
Dummy 21	1.6375	0.56		-2.1288	-0.72	
Dummy 22	2.7664	0.93		-0.3321	-0.11	
Dummy 23	13.4309	4.55	***	4.8469	1.56	
POT	0.4618	3.39	***			
POV				1.1103	8.38	***
adjRsq	0.0404			0.0577		

Regression results from Table 6.7 reject both the public information and stealth-trading hypotheses. In regression 6.1 the coefficients for the small-size and large-size categories are 3.0421 and 3.1156, whereas the medium sized category has a coefficient of -1.8459. The results are presented more clearly from the twenty-three subcategories with only the trade-size categories of 100-199, 200-299,300-399, and 25000 and over having significant effect on cumulative price increases. One interpretation of these results is that the manipulators take large positions so as to maximize profits and thereby move prices up, and individual investors follow the price increases.

6.5 Conclusions

This chapter has extended Barclay and Warner's (1993) work on stealth trading to the emerging China's stock market. While some support is found for stealth trading, the results point towards large size trades having the greatest disproportionate effect on price changes and this is especially the case for price increases.

While we are unable to isolate the motivations behind this 'large trade size' effect, the results are aligned with a concern noted by a number of eminent individuals in China. At the National People's Congress (NPC) in spring 2000, Premier Zhu Rongji remarked that China's stock markets had developed quickly, achieved much but was still not well regulated with concerns over rampant speculation, poor-quality listed firms, defective regulation and widespread corruption. In 2001, Professor Wu Jinglian condemned that 'China's stock market is no better than a casino. At least in a casino there are rules.' (Wu, 2001)

If the current results are confirmed by further research, the policy conclusions are both stark and obvious. First, there will need to be a stricter regime tracking the source of large block trades and large fluctuations in share prices. Second, penalties for purposeful price manipulation will have to be material and strictly enforced. Only then will China's stock market have the opportunity to benefit from an orderly price discovery process.

More recently, Kang, Liu and Ni (2002) found that the price manipulation could be explained by behavioural factors. They argued that the syndicate speculators like to create bullish sentiment on China's stock market, which might lead to individual investors' overreaction and make them fall into the trap. Due to stock prices' overreaction, they found statistically significant abnormal profits for some short-horizon contrarian and intermediate-horizon momentum strategies in China's stock market. On one hand, their results broadly confirm the results of this current chapter that price manipulation exists in China's stock market, especially during the price increase period. On the other hand, they provide behavioural explanations for stock price behaviours, which has become increasingly popular among financial economists (e.g., Wang and Cheng, 2004, and Coval and Shumway, 2005, etc.). The next chapter of thesis will examine the issue of investors' psychology. It will investigate the effect of cultural factors on price clustering and price resistance in China's stock market.

CHAPTER 7

CULTURAL INFLUENCE ON PRICE CLUSTERING AND RESISTANCE

7.1 Introduction

Financial economists have become increasingly interested in the behavioural and psychological explanations for asset pricing anomalies since the emergence of behavioural finance. O'Hara (1997) viewed trading mechanism as 'a type of trading game in which players meet at some venue and act according to some rules.' He also argued that market participant is one of the three dimensions of a trading mechanism. Hence, the analysis of market participants' behaviour and psychology will enrich the traditional market microstructure research and provide further insights into the price formation process.

'Man is neither infinite in faculties, nor in apprehension like a god (Hirshleifer, 2001, p1576).' The behaviour and psychological explanations have promise of capturing this reality. One of the fascinating subjects that should receive more attention from investors is the psychology of numbers. Psychological experiments demonstrate more generally that clustering of outcomes at round numbers is a fundamental attribute of human behaviour. It is important to understand stock price clustering, for it is inconsistent with share prices following a simple random walk process. Recent studies document the tendency of prices to cluster at round numbers. These effects are remarkably persistent through time and across markets. The evidence seems to show that this phenomenon depends on the prediction of investors to place orders at round numbers. From a scientific view the research gives some insights in the way investors make their decision.

Brown, Chua and Mitchell (2002) analysed the effect of Chinese cultural factors, such as preferences for specific numbers, on price clustering for six Asia-Pacific stock markets (Australia, Hong Kong, Indonesia, Philippines, Singapore and Taiwan). They only found support for Chinese cultural factors having an influence on price clustering in the Hong Kong (HK) market and explained the result by the cultural factors concerning numbers being stronger in the Cantonese speaking HK market than in the Mandarin speaking states such as Singapore and Taiwan, and because the HK market has a relatively high proportion of local individual traders, who are more likely to be influenced by cultural effects than foreign and institutional traders.

The primary purpose of this chapter is to extend the analysis of Brown et al. (2002) by testing whether cultural factors help explain price clustering in China's stock market. In addition to extending the analysis to the Chinese markets, it develops the analysis in a number of ways. First, it uses intraday data and a range of tests to give a more refined characterisation of price clustering. Second, it tests whether limit order prices explain price clustering. Third, it tests whether cultural factors explain price resistance levels in the Chinese markets.

The results of the paper offer support for Chinese cultural factors affecting price clustering and limit order prices in the Chinese markets but this support does not extend to the analysis of price resistance levels. In addition to the price clustering at digit 0 and 5 as found commonly in previous studies, this study finds that prices tend to cluster on digit 8 in China's stock market. It also finds that there is a lower propensity of price to cluster on digits 4 and 7. The results are clearly consistent with the predictions that Chinese people like the lucky number 8, and dislike the unlucky numbers 4 and 7. However, the cultural factors do not have impacts on price resistance level, with only the digit 0 being found to be a resistance point. The results of this study have implications for practitioners, especially global investors, that the unique Chinese culture has impacts on the price formation process. A good understanding of Chinese culture would help them make right investment decisions.

The structure of this chapter is as follows. Section 7.2 briefly reviews the behavioural finance literature. Section 7.3 reviews the empirical evidence, and section 7.4 discusses the relevant theoretical explanations. Section 7.5 discusses the data and methodologies used to analyse price clustering and resistance in China's stock markets. Section 7.6 presents the results, while section 7.7 offers conclusions.

7.2 Review of Behavioural Finance Literature

The EMH has been the central proposition of finance for nearly thirty years. However, in the last twenty years both the theoretical foundations and the empirical evidence purporting to support it have been challenged. Behavioural finance has emerged as an alternative view of financial markets. Behavioural finance theory rests on two major foundations: investor sentiment and limited arbitrage.

First, Shleifer (2000) argued that investors are not fully rational in general. Many investors react to irrelevant information in forming their demand for securities and act as noise traders in the market because of their irrationality. Black (1986) confirmed that they trade on noise rather than information. If the theory of efficient markets relied entirely on the rationality of individual investors, the theory is questionable because investors' psychology has great influence, which is referred as investor sentiment.

Second, the central argument of behavioural finance also states that real-world arbitrage is risky and therefore limited. The effectiveness of arbitrage relies crucially on the availability of close substitutes. However, securities do not have obvious substitutes in many instances. Even when individual securities have close substitutes, arbitrage is still risky because of the fundamental risk. Miller (1977) argued that the uncertainty and risk would imply divergence of opinion. If there is little or no short selling in a market, the demand for securities should come from those who have the most optimistic expectations about them. However, with increasing risk the divergence of opinion is likely to increase as well, making the expected returns lower for those risky securities. Even for risk neutral investors, their strategy will involve the use of risk premiums in evaluating securities. Furthermore, De Long et al. (1990) argued that even when individual securities have perfect and identical substitutes, the 'noise trader risk' still makes the real-world arbitrage quite risky and therefore limited.

A number of recent papers in finance literature have argued that behavioural and psychological factors account for asset pricing anomalies (Coval and Shumway, 2005, Barberis et al., 1998, Daniel et al., 1998, Odean, 1998, Benartzi and Thaler, 1995, Shumway, 1998, Barberis and Huang, 2001, and Barberis et al., 2001). Even some reputable economists in old days thought that individual psychology affects prices. For example, Keynes (1936) argued that animal spirits affect prices in stock markets. Markowitz (1952) proposed that people focus on gains and losses relative to reference points, which helps explain the pricing of insurance and lotteries.

In an effort to explain the anomalies caused by investors, it becomes popular to introduce psychological observations in financial research. This section provides the review of studies of behaviour finance and investors' psychology, and examines how the behavioural and psychological factors affect price formation process.

7.2.1 Overreaction

De Bondt and Thaler (1985) are one of the first who introduced the psychological conception of 'overreaction' of investors and investigated whether such behaviour affects stock prices. They compared the performance of two groups of companies: extreme losers and extreme winners. They formed portfolios of best and the worst performing stocks over the previous three years. They then computed the returns on these portfolios over the following five years. They documented that the portfolios of prior losers outperform prior winners. They advanced the explanation of overreaction that the extreme losers have become too cheap and bounce back, whereas the extreme winners have become too expensive and earn lower subsequent returns. Similarly, Lehamann (1990) documented price reversals at monthly and weekly intervals.

Subsequent to De Bondt and Thaler's (1985) study, Jegadeesh and Titman (1993) recognized momentum phenomenon, which cannot be explained by Fama and French's (1996) three-factor model. They showed that movements in individual stock prices over the period of six to twelve months tend to predict future movements in the same direction. They predicted that short-term trends continue. Recently, Daniel and Titman (2001) and Cohen et al. (2002) enriched the understanding of momentum by focusing on the specific meaning of information rather than how people hear it.

Fama (1998) argued that both contrarian and momentum phenomena tend to disappear in the long run, and therefore, they are not incompatible with efficient market hypothesis. However, Shleifer (2000) argued that 'ultimately efficient, however, does not mean efficient'.

Some research uncovered other variables that predict future returns, for example, the market to book ratio. The market to book ratio are thought as a measure of the cheapness of a stock. Companies with high market to book ratios are the expensive growth firms, whereas those with low ratios are relatively the cheap value firms. The principal of value investing suggests investing in low market to book companies, because the high market to book ratios may reflect the overreaction to past good news and the over-optimism about the companies' future profitability. De Bondt and Thaler (1987), Fama and French (1992), and Lakonishok et al. (1994) found that portfolios of high market to book companies have earn much lower returns than those with low ratios.

7.2.2 Beliefs and Mood

Daniel et al. (1998) developed a theory based on investors' overconfidence and changes in confidence resulting from biased self-attribution of investment outcomes. The theory suggests that investors overreact to private information signals and underreact to public information signal. They found that positive return autocorrelation can be a result of continuing overreaction, which is followed by a long-term correction. Alternatively, Barberis et al. (1998) argued that a representative investor suffers from conservatism bias, and is reluctant to update his beliefs sufficiently even when observing new public information. In their theory individuals believed that earnings either follow a steady growth trend or are mean-reverting, while the actual earnings follow a random walk.

An interesting paper written by Hirshleifer and Shumway (2003) investigated the relationship between morning sunshine in the city of a country's leading stock exchange and daily market index returns. The analysis was carried out across 26 countries from 1982 to 1997, and it found that sunshine is strongly significantly correlated with stock returns. These findings are difficult to reconcile with fully rational price setting. It could only be explained by psychological evidence that sunny weather is associated with upbeat mood, and mood affects prices. The implications of the analysis of mood suggest that negative moods tend to stimulate effort at careful analysis, whereas positive moods are associated with less critical and more receptive information processing.

7.2.3 Preferences

Most literature that employs preference-based deviations from rationality is based on the prospect theory of Kahneman and Tversky (1979). They argued that the utility functions are derived as convex in the region of losses, kinked at zero, and concave in the region of gains. Kahneman and Tversky (1982) found extreme risk aversion in the neighbourhood of zero, which perhaps is the most salient feature of prospect theory. Using experimental data, they estimated the slope below zero to be 2.25 times that above zero. Benartzi and Thaler (1995) and Barberis et al. (2001) modelled the behaviour of a representative investor with such preferences and explained the equity premium puzzle. Since the trader's utility is a function of daily gains or losses, the profits near zero will lead to extremely high subsequent risk aversion. A second aspect of prospect theory is that of risk-seeking behaviour in the region of losses. Kahneman and Tversky (1979) stated that a person who has not made peace with his losses is likely to accept gambles that would be unacceptable to him otherwise. It suggests that traders who have experienced losses are most inclined to take subsequent risks. Conversely, traders with profitable mornings tend to reduce their exposure to afternoon risk.

Moreover, Thaler and Johnson (1990) documented the house-money effect that individuals have increasing risk tolerance as their wealth exceeds the reference point. Barberis et al. (2001) employed the house-money effect, and found that investors are becoming more risk tolerant when their risky asset holdings earn returns exceeding a historical benchmark.

7.3 Empirical Evidence

7.3.1 Price Clustering

Osborne (1962) and Niederhoffer (1965, 1966) seem to have been the first to test whether some prices are more frequently observed than others and they found that stock prices in the US markets are clustered on whole numbers, less on halves or quarters and least commonly on the odd eighths. Osborne (1962) sampled closing prices and found that 60.8 percent were at even eighths; hence, the tendency for even eighths to appear more frequently than odd eighths being termed the 'Osborne Effect'. Niederhoffer (1965) documented clustering of limit orders on the books of specialists on the NYSE and found 84 percent of them are at the even eighths. The ratio of limit order closing prices at the even eighths (0, 2, 4, 6) to those at the odd eighths (1, 3, 5, 7) was 8.8:1. He found clustering in the closing prices of actively and inactively traded shares, in high- and low-priced shares, and in noon closing prices. Higher-priced shares traded mostly at the integers and lower-priced shares settled at even numbers of eighths. Moreover, Niederhoffer (1966) suggested there is also a tendency for limit orders to be placed at familiar whole numbers, such as 10, 25, 50, etc.

Harris (1991) confirmed that stock price clustering is pervasive and the clustering distributions from the mid-nineteenth century appear to be no different from those observed in the late twentieth century. He found that clustering increased with price level and volatility. Moreover, price clustering is also found in international markets, such as in the Australian Stock Exchange by Aitken et al. (1996) and on the Stock Exchange of Singapore (SES) by Hameed and Terry (1998). Aitken et al. (1996) found that clustering increases with the price of the stock, with market volatility, own stock volatility, trade size and the size of the bid-ask spread. It decreased with trading frequency and also was lower for stocks with options traded on them. Hameed and Terry (1998) investigated the distribution of daily closing prices for 234 stocks that were traded on the SES Main Board between January 1980 and July 1994. The SES is an order-driven market with no market maker. Prices ending in multiples of ten cents were more common than prices ending in odd multiples of five cents; prices were more likely to end in even cents than odd cents, and least likely to end in fractional cents; and whole dollars occurred more frequently than half dollars, which were more frequent than price multiples of 10 cents. They also found that price clustering increased with a stock's price level and decreased with trading volume.

Brown et al. (2002) analysed price clustering for large and small stocks for six Asian-Pacific stock markets and found evidence that clustering occurs at 0, 5 and even integers. Furthermore, they found that clustering at 0 and even numbers increases with the level of the stock price and declines with the precision with which a price is known. They also found that in the case of the Hong Kong market there is some support for cultural factors explaining a preference for 8 and the avoidance of 4.

In terms of the impact of cultural factors on price clustering, Heeler and Nguyen's (2001) work on the patterns of price endings for samples of online shopping retail prices in American and five Asian markets (Malaysia, Hong Kong, Singapore, Japan and China) is of interest. Similar to the US, they found for the Asian markets that 0 and 5 are over-represented as compared to 1, 2, 3, 4, 6 and 7. They also found significant over-representation of 8 as compared to 9 for the Asian markets. The percentage of 8-endings for online prices in these markets is as follows; Malaysia 19.8%, Hong Kong 14.8%, Singapore 13.1%, Japan 24.4%, and China 19.3%, compared with 17.3%, 3.0%, 26.6%, 1.8%, and 9.9% for the 9-ending, respectively.

7.3.2 Price Resistance

As well as prices showing clustering effects, there is also evidence that price barriers can also occur. Most research concerning price barriers has been carried out on stock indices. Donaldson and Kim (1993) examined the Dow Jones Industrial Average (DJIA) for the period 1974-1990 and found round numbers (such as 100 levels) functioned as support or resistance levels. When such a level was passed through, the DJIA moved more up or down more than usual. Ley and

Varian (1994) analysed the DJIA over the period 1952-1993 and found fewer observations around the 100-levels. Koedijk and Stork (1994) studied indices in the US, Belgium, Germany, Japan and the UK stock markets over the period 1980-1992 and found relatively few observations near 100-levels and furthermore, these levels were less often passed through.

7.4 Theoretical Explanations

Given the objectives of this study and the fact that Brown et al. (2002) reviewed a range of theoretical explanations, only cultural explanations of price clustering and price barriers are considered here.

In Chinese culture numbers are not just figures, but they also carry special significance and symbolism. Even the pronunciations or sounds of the numbers can suggest good or bad luck. The number 8 presents good luck to the Chinese because it sounds like *multiply* in Chinese, which indicates getting wealthy. Telephone numbers, licence plates and even residential or business addresses which use any of or a combination of those numbers are extremely popular and often cost more. For example, a special phone number, '88888888', was auctioned in China's Sichuan Province, for 2.33 million Yuan (US$280,723) (from China daily, 19/08/2003). More interestingly, the 2008 Beijing Olympics will begin at 8pm on 8 August, in keeping with one of the nation's lucky numbers (from BBC news, 05/11/2004). These evidences suggest that the number 8 is well preferred in Chinese culture.

This explanation is consistent with the results of Heeler and Nguyen where the 8-ending is found to be popular in Hong Kong and Malaysia, where Cantonese Chinese is the major dialect. In Japan, the number 8 also has great symbolic significance. The Japanese writing of number 8 looks like the shape of a mountain (Sue-hirogari in Japanese), and thus the number 8 signifies 'fan out', 'grow', and 'be prosperous'. On the other hand, the number 4 in China suggests bad luck, as it sounds like *die* in Chinese and the number 7 sounds like *anger*, which is also not 'fancied' by the Chinese. From this perspective, there should be more price clustering on the number 8 and less on the numbers 4 and 7 in China's stock market.

Prior work (e.g., Aitken et al., 1996, and Hameed and Terry, 1998) has established that individual stock prices cluster on round numbers and also Sonnemans (2003) finds that in individual stocks round numbers also act as price barriers. There is, therefore, a suggestion of a relationship between price clustering and price barriers. One possible explanation of this relationship is the use of limit orders. If stock price clustering is caused by a relatively large number of limit orders at round numbers, this may also cause barriers or resistance points at these numbers. Accordingly, the limit order book is studied as a means of further testing the potential importance of cultural factors as explanations of price effects in the Chinese stock markets.

7.5 Data and Methodology

7.5.1 Data

The data used in this study consist of time-stamped (to the second) intraday best bid and ask prices and volumes, and transaction prices and volumes. The sample period is from the 1st to 30th September, 2001. The results are shown for a sample consisting of 566 stocks trading on the Shanghai Stock Exchange (SHSE).[13] Only regular trades transacted in the four hours of normal trading hours are considered in this study, which is from 09:30 to 11:30 and 13:00 to 15:00. Opening trades are excluded, because they are traded under a different mechanism. Each regular trade's price and volume, and the best bid & ask price and volume are extracted, and additional variables are derived from the existing database. The last significant digit of each price (from digit 0 to 9) is extracted in order to test whether it is a clustering/resistance point or not.

[13] The analysis was conducted for stocks traded on both SHSE and SZSE for September 2001 and May 2002 but as all four samples gave similar results, only the results for the 566 stocks listed on the SHSE during September 2001 are reported are here.

7.5.2 Measures of Price Clustering and Price Resistance

As a means of providing a comprehensive and detailed analysis of price clustering and price resistance a range of measures are considered. First, price clustering is measured from transaction price data with four measures. Second, limit order prices are analyzed to examine price resistance with two measures. Third, another four measures are constructed from transaction prices to study price resistance.

7.5.2.1 Price Clustering – Transaction Price Analysis

Prior studies (e.g., Sonnemans, 2003) have used the occurrence of prices (frequency) to measure price clustering. However, since price clustering means that some prices are more frequently 'observed', a single measurement of the appearance frequency may not to be sufficient; more specifically, price clustering may have volume and duration characteristics. For example, it would seem reasonable for price clustering to be associated with greater volumes of transactions at certain prices and for prices to stay longer at the clustering points. To capture these different aspects, price clustering is examined from the three-dimensional perspective of *Frequency* (*F*), *Percentage Trading Volume* (*PcntV*) and *Percentage Time Duration* (*PcntTD*). The measures of these dimensions are constructed as follows.

Frequency (F)

The frequency F_i of each digit is calculated as follows.

$$F_i = \frac{N_i}{\sum_{i=0}^{9} N_i} \qquad \text{Equation 7.1}$$

where $i = 0, 1, 2, \ldots, 8, 9$, and N_i is the number of transactions of each digit group.

Percentage Trading Volume (PcntV)

Trading volume of each transaction (V_t) within each digit group is summed to get *Volume* (V_i). In order to create a measure, which is comparable across different stocks, the *Percentage Volume* ($PcntV_i$) is used.

$$PcntV_i = \frac{V_i}{\sum_{i=1}^{9} V_i} \qquad \text{Equation 7.2}$$

where $i = 0, 1, 2, \ldots, 8, 9$, and $V_i = \sum V_t$

Percentage Time Duration (PcntTD)

The time duration of each trade (in seconds) is calculated by using the next trade's trading time T_{t+1} minus the current trade's time T_t. All the time durations are summed within each digit group to get *Time Duration* (TD_i).

$$TD_i = \sum (T_{t+1} - T_t) \qquad \text{Equation 7.3}$$

where $i = 0, 1, 2, \ldots, 8, 9$, T_t is the time stamp of each transaction t, and T_{t+1} is the time stamp of the transaction after transaction t. The time duration is then standardized to get *Percentage Time Duration* ($PcntTD_i$) as follows:

$$PcntTD_i = \frac{TD_i}{\sum_{i=0}^{9} TD_i} \qquad \text{Equation 7.4}$$

7.5.2.2 Price Resistance – Limit Order Price Analysis

As discussed above, price resistance may be caused by limit orders submitted at certain prices. Both exchanges in China have a centralized electronic order-driven system where the trading mechanism is a continuous market during normal trading hours. Orders are matched with a price and time priority scheme. Limit orders are submitted by buyers and sellers and auctioned off continuously. Matched orders are executed and then dispatched from the system, whereas unmatched orders remain in the system until they are executed or deleted. The transaction prices of a particular trade are generated contingent upon the best bid or ask prices and the time of order submissions. The *Percentage Time Duration* (*QPcntTD*) and *Standardized Time-Weighted Volume* (*QStdTWV*) at the best bid and ask prices are used to examine price resistance.

Calculation of *QPcntTD* is carried out in the same manner as of *PcntTD* above. It is worth noting that *Standardized Time-Weighted Volume* (*QStdTWV*) is used as a proxy to examine the market depth at each single time unit. In other words, it examines how fast and how much volume traders need to clear the limit order submitted and thus move the price.

$$QStdTWV_i = \frac{QTWV_i}{\sum_{i=0}^{9} QTWV_i} \qquad \text{Equation 7.5}$$

where $QTWV_i$ is the *Time-Weighted Volume* of each digit group, and

$$QTWV_i = \sum (QV_t \times (QT_{t+1} - QT_t)) \qquad \text{Equation 7.6}$$

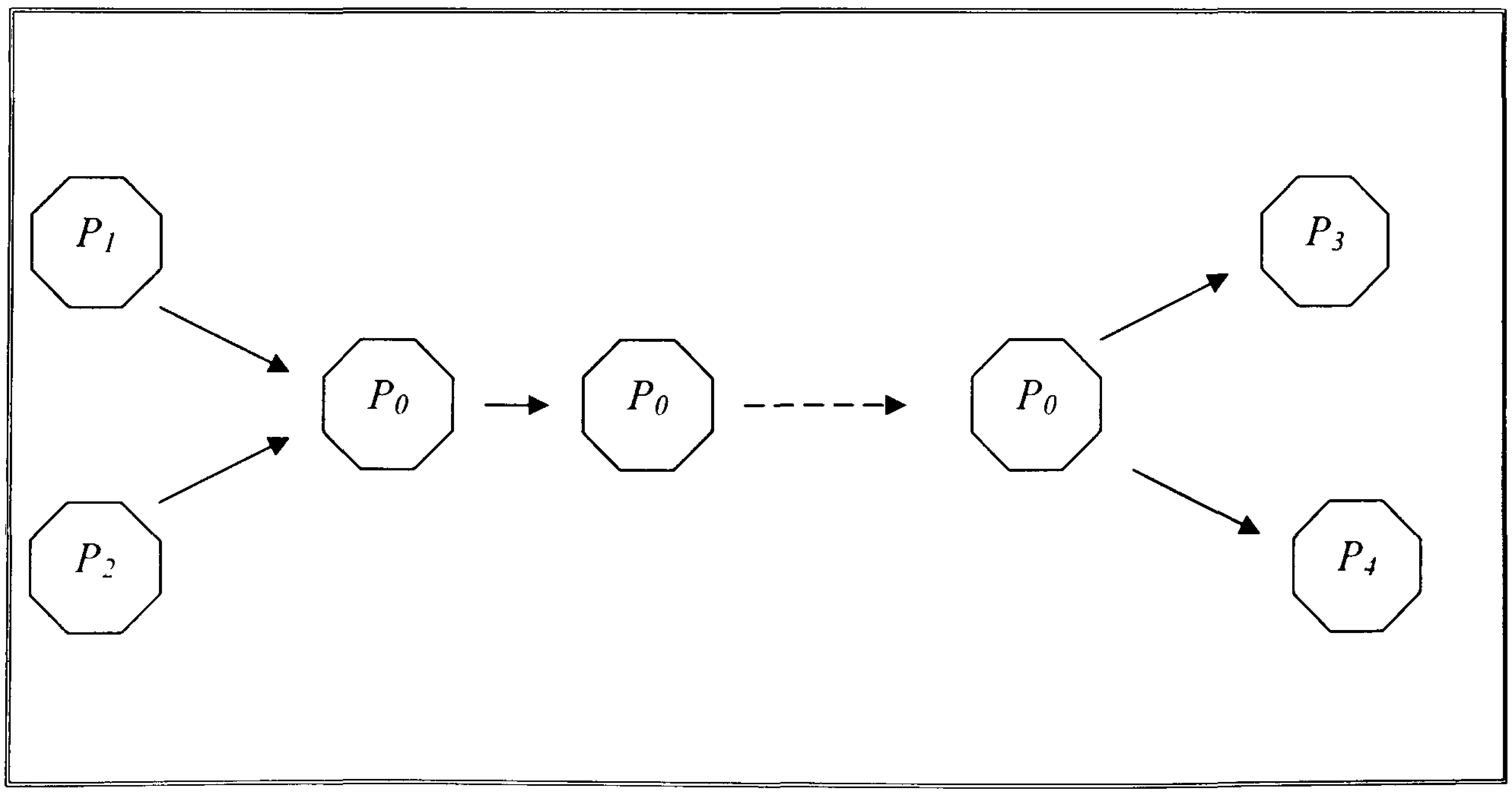
where $i = 0, 1, 2, \ldots, 8, 9$. QV_t is the quote volume of each observation. QT_t is the time stamp of each observation.

7.5.2.3 Price Resistance – Transaction Price Analysis

Prior studies have examined the price resistance within the context of stock indices. Donaldson and Kim (1993) found that the Dow Jones Industrial Average (DJIA) closed on average fewer times on index values in the neighbourhood of 100-levels. Ley and Varian (1994) also found fewer observations around the 100-levels for the DJIA. In contrast to these prior studies, the purpose here is to analyse price resistance in the context of individual stocks. In addition, some new measures of price resistance are developed.

A resistance point makes it difficult for prices to cross; for example, it takes more volume and more time to cross a price resistance level. First, consider the price movements summarized in Figure 7.1.

Figure 7.1 Illustration of Price Movement



In Figure 7.1, there are four types of price movement around P_0, *DU*, *UD*, *DD* and *UU*. The *DU* (down/up) price movement means the previous price P_1 drops to P_0, and (no matter how many transactions trade at price P_o) then rises to P_3; whereas, with the UD (up/down) price movement, price moves up from P_2 to P_0 and then down to P_4. Neither of these price movements can be classed as crosses and would indicate a price resistance level. In contrast, the *DD (down/down) Cross* is the combination of $P_1P_0P_4$, and the UU (up/up) Cross is the $P_2P_0P_3$ combination. With these different possible price movements, a digit would be seen as a price resistance level if statistics for *DU+UD* are larger than those for *DD+UU*.

Within the 4 types of *price movement*, the Frequency (*F*), Average Number of Trades (*AvgNT*), Average Volume (*AvgV*) and Average Time Duration (*AvgTD*) are all examined. First, the Frequency (*F*) is carried out for each digit group's 4 types of price movement (*UD*, *DU*, *UU*, and *DD*). Second, the Average Number of Trades (*AvgNT*) of each type of price movement within each digit group is calculated. For example, let the price of the first transaction move from £1.95 and stay at £1.96 for the next 3 transactions, and then move to £1.97. In this context, it is a *UU-Cross* with the number of trades equalling 5. It will then be divided by the number of *UU-Crosses* to get the average number of trades of digit 6 for a *UU* cross. Similarly, continuing the *UU-Crosses* example, the Average Volume (*AvgV*) and Average Time Duration (*AvgTD*) are also averaged by the number of *UU-Crosses*.

7.5.3 Empirical Methods

The last significant digit of prices should be uniformly distributed, if there is no clustering or resistance point. Moreover, if the last significant digit is not uniformly distributed, the statistical significance needs to be tested via nonparametric tests. The Wilcoxon (ranks of the observations) scores are reported and the Kruskal-Wallis (*K-W*) test is used to test whether the differences among the digits are statistically significant. More specifically,

$$a(R_j) = R_j \qquad \text{Equation 7.7}$$

where R_j is the rank of the observation j and $a(R_j)$ is the Wilcoxon score.

The *K-W* statistic is:

$$W = \left[\frac{12}{n_T(n_T+1)}\sum_{i=1}^{k}\frac{R_i^2}{n_i}\right] - 3(n_T+1) \qquad \text{Equation 7.8}$$

where

k = the number of populations

n_i = the number of items in sample i

$n_T = \sum n_i$ = total number of items in all samples

R_i = sum of the ranks for sample i

7.6 Empirical Results

7.6.1 Price Clustering – Transaction Price Results

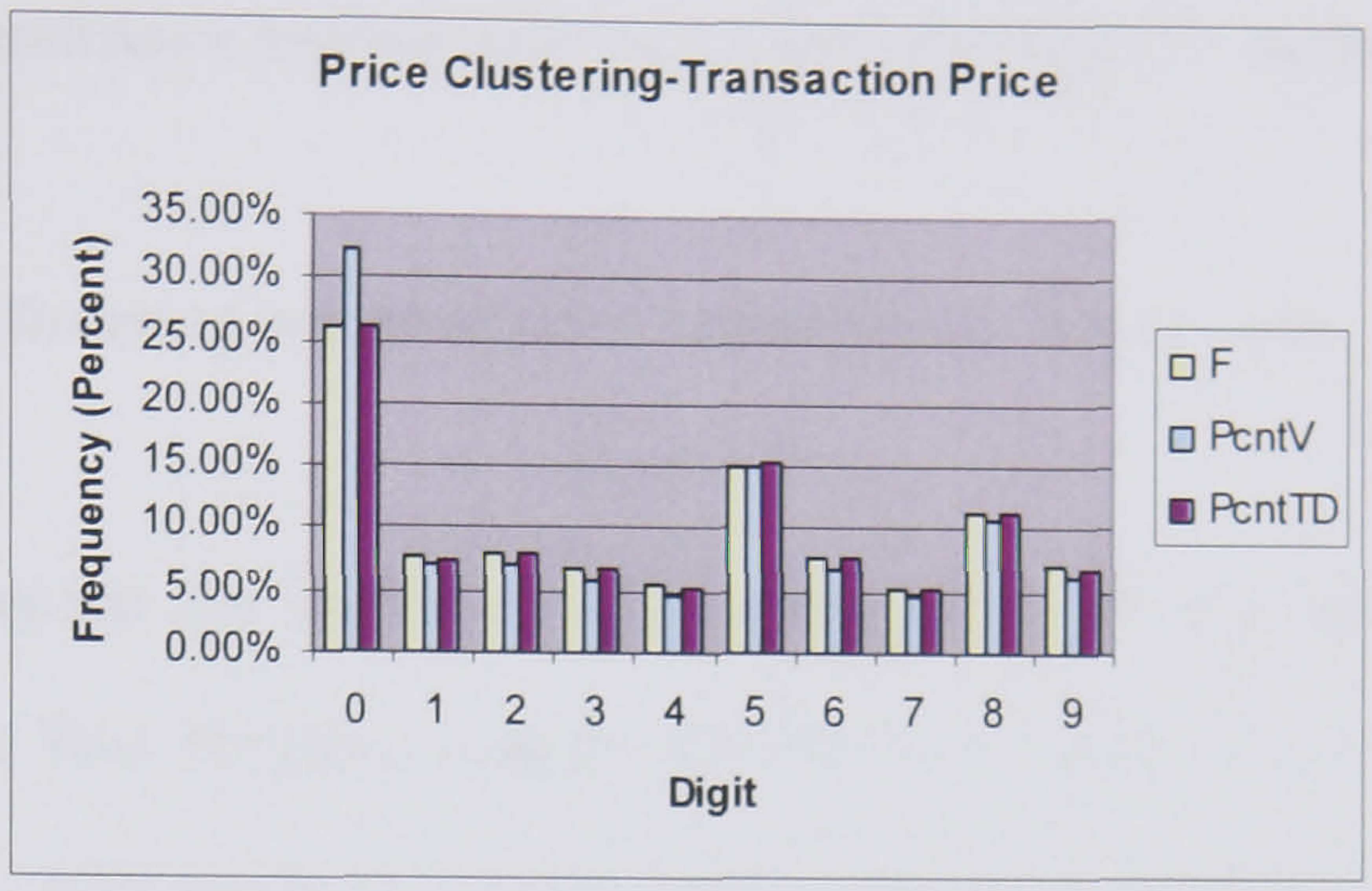
Table 7.1 reports the results for *Frequency (F)*, *Percentage Trading Volume* (*PcntV*) and *Percentage Time Duration* (*PcntTD*) for digits 0 to 9. Trading volume is measured as the percentage volume and time duration is measured as the percentage time duration. For each of the measures, Table 7.1 reports the mean, standard deviation, and the mean Wilcoxon Score (across the 566 stocks). The *K-W* statistics are also reported, which test whether the digit groups are identical, together with the degrees of freedom and their *p*-values. Figure 7.2 shows the results for the first column of each measurement in Table 7.1, which is the mean of the trading frequency, percentage trading volume and percentage time duration measures for each digit group.

Table 7.1 Price Clustering – Transaction Price Results

Table 7.1 reports the results for *Frequency* (*F*), *Percentage Trading Volume* (*PcntV*) and *Percentage Time Duration* (*PcntTD*) for digits 0 to 9. Trading volume is measured as the percentage volume and time duration is measured as the percentage time duration. For each of the measures, Table 7.1 reports the mean, standard deviation, and the mean Wilcoxon Score (across the 566 stocks). The *K-W* statistics are also reported, which test whether the digit groups are identical, together with the degrees of freedom and their *p*-values.

	F			PcntV			PcntTD		
Digit	mean	STD	MeanScore	mean	STD	MeanScore	mean	STD	MeanScore
0	26.07%	6.95%	5350.01	32.36%	7.91%	5368.11	26.08%	7.22%	5338.19
1	7.56%	1.57%	2488.34	6.99%	1.91%	2623.60	7.47%	1.64%	2453.85
2	8.08%	1.71%	2787.09	7.08%	1.86%	2659.87	8.08%	1.85%	2793.40
3	6.74%	1.76%	1933.49	5.79%	1.90%	1878.48	6.73%	1.83%	1985.55
4	5.39%	1.64%	1122.48	4.56%	1.71%	1161.91	5.31%	1.69%	1150.37
5	14.91%	2.18%	4775.36	15.01%	2.35%	4760.89	15.24%	2.42%	4775.23
6	7.68%	1.70%	2545.44	6.66%	1.79%	2435.22	7.74%	1.90%	2592.60
7	5.37%	1.59%	1086.03	4.64%	1.75%	1175.36	5.31%	1.68%	1131.19
8	11.26%	1.45%	4158.74	10.63%	1.96%	4091.64	11.30%	1.67%	4124.58
9	6.94%	1.42%	2058.02	6.27%	1.96%	2149.92	6.73%	1.59%	1960.05
_KW_			4124.36			4001.63			4054.50
DF_KW			9			9			9
P_KW			<.0001			<.0001			<.0001

Figure 7.2 Price Clustering-Transaction Price



Overall, the statistics for digits 0, 5, and 8 for all three measurements are higher than those for the other digits. There are more than 25% of transactions trading on digit 0, 15% of transactions on digit 5 and 11% on digit 8. In contrast, transactions on all the other digits are less than 10%, which is the theoretical probability of each digit's frequency. Especially, those statistics for digits 4 and 7 are exceptionally lower. Only about 5% of trades occur on digits 4 and 7. The percentage volume and duration measures show similar results as reported for frequency. In addition, all the *K-W* statistics in Table 7.1 confirm the statistical significance of the differences across the digits.

The finding of price clustering at 0 and 5 is consistent with previous research (e.g., Osborne, 1962, Niederhoffer, 1965, 1966, Harris, 1991, and Brown et al., 2002). The results also support the finding in marketing research by Heeler and Nguyan (2001), who find that not only digits 0 and 5 are over-represented in Asia, but also digit 8 is significantly over-represented in pricing commodities.

Furthermore, the preference for digit 8 and an aversion to digits 4 and 7 support the cultural preference hypothesis in the context of the Chinese markets.

7.6.2 Price Clustering and Resistance – Limit Order Price Results

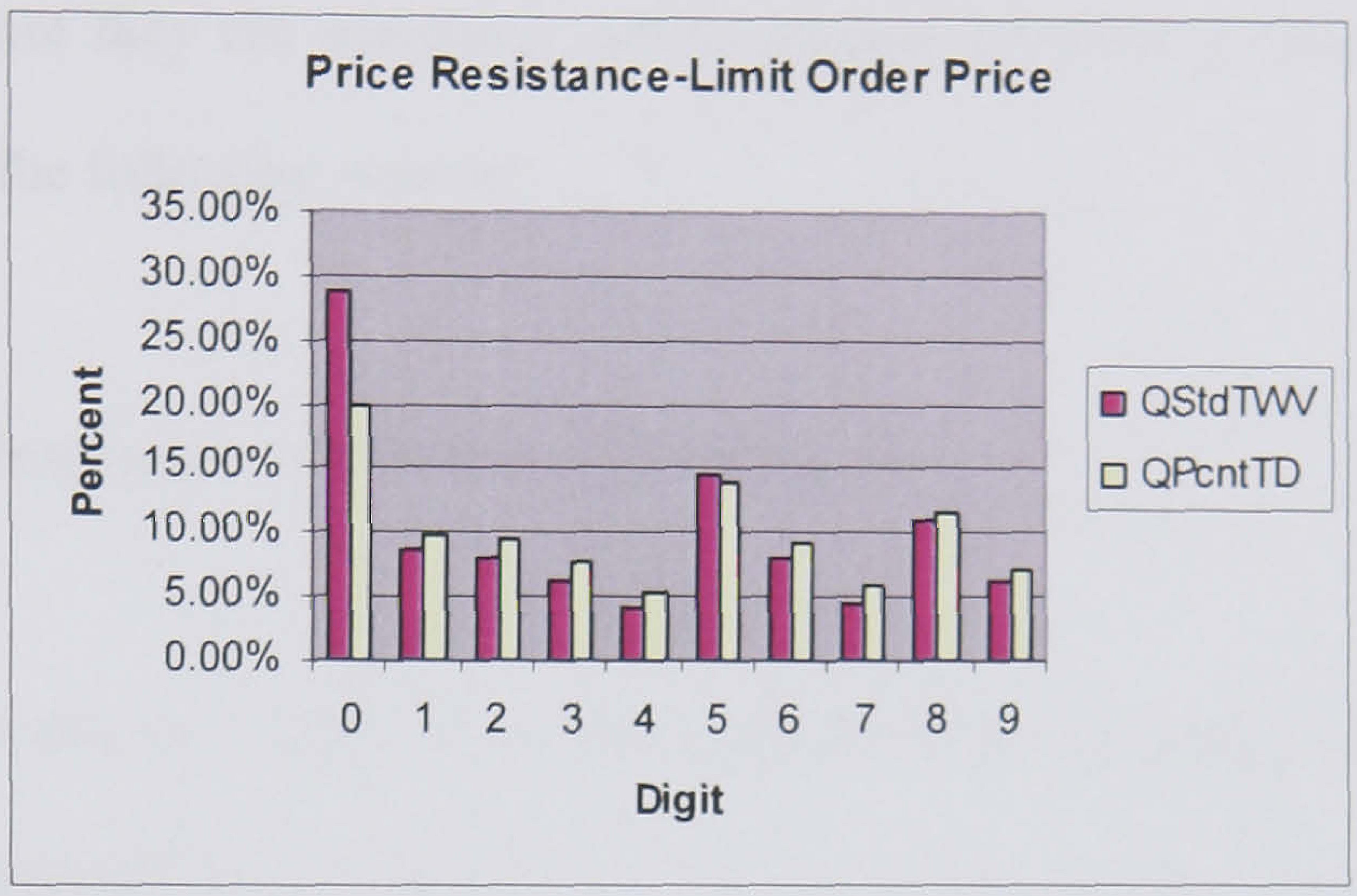
Table 7.2 reports the results for *Percentage Time Duration* (*QPcntTD*) and *Standardized Time-Weighted Volume* (*QStdTWV*) by examining the limit order prices ending with the digits between 0 to 9. Similar to Table 7.1, it also shows the mean, standard deviation, the mean Wilcoxon Score (across 566 stocks), and the *K-W* statistics together with the degrees of freedom and their *p*-value. Figure 7.3 shows the results of the first column of each measure in Table 7.2, which is the mean of those measurements for digits from 0 to 9.

Table 7.2 Results for Limit Order Price Analysis

Table 7.2 reports the results for *Percentage Time Duration* (*QPcntTD*) and *Standardized Time-Weighted Volume* (*QStdTWV*) by examining the limit order prices ending with the digits between 0 to 9. Similar to Table 7.1, it also shows the mean, standard deviation, the mean Wilcoxon Score (across 566 stocks), and the *K-W* statistics together with the degrees of freedom and their *p*-value.

	QStdTWV			QPcntTD		
Digit	mean	STD	MeanScore	mean	STD	MeanScore
0	28.82%	9.06%	5269.94	19.86%	5.91%	5221.00
1	8.68%	3.87%	3040.00	9.91%	1.91%	3166.62
2	8.14%	4.25%	2804.73	9.54%	1.74%	2960.35
3	6.14%	3.00%	2037.45	7.84%	1.86%	2029.03
4	4.28%	3.47%	1145.04	5.26%	1.86%	857.82
5	14.56%	5.07%	4422.46	13.98%	2.72%	4631.26
6	8.03%	4.30%	2755.13	9.31%	1.81%	2835.11
7	4.38%	2.75%	1231.71	5.82%	1.83%	1067.42
8	10.85%	5.32%	3686.60	11.43%	1.93%	3887.93
9	6.13%	4.22%	1911.94	7.04%	2.27%	1648.46
_KW_			3420.87			4079.44
DF_KW			9			9
P_KW			<.0001			<.0001

Figure 7.3 Price Resistance-Limit Order Price



The results in Table 7.2 and Figure 7.3 confirm the finding of the last section that the digits 0, 5, and 8 are preferred in China's stock markets. It indicates that investors like to put more limit orders at prices ending with digits 0, 5 and 8 and consequently form clusters. About 29% of the limit order prices end with digit 0 and these orders stay on the limit order book for about 20% of the time in the trading period. Moreover, digit 5 (or 8) also shows a higher propensity with about 15% (11%) of the limit order prices ending with digit 5 (or 8) and these orders staying on the limit order book for about 14% (11%) of the time in the trading period. On the other hand, digits 4 and 7 show a lower propensity with only about 4% of the limit order prices ending with these digits and only about 5% of the time in the trading period being on these digit endings. The *K-W* statistics also indicate that the digit groups are significantly not identical.

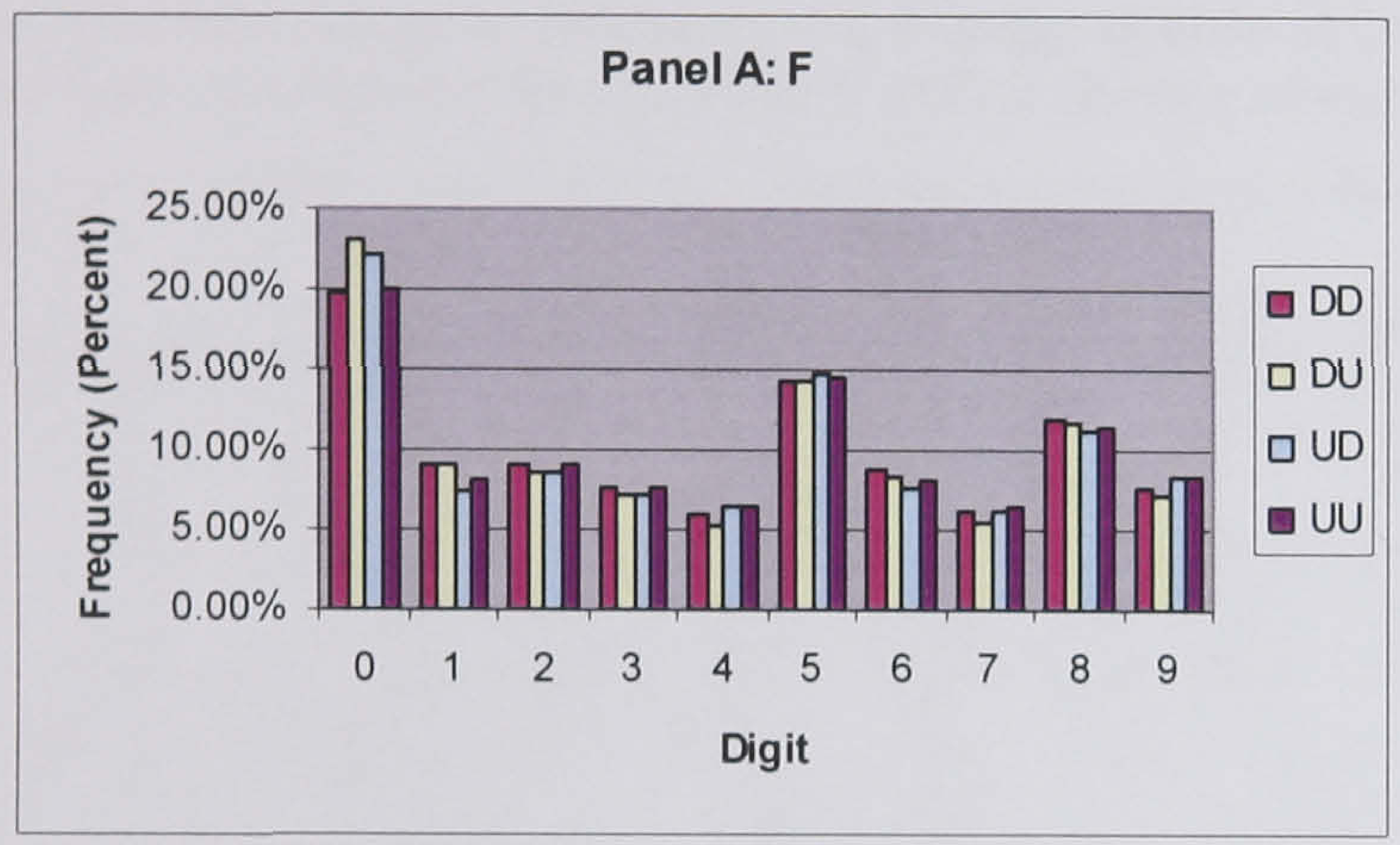
The findings tend to support Sonnemans's (2003) hypothesis that price clustering is caused by limit order submission, which could also cause resistance points. Whether or not they are resistance points depends on further results, which are discussed in the following section.

7.6.3 Price Resistance – Transaction Price Results

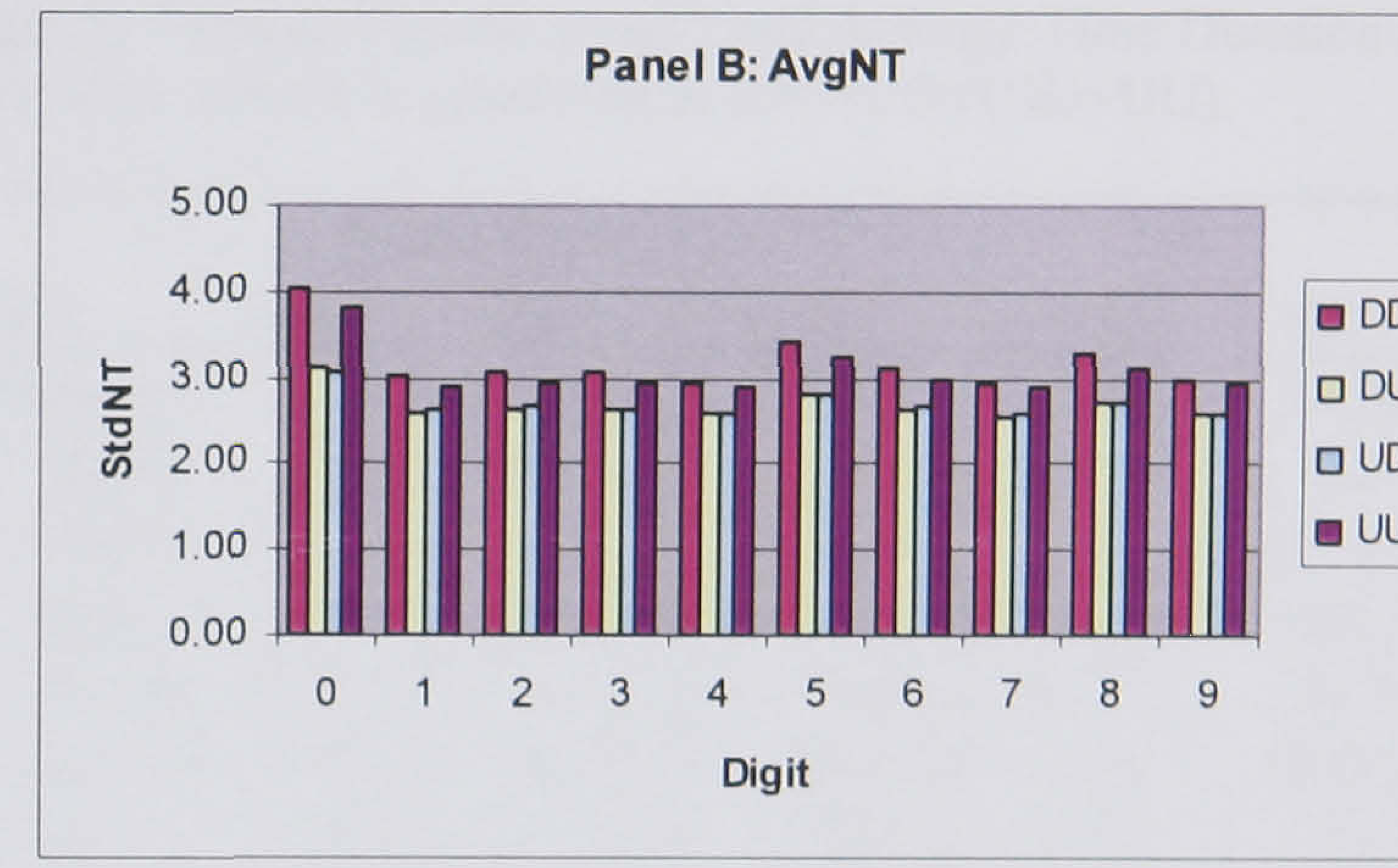
The results in this section are from examining resistance points directly. Table 7.3 reports the mean of the four measures: Frequency (*F*), Average Number of Trades (*AvgNT*), Average Volume (*AvgV*) and Average Time Duration (*AvgTD*). The measurements are reported for the 4 types of price movements for digits 0 to 9. The R/C is the ratio resistance over cross, which is calculated as (DU+UD)/(DD+UU).

Figure 7.4 All Types of Price Movements

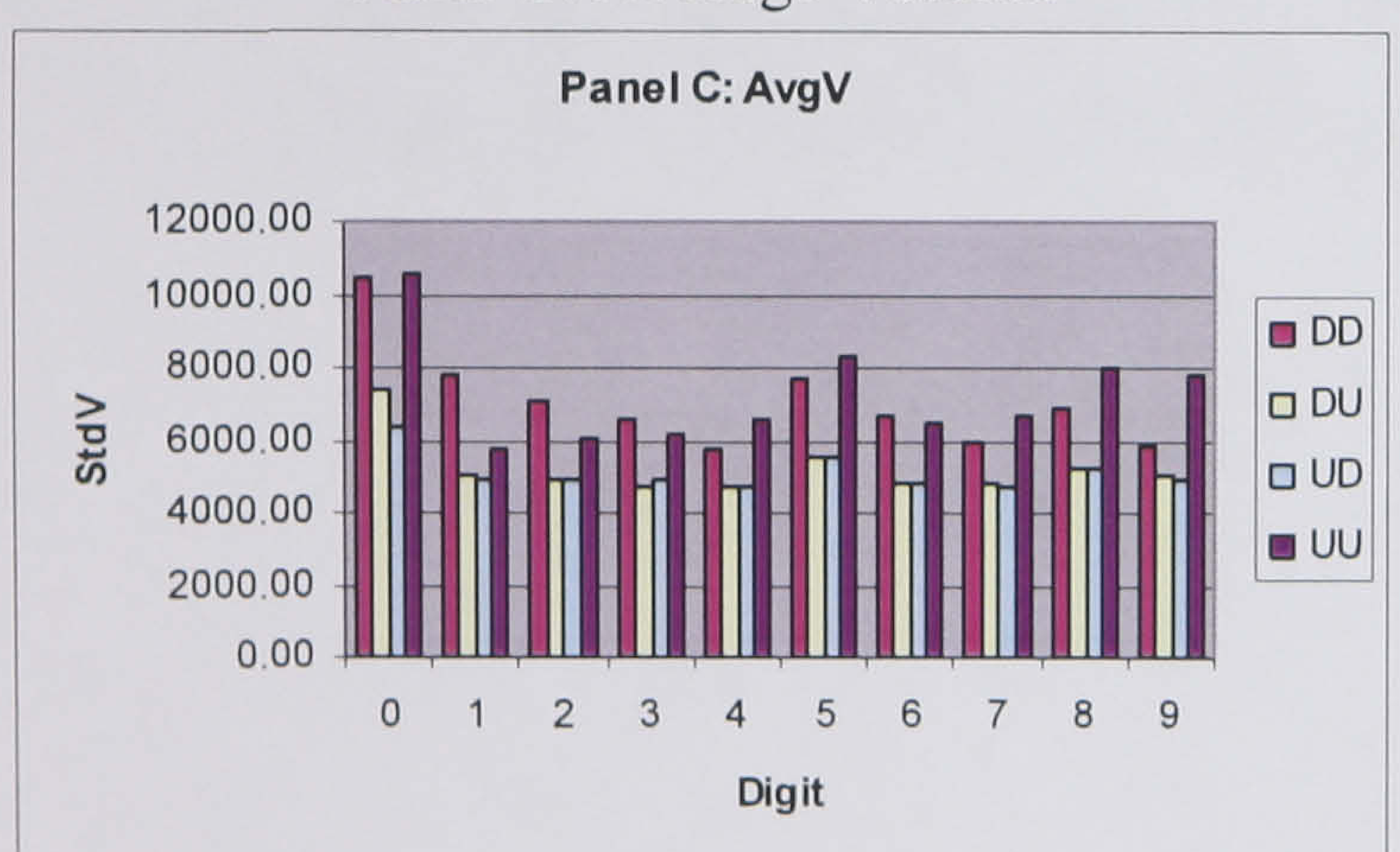
Panel A: Frequency



Panel B: Average Number of Trades



Panel C: Average Volume



Panel D: Average Time Duration

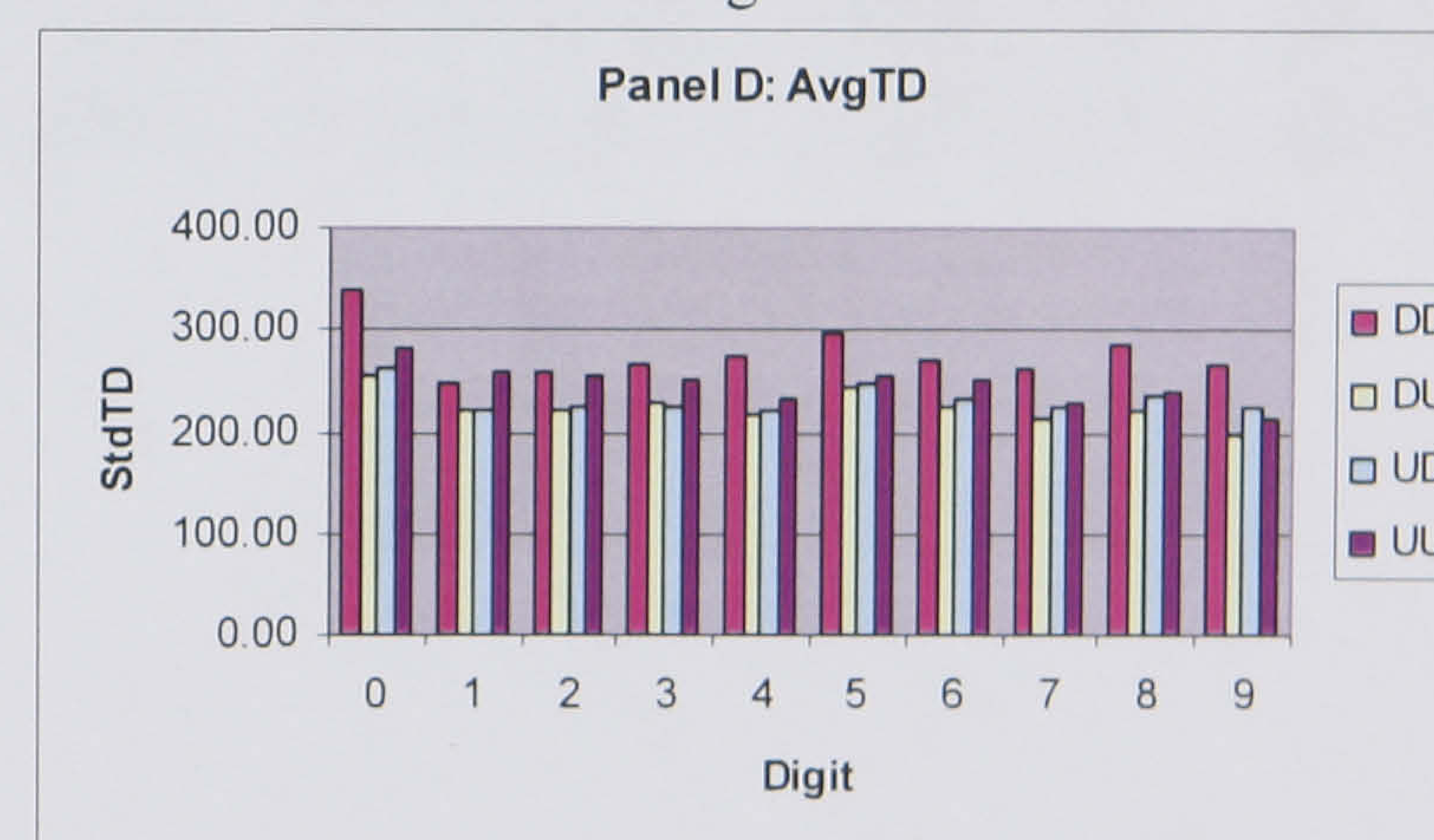


Table 7.3 Price Resistance – Transaction Price Results

Table 7.3 reports the mean of the four measures: Frequency (*F*), Average Number of Trades (*AvgNT*), Average Volume (*AvgV*) and Average Time Duration (*AvgTD*). The measurements are reported for the 4 types of price movements for digits 0 to 9. R/C is the ratio of resistance over cross, which is calculated as (DU+UD)/(DD+UU).

	mean_F					mean_AvgNT					mean_AvgV					mean_AvgTD				
digit	DD	DU	UD	UU	R/C	DD	DU	UD	UU	R/C	DD	DU	UD	UU	R/C	DD	DU	UD	UU	R/C
0	19.66%	23.06%	22.09%	19.91%	1.14	4.03	3.1	3.05	3.81	0.78	10484.84	7355.24	6384.61	10547.99	0.65	340.92	256.91	264.75	283.18	0.84
1	9.06%	9.01%	7.45%	8.17%	0.96	3.02	2.59	2.62	2.91	0.88	7838.9	4990.69	4927.82	5774.85	0.73	246.1	222.81	220.13	260.19	0.87
2	9.00%	8.60%	8.59%	8.99%	0.96	3.05	2.62	2.68	2.96	0.88	7078.58	4875.69	4874.76	6083.07	0.74	259.81	221.74	225.41	253.78	0.87
3	7.60%	7.13%	7.16%	7.51%	0.95	3.06	2.64	2.63	2.94	0.88	6541.35	4741.18	4874.62	6186.45	0.76	268.03	229.02	223	250.55	0.87
4	6.03%	5.29%	6.54%	6.53%	0.94	2.96	2.58	2.58	2.91	0.88	5710.96	4746.43	4754.21	6580.42	0.77	273.47	218.53	219.58	231.35	0.87
5	14.35%	14.20%	14.73%	14.50%	1.00	3.42	2.8	2.8	3.26	0.84	7654.69	5575.31	5496.92	8312.22	0.69	298.35	242.47	247.31	253.41	0.89
6	8.71%	8.36%	7.70%	8.19%	0.95	3.13	2.64	2.67	2.99	0.87	6683.14	4842.28	4855.62	6452.51	0.74	270.6	224.6	230.5	250.6	0.87
7	6.20%	5.56%	6.22%	6.44%	0.93	2.94	2.56	2.57	2.9	0.88	5945.67	4824.39	4755.32	6639.6	0.76	262.92	213.62	223.99	230.2	0.89
8	11.86%	11.62%	11.31%	11.43%	0.98	3.27	2.71	2.71	3.1	0.85	6831.94	5210.68	5184.4	7964.85	0.70	286.86	222.13	235.62	239.55	0.87
9	7.54%	7.19%	8.22%	8.34%	0.97	2.98	2.57	2.59	2.92	0.87	5865.73	5013.1	4920.34	7772.46	0.73	266.13	196.96	225.32	214.15	0.88

Figure 7.4 shows the mean of the measurements by different types of price movement for digits 0 to 9. Panel A shows that the frequency of trades not crossing digit 0 (i.e., DU and UD) is substantially higher than that of trades passing through it (i.e., DD and UU). For the other digits the frequencies of trades not crossing the digit are lower than those of trades which pass through them. These results suggest that digit 0 is the only resistance point. When the price reaches this point, it is more likely to bounce back than pass through. Although digits 0, 5 and 8 are found to be clustering points, only digit 0 is a resistance point. These results confirm previous findings of Donaldson and Kim (1993) and Ley and Varian (1994).

Panel B of Figure 7.4 presents the average number of trades. Although the statistics for DU+UD are not larger than UU+DD within each digit, the digit 0 is found to be different from the other digits in at least two ways. First, the number of trades it takes to leave this digit is larger than the others. For example, for a *DD-Cross* it takes 4 trades to leave digit 0 and only about 3 trades to leave digits such as 1, 2, 3, 4, 7 and 9. Second, the ratio of (DD+UU)/ (DU+UD) for digit 0 is larger than others. These results confirm the findings in panel A that it takes more trades, or in other words it is more difficult to pass through digit 0. Hence, digit 0 is a resistance point.

Panel C (Figure 7.4) shows average volume and Panel D (Figure 7.4) shows average time duration, respectively. The results in Panel C are similar to those in

Panel B because the volume of trades is highly correlated with the number of trades. Panel D shows that in general it takes longer to pass through a digit (DD+UU) than to bounce back (DU+UD).

In summary, the results confirm that prices are more likely to bounce back than pass through those prices ending with the digit 0. It also takes more trades, more volume and more time to cross the digit 0 than to bounce back. So prices ending with digit 0 form the only resistance point in China's stock markets, which is consistent with the previous findings of Donaldson and Kim (1993), Ley and Varian (1994) for the DJIA, and Koedijk and Stork (1994) for the indices in four major stock markets (Standard and Poor Composite in the US, Brussels Stock Exchange Belgium, FAZ General Germany and the FTSE 100 in the UK).

7.7 Conclusions

The purpose of this chapter has been to extend the work of Brown et al. (2002) on the impact of Chinese cultural factors on price clustering to China's stock markets. The results show clearly the impact of cultural factors with there being a higher propensity to cluster on digit 8 (along with the digits 0 and 5 which has been a common finding in most prior work on price clustering in stock markets) and a lower propensity to cluster on digits 4 and 7. While these results are further supported by an analysis of limit order prices, a range of measures for price resistance levels shows no support for cultural factors, with only the digit 0 being found to be a resistance level. In conclusion, while cultural factors help to explain price clustering in the Chinese stock markets. they do not help to understand price resistance levels.

Since the emergence of behavioural finance financial economists have grown more receptive to entertaining behavioural and psychological explanations. In the case of China, the special characteristics and unique culture might provide interesting insights. Broadly speaking, the Chinese culture is distinguished from the Western culture in many ways, even including how business is conducted. For example, in China it is the right *'Guanxi'* that makes all the difference in ensuring that business will be functioned effectively and be successful. *'Guanxi'* literally means 'relationships', and stands for any type of relationship. In the Chinese business world, it is the *'Guanxi'* that smoothes all operations and minimizes risks, and thus is vital to any successful business strategy in China. This relationship is not simply between companies but also between individuals at a personal level. The relationship is not just before sales take place but it is an ongoing process. Western companies must pay close attention to this unique Chinese culture in order to achieve successful commercial activity in China.

Since China has opened its door to the world, it becomes increasingly important for global investors to understand the influence of Chinese culture. This study has implication for practitioners, especially global investors, that it highlights the importance of the Chinese culture. In equity market, a good understanding of

Chinese culture would be of great benefits for global investors in making their investment decisions. Future research could further analyze the influence of some other special behaviour or psychology of the Chinese. Together with the studies of market microstructure, the analysis of investors' behaviour and psychology would provide more comprehensive understanding of the Chinese equity market for both practitioners and academics.

CHAPTER 8

CONCLUSIONS

8.1 Introduction

Copeland and Weston (1988) argued that in an efficient capital market, prices fully and instantaneously reflect all available relevant information. To study the market efficiency, the perfect market assumptions need to be relaxed. Perfect capital markets require the following conditions: markets are frictionless, there is perfect competition, markets are informationally efficient, and all individuals are rational expected utility maximizers. However, equity markets do not behave like that in real world: transaction costs exist, competition is not perfect, information costs, and investors are not fully rational. Since the equity markets are not a frictionless environment, the institutional design of a market will affect market efficiency.

Market microstructure research examines how prices are set under specific trading mechanisms. Broadly speaking, a trading mechanism consists of three dimensions: the market participants, the exchange and the trading rules. There are many factors under the heading of market microstructure that can affect the price formation process; for example, order driven versus quote driven markets, traders' trade size and even investors' psychology. This study employs microstructure analysis to examine various issues about the market efficiency and investors' trading strategies in the Chinese equity market.

This research first investigates the market efficiency and evolution of China's stock market via analyzing the ongoing predictive ability and profitability of simple, well known technical trading rules. Second, it employs high-frequency data to document the intraday patterns of price behaviours. Third, it examines informed traders' trading strategy by analyzing which trades move prices. Finally, it studies the irrationality of investors by analyzing the effect of Chinese cultural factors on price clustering and resistance.

The completion of this study answers the questions raised in chapter 1. While the financial markets throughout the world are being driven to achieve greater efficiencies and transparency, China's stock market has been evolving towards efficiency. However, the market is not yet efficient: for example, the calendar anomalies are found to exist. Moreover, prices could even be manipulated by large block trades. Consistent with behavioural finance studies, Chinese culture provides interesting insights into the price discovery process.

The findings of this research have implications not only for practitioners but also, more importantly, for regulators and policy makers who are involved in the design of an efficient market. Firstly, the QFII scheme in 2002 makes it possible for foreign investors to invest in the A share market for the first time, and this thesis hopes to help overseas' investors understand the characteristics, the microstructure and the efficiency of markets better. It could also improve domestic investors' understanding as well.

Secondly, in recent years, several related strands of literature on law, institutions, finance and economic growth have emerged in financial economics. The research started from La Porta et al. (1998) that first established a significant positive correlation between law and finance (and hence economic growth). The central proposition in the law and economics literature is that laws matters for economic and market development. In the case of China, two excellent studies of Chen (2003) and Allen et al. (2005) have discussed issues of the legal development. In China, neither the legal nor financial system is well developed. Chen (2003) argued that in China the experience of economic growth and capital market development is more like 'growth-then-law', which is consistent with Coffee's (2001) 'crash-then-law'. Moreover, he confirmed that capital markets are the most conducive to the formation of a politically powerful constituency and hence more aggressive legal change. In order to improve the market design and the legal system, a thorough understanding of the characteristics, the microstructure and the efficiency of the equity market is needed in the first place. This thesis hopes to serve as a reference for the policy makers and the regulators, such as the CSRC, to design an efficient market.

The present chapter has two objectives. First, it is to summarize the major findings. Second, it is to discuss the limitations of this study and the future direction of research. Therefore, the structure of this chapter is as follows. Section 8.2 summarizes the major findings. Section 8.3 comments on the limitations of this study and discusses the future research direction.

8.2 Summary of Major Findings

8.2.1 Market Efficiency and Evolution

Since there has been a long debate about whether the stock market is efficient, people might ask a very simple question whether China's stock market is efficient or not. If not, given the rapid development of the market has it been evolving towards efficiency? Chapter 4 investigates the market efficiency and evolution of China's stock market, and concludes that the market is not efficient but has been evolving.

Chapter 4 extends the work of Brock et al. (1992) and Tian et al. (2002) investigating the evolution of China's stock market via analysing the ongoing predictive ability and profitability of simple, well known technical trading rules.

It analyses a wider range of developed stock markets and sub periods across the 1990's in the case of China's stock market. The results suggest that while technical trading rules had short term predictive ability and profitability in the Chinese stock markets during the 1990's, this lessened as the decade progressed and the markets evolved. The notion of stock markets evolving is supported by results for a number of the main developed markets where the technical trading rules had predictive ability during the 1970's that disappeared by the 1990's.

The evolution of markets is supported by the results for both the main developed markets and Chinese markets. It is consistent with the prediction of market evolution that if markets are not efficient, and in the absence of an alternative mechanism, the theory of financial market efficiency seems to have to rely on an evolutionary mechanism. Overall, the results for the evolution of both the developed and Chinese markets bode well for China having stock markets that will underpin its development over the coming years.

8.2.2 Intraday Patterns

Chapter 5 examines the intraday variation in the bid-ask spread, trading volume and volatility in China's stock market. The results can be summarized as follows. First, the bid-ask spread has an L-shaped pattern. The spread opens wide and narrows down in the first trading hour and is relatively stable for the rest of the trading day. It shows only a marginal increase at the end of the trading day. The

90-minute lunch break does not change the spread. Second, the volume pattern is relatively flat in the morning session with a marginal increase at the open and marginal decrease at the close: while it shows a J-shaped pattern in the afternoon session. Moreover, both the numbers of trades and trade size contribute to the volume pattern. Third, the pattern of volatility is similar to the spread pattern in that it exhibits an L-shaped pattern.

Although the findings suggest that the existence of the intraday anomalies is not due to the peculiarities of the US markets, the different shapes of intraday patterns provide further insights. The evidence in support of the two main theoretical models of intraday behavior is very mixed. None of the theoretical models could explain the intraday patterns of all three variables in China's stock market, not even in the US or any other markets. Moreover, as these models have been developed in the context of quote-drive market, it is felt that there is a room for a theoretical model to explain the intraday behavior in an order-driven market.

8.2.3 Price Manipulation

Chapter 6 has extended Barclay and Warner's (1993) work on stealth trading to the emerging China's stock market examining which trades move prices. Given the nature of the China's stock market, the price manipulation hypothesis is proposed in addition to the stealth trading and public information hypotheses examined by Barclay and Warner. Using high-frequency data the results show that while medium and large-size trades are associated with disproportionately large, overall, cumulative stock price changes, it is the large-size trades which have the largest effect on cumulative price increases. Thus, while there is some support for stealth trading in the Chinese market, the price manipulation hypothesis finds stronger support.

The results are aligned with the concerns noted by a number of eminent individuals in China. If the current results are confirmed by further research, the policy conclusions are both stark and obvious. First, there will need to be a stricter regime tracking the source of large block trades and large fluctuations in share prices. Second, penalties for purposeful price manipulation will have to be material and strictly enforced. Only then will China's stock market have the opportunity to benefit from an orderly price discovery process.

8.2.4 Investors Psychology

Chapter 7 extends the work of Brown et al. (2002) on the impact of Chinese cultural factors on price clustering in China's stock markets. The results show clearly the impact of cultural factors with there being a higher propensity to cluster on digit 8 (along with the digits 0 and 5 which has been a common finding in most prior work on price clustering in stock markets) and a lower propensity to cluster on digits 4 and 7. While these results are further supported by an analysis of limit order prices, a range of measures for price resistance levels shows no support for cultural factors, with only the digit 0 being found to be a resistance level. In short, the results suggest that investors' psychology does have effects on prices, which is broadly consistent with the proposition of behavioural finance theory. It also enriches the market microstructure literature that not only the trading mechanism affects prices but the psychology of investors does so as well.

8.3 Constraints of the Thesis and Future Research Directions

The advent of high frequency data has been a unique opportunity for researchers to study market microstructure at the finest level of data. Unfortunately, the data used in this study does not include some useful information, such as news data. The lack of the news data limits this study to explore further insights.

First, due to the unavailability of the news data, this study fails to examine any subject associated with information diffusion. For example, Barclay and Warner's (1993) work of stealth trading has focused on a sample of tender-offer targets that have large abnormal price increases before the initial tender-offer announcement. They believed that some traders have valuable private information during the preannouncement period, which provides a good testing ground for their predictions. Although they also investigate all NYSE firms in the 1981-1984 period, the results are weaker than for the tender-offer preannouncement period. Chapter 6 of this thesis is not able to condition any particular information on the sample. Moreover, it becomes more important to examine information diffusion when the price manipulation hypothesis finds support. Chakravarty (2001) extended the framework of Allen and Gale (1992), and presented empirical evidence on stock price manipulation in the United States. They considered what happens when a manipulator can trade in the presence of other traders who seek out information about the stock's true value. In a market without manipulators, the information seekers unambiguously improve market efficiency by pushing prices up to the level indicated by the informed party's information. In a market with manipulators, more information seekers imply greater competition for shares, making it easier for a manipulator to enter the market and potentially worsen market efficiency.

The relationship between the incidence of information and market activity is of fundamental importance to financial economics, because the EMH is concerned about the link between information and the change in asset's price. In broad terms, it suggests that all relevant information should be incorporated in the price. O'Hara (1997) argued that knowing how quickly information is assimilated into security prices might yield new insights into the nature of market efficiency. Research has been undertaken to consider the speed of adjustment of security prices to new information (Hong et al., 2000). Future research should pay more attention to examine the relation between price behavior and information flow, if data is not a problem.

Second, compared with extensive research on the quote-driven markets, theoretical models on the order-driven market is sparse. For example, significant intraday patterns have been documented in chapter 5 and previous literature. However, the intraday patterns found in order-driven market, which is different to those found in quote-driven markets, cannot be fully explained by existing theoretical microstructure models. The existing literature on market microstructure suggests that trading systems have important effects on the price discovery process (see Cohen et al., 1986, and Schwartz, 1988). Order-driven systems and quote-driven systems have quite different price formation and return generating processes. These differences in trading systems may lead to different empirical findings.

In a quote-driven market, investors can obtain price quotations from market makers prior to order submission and trade immediately with a market maker. By contrast, in an order-driven system investors submit their orders for execution through an auction process. The differences between the two systems provide an important area of further study. First, more empirical research should be carried out in order-driven markets to examine whether it is the fundamental difference in trading systems that generates different intraday patterns. Second, theoretical models are definitely needed.

Finally, although the institutional structure of the stock market is found to affect prices, it is difficult to specify the models in the actual microstructure setting. In the real world it is the investors, no matter whether they are rational or irrational, who actually trade. Their behaviors are too complex to be modeled accurately. This makes it more interesting to analyze traders' behavior and psychology and how they affect the price discovery process. Financial economists have grown more receptive to entertaining psychological explanations: for example, Hirshleifer's (2001) survey assessed the theory and evidence regarding investor psychology as a determinant of asset prices. More recently, Coval and Shumway (2005) documented strong evidence that behavioral biases have effects on prices. Not surprisingly, strong demand has emerged for empirical work to investigate how behavioral and psychological factors influence investors' decisions. Therefore, the future research direction should pay more attention to investors' behavior and psychology.

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