Commonality in liquidity : evidence from the Chinese stock market

Zheng, Xinwei

Commonality in Liquidity: Evidence from the Chinese Stock Market

XINWEI ZHENG

PhD THESIS 2008

UNIVERSITY of DURHAM

To my parents

ACKNOWLEDGEMENTS

First of all, I would like to express my sincere gratitude to my supervisor, Dr Zhichao Zhang, who has been so generous with his time and in sharing his expertise. Without his encouragement, advice and inspiration, this thesis would have not been possible. I am deeply indebted to him for his valuable supervision.

I am grateful to Mr Don Starr for providing me with the opportunity of teaching the module of Modern Chinese economics. The experiences I have gained are invaluable.

Finally, I wish to express my thanks and appreciation to my colleagues of the Business School at the University of Durham who have shared their considerable expertise, and their suggestions, critiques and comments by seminars and annual reviews. I have been fortunate indeed to have had the chance to work with them.

My family have supported me throughout the year of my study. I would like to record here my gratitude for their endless love and encouragement.

Commonality in Liquidity: Evidence from the Chinese Stock Market

By Xinwei Zheng

ABSTRACT

The thesis examines the commonality in liquidity on the Chinese stock market from three different aspects. Using a proprietary set of data from China, I confirm that commonality in liquidity is present in China and seems more significant and pervasive than that of similar markets. Its existence is robust to the influences of the size, industry, and up and down markets effects. In parallel to a market-wide component, I find in the commonality construct an industrial component. Liquidity of large firms' stocks is found to be more likely to move with market liquidity. I also find that Chinese investors exhibit herding behaviour in their liquidity management. In the face of shocks to market liquidity, Chinese market participants tend to adjust both the spread and the depth. In a down market, market liquidity moves more widely and commonality in liquidity becomes more significant.

Sources of commonality in liquidity in China are multitude. Using the number of trades as an indicator of informed trading, results suggest a common component in asymmetric information at the market and industry levels. Following the market

conditions approach, I find that commonality in liquidity is determined by common factors in market volatility and market liquidity. But common factors in interest rate and market return are insignificant. In addition, market return, volatility, and share turnover can significantly influence liquidity. Thus, market liquidity is found to be resilient to both market-level and economy-wide shocks. Inflation and monetary policy are particularly important in explaining liquidity's variation.

Existence of commonality in liquidity has found implications for asset pricing. The impacts of commonality in liquidity showed the cross-section of average returns in China derived from a priced liquidity risk factor. In a dynamic asset pricing model, aggregate liquidity is found to be a priced risk factor and a significant liquidity risk premium is present on the Chinese stock market when dispersing average returns in the portfolios and adopting relevant measure of market-wide illiquidity.

DECLARATION

Contents

Tables

Figures

Chapter 1

Introduction

I. Liquidity as an Attribute of Financial Assets

1.1 Definition of Liquidity

Liquidity is generally recognised as a critical attribute of financial assets and is vitally important to the proper functioning of financial markets. Although its definition is illusive, the literature on market microstructure generally agrees that liquidity is related to the ability to buy and sell assets easily, and this ability enables buyers and sellers to trade into and out of positions quickly without having a large effect on prices (O'Hara, 2004).

In the literature, liquidity is usually considered in terms of such dimensions including tightness, depth and resiliency. According to Kyle (1985), tightness refers to how far transaction prices diverge from mid-market prices and it is measured by bid-ask spread. Depth describes the size of an order flow innovation required to change a given amount of prices. Resiliency refers to the speed with which prices recover from a random, uninformative shock. In addition, the

measures of liquidity also include, for example, the price impact of order flow and trading volume-based measures. In empirical research, various proxies have been suggested as measures of liquidity. Demsetz (1968) was among the first to propose the bid-ask spread as the liquidity measure and to show that spread can be regarded as the cost of immediacy. This has greatly facilitated the subsequent research on various aspects of liquidity.

1.2 Importance of Liquidity

The importance of liquidity reflects in almost all aspects of the working of financial markets. Liquidity enables individual traders to meet unforeseen financial needs without incurring major losses. For institutions, illiquidity means abnormal returns on assets, less trade volume and more risks (Instefjord, 1999). Liquidity is also an important determinant of the firm's cost of capital. It may critically influence investors' portfolio decisions because it closely relates to transactions costs, and because low transaction costs can result in high liquidity and vice versa.

On the other hand, the lack of liquidity can have adverse effects on the value of an asset (Amihud and Mendelson, 1986). In their examination of the return-illiquidity relation, Brennan and Subrahmanyam (1996) combine a number of empirical techniques from asset pricing and market microstructure research. Using transactions data, they estimate both the variable (trade-size-dependent) and the fixed costs of transaction, and show that the components of illiquidity on asset returns represent an important bridge between the empirical measures of adverse

selection and asset returns. Datar, Naik and Radcliffe (1998) propose the turnover rate of an asset as a proxy for its liquidity, and show the importance of liquidity in explaining the cross-sectional variation in stock returns.

The capacity of a market participant searching for potential gains of trade is dependent on the level of liquidity. Wurgler (2000) suggests that there is more price information in larger markets, possibly because liquidity and low transaction costs lead to more effective arbitrage. This allows investors and fund managers to distinguish between good and bad investments.

Liquidity could also be a major policy concern for regulators. For example, the sharp evaporation of liquidity from some markets can pose a fatal threat to financial stability, as happened after the stock market crash in October 1987 and the financial crises in Asia and Russia during 1997-1998 (BIS, 1999).

II. Determination of Liquidity

2.1 The Determinants of Liquidity in Quote-driven Markets

Harris (2003) shows everyone in the markets has some effect on liquidity. Impatient traders take liquidity. O'Hara (2004) suggests that disclosure rules, greater transparency, insider trading laws and lower transactions costs would enhance market liquidity and make markets more attractive to investors. Traders

will choose instead other portfolio choices, and illiquid markets are prone to instability. It is then critically important to understand how liquidity is created and consumed and the forces driving the movement of liquidity.

Three factors have been identified in the literature as the main determinants of liquidity in a quote driven trading system: order processing costs, inventory risk and asymmetric information (Stoll, 1978a). Order processing costs comprise all the transaction costs incurred by the market maker, who is the main provider of liquidity in quote-driven markets. These costs include the fixed, direct costs of arranging, recording and clearing the transactions, information technology equipment and software and variable costs such as exchange seat fees and staffing costs (Saad, 2002).

However, the most important determinants of liquidity are inventory risk and asymmetric information. Dealers must control their inventories if they are to trade profitably, and thus they will incur the costs of inventory management. Inventory costs comprise the opportunity cost of the funds tied to the inventory that a market maker has to hold to provide immediacy, and the cost due to exposure to the risk of adverse price changes affecting the value of the inventory. Stoll (1978a) shows that large inventory positions are expensive to finance and will expose dealers to the risk of serious losses if the movement of prices is not in their favour. In addition, in the case where a seller cannot afford to delay, he may have to sell not to the natural buyer but to a dealer who anticipates being able to lay off the position later. For the dealer, this involves being exposed to the risk of adverse

price changes while holding the asset in inventory due to demand pressure. The dealer will require compensation for the risk in the form of bid-ask spread, and this will be realised as a cost to the seller (Amihud, Mendelson and Pedersen, 2006).

The impact of inventory control on liquidity has been extensively researched in the literature (Demsetz, 1968; Bagehot, 1971; Tinic, 1972; Stoll, 1978a; Amihud and Mendelson, 1980; Ho and Stoll, 1981; Zabel, 1981; O'Hara and Oldfield, 1986; Madhavan and Smidt, 1993, among others). In the process of inventory control, the bid and ask prices are set to influence their clients' decisions to buy or sell. Dealers can effectively decrease their inventories by lowering their bid and ask prices, thus encouraging traders to buy from, but not sell to them. Alternatively, they might decrease their bid sizes while increasing their ask sizes, thus once again encouraging traders to buy from them, but not to sell to them. In order to increase their inventories, dealers can take the opposite approach, raising bid and ask prices, increasing bid sizes, and decreasing ask sizes, thus encouraging traders to sell to, but not buy from them. By buying and selling in equal quantities, dealers ensure that their inventories remain balanced, as close as possible to their fair and orderly market levels (Chordia et al., 2000; Harris, 2003). As a result, inventory management induces changes in the spread, and hence liquidity.

Complex choices would be presented to the dealer by uncertainty in future order flow and value of the stock. O'Hara and Oldfield (1986) demonstrate that the

bid-ask spread comprises three components: (1) the known limit-orders; (2) a risk-neutral adjustment for expected market orders; and (3) a risk adjustment for uncertainty regarding market orders and inventory value, because dealers' attitudes to risk may affect liquidity through its effect on both the level and the size of the spread.

Asymmetric information and the resultant adverse selection cost represent another major determinant of the provision of liquidity. Gloston and Milgrom (1985) show that, even without transaction costs and inventory risk, spreads will still be required due to the presence of asymmetric information. This is because market makers must require compensation for possible losses from trading with informed traders when providing immediacy to the market. This is the cost of adverse selection paid for by all traders on the market, hence it is also the cost imposed by the informed traders on other market participants (Chan, 2000). During periods of large market-wide information asymmetry, market makers tend to widen their spreads further to cover their consequent exposure to the risk of possible large losses. Because these periods are characterized by high informed trading across stocks, it is unlikely that the market maker will be able to balance losses made from trading one group of stocks against gains from another trade. Therefore, market makers will only supply liquidity when they are confident that their losses to informed traders will be offset by their gains from uninformed traders (Bagehot, 1971; Copeland and Galai, 1983; Glosten and Milgrom, 1985; Kyle, 1985; Admati and Pfleiderer, 1988; Menyah and Pauldyal, 2000).

Adverse selection models have become the centre of recent research in the field. Empirically, Glosten and Milgrom (1985) show that the bid-ask price will rise alongside an increase in information asymmetry and with the degree of uncertainty regarding asset value. In the empirical literature, many believe that the real indicator of asymmetric information is better proxied by the number of trades rather than by the volume. Barclay and Warner (1993) suggest that informed traders tend to split orders into small units, thus concealing their activities. For volume, Jones et al. (1994) show that it has little impact on volatility once trading frequency has been taken into account.

Inventory control models and asymmetric information models are not necessarily in opposition to one another. Rather, inventory risk and asymmetric information risk may combine to affect the level of liquidity provision. According to the traditional inventory model, a dealer holding an optimal inventory will react to the effect of order flows on his inventory position by adjusting prices. This effect will be transitory. In information models, the order flows provide information regarding future values. Thus, changes in order flows can also affect beliefs and so have a permanent effect on prices (Saad, 2002). While inventory models focus mainly on the relationship between the spread and the dealer's inventory costs, the asymmetric information models concentrate on the implications for the dealer of traders who have better information about future prices, and gives prominence to the role of information asymmetry in determining the size of the spread (Menyah and Pauldyal, 2000).

These two determinants may also explain other liquidity measures of a quote-driven system. For example, for depth as a measure of liquidity, Stoll (1978a) shows that in the absence of asymmetric information, depth is positively influenced by individual trading frequency and the size of the average individual trade. However, with asymmetric information, the opposite results are obtained. Furthermore, in the presence of asymmetric information, a specialist fearful of more informed traders may quote less depth (Admati and Pfleiderer, 1988). Once again, this may be because informed traders tend to split orders, so their transactions are frequently smaller than the quoted depth, and depth becomes irrelevant to all but uninformed traders.

2.2 Liquidity Determination in Order-driven Markets

Recent years have witnessed a rise in the popularity of order-driven trading systems, and their adoption by a number of countries. Ahn and Cheung (1999) report that by the late 1990s, around 34 important financial markets outside the USA had implemented order-driven market mechanisms. This growth has attracted an increase in research interest in order-driven markets. For the purpose of this research, the order-driven market mechanism is of particular importance, since the market under our examination, i.e. the Chinese stock market, has adopted an order-driven system.

An order-driven market differs from a quote-driven market in a number of ways. First, there are no dedicated market makers in an order-driven system. Second, unlike a quote-driven market where only the bids and asks of market markets and

other designated parties are displayed, the order-driven market displays all the bids and asks, making such markets transparent. Third, order-driven trading systems are anonymous, because prior to a trade the identities of the participating agents are unknown.

The mechanisms for liquidity provision and consumption also differ between the two types of market. Typically, in an order-driven environment, the public investors separate into limit order and market order traders (Handa, Schwartz and Tiwari, 1998). Market orders are executed immediately at the best price available when they arrive at the exchange. As such they demand immediacy of execution and hence, in general, represent demand for liquidity. Limit orders are kept in a limit order book waiting to be executed at the price specified by the order placer. Therefore, they supply liquidity to future traders (Handa and Schwartz, 1996; Cheung and Song, 2005; Foucault, Kadan and Kandel, 2001).

Demsetz (1968) stresses the importance of limit orders as a source of liquidity. In the hybrid markets in America where both market markers (specialists and dealers) and limit order traders supply liquidity, limit orders account for 54% of all orders submitted through the SuperDot system (Harris and Hasbrouck, 1996). In pure order driven markets, because there are no market makers, liquidity is supplied solely by limited orders. This means that an order-driven market relies exclusively on market participants placing limit buy and sell orders for liquidity (Frey and Grammig, 2006).

Depending on the type of order submitted, any market participant may be a demander or a provider of liquidity in an order-driven trading environment. Market orders can guarantee an immediate execution at the best available prices, but the placers have no control over such prices. Placers of limit orders have control over the prices, but face two kinds of risk: non-execution and adverse selection (Handa and Schwartz, 1996b). The limit orders either are not executed at all, or receive delayed execution at the prices at which they are written. Furthermore, since the prices of limit orders are fixed, the late arrival of new information may invalidate those prices. As a result, adverse information may trigger harmful execution and for the placers there may be adverse selection costs to pay.

Naturally therefore, the first question one would ask about the supply and demand for liquidity in an order-driven environment is what will determine a trader's choice between submitting a limit or a market order. This essentially implies the question of who will be the liquidity providers or demanders in an order-driven architecture. Glosten (1994) classifies traders into patient and urgent traders and relates the traders' characteristics to the order types they would place. Within this framework, an informed trader tends to be an urgent trader because she wants to exploit her superior information quickly, as the value of private information she possesses may depreciate over time. She therefore places market orders and thus, informed traders tend to be demanders of liquidity. On the other hand, patient traders who may gain from trading with liquidity traders may suffer a loss from trading with informed traders. They will place limit orders when they believe the

expected gains exceed the possible losses. These patient traders therefore supply liquidity to the market (Glosten, 1994).

Bloomfield, O'Hara and Saar (2005), however, argue that informed traders supply liquidity to the market. Using experimental analysis, they illustrate how electronic markets can endogenously create liquidity even in the presence of information asymmetry. They show that informed traders capitalize on their informational advantage by changing their use of market and limit orders, usually starting by employing market orders, then moving gradually to limit orders, thus reflecting their better information regarding the true value of the asset.

In an effort to endogenize the traders' order choice in an equilibrium model, Handa and Schwartz (1996b) postulate that the traders' choice between market orders and limit orders is dependent on the beliefs that investors hold about the probability of orders being executed against an informed or a liquidity trader. In addition they, and also Foucault (1999), point out that in periods of high price volatility, investors will place more limit orders than market orders. Foucault, Kandan and Kandel (2005) develop a dynamic model to explore interactions between traders' impatience, order placement strategies and waiting times. They also show that patient traders post limit orders and impatient traders opt for market orders. A trader's impatience is determined by the level of the waiting cost, which is related to the cost of delayed execution. So behind the order choice lie traders' comparisons between the cost of a delayed execution and the benefit of immediate execution. Other factors affecting the equilibrium include the

proportion of impatient traders in the population, which determines the degree of competition among liquidity providers, and the tick size as the cost of the minimal price improvement. Cheung and Song (2005) argue that the use of market orders depends on the size of the premium included in the transaction cost, which is reflected in the bid-ask spread. The use of limit orders depends mainly on the sum of execution and adverse selection risks, which in turn is dependent on the depths and sizes of the orders in the primary bid and ask queues.

Biais, Hillion and Spatt (1995) use the example of the Paris stock market to show how liquidity is supplied and consumed in an order-driven marketplace, as well as the interaction between liquidity and priority considerations. They find that investors are more likely to place limit orders when the bid-ask spread is large or the order book is thin. When the spread is tight, investors are more likely to hit the quote. This means that investors will supply liquidity when it is valuable to the marketplace, and will consume liquidity when it is plentiful.

In empirical research, the most popular measure of liquidity in an order-driven architecture is again the bid-ask spread, but unlike its quote-driven market counterpart, here it is given by the difference between the lowest ask price of a sell order and the highest price of the buy order that was not executed (Mendelson, 1982; Friedman, 1993). Most studies focus on the components of this bid-ask spread and the responsiveness of the spread to the changes in these components. Empirically, this is equivalent to investigating the determinants of liquidity and their effects.

According to Glosten (1994), in an order-driven trading environment, adverse selection costs are a critical determinant which generate positive bid-ask spreads. In their study of the Tokyo Stock Exchange (TSE), Ahn, Cai, Hamao and Ho (2002) analyse the components of the bid–ask spread, and find an important role of adverse selection cost in those components. Handa, Schwartz, and Tiwari (2003) show that the size of the spread is a function of asymmetric information and the difference of valuation among investors. Frey and Grammig's (2006) empirical results confirm that in a limit order market, liquidity and adverse selection effects are inversely related. They also provide evidence that in these markets, adverse selection effects are more severe for less frequently traded stocks and stocks with smaller capitalization.

These empirical findings highlight the critical importance of adverse selection in determining liquidity. As for its relative importance in relation to that in a quote-driven market, this may be gauged in the finding that, on the NYSE, the adverse selection component of the spread from limit-order quotes is greater than the corresponding part from specialist quotes (Chung, Van Ness and Van Ness, 2004).

Through for example their effects on price volatility, market conditions are also a critical argument in the determination of liquidity in order-driven markets. In his study, Foucault's (1999) main finding is that limit order traders facing adverse selection risks and high asset volatility demand greater compensation. This means that the volatility of risky assets is also a key determinant of the order strategy decision. From this, one may infer that the posted spreads are positively related to

asset volatility. Sandas (2001) finds that the risk of adverse selection is more severe in order-driven markets with higher stock-specific or market-wide volatility, and less severe in markets where there is less volatility.

Employing empirical and numerical tests to find the fundamental elements for the formation of the bid-ask spread, Wang, Zu and Kuo (2007) find that the most important elements are the characteristics of traders and market competition. Previous studies had identified traders' valuations and asymmetric information as the basic rationales of order strategy. Wang, Zu and Kuo (2007) refine and extend these rationales, including within their model heterogeneous beliefs, adverse selection and the reward-to-variability ratio of investment. Choi and Cook's (2005) study of liquidity on the Japanese stock market also confirms that liquidity shocks are associated with macroeconomic events, such as those in September 1998 when the Asian financial crisis broke out, and in September 2001 when the financial reform package was announced in Japan.

In their 2001 study, Hollifield et al. find that the conditional probability of a limit order submission is shifted by greater book depth and by higher trading volume and that in each case the difference is more than that predicted by the change in profitability alone. This leads to an increase in the supply of liquidity. Their findings also show that liquidity supply is positively related to the expected fill ratio and negatively related to the degree of adverse selection risk. They find some evidence for a reduction in demand for liquidity during periods of high volatility, perhaps as a result of uncertainty about asset values. In cases where lagged

volume is allowed to become a factor, it has a positive effect on arrival rate, but the effect on liquidity demand is insignificant.

In short, order-driven markets provide a new ground for research into liquidity provision and consumption. While liquidity in a quote-driven market is provided by market makers and other designated parties, in an order-driven environment it is exclusively provided by limit orders. On the other side of the order-driven market, demand for liquidity is from market orders. In such an order-driven market, the microstructure literature recognizes the adverse selection risk as a major determinant of a security's liquidity. Other contributing factors may also be at work. Empirical evidence indicates that attributes of microstructure are important to the determination of liquidity. These include characteristics of traders, levels of traders' impatience, relative proportions of order types, tick size, trading volume and numbers. In addition, through their effects on traders' valuation or price volatility, the market and macroeconomic conditions are also determinants.

III. Commonality in Liquidity

Conventional research on liquidity has been mainly concerned with liquidity of individual securities. In such models, liquidity is generally viewed as a transaction cost that has only a secondary effect on the level of asset prices (O'Hara, 2003). Moreover, determination of liquidity is being examined from the perspectives of

factors that are particular to a security. However, Domowitz, Hansch and Wang (2005) show that it is not sufficient to examine individual securities in isolation, because securities are often related to one another and investors often trade in a portfolio of securities. These inadequacies in the conventional literature have inspired new research to deal with liquidity in a market-wide context. As a result, there has recently emerged a burgeoning literature on commonality in liquidity.

Commonality in liquidity refers to the common underlying determinants of liquidity across securities. Its empirical manifestation is the co-movement between variations in individual stock liquidity and variations in market- and industry-wide liquidity (Chordia, Roll, and Subrahmanyam, 2000). According to Brockman and Chung (2002), commonality refers to the proposition that an individual firm's liquidity is at least partly determined by market-wide factors.

In a series of papers referring to the New York stock market, Chordia et al. (2000; 2001; 2002) demonstrate the existence of commonality in liquidity, postulating as its sources inventory effect and asymmetry information. In their seminal 2000 article, they demonstrate that liquidity measures co-vary significantly. Using quoted spreads, proportional spreads, effective spreads, proportional effective spreads and quoted depths as proxies for variation in individual stock liquidity, they find that market-wide liquidity is a significant determinant of the liquidity of individual assets, even after accounting for determinants of liquidity of individual firms. In their subsequent paper (2001), they find that measures of liquidity

market-wide are also significantly related to trading volume. Their 2002 article further explores order imbalances as a measure of trading activity, finding that order imbalances reduce liquidity.

Chordia et al.(2000) were among the first to provide evidence for the existence of such liquidity commonality and to articulate its potential sources. Since the publication of their first seminal paper, there has surfaced an increasing number of papers exploring the existence of commonality in liquidity, and the role of systematic liquidity in various markets (Lo and Wang, 2000; Hasbrouck and Seppi, 2001; Huberman and Halka, 2001; Brockman and Chung, 2002; Fernando, 2003; Fernando and Herring, 2003; Pastor and Stambaugh, 2003; Bauer, 2004; Chollete, 2004; Coughenour and Saad, 2004; Gibson and Mougeot, 2004; Henker and Martens, 2004; Domowitz, Hansch and Wang, 2005; Martinez, Nieto, Rubio, and Tapia, 2005; Fernando, Herring, and Subrahmanyam, 2006).

At least three reasons can be cited for the importance of commonality in liquidity and its related research. First, given that liquidity is a determinant of asset prices, commonality in liquidity will have an impact on asset prices. However, this is largely ignored by conventional asset pricing models. Fundamental changes are therefore required for these models to incorporate this effect. Future models will not only have to explain the impact of individual liquidity on an asset's price, but must also consider common determinants of liquidity. Eventually, this research will make contact with monetary theory (how aggregate liquidity shocks are

propagated across different types of asset) and will also have to be considered in the regulation of financial markets.

Second, for market participants, the issue now becomes whether market liquidity is priced on the stock market, or whether a liquidity risk factor enters the stochastic discount factor. Given that individual stock liquidity is at least partly driven by common determinants, shocks to these common factors tend to generate market-wide effects. If asset returns and market liquidity are correlated, the source of common liquidity effects could constitute a non-diversifiable risk factor. In other words, systematic liquidity variation is non-diversifiable, and so is a priced risk factor. Thus, investors holding such assets will demand a systematic liquidity premium to bear the risk (Fujimoto, 2003). As such, commonality in liquidity also poses a problem to diversification strategies that rely on picking stocks that do not correlate in returns (Domowitz, Hansch and Wang, 2005).

Third, commonality in liquidity is also important to central bankers and regulators. As a market risk factor that is non-diversifiable, it is naturally a policy concern. By its very nature, shocks to commonality will have market-wide effects and hence affect the functioning of the financial market as a whole. In more serious cases, a financial crisis can be triggered by shocks to liquidity commonality. Fernando and Herring (2003) show that common liquidity shocks may precipitate a shift in investors' beliefs about the market, which in turn could lead to market collapse. In fact, the simultaneous decline in liquidity across several markets was a major contributory factor in the Asian and Russian crises in 1997-1998.

Empirical evidence for common liquidity movements will therefore assist regulators to improve market design (Coughenour and Saad, 2004). As a result, exchange organisations, regulation, and investment management could all be improved (Chordia et al., 2003). Knowledge of what drives liquidity, and the characterisation of its effects, will prove to be critical in preventing market crashes due to sudden evaporation of liquidity (Persand, 2000). The findings of the study on commonality should also shed light on how aggregate liquidity shocks are propagated across different types of assets, and may thereby help formulate a better monetary policy.

Academically, research on commonality opens an entirely new avenue for exploring the dynamics of liquidity, through a shift of emphasis from the single-asset focus to a market-wide common determinant view. Furthermore, future asset pricing models must consider the influence not only of individual liquidity, but also of those common determinants. For practical investment, a better understanding of the dynamics of liquidity both within and across markets could help investors design improved trading strategies. Findings about the properties of common determinants will also help investors to decide on their liquidity exposures and the rewards they would require. With an improved knowledge of factors that influence liquidity, investors will increase their confidence in financial markets, and will thereby enhance the efficacy of corporate resource allocation (Chordia et al., 2003).

However, the current literature is primarily concerned with the most liquid markets, such as that of the US, and there has been very little research on commonality in the liquidity of emerging markets while liquidity commonality is a major factor contributing to financial crises in emerging economies during 1997 – 98.[1] This suggests that there is a critical gap in the current literature. This paper, with its distinctive emphasis on the case of China, a major emerging market, attempts to fill that gap.

Emerging markets represent an ideal setting for the study of liquidity issues (Bekaert, et al., 2006). In addition to cross-sectional and temporal variations in liquidity on these markets, liquidity effects in emerging markets turn out to be more acute than in developed markets. This is because, in the US market for example, liquidity effects can be mitigated by large numbers of traded securities, diversified ownership structures, and combinations of long- and short-term investors (Bekaert, et al., 2006).

Liquidity on emerging markets is also a major concern for international investment. Chuhan (1992) indicates that poor liquidity was one main reason that prevented foreign institutional investors from investing in emerging markets. Lesmond (2005) points out that investments in emerging markets can yield substantial but volatile returns. The fact that spectacularly high returns can be significantly reduced by the increased illiquidity highlights the importance of

[1] Only since the completion of this thesis have there appeared two other working papers that involve emerging markets. In Brockman, Chung and Perignon (2006a), 47 exchanges, including 17 of emerging economies, are investigated for the existence of liquidity commonality. Kumar and Shah (2006) examine commonality in the liquidity of Indian markets.

addressing concerns about liquidity and its determinants on emerging markets (Lesmond, 2005).

Another significant aspect of this research derives from its focus on order-driven trading systems. Existing research is mainly interested in mature markets that operate a quote-driven system. However, trading systems on emerging markets can be considerably different from those of mature markets. Many emerging markets, including China, have adopted order-driven systems. Brockman and Chung's (2002) study was the first to extend the literature to the order-driven trading system in Hong Kong. However, there has been a lack of research on commonality in emerging order-driven systems.

As arguably the most important emerging economy, China is rapidly becoming a global influence. Research on a critical issue concerning emerging financial markets at large is unlikely to be totally convincing if it does not engage the Chinese case. In fact, the growing size and great potential of the Chinese stock market warrants a closer look at commonality in the liquidity of that market. China today provides perhaps the most important investment opportunity among emerging markets. If the liquidity of emerging markets is a major concern for international investors, it would be most critical for international investments in China. Furthermore, it is imperative to understand liquidity variations in China since illiquidity has proved to be a triggering mechanism of financial crises in emerging economies; if there were to be a financial crisis originating from the China market, the global impact could be huge.

In addition, despite the widespread evidence of commonality in liquidity, there is debate on whether commonality is a widespread phenomenon and hence a general attribute of financial assets. Hasbrouck and Seppi (2001) find that there is only weak evidence of liquidity commonality on the New York market. Fabre and Frino (2004) believe there is no common movement of liquidity on the Australian market. Evidence from China can provide a weighty contribution to this debate.

IV. Research Questions and Organisation of the Thesis

This research is devoted to the study of commonality in liquidity in China, as perhaps the most important emerging market. The governing questions that this research endeavours to solve are whether liquidity commonality is present in China, and if it is, what are the causes and consequences. Understanding these major aspects of liquidity commonality will shed critical lights on the properties of the level and change of liquidity in China, and in view of China's increasing role on international financial markets, it may make an important contribution to the commonality literature.

In the empirical investigation, my datasets are from the Chinese Stock Market and Accounting Research (CSMAR) which includes transactions and quote data from July 2000 to June 2002 for A-shares traded on the SHSE and the SZSE. This is the most extensive and widely used security database in China. CSMAR covers all details of every transaction and related information, providing data on bid and

ask records and also both trading and financial statement data of all listed Chinese companies since their IPOs. My sample used to investigate the existence and causes of commonality in China covers daily data from July 2000 to June 2002. This was a period of wide market variations, so provides rich information about market activities in different market states. In July 2000 and June 2001 the Chinese market was bullish, whereas in July 2001 and June 2002 the trend was for a bear market. For the research on the impact of commonality in liquidity, I also use individual daily and monthly returns for all stocks traded on the Chinese continuous market from January 1993 to December 2003.

In the chapters that follow, I begin by introducing the development of the Chinese stock market, market trading system and liquidity of the market. This is intended to establish the background for understanding the institutional details and the trading mechanism of the Chinese system, which is a pure order driven market. In particular, I will discuss the supply and consumption of liquidity in China's order driven environment, and their determinants.

Next, following the seminal work of Chordia et al. (2000), I empirically investigate whether or not commonality in liquidity exists in China. Using a broad sample of stocks on two separate Chinese stock exchanges, I measure and analyse market-wide movements in liquidity on the Chinese stock market. After filtering, the sample allows us to select a total of 113,960 stock-trading days for the Shanghai Stock Exchange and 130,092 stock-trading days for the Shenzhen Stock Exchange. In testing for the co-variation of liquidity, I examine the

contemporaneous adjustment in liquidity as well as one lead and lag of the market average liquidity variable. Both equal-weighted and value-weighted market liquidity variables are used in the estimation. My empirical evidence confirms that commonality in liquidity is present in China and seems more significant and pervasive than in mature markets. Its existence is robust to the influences of the size, industry, and up and down markets effects.

The new theory of commonality in liquidity calls for attention to the facts that individual stock liquidity can be driven by common underlying determinants. Shocks to these common factors tend to generate market-wide effects. However, it is not fully known what precisely these common factors are. This means the underlying economic drivers of this 'commonality in liquidity' are not well understood (Fujimoto, 2004). Therefore, I go on to explore the sources of common liquidity movements. As the evolution of the literature shows that commonality in liquidity in emerging order-driven markets is likely to be caused by market risks due to common changes in market states or conditions, I adopt a synthetic approach to investigating sources of liquidity co-variation in China. More specifically, I test for information asymmetry and market factors as possible determinants of commonality in liquidity in China using an extensive data set from Chinese sources.

I show that common factors are evident in measures of asymmetric information based on trading frequency in market-wide and industry-wide components by transactions and quote data for July 2000 and June 2002 for A-shares between the

SHSE and the SZSE. For both the SHSE and the SZSE the sum of lead, lag, and concurrent market coefficients, and the sum of lead, lag, and concurrent industry coefficients, are positive and highly significant. Assuming that the number of trades can be used as a reliable indicator of informed trading, these results suggest a common component in asymmetric information at both market and industry levels. I also find that on the Chinese stock market the common factors in market volatility and market liquidity are significantly related to commonality in liquidity. In addition, evidence shows that significant common elements in various macroeconomic factors also cause commonality in China in the period under examination.

This is followed by my study in Chapter 5 of the implications of commonality in liquidity for asset returns. Following the research of Martinez et al. (2005), my empirical work analyses whether the Chinese expected returns between 1993 and 2003 are associated with different liquidity risk factors. Evidence shows that liquidity is a relevant risk factor in explaining average returns in China and that a liquidity risk premium exists on the Chinese market. These results are in agreement with the evidence found in the US and Spanish markets.

Chapter 6 summarizes the main findings of the research and concludes the thesis.

Chapter 2

Trading System and Liquidity of the Chinese Stock Market

I. Development of the Chinese Stock Market

The development of the stock market in China has been an eventful process. Starting at the end of the 19th century, the Chinese stock market was historically one of the oldest and the largest in Asia. In 1891, a Share Brokers Association was formed in Shanghai. This was to be followed by the formal establishment of the Shanghai Stock Exchange in 1904. Following its foundation, the Shanghai stock market experienced dramatic growth and it remained the largest exchange in Asia until shortly after the 1949 Revolution which forced its closure. From then until 1984, the development of the Chinese stock market was completely halted due to the elimination of private ownership (Xu, 1993).

During the first three decades of the command economy under central planning, there was strict government control over all channels of investment. Enterprises could invest only by using direct grants from state budgetary funds or government

allocated bank credits. Shanghai, once an international financial and commercial centre, became just another Chinese domestic industrial city. The financial system was dominated by the state-owned banks and their local branches. Procedures for allocating investment across regions and industrial sectors were more often than not bureaucratic and inefficient (Su, 2003).

The late 1970s witnessed China's launching of economic reforms, including the restructuring of the financial system of the country. Since then, China has undergone fundamental economic transformation, within which the re-opening of the stock market is a milestone of financial reform. In 1981, the Chinese government issued long-term Treasury Bonds, to be distributed through mandatory purchase quotas divided among local governments, enterprises and individuals. This was the first step in a strategy designed to raise capital to cover the budget deficit caused by the decline in fiscal revenues and changes in savings patterns. It marked the official re-opening of China's securities markets. The issuance of treasury bonds was followed by new regulations allowing the issuance of various provincial and local government bonds. There were also enterprise bonds, although these bonds were strictly controlled so as to avoid conflicts with the priorities set in the credit plan. By the end of 1989, the total issue of Chinese securities amounted to 166 billion Chinese Yuan. Of this total, 99% were bonds (World Bank, 1995).

In the early 1980s, China began to experiment further with market oriented economic reforms. Following on from the issuance of bonds, the authorities now

turned to stocks as an alternative channel for raising capital. Thus, in 1984, 11 state-owned enterprises (SOEs) became shareholding corporations, and in November of that year the first publicly issued stocks, Feile Acoustics, became available, with 10,000 shares at 50 RMB per share. In January 1985, Yenchung Industrial Corporation and Beijing Tianqiao Department Store issued shares to the public. However, there was still no over-the-counter market, and trading of stocks and bonds did not begin properly until 1986 (Su, 2003).

In response to the needs of economic transition, the Shanghai Stock Exchange (SHSE) was reopened in December 1990. The establishment of the SHSE was significant not only for the introduction of organized securities sales, but also because for the first time in China, computers were used for stock and bond trading. This marked the end of paper transactions and offered investors the improved efficiency of computer-aided transactions. The Shanghai Exchange adopts a non-profit corporate membership system and deals with spot transactions, not including derivative securities. Most of the listed companies on the SHSE are based locally in Shanghai or nearby areas (Fang, 1991).

The Shenzhen Development Bank issued its first shares to the public in 1987. Over the next three years, this was followed by the flotation and trading of five more issues in the OTC market in Shenzhen. The Shenzhen Stock Exchange (SZSE) was established in July 1991. The SZSE listed companies are based mainly in industrial and commercial cities in inland China (Liu and Green, 2003).

Since then, the Chinese stock market has experienced extraordinary growth, to become the second largest in Asia after Japan in terms of capitalisation (Green, 2003). The statistics can be found in Table 2.1.

Table 2.1 The Largest Stock Markets in Asia, year-end 2001

Sources: Standard and Poor's; Economist Intelligence Unit.

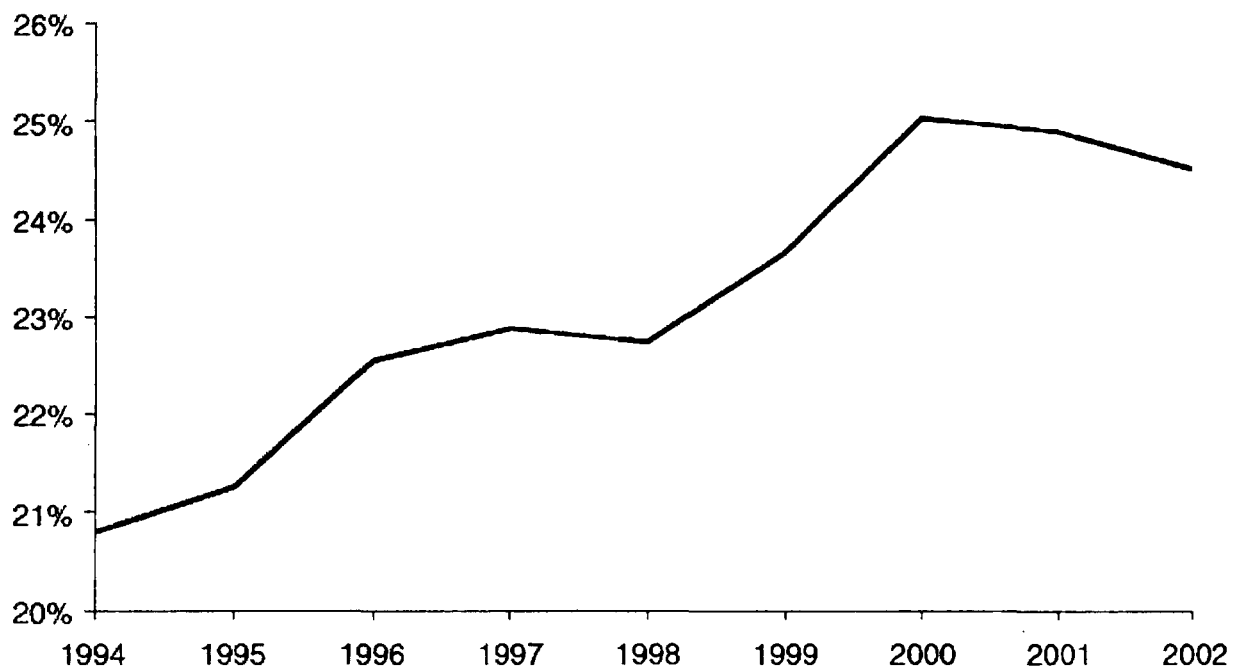
Country	Market capitalisation, $bn	GDP, $bn at market exchange rates	Market capitalisation as a proportion of GDP, %
Japan	2,252	4146	54
China (1)	524	1159	45
Hong Kong	506	162	312
Taiwan	293	282	104
Korea	220	422	52
China (2)	170	1159	17
Malaysia	120	88	136
Singapore	117	86	136
Philippines	42		
Indonesia	23	145	16

Notes: China (1) shows the official market capitalisation. China (2) shows the 'real' market capitalisation, i.e. with non-tradable shares excluded.

Under the supervision of the China Securities Regulatory Commission (CSRC), the two exchanges operate a modern system under which companies must select one exchange to list their shares; cross listing is not allowed. No rule exists governing which exchange a company may choose, but the larger state-owned enterprises tend to list on the Shanghai Exchange, while the smaller and export-oriented companies tend to choose the Shenzhen Stock Exchange (Guo, 2006).

On these two exchanges, most Chinese listed companies are state-owned and they have issued two types of shares that have different properties of liquidity. One

category is the tradable shares (TS). They are usually in the form of new issues to the public, the funds from which are used to develop the issuing company. They are the only shares that can be openly traded on both exchanges. The other type of shares is non-tradable shares (NTS) which are in essence the certificates of existing assets assessed and valued before listing (Beltratti and Bortolotti, 2006; Guo, 2006). Figure 2.1 plots the TS relative to the total market capitalisation.



Source: China Securities and Futures Market Statistical Data, 2002

Figure 2.1: Development of Tradable Share Value in billion Yuan relative to Total Share value.

Sixty percent of shares held by the Administration of State-Owned Property and State-Owned Corporation bodies are non-tradable, while only 30% are circulating shares held by general investors. Wu and Wang (2005) point out that this ownership structure results in a thin stock market. Furthermore, there is a danger of an event risk whereby the illiquid shares may one day be circulated unexpectedly.

In January 2004, the Chinese government officially recognized NTS as a significant obstacle to domestic financial development. As a result, on April 29, 2005, the China Securities Regulatory Commission (CSRC) announced a pilot program to allow four companies (Tsingua Tongfang, Hebei Jinniu Energy Resources, Shanghai Zi Jiang Enterprise Group, and Sany Heavy Industry) to transform their NTS into TS. Existing shareholders would be compensated through an offer of bonus shares, cash, and options. This project was different from earlier moves in that holders of non-tradable and tradable shares may enter into negotiations over the transfer of NTS. The scheme has been seen as a success, with only one of the four pilot companies, Tsinghua Tongfang, failing to win approval of its reform proposal owing to shareholders' disagreement on the compensation plan (China Securities Regulatory Commission, 2005). The NTS reform therefore continued into 2005 and 2006, and successfully turned many NTS into TS (Beltratti and Bortolotti, 2006).

According to Beltratti and Bortolotti (2006), the NTS reform had a significant impact on the behaviour of Chinese listed firms. Once all NTS become tradable, minority shareholders will be able to play a greater role in management decisions, and this may lead to better corporate governance. The reform will facilitate privatisation via the issuing of secondary equity, thus curbing political interference and improving operating performance. The substantial increase in the free float will lead the market to expect better liquidity for the stocks. Furthermore, the market will resolve uncertainty about the timing of the reform process, and this will have positive effects on valuation.

At market prices, NTS have a capitalisation value of about RMB 7883.44 billion ($US1010.70 billion). Most of the NTS are owned by the government and legal entities, which can be in any form of corporation such as privately owned companies, state-owned enterprises or a combination of the two. In 2007, the non-tradable equity of all listed companies was about 947.54 billion shares, or 61.77% of total market equity. Of these NTS, the government owns 80.12%, the legal-entities 17.81%, and others about 2.07% (see Figure 2.2).

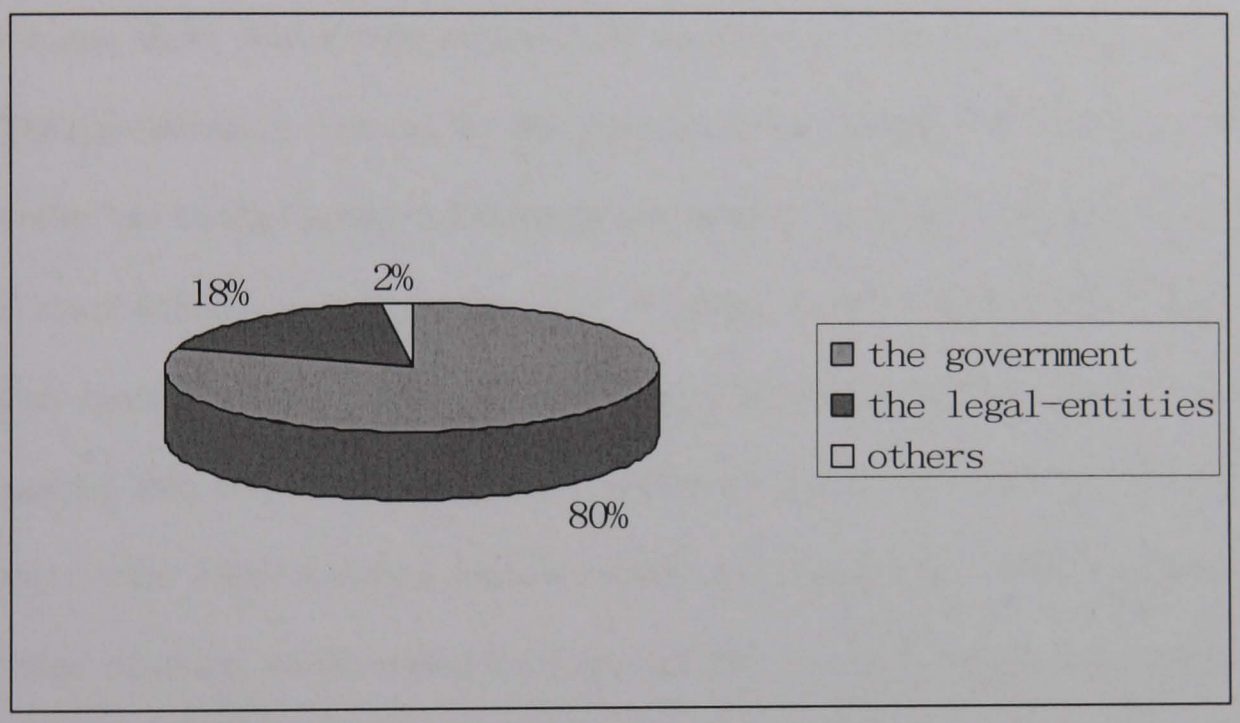
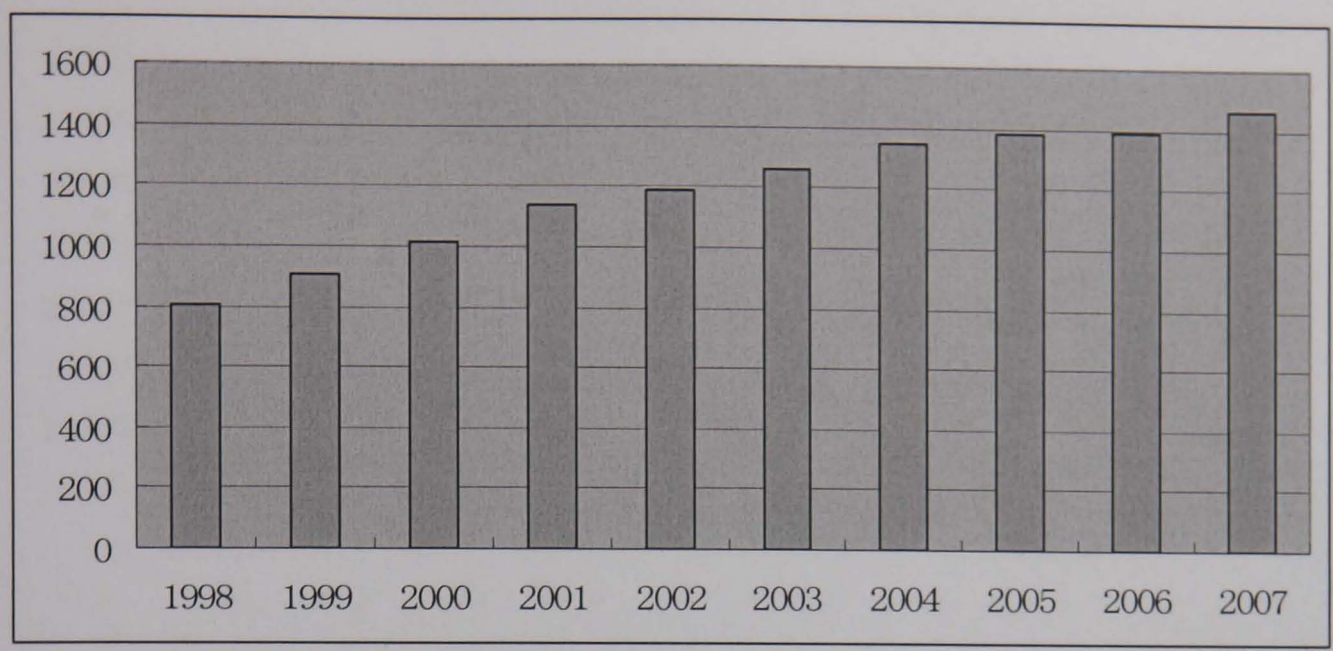


Figure 2.2: NTS Composition.

TS can be further classified into two types: A-shares and B-shares. A-shares are domestic common stocks issued by Chinese companies listed on the SHSE or the SZSE. Since 1991, the two exchanges have been permitted to trade these shares, which are only available to, and can be traded by, Chinese citizens and institutions. Under the Securities Law, Chinese companies wishing to issue or list their A-shares must gain approval from the CSRC. The 'B' shares issued by Chinese

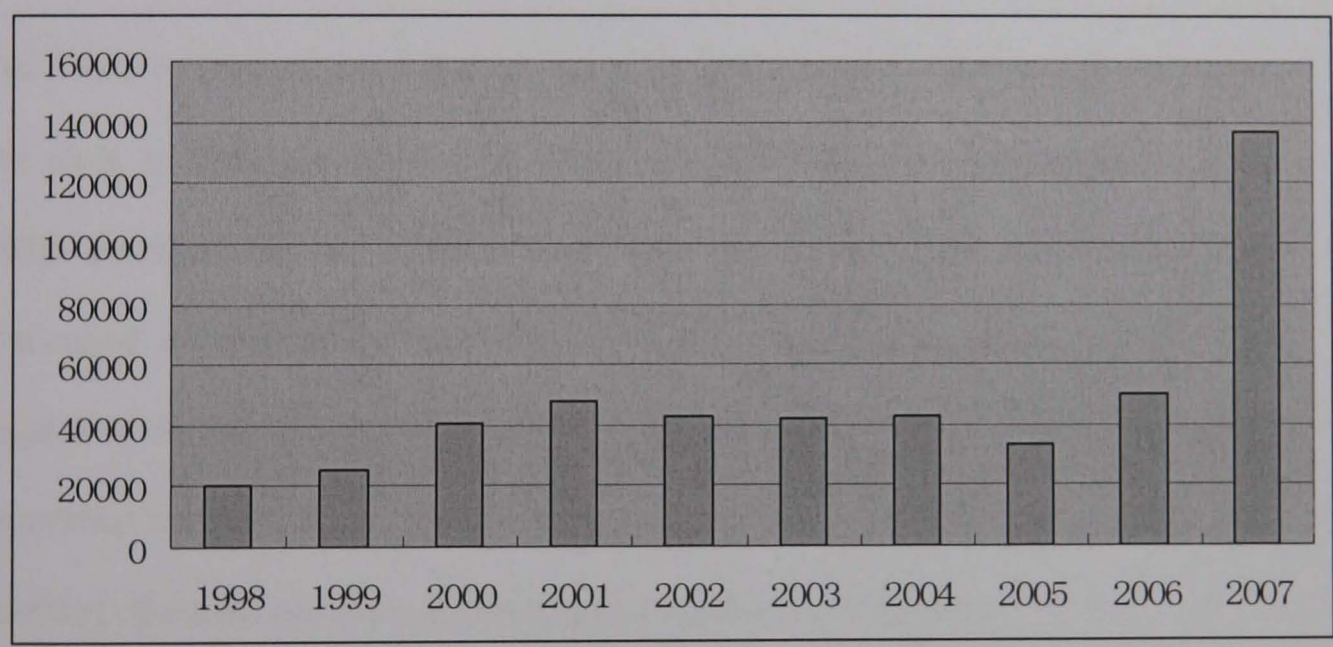
companies since 1992 are shares denominated in foreign currency (Guo. 2006). Between 1992 and 2001, they were exclusively available to overseas investors. As a result, while A-shares and B-shares of the same company would be listed on the same stock exchange, local and overseas investors were separated in the Chinese market because of this system. The chief reason for the segmentation was the existence of China's capital controls. The A-shares are denominated in Chinese currency, i.e. the RMB, which foreign individuals or institutions were not allowed to directly buy and sell. Domestic investors were not able to purchase B-shares because these shares were denominated and must be traded in foreign currency. The denomination currency for the B-shares on the Shanghai Exchange is the US dollar, but on the Shenzhen Exchange the Hong Kong dollar is the main currency. B-share holders can receive the same dividends as the owners of 'A' shares, but they have no voting rights. The total capitalisation of B-shares has been much smaller than that of A-shares (Chan, Menkveld and Yang, 2008). On May 2007, there were 1365 A-shares listed on both exchanges with a total capitalisation value of about RMB 1668.74 billion. At the same time, there were only 109 B-shares listed on both exchanges, with a total capitalisation value of about RMB 1086.52 billion.[2] The yearly statistics for both A-shares and B-shares between 1998 and 2007 can be found in Figure 2.3, Figure 2.4 and Figure 2.5.

[2] http://www.csrc.gov.cn/n575458/n775121/index.html, as accessed on 07/2007.



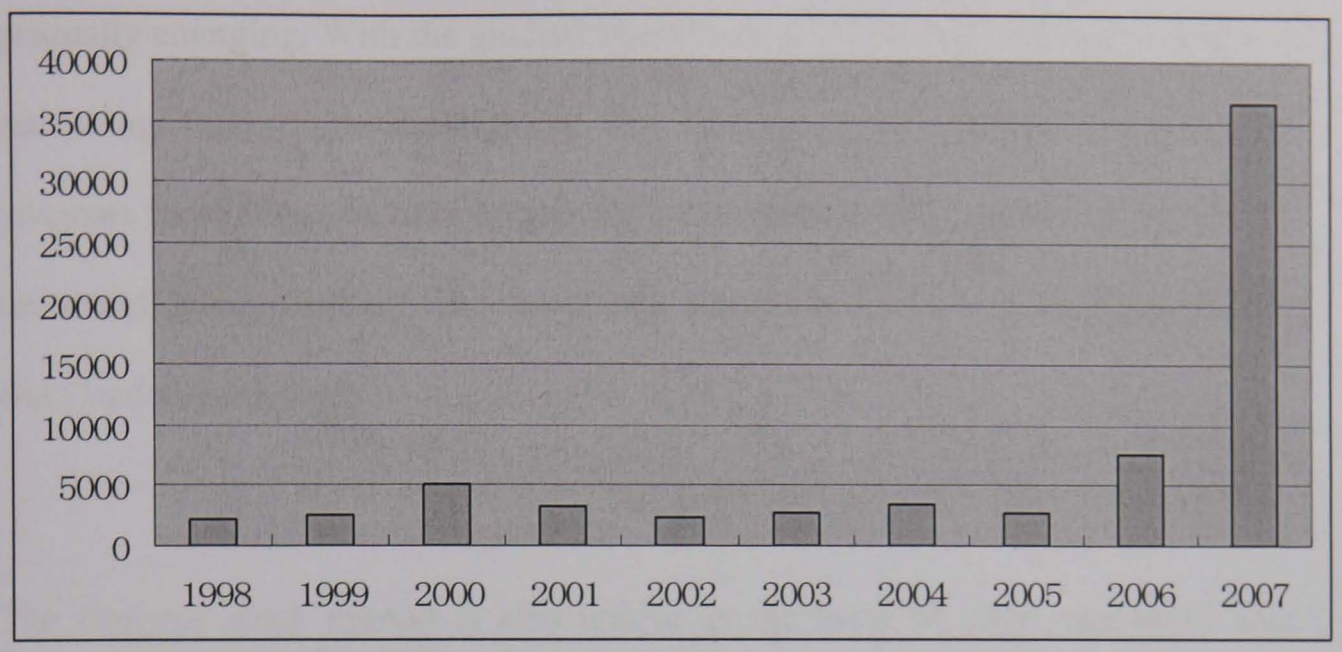
Sources: China Securities Regulatory Committee, 2007

Figure 2.3: Shares issued (A shares and B shares), 1998-2007.



Sources: China Securities Regulatory Committee, 2007

Figure 2.4: Total Market Capitalisation (RMB 100 Million), 1998-2007.



Sources: China Securities Regulatory Committee, 2007

Figure 2.5: Trading Volume (in 100 Million), 1998-2007.

In February 2001 China lifted the restrictions that allowed only foreign investors to trade in B-shares. Chinese domestic investors can now trade in these shares with foreign currency (Chan, Menkveld and Yang, 2008). In 2002, China launched a program of Qualified Foreign Institutional Investors (QFII) under which overseas investors may invest in and trade Chinese A-shares through qualified institutional investors. This marks another step of China's move towards market openness and reducing market segmentation (Guo, 2006).

II. Characteristics of the Chinese Stock Market

The Chinese stock market has certain distinctive features. First, it is relatively isolated from major international markets, although in recent years, this has been

gradually changing. With the gradual liberalisation of the financial sector, there is increasing foreign participation on the Chinese stock market, and Chinese investors have begun to have opportunities for contact with markets in the rest of the world. Many Chinese firms have dual listing on the New York, Hong Kong, and London exchanges.

The Chinese stock market is also unique in the level of state regulation. The government controls the size of the stock market, the pace of issuance and the allocation of resources. Although it no longer determines where new stocks will be listed, central government still controls the annual quota for new public offerings and the selection of qualified companies for listing. Current legislation dictates that no company is allowed to list without three years of continuous profitability. This conservative policy stifles market dynamism because it gives an advantage to established state-owned companies, while making it very difficult for young, dynamic enterprises to be listed (Gao, 2002).

Gao (2002) also point out the Chinese stock market is dominated by retail rather than institutional investors. Individual investors hold a higher percentage of the market, and institutional investors such as insurance companies play a much smaller role than in other comparable markets. Foreign investment is also much smaller, representing less than 2.5% of total capitalisation of the A-share market, compared with 11% for US markets and 19% in Japan.

Among the retail investors, the majority are small individuals, who lack the expertise and experience of investment analysis and management. This structure of investor groups leads to a focus on short term capital gains and makes the market vulnerable to panic. The combination of high turnover and short investment horizons in turn promotes high volatility of the share prices, as evidenced by the fact that in the Chinese market movements of many share prices would easily touch the 10% upper and floor limits of daily price fluctuations for a single share (Girardin and Liu, 2003). In 1997, in an effort to stabilize the market, the authorities introduced Mutual Funds. However, rather than counter the 'herd' behaviour of the small investors, these funds have been tainted by it, and have had little or no beneficial effect (Nam, et al., 1999).

Zhou and Sornette (2004) point to the evolution of the SHSE Composite Index between May 1999 to June 2001 to show that, despite influence from government policy, stock traders in China do exhibit herding behaviour. This is probably explained by the immaturity of the Chinese market, and the prevalence of short-term investors. Tan (2005) finds evidence of herding behaviour in both the Shanghai and Shenzhen A-share markets. In the Chinese markets herding behaviour demonstrates similar patterns of asymmetric effects: as the market goes up, trading volume and volatility become excessively high; as the market goes down, trading volume and volatility become excessively low.

The short-termism and volatility that characterise the A-share market can be exacerbated by a number of market developments. The excessive under-pricing of

initial public offerings, which is extremely excessive in China, encourages a high initial turnover in new stocks. The concealment of information under limited disclosure leaves inexperienced investors no choice but to follow other investors. Securities firms lack long term sources of finance, and so tend to match short term liabilities with a short horizon for the holdings of assets. Finally, because the state dominates corporate governance, shareholders have no incentive to monitor market activity to influence the profitability of firms. As a result, investors tend to ignore even the information that is open to them (Girardin and Liu, 2003).

III. The Trading System

Operation of the Chinese stock market is based on a modern infrastructure that includes an automated trading regime, a high-speed nationwide satellite communications system backed by digital data networks, a paperless depository, and a rapid clearing and settlement system (Wong, 2005). With the exception of public holidays, the exchanges are open 5 days a week, from 09:30 until 15:00. There is also a pre-trading session which runs from 09:15 to 09:25 on each trading day, during which the morning opening prices are generated. In common with other Asian markets, there is a lunch break between the morning and afternoon trading sessions, from 11:30 to 13:00. This means that there are, in effect, three sessions in each trading day: the pre-opening auction from 09:15 to 09:25, morning trading from 09:30 to 11:30 and afternoon trading from 13:00 to 15:00 (Yang, Li and Liu, 2002).

The system runs two formal trading sessions, a periodic call auction and a continuous, discriminating auction (Xu, 2000). The call auction session takes place when trading opens, while the continuous auction occurs later in the trading day (Su, 2004). According to the regulations, a call auction is defined as the process of one-time centralised matching of buy and sell orders accepted during a specified period. The continuous auction refers to the process of continuous matching of buy and sell orders on a one-by-one basis. The buy or sell orders not executed during the call auction automatically enter the continuous auction (Shanghai Stock Exchange, 2006). As reported by Wang et al. (2003), the merits of these trading procedures are constantly debated among academics and policy makers.

The opening call auction generates the execution price, which serves as the opening price of a security for the trading day. The execution price is determined based on the principle that such a price can generate the greatest trading volume. The mission of this opening call auction procedure is to stabilise prices after the overnight halt in trading. However, the lack of transparency undermines this purpose.

In the continuous auction session throughout the trading day, buy and sell orders are submitted and auctioned. Matching of the orders is automated through a computer system, which executes the matching transactions according to a time and price priority scheme. The Shanghai Exchange runs a time-price priority scheme that prioritises the matching first by price and then by time. The Shenzhen

Exchange has a scheme of price-time-order priority (Sun and Shi, 2002). Transactions are continuous and transparent. All trading goes through the computer systems in each exchange's trading hall and terminals at the members' offices.

As an order-driven market, there are no designated market makers on the Chinese exchanges to stabilise stock prices by trading on their own accounts. Individual investors wishing to trade A-shares are required to act through a broker. The broker provides the investor with an account number to be quoted on all exchange settlements. Brokers are forbidden to engage in floor trading or short selling. To be legally recognised, transactions must take place through the automated order matching system, and trading must be in units of at least 100 shares (Xu, 2000).

The Chinese regulations allow limit orders and market orders, both of which are valid only on the day of placement. The Chinese trading rules define a limit order as an instruction given by a client to a broker to buy a particular security at a specified price or lower, or to sell at a specified price or higher. A market order is an instruction given by an investor to a broker to buy or sell a particular security at the current best market price. Any portion of an order that is not executed in its entirety at one time continues to line up for the auction of the same day. Market orders may, however, be in the format of Five Best Orders Immediate or Cancel, i.e. the orders are executed in sequence against the current five best prices on the opposite side, with the unexecuted portion cancelled automatically. Or, they may be in the format of Five Best Orders Immediate to Limit, under which the orders

are executed in sequence against the current five best prices on the opposite side, with unexecuted portions changed to a limit order whose limit price is set at the last executed price on the same side. Any order must specify the instructed price and the instructed quantity of shares to be purchased or sold. Margin trading and securities lending services may be provided by a qualified member of the exchanges subject to relevant regulations (Shanghai Stock Exchange, 2006).

Purchases of stocks are in round lots of 100 shares or multiples thereof. Sales of stocks follow the same principle, but for those sales with an odd lot of less than 100 shares, they shall be made in one order. The maximum quantity of one order for stocks is 1 million shares. The quotation units for stocks are in price per share. The tick size of the quotation price of an order for A shares is RMB 0.01 Yuan, while that for B shares is USD 0.001. The daily price limits on trading of stocks imposed by the Chinese regulations are plus/minus 10% in relation to the previous closing price. The calculation result shall be rounded to the tick size. An order whose quotation price is outside the price limit is invalid (Shanghai Stock Exchange, 2006).

The Chinese trading process begins when investors place a buy or sell order with the broker. The broker then relays the order to one of the exchange's main frameworks via terminals, either on the floor or with member firms. Once arrived, these orders can be executed immediately through the computerised trading system with matching priority schemes. On the SHSE, the broker sends orders to his member broker on the floor of the exchange, who then records the order in the

centralised order matching system (Yang, Li and Liu, 2002). The trading process on the SZSE uses a dual clearing system whereby stocks are registered locally but are centrally cleared (Jiang, 2005).

The Chinese exchanges disseminate real-time quotations. Quotations made during the opening call auction include the share's name and code, previous closing price, virtual opening reference price and virtual matched volume and unmatched volumes. The real-time quotations during the continuous auction also include last executed price, highest and lowest prices, accumulated trading volume and trading value, the five real-time highest bid and lowest offer prices and their quantities (Shanghai Stock Exchange, 2006).

During continuous trading, if investors believe that their orders cannot be executed at the given price, they are permitted to change or reverse them. Transparency is ensured by the recording of all transactions, stating the exact order, the price, the precise time of the trade and the transaction volume.

A buyer-initiated trade takes place where a buyer requires an immediate fill and so she submits a limit bid that is high enough to touch the lowest posted ask. The buy order is then executed at the best ask. A seller-initiated trade takes place where a seller requires an immediate fill and so she submits a limit ask that is low enough to touch the highest posted bid. The sell order is then executed at the best bid. In each case, the party initiating the trade bears the execution cost. The gains from the bid/ask spread received by the counter party are treated as compensation for

the expected loss to the traders and for providing liquidity.

Some aspects of the Chinese trading mechanism are unique. For example, during the opening call auction there is no information available to investors, other than the final clearing price generated at the end of the auction. The Chinese trading system accepts auction order routing between 09:15 – 09:25, 09:30 – 11:30 and 13:00 – 15:00 on each trading day. Unexecuted orders may be cancelled on each trading day, but not between 9:20 – 9:25. Furthermore, while all other markets switch to continuous trading immediately following the opening call auction, in China there is a five minute break from 9:20 – 9:25 between the two trading mechanisms (Tian and Guo, 2006).

IV. Liquidity of the Chinese Stock Market

On the Chinese stock market, transaction prices are generated according to the bid/ask prices and time of order submission. A broker on the SHSE and the SZSE has responsibility not only for the buyers but also for the sellers. According to Yang, Sun and Shi (2002), the biggest difference for brokers between the Chinese stock markets and the dealership markets is that spread does not form part of the profits on the Chinese stock markets, but does in the dealership markets. Wang and Chen (2006) argue that, of the three main determinants in the conventional liquidity models, the inventory costs are irrelevant for China because there is no need for traders to hold inventories in China's order-driven market. On the other

hand, as China has adopted a computer based automated trading system, the order processing costs are more or less fixed, and hence cannot be a significant factor causing changes in liquidity of individual assets. Thus, in theory, the adverse selection costs due to asymmetric information are left to be the main determinants of liquidity.

Much research has confirmed that adverse selection is a significant factor influencing liquidity in China. Using depth as a measure of liquidity, Yang, Sun and Shi (2002) find that, on average, the adverse selection effect accounts for 36.2 % of liquidity changes. Mu, Wu and Liu (2004) provide evidence that, both in relative and absolute terms, adverse selection costs are greater than order processing costs in China. Other researchers' estimates of the adverse selection component in the total bid-ask spread vary, from 0.186 (Han, Wang, Yue, 2006) to 0.3908 for the SHSE, and from 0.3621 (Wang and Chen, 2006) to 0.62 (Lei and Zheng, 2006) for the SZSE, depending on the selection of shares in the portfolio and the time period under examination. However, they all confirm that the adverse selection effect is a significant liquidity determinant. Moreover, it is also generally agreed that on the Chinese market adverse selection has a stronger effect than in other, mature order driven markets such as Hong Kong (Wang and Chen, 2006).

The importance of adverse selection as a liquidity determinant is also reflected in its effect on liquidity variations with time. The intraday spreads on both the SHSE and the SZSE exchanges display an L-shaped pattern, similar to the pattern

reported in Foster and Viswanathan (1990). This pattern occurs because shortly (about 10 minutes) after the morning trading session starts in China, the relative spread would be very wide, but after about one hour it starts to narrow and gradually stabilises at the daily mean level. This continues throughout the rest of the day with no widening again around the closing time. This pattern differs from the usual U-shaped pattern seen in other markets such as in Hong Kong (Qu and Wu, 2002; Sun and Shi, 2002; Yang, Li and Liu, 2002). The changing level of adverse selection within the day has been identified as the main cause of this pattern. During the overnight halt, it is likely that new information may have arrived. However, since the Chinese call auction in the opening session is closed to the public, no information is to be released. While informed traders may take advantage of this by engaging in transactions soon after the session opens to the public, liquidity traders tend to withdraw during this time. With the passage of the day, new information will gradually become known and so adverse selection will decrease (Yang, Sun and Shi, 2002; Qu and Wu, 2002; Mu, Wu and Liu, 2004; Han, Wang and Yue, 2006; Lei and Zheng, 2006; Wang and Chen, 2006). A similar adverse selection effect may also be found in the bid-ask spread on Mondays, which is higher on both the Shanghai and the Shenzhen exchanges, perhaps because on Mondays more information is available after the non-trading period of the weekend (Yang, Li and Liu, 2002).

The Chinese stock market is dominated by large numbers of small and individual investors. Because of their limited financial resources and sectoral expertise, and their inadequate investment training, they are disadvantaged in acquiring and

processing information. They are therefore usually uninformed traders on the market. To protect their interests, they tend to migrate to the market of shares with large capitalisation, where the issuing firms are subject to greater scrutiny from regulators, investment analysts and general investors due to their market influence. These big firms are under greater pressure to have a relatively better structure of corporate governance, and higher standards of information disclosure. This is helpful for reducing possible information asymmetry, which in turn attracts individual investors. Institutional investors on the other hand, are then left to explore their informational advantage in small-cap markets. Thus the small-cap Chinese shares tend to be subject to larger effects of adverse selection (Song and Tang, 2002). Han, Wang and Yue (2006) and Wang and Chen (2006) all empirically demonstrate that adverse selection components of the bid-ask spread of large firms are smaller than those of small-cap firms. It follows that there are differences in the level of adverse selection, hence differential impacts of adverse selection across firms. Large companies, because of the relatively low degree of adverse selection, tend to have higher levels of liquidity. The higher degree of adverse selection in the shares of small-cap firms means that for those firms, liquidity is lower.

On the Chinese markets, adverse selection is also found to be associated with trading volume and stock prices. Evidence has shown that non-actively traded shares usually have a larger adverse selection component and are less liquid, while the reverse is true for shares with active trading and large transaction volumes. Adverse selection is also negatively related to share prices. High price

shares show less effects of adverse selection than do low priced shares. Again, it is plausible that these differential impacts are because heavily traded and high priced shares are subject to more stringent scrutiny from regulators and the market, so asymmetric information is relatively less prevalent (Mu, Wu, and Liu, 2004; Han, Wang, and Yue, 2006; and Wang and Chen, 2006).

To understand the properties of liquidity creation and consumption on the Chinese market, it is important to know which group of traders provide liquidity and which group demands it. Pan and Shi (2004) suggest that order placement depends on the Chinese trader's desire for transaction. This desire is reflected in a measure of order aggressiveness, given by the difference between new order price and the best opposite price in the limit order book. This aggressiveness in turn will determine traders' order choice between market and limit orders, hence liquidity provision or utilisation. Grouping the population of Chinese investors into institutional and individual investors, Pan and Shi (2004) show that, in the period under their examination from October 2003 to March 2004, 98% of the total 113.983 million orders are from individual investors. Institutional investors account for only 2%, although lately their importance has been increasing. In terms of order aggressiveness, they find that the average value of the measure for individual investors is negative, implying that individual investors in China have very weak desire to initiate transactions. This means they tend to submit limit orders. Therefore, as a group, Chinese individual investors are liquidity providers. Meanwhile, the average order aggressiveness of institutional investors is positive in value, suggesting that these institutional investors are liquidity demanders. Shi

and Sun (2003) reach a similar conclusion, that in China, individual investors supply liquidity to institutional investors.

In addition, some attributes of microstructure are proved to have impacts on liquidity in China. A special factor in this regard is the existence of illiquid shares. These NTS, which represent a considerable proportion of outstanding Chinese shares owned by the State or legal persons, are neither negotiable nor tradable on the market (Yang, Li and Liu, 2002). As a consequence, the illiquid shares tend to overvalue the price of tradable shares, since their existence creates the liquidity premium to tradable shares.

These illiquid shares also enhance the level of asymmetric information among investors. Owners of non-tradable shares are usually the state government or their representatives. They play a more important role in corporate governance than do investors in secondary markets. Because of this, they possess insider information about the companies under their control and can decide the announced prices of their stocks which are not open to public trading, whilst the common traders receive little information. This fact leads to high adverse selection costs and hence the wider bid-ask spread. As a result, market liquidity tends to decrease with the increase in the proportion of illiquid shares (Yang, Li and Liu, 2002). Mu et al. (2004) find similar empirical evidence, showing that the proportion of non-tradable shares in the total outstanding shares is a significant determinant of liquidity. It is negatively correlated with the level of liquidity of a security.

Another microstructure factor affecting liquidity in China is that China imposes a price limit on stock prices, which allows a stock to trade within plus or minus 10% of its closing price on the previous day. Research has shown that appropriate price limits cannot restrict, and may actually augment, market liquidity. However, improper price limits do to some extent restrict the market liquidity (Liu et al., 2004). Jiang (2005) observes that market liquidity increases as prices rise to the upper price limit (10%), then decreases. Conversely, it decreases when prices fall to the price floor (10%).

The minimum tick size for all Chinese A-shares is 1 cent (RMB0.01 Yuan). Shi and Sun (2003) studied the relationship between liquidity and the minimum tick size and found that both bid-ask spread and depth would decrease when the minimum tick sizes decrease, and increase when the minimum tick sizes increase. However, Qu (2006) reports that on the whole the role of the minimum tick size in the determination of liquidity is limited. However, it could be important to low priced shares or actively traded shares.

These factors often work in tandem. For example, using sample data between January 1997 and December 2000, Shi and Sun (2003) find that liquidity would decrease significantly after a dramatic change in share prices, regardless of whether the share prices have reached the price limits. They use the turnover rate as a measure of liquidity, and consider that the decrease in liquidity would be significantly affected by firm size, with small firms being most affected.

Indeed, the determination of liquidity in an order-driven architecture may also be fruitfully looked at in terms of some underlying factors. Pan and Shi (2004) suggest that, as a determining factor, order aggressiveness in turn is determined by stock prices, liquidity levels, price volatility, order imbalance, and order size. Following Bagehot (1971), Copeland and Galai (1983) and Glosten and Milgrom (1985), Mu et al. (2004) find that liquidity in China is determined by factors such as the turnover rate, average transaction size per order, price volatility and proportion of non-tradable shares. Ji and Yang (2002) and Wan (2006) examine the impacts of trading volume, share prices and price volatility on liquidity *a la* the model developed in Brockman and Chung (1999).

These factors are either deployed as proxies for adverse selection (Mu et al., 2004), or are a reflection of the effects of the market or macro-economic conditions (Ji and Yang, 2002; Pan and Shi, 2004; Wan, 2006). They imply that, in the Chinese order-driven environment, liquidity determination of a security is a complex process. In addition to the prominent effect of adverse selection, institutional details of the microstructure, and market- and economy-wide influences may also contribute to affecting the level and change of liquidity on the Chinese stock market.

Chapter 3

Evidence of Liquidity Commonality on the Chinese Stock Market

I. Introduction

Chapter 2 introduced the development of the Chinese stock market and its trading mechanism. This chapter examines the commonality in liquidity on the Shanghai Stock Exchange and the Shenzhen Stock Exchange. The objective of this chapter is to provide an initial understanding of the identification of co-movement between individual liquidity measures and market- and industry-wide liquidity on the Chinese stock market, a limited order-driven market using electronic trading without market makers. This chapter will investigate whether there is commonality in liquidity on the Chinese stock market, and will apply robust analysis of the influence of size, industry, and the effects of up and down markets.

High-frequency financial data are crucial in empirical research on commonality in liquidity. I use the China Stock Market and Accounting Research (CSMAR) to obtain transactions and quote data in high frequency for July 2000 to June 2002

for A-shares traded on the SHSE and the SZSE. CSMAR covers all details of every transaction and related information, providing data by bid and ask record. I use the transaction data for each daily liquidity measure by averaging across all trades for each daily stock. Thus I smooth out intraday effects to achieve greater synchronicity. Following the data filtering method of Chordia et al. (2000), I will delete some biased factors, such as possible problems with trading units, insufficient observations, abnormal trading activity, the extreme fluctuations of stock prices in a few special days with severe market shocks. I use high frequency intra day transaction data during a sample period that lasts for two years, believing that this will provide better and richer information than that is contained in previous studies, which tend to use only one year of data. The sample period is from July 2000 to June 2002, which covers both bullish markets and bear markets.

I detect the presence of significant commonality for all liquidity proxies in my models. I calculate six different liquidity measures for every transaction: quoted bid-ask spread, percentage quoted bid-ask spread, depth, dollar depth, a bi-dimensional liquidity measure, and the turnover rate. Quoted bid-ask spread, percentage quoted bid-ask spread and depth are from Chordia et al. (2000), while dollar depth, a bi-dimensional liquidity measure, and the turnover rate are from Fabre and Frino (2004), and Sujoto, Kalev and Faff (2005).

In testing for the co-variation of liquidity, I examine the contemporaneous adjustment in liquidity as well as one lead and lag of the market average liquidity variable. Both equal-weighted and value-weighted market liquidity variables are

used in my estimation. To further detect the existence of commonality in China, I portion the sample into five quintiles based on market capitalisation at the beginning of the sample period. To test commonality both within the industry and within the market as a whole, I also classify my sample firms into three categories: industrial, resources and financial. Finally, I test whether there is commonality in liquidity in up and down markets.

The chapter is organised as follows. Section II reviews the theory and empirical work on the identification of commonality in liquidity; Section III explains the data and methodology; Section IV provides empirical evidence of commonality in liquidity on the Chinese stock market; Section V provides further empirical evidence, including the size effect, industry effect and effects in up and down markets; Section VI comprises concluding marks.

II. Review of the Literature

The first published empirical study that provided evidence for the existence of commonality in liquidity was by Chordia et al. (2000). They argue that liquidity is not just an attribute of a single asset, and prove that individual liquidity measures co-move with each other. Even after accounting for individual determinants of liquidity such as trading volume, volatility, and price, commonality remains significant and material. They find that concurrent slope coefficients are positive and statistically significant for nearly 30% to 35% of the NYSE firms. As a result,

both spreads and depths are significantly affected by changes in market liquidity. They suggest that there is an industrial component of liquidity. and find commonality to be present in this component as well.

In addition, they find evidence for the size effect of commonality, whereby market-wide changes in spreads have a greater effect on large firm spreads even though large firms have smaller average spreads, while small firms cannot be influenced by prevalent asymmetric information. At the same time, size has little effect on depth, although depth also shows commonality. Overall, commonality in liquidity has a significant size effect (Chordia et al., 2000).

Huberman and Halka (2001) also point out that most of the current theories focus on the liquidity of individual securities; little can be learned from them about variations in liquidity that affect many stocks simultaneously. They argue that liquidity of individual stocks varies over time and cross-sectionally, and show that this variation has a common component. To statistically detect the presence of such a systematic component of liquidity, they estimate the autoregressive structure of each of the four liquidity proxies: spread, spread/price ratio, quantity depth, and dollar depth, to derive a series of the residuals of autoregressive processes. They find these innovations are positively correlated for each liquidity proxy, indicating the presence of liquidity commonality.

Hasbrouck and Seppi (2001) argue that a focus on stocks in isolation has led to researchers being ignorant of the most basic facts about interactions between

stocks. Thus, they also support the shift of research focus away from analysing individual stocks in isolation to an emphasis on analysing variations between stocks. However, using principal components and canonical correlation analyses, they find no conclusive evidence of the existence of commonality. While there is strong evidence for common factors in order flows and stock returns, the evidence for commonality in liquidity proxies is not significant.

Hasbrouck and Seppi (2001) claim that their methodology is better than that of Chordia et al, because their intervals of observation are shorter, their liquidity variables are in levels, which is more meaningful than Chordia et al.'s focus on changes, and they impose fewer restrictions in their research. However, Chordia et al. use longer samples: a cross-section of one thousand stocks compared to Hasbrouck and Seppi's cross-section of 30 Dow Jones firms.

Brockman and Chung (2002) held that, since Hasbrouck and Seppi's (2001) sample consisted of only thirty companies of the Dow Jones Industrial Average, this absence of evidence might be caused by a small sample with little industry overlap. Brockman and Chung (2002) construct a similar index by selecting the four largest companies from each of seven industries. Using this sample of twenty-eight firms, they estimate their model and find strong evidence of commonality.

While Chordia et al. (2000) and other studies all use only a single year of data, Eckbo and Norli (2002) extend previous work by employing monthly data over a

much longer period, from 1963 to 2000. Their results are similar to those reported by Chordia et al. (2000), although they use a different regression model.

Henker and Martens (2004) try to detect the presence of commonality by using a spread cost decomposition model. Under their model, the traded spread can be decomposed into adverse selection costs, stock specific inventory cost, order processing costs, and a market buying and selling pressure cost component that is common to all stocks. They find that a significant proportion of the spread is explained by market buying and selling pressure, hence providing strong evidence of commonality in liquidity.

Another critical new development in current research on commonality is to extend the analysis to other markets. Martinez, Nieto, Rubio, and Tapia (2005) broaden the literature to include the Spanish case. In their study of the relationship between asset pricing and systematic liquidity risk, they confirm that commonality in liquidity also exists on the Spanish stock market. Meanwhile, Bauer (2004) extends the research to Switzerland and detects the presence of commonality there.

In another direction, Coughenour and Saad's (2004) research focuses on the existence and relative importance of supply generated liquidity co-variation. Using an approach that combines favourable elements of Chordia et al. (2000) and Hasbrouck and Seppi (2001), they find that individual stock liquidity co-varies with both market liquidity and specialist portfolio liquidity, and that for the

variation of each measure of spread, over 90 percent of the individual market-liquidity betas are significant and positive. These results indicate the presence of common liquidity variation, which is consistent with previous studies, although the degree of commonality is greater.

The most exciting development in this field however, has been the extension of research to the order-driven market. Brockman and Chung (2002), who are among the first to focus on commonality in liquidity in an order-driven market structure, maintain that, unlike specialist markets where there are barriers to entry and exit, order-driven systems generate liquidity demand and supply schedules that more closely approximate equilibrium under perfect competition.

They show that, in their sample, the sum of all liquidity coefficients is highly significant, and that in order-driven markets overall, both the average relative spread coefficient and the average depth coefficient are smaller than those reported for specialist-based markets. The results show that commonality is an important trait, influencing the liquidity provision process in an order-driven market (Brockman and Chung, 2002).

Bauer's (2004) work on commonality in the order-driven market in Switzerland follows the modelling strategy developed by Hasbrouck and Seppi (2001). He adopts the principal components analysis by using data over three months on the order books of 19 stocks traded on the Swiss Stock Exchange (SWX). His evidence shows the existence of three to four common factors, and the proportion

of the variation in liquidity explained by common factors is higher than in previous studies for quota driven markets.

According to Pascual, Escribano and Tapia (2004), it is possible to measure variations in overall liquidity by simultaneous changes in immediacy costs and depth. However, when these liquidity dimensions do not reinforce each other, liquidity changes will be ambiguous. In their 2004 paper, they characterise ambiguity using an instantaneous time-varying elasticity concept. To cope with the ambiguity problem they construct several bi-dimensional liquidity measures. When overall liquidity increases these measures are larger than zero, and when overall liquidity decreases the measures are smaller than zero. Using an intra-daily panel data of NYSE-listed stocks, and following the methodology proposed by Hasbrouck and Seppi (2001), Pascual, Escribano and Tapia (2004) begin by using principal components analysis to discover the common factors in the bi-dimensional and one-dimensional measures of liquidity discussed earlier. Next, using canonical correlation analysis, they evaluate the correlation between the common factors in these liquidity measures. Then, after accounting for the part associated with the one-dimensional measures of liquidity, they study how much co-variability remains in the bi-dimensional liquidity measures. A finding that residual commonality is negligible would indicate that there is an informational gain in considering bi-dimensional liquidity measures. Pascual, Escribano and Tapia (2004) find that commonalities in overall liquidity cannot be fully explained by the common factors in one-dimensional proxies of liquidity. Therefore, bi-dimensional measures are superior.

Fabre and Frino (2004) reconfirm the existence of commonality in order-driven markets in their study of 660 stocks on the Australian Stock Exchange (ASX) during the year 2000. They apply the same filter and regression models as Chordia et al. (2000), but redefine the market liquidity measures by deleting the effective spread and the proportional effective spread because the possibility of price improvement has been included in electronic trading on the ASX. They also add dollar depth, which is more sensitive for the results measuring depth. Their statistics summary shows that commonality in liquidity exists on the ASX but is weaker than for the NYSE. To strengthen the regression results, they use Z-statistics, whereas Chordia et al. do not. Their results for the size effect reveal that the co-movement in individual liquidity is not as significant as in Chordia et al. (2000).

In contrast, Sujoto, Kalev and Faff (2005) find very strong evidence for commonality in liquidity on the ASX. Their two years sample of 2001 and 2002 is longer than previous research and includes bullish and bearish markets. They test commonality in liquidity not only in conventional liquidity measures but also in new liquidity proxies (the turnover rate and bi-dimensional liquidity measure). In addition, they consider long run commonality in liquidity. Commonality in liquidity is found in up and down markets as well as in a quadratic specification.

Bailey, Cai, Cheung and Wang (2006) use a unique dataset from the Shanghai Stock Exchange to study the relation between daily open-to-close stock returns and order imbalances and the commonality in order imbalances, across individual,

institutional, and proprietary investors. They find that commonality of individual order imbalances is stronger for small and medium performing stocks, and for stocks with light and infrequent institutional (proprietary) trading. In these cases 96 percent of slope coefficients are positive and the statistically significant and median explanatory power is high at 27.9 percent. Co-movement in institutional order imbalances is stronger for the large capitalisation stocks favoured by institutional investors.

In their 2006 study, Beltran-Lopez, Giot and Grammig use the price-depth pairs in a limit order book of the Frankfurt Stock Exchange (FSE) to consider the sources of commonality in liquidity. Using the results of the stock specific analysis and quantifying cross-sectional commonalities of liquidity, they show that order book commonalities are much stronger than liquidity commonality across stocks. They point to their finding that bid and ask side and both visible and hidden parts of the order book, exhibit specific dynamics, as evidence that open order book markets attract a trader population that is heterogeneous in terms of asset valuations and levels of patience. Their finding that there is evidence of liquidity commonality across stocks is in line with previous research, but in this study the total explanatory power of the principal components is considerably smaller than in the stock specific analysis. Nevertheless, their cross-sectional commonality results are broadly in agreement with those reported in Hasbrouck and Seppi (2001) and Bauer (2004).

In contrast to the studies discussed above, Beltran-Lopez, Giot and Grammig (2006) use their principal components analysis to link variation of the price-depth pairs within the order book of single stocks to microstructural factors. Kempf and Mayston (2008), in their investigation into commonality of liquidity on the German stock market, an open limit order book market, focus on the variation of liquidity across stocks, and find that the deeper into the limit order book they look, the stronger the commonality in liquidity becomes. They believe that because orders from investors who wish to trade large positions will walk up the book, those investors will be concerned with liquidity not only at best prices from spread or depth, but also beyond best prices. Furthermore, competition amongst liquidity suppliers for new price priority means that bid-ask spread and depth at best prices are subject to strong idiosyncratic variation. Commonality at best prices is only around 2%, while inside the limit order book it can be as high as 20%. These considerations mean that best quotes are not really suitable for the study of commonality.

Kempf and Mayston (2008) also find strong time variation in commonality both on an intradaily basis and with the movement of the market return. Even after controlling for time-of-day effects in liquidity, commonality is found to be much stronger at the opening and closing of the trading day. These increased levels of commonality may be caused by the market-wide information flows from the overnight period and from the opening of the US market. Commonality is found to be much higher in down markets than in up markets. Whereas values over the whole sample are 16% and 8%, in a falling market environment these rise to 22%

and 14%. These findings suggest that earlier estimates of commonality are not valid for liquidity beyond best prices, and that systematic liquidity risk in a limit order book market is therefore much higher than the evidence in earlier studies implies.

Kumar and Shah (2006) examine the existence of commonality in liquidity on the Indian National Stock Exchange, an open electronic limit order book market. Taking the sample period Jan 1997 to Dec 2002 they observe weekly and monthly patterns. Impact cost is calculated and used as the proxy for liquidity. This is a better proxy than bid-ask spread, because it captures information about trade size as well as price information. Kumar and Shah (2006) find that whereas for large firms, impact costs fall together more often than they rise together, for small firms the opposite is the case. Their finding that commonality in liquidity is stronger during bear markets, and that portfolio managers will find it more difficult to change their holdings during such markets, contradict those of Sujoto, Kalev & Faff (2004), who report that commonality in liquidity is higher during bull markets in all proxies except percentage bid-ask spread.

The first evidence of the presence of systematic liquidity in the UK is presented by Galariotis and Giouvris (2007), in their study using FTSE100 and FTSE250 stocks. For the FTSE100, the last few years have seen a shift from quote-driven markets to order-driven markets. This means that market makers are no longer obliged to provide liquidity. The change in the trading regime for the FTSE250, on the other hand, from quote-driven to hybrid, has not changed the nature of

liquidity provision. Thus the London stock exchange provides an ideal case study for research into the effect of changes in the nature of market making from obligatory to non-obligatory on commonality in liquidity. The results show that for the FTSE250, commonality is strong only at portfolio level. However, for FTSE100 stocks, commonality is quite strong at both individual and portfolio level, implying that stocks on the LSE will collectively experience periods of high liquidity. Therefore, since it can be quite costly to restructure portfolios in periods of high spreads, it will be in the interest of fund managers and other institutional investors to minimise liquidity costs by carefully timing the restructuring of portfolios. The findings indicate that commonality does not differ hugely between different trading regimes, and this, alongside the fact that for the FTSE100 market makers are obliged to quote bid and ask prices under SEAQ but not under SETS, while for the FTSE250 they must accommodate liquidity under both regimes, suggests that commonality is not affected by changes in the obligatory nature of market making. Overall, commonality is broadly similar across trading regimes, regardless of the nature of the provision of liquidity.

The first paper to link movements in liquidity across equity and fixed-income markets is by Chordia et al. (2005). They apply their vector autoregressive model, estimated using quoted bid-ask spreads, quoted depth, returns, volatility and order flow, to a sample of NYSE stocks and the US dollar Treasury bond market for the period June 1991 to December 1998. Their results show that innovations to the stock and bond market are significantly correlated, implying that in these security markets there is commonality in both liquidity and volatility. Their findings that

liquidity and volatility shocks are positively and significantly correlated across stock and bond markets at daily horizons suggest that liquidity and volatility shocks are often systemic in nature. Chordia et al. (2005) also suggest that an unexpected loosening of monetary policy, as measured by a decrease in net borrowed reserves, is associated with a contemporaneous increase in stock liquidity and has modest ability to forecast liquidity during crises. Innovations to bond fund flows on the other hand, are informative in forecasting both stock and bond market liquidity. Their findings also indicate that weekly regularities in stock and bond market liquidities closely mimic each other, with both markets experiencing the lowest levels of liquidity on Fridays. In both stock and bond markets, liquidity is found to be higher during the period July to September. In addition, their finding that a large fraction of the error variance in forecasting liquidity can be explained by daily innovations in volatility and liquidity, suggests that past volatility and liquidity are the most important variables in forecasting future liquidity.

The studies by Chordia, Roll and Subrahmanyam (2000), and Chordia, Sarkar and Subrahmanyam (2005), on commonality in stock liquidity and common factors influencing the liquidity in stock and bond markets, and the research by Hasbrouck and Seppi (2001) and Chordia, Roll, and Subrahmanyam (2002) into whether order flow commonality in large stocks has an economically significant effect on contemporaneous returns, was followed by Hughen and McDonald's (2006) examination of commonality across different trade sizes and types of stocks. Using data from the NYSE Trade and Quote (TAQ) database for the

sample period 1997 to June 2000, Hughen and McDonald (2006) classify trades as buyer-initiated when the price is above the previous price and as seller-initiated when the price is lower than the previous price. Subsequent transactions at the same price are assigned to the trading direction of the first trade in the series. Their results show that order imbalances in portfolios of small stocks, large stocks, and closed-end funds have predictive ability for other portfolio returns even in the presence of own order flow. They then partition order imbalance by trade size, thus showing that while imbalances from small and medium trades exhibit positive correlations across portfolios, no such characteristics of commonality are observed in order flows from large trades.

Following the same approach as Chordia et al. (2005), De Jong and Mentink (2006) test for commonality in liquidity in Europe stock, government bond and corporate bond markets. They use daily and weekly data for the sample period September 2002 to September 2003. By employing Granger causality tests and impulse response functions with the liquidity measures in the average quoted bid-ask spreads of each of the three markets as well as the average total turnover of the equity market for the whole of the sample period, they find that there is commonality in liquidity between the Euro security markets. Shocks in liquidity propagate with a time lag of one day or one week. In addition, links between liquidity and total returns and volatility within and between Euro security markets can be significant.

Stahel's (2005) study of commonalities in liquidity in an international framework uses a sample from Japan, the UK, and the US for the period 1980 to 2001. The findings show that three different monthly measures of individual stock liquidity exhibit commonalities within and across countries. Stahel argues that international commonalities might be induced by common factors that determine the supply of immediacy via inventory cost and inventory levels for many assets and across markets. Investors demanding immediacy might reallocate portfolios after a common shock to asset prices or interest rates, thus leading to international liquidity effects. Alternatively, where investors are required to satisfy margin calls after a negative shock to asset values in one market, they might respond by liquidating assets with non-depressed values on other markets, thus creating cross-border liquidity effects. Stahel's (2005) empirical results suggest that individual stock liquidity co-moves within countries and industries, as well as with global liquidity.

Brockman, Chung and Pérignon's (2006a) research is the first comprehensive study of commonality in liquidity using intra-day spread and depth data from 47 stock exchanges, and it confirms that commonality is a global phenomenon. On the majority of the world's stock exchanges, firm-level changes in spreads and depths are significantly influenced by exchange-wide changes in liquidity. The strongest commonality in spread is found on the emerging Asian exchanges, while the strongest commonality in depths is observed on the exchanges of North America. Latin American exchanges on the other hand exhibit little if any commonality. Their findings that commonality in bid-ask spreads is most

prevalent among small firms, while commonality in depths increases monotonically with firm size, contradict those of earlier studies based on the NYSE.

In the same study, Brockman, Chung and Pérignon (2006b) examine commonality across exchanges. Extending the empirical model of Chordia, Roll, and Subrahmanyam (2000) they find the first empirical evidence of a distinct, global component in bid-ask spreads and depths. At the exchange level, changes in global spreads and depths have a significant effect on changes in liquidity. Their findings also indicate that global commonality is not driven solely by regional co-movements. Whereas for developed markets, a larger portion of spread and depth commonality is attributable to regional sources, for emerging markets, global sources are more dominant. Brockman, Chung and Pérignon (2006b) show that while exchange size (total market capitalisation) is an important factor in the liquidity transmission process, global commonality is not driven by a subset of large exchanges.

According to Brockman, Chung and Pérignon (2006b), previous research has shown that when a domestic firm expands its operations into the global marketplace, it undergoes significant changes to its investment opportunity set, sources of financing, and ownership structure. Their own study provides the first examination of the impact on the firm's secondary-market liquidity. Using intra-day trade and quote data for a unique set of Swiss multinationals trading on the London-based Virt-X exchange from October 2002 to June 2004, they test

their hypothesis that commonality in a multinational firm's liquidity will follow its revenues, expenses and owners away from the domestic market and toward the global capital market. Their findings show that changes in the firm's liquidity remain unaffected by changes in aggregate liquidity from either the country of origin (Switzerland) or the physical location of trading (London). The main driver of multinational commonality in liquidity is changes in a global liquidity factor. For example, changes in the multinational firm's bid-ask spreads and depths co-vary significantly with changes in global spreads and depths. This is consistent with their hypothesis.

In short, since the seminal work of Chordia et al. (2000), the nascent literature on commonality has been expanding rapidly. New research has emerged, extending the analysis to various aspects of commonality, including larger sample size, higher data frequency, cost decompositions, and introduction of demand and supply conditions. The most recent development has been the extension of investigation to commonality in order-driven markets. Most of the research has confirmed the presence of commonality in liquidity, hence the critical importance of characterising stocks with liquidity.

Despite its rapid growth, the commonality literature is mostly concerned with quote-driven markets in industrial economies. Only recently have order-driven systems received attention from researchers, and almost without exception, emerging markets have been ignored. The consequent critical void in my

knowledge invites research on order-driven markets in emerging economies. This persuades me to study the Chinese case.

III. Data and Methodology

China publishes a range of value-weighted stock indices, aggregate, and sector indices, of which the most widely cited are the SHSE Shanghai Composite Index (SHCI) and Shanghai B Share Index; and the SZSE Shenzhen Component Index (SZCI) and Shenzhen B Share Component Index (Gao, 2002).

I use the China Stock Market and Accounting Research (CSMAR) to obtain transactions and quote data from July 2000 to June 2002 for A-shares traded on the SHSE and the SZSE. CSMAR covers all details of every transaction and related information, providing data by bid and ask record. The record includes current transaction price, day-to-second highest price, day-to-second lowest price, previous closing price, last record price, stock suspension indicator, day-to-second shares traded, day-to-second turnover, primary bid price, second bid price, third bid price, primary ask price, second ask price, third ask price, primary buy queue quantity, second buy queue quantity, third buy queue quantity, primary sell queue quantity, second sell queue quantity, third sell queue quantity, bid-ask spread, and closing price. Using a two year period as a sample will provide better evidence than that produced in previous studies, which tend to use only one year of data. The period between July 2000 and June 2002 is suitable because of the wide

variations in market trends. In July 2000 and June 2001 the market was bullish, whereas in July 2001 and June 2002 the trend was for a bear market.

I apply the same method as Chordia et al. (2000) to set up the sample selection filter, taking consideration of trading mechanisms on the Chinese exchanges. A stock included in the sample should be listed on the SHSE and the SZSE constantly throughout 24 months in the sample period. To avoid possible bias due to trading units, no stocks which had paid dividends or been split during the sample period are selected and these stocks must be traded at least once in at least ten trading days over the sample period of 24 months. To focus on normal trading activity during the continuous trading session, opening trades were deleted from the study. In addition, I deleted trades and transactions with ST and PT conditions[3] to avoid eruptive movement of stock prices. Finally, observations of all shares for June 24th, 2002 are not included, because there was an unusually large market shock in China on that day due to the announcement by the government of the decision to shelf the state stock reduction program.

The selection finally leads to a sample of A-shares on the SHSE whose transactions totalled 34,484,632. In the sample, 259 stocks are initially chosen over 468 trading days which is reduced to 13,960 stock-trading days due to the filtering. The average, median and minimum number of trading days per stock is

[3] According to Chinese regulations, firms that have suffered losses for two consecutive years since 1996 should be put under special treatment (ST). Since 1998, firms that have suffered losses for three consecutive years are treated under particular treatment (PT). The shares with PT firms can only be traded on Fridays with a price limit of plus or minus 5 per cent fluctuations per day. The shares with PT firms will be suspended from trading on the market if their losses cannot be reversed in a year (Lee and Xue, 2002).

440, 463, and 59 respectively. For A-shares on the Shenzhen stock market (the SZSE's A-shares), my filtering produces a sample of 48,789,363 transactions. My sample for this group of shares initially comprises 293 stocks over 468 trading days. After filtering, the sample is reduced to 130,092 stock-trading days. The average, median and minimum number of trading days per stock on the SZSE is 444, 458, and 146.

Following Chordia et al. (2000), I calculate three different liquidity measures for every transaction. They are quoted spread, percentage quoted spread, and depth. No effective spread and proportional effective spread are calculated, because Chinese stock exchanges have adopted an electronic trading system that allows the possibility for price improvement, leading to the identical quoted and effective bid-ask spread (Fabre and Frino, 2004; Sujoto et al., 2005). In addition I construct the liquidity measures recently suggested by Fabre and Frino (2004), and Sujoto, Kalev and Faff (2005). These measures include depth, a bi-dimensional liquidity measure, and the turnover rate. To smooth out intraday effects to achieve greater synchronicity, the transaction data for each daily liquidity measure is averaged across all trades for each daily stock (Chordia, et al., 2000). The definition of each liquidity measure constructed is given in Table 3.1 and Table 3.2.

My results show quoted spread (QSPR) and percentage quoted spread (PQSPR) in China are consistently lower than the corresponding values in the US and both the mean and median of the turnover rate (TR) are higher than those on the Australian market as reported in Sujoto et al. (2005). Both mean and median of the

bi-dimentional liquidity measure (BLM) are negative, while Sujoto et al. (2005) report the opposite results for shares on the Australian market. These results are likely due to institutional arrangements and trading rules on the Chinese stock exchanges that differ from their counterparts in the world.

The correlations between the depth measures and the spread measures are marginally negative. On the SHSE, the lowest of the correlations between the two measures is -0.0086 and the highest is 0.1934. On the SZSE, the lowest correlation between the two measures is -0.0130 and the highest is 0.3825. These results are largely consistent with the previous findings such as in Fabre and Frino (2004) where the correlation range is between -0.095 and 0.004, and in Sujoto et al. (2005), where the correlation range goes from -0.0159.

Table 3.1 Summary Statistics of Liquidity Measures for Shanghai Stocks

Panel A: Definitions

Liquidity Measures	Definition	Units
Quoted Spread (QSPR)	$P_A - P_B$	Yuan
Proportional Quoted Spread (PQSPR)	$(P_A - P_B)/P_M$	None
Depth (DEP)	$(Q_A + Q_B)/2$	Shares
Dollar Depth (VDEP)	$(P_A Q_A + P_B Q_B)/2$	Yuan
Turnover Rate (TR)	$Shares_{traded}/Shares_{outstanding}$	None
Bi-dimensional Liquidity Measure (BLM)	$BLM_t = \frac{\Delta D_t}{D_{t-1}} - \frac{\Delta I C_t}{I C_{t-1}}$	None

Panel B: Cross-sectional statistics for time series means

	Mean	Median	Standard Deviation
Quoted Spread (QSPR)	0.0320	0.0210	0.1673
Proportional Quoted Spread (PQSPR)	0.0104	0.0017	0.6514
Depth (DEP)	434.6500	36.2670	2181.396
Dollar Depth (VDEP)	6335.921	474.2194	35489.10
Turnover Rate (TR)	1.2278	0.7002	1.7770
Bi-dimensional Liquidity Measure (BLM)	-0.1400	-1.69e-08	33.5416

Panel C: Cross-sectional means of time-series correlations between liquidity variable pairs for an individual stock

	Quoted Spread (QSPR)	Proportional Quoted Spread (PQSPR)	Depth (DEP)	Dollar Depth (VDEP)	Turnover Rate (TR)
Proportional Quoted Spread (PQSPR)	0.0502				
Depth (DEP)	0.1810	-0.0086			
Dollar Depth (VDEP)	0.1934	-0.0044	0.9397		
Turnover Rate (TR)	0.1669	-0.0065	0.2928	0.2803	
Bi-dimensional Liquidity Measure (BLM)	-0.0002	-0.0006	0.0001	-0.0005	0.0004

Notes: This table presents the descriptive statistics of the stock liquidity measures on the Shanghai Stock Exchange (SHSE) between July 2000 and June 2002. Panel A gives the explanations of the liquidity measures. Panel B shows the cross-sectional statistics for the means of these liquidity measures on the time series basis. Panel C shows the cross-sectional means of correlations between liquidity variable pairs on the time series basis of individual firm. P_A is the quoted ask price, P_B being the bid price, P_M is the mid-quoted price. Q

stands for quoted share quantity for the trading, subscripts A=ask and B=bid. When calculating the bi-dimensional liquidity measure, depth (D) is computed as $D_t = Log\{(\sum_{j=1}^{t}[DEP_j T_j])\sum_{j=1}^{t} T_j\}$ and IC is the immediacy cost according to Pascual, Escribano and Tapia (2004), defined as: $IC_t = Log\{(\sum_{j=1}^{t}[PQSPR_j T_j])\sum_{j=1}^{t} T_j\}$. There were 468 trading days and 113,960 stock-days in SHSE from July 2000 to June 2002. The proxies for each liquidity measure are averaged across all trades for each daily stock.

Table 3.2 Summary Statistics of Liquidity Measures for Shenzhen Stocks

Panel A: Definitions

Liquidity Measures	Definition	Units
Quoted Spread (QSPR)	$P_A - P_B$	Yuan
Proportional Quoted Spread (PQSPR)	$(P_A - P_B)/P_M$	None
Depth (DEP)	$(Q_A + Q_B)/2$	Shares
Dollar Depth (VDEP)	$(P_A Q_A + P_B Q_B)/2$	Yuan
Turnover Rate (TR)	$Shares_{traded}/Shares_{outstanding}$	None
Bi-dimensional Liquidity Measure (BLM)	$BLM_t = \frac{\Delta D_t}{D_{t-1}} - \frac{\Delta I C_t}{I C_{t-1}}$	None

Panel B: Cross-sectional statistics for time series means

	Mean	Median	Standard Deviation
Quoted Spread (QSPR)	0.0313	0.0200	0.1095
Proportional Quoted Spread (PQSPR)	0.0424	0.0281	3.8589
Depth (DEP)	401.4336	40.0890	2088.976
Dollar Depth (VDEP)	5686.052	488.4150	33515.82
Turnover Rate (TR)	1.2278	0.7002	1.7770
Bi-dimensional Liquidity Measure (BLM)	-0.0007	-1.91e-08	0.1488

Panel C: Cross-sectional means of time-series correlations between liquidity variable pairs for an individual stock

	Quoted Spread (QSPR)	Proportional Quoted Spread (PQSPR)	Depth (DEP)	Dollar Depth (VDEP)	Turnover Rate (TR)
Proportional Quoted Spread (PQSPR)	0.0087				
Depth (DEP)	0.3623	-0.0130			
Dollar Depth (VDEP)	0.3825	-0.0100	0.9185		
Turnover Rate (TR)	0.2512	-0.0330	0.4469	0.4376	
Bi-dimensional Liquidity Measure (BLM)	-0.0008	-0.0006	0.0001	-0.0003	0.0004

Notes: This table presents the descriptive statistics of the stock liquidity measures on the Shenzhen Stock Exchange (SZSE) between July 2000 and June 2002. Panel A gives the explanations of the liquidity measures.

Panel B shows the cross-sectional statistics for the means of these liquidity measures on the time series basis. Panel C shows the cross-sectional means of correlations between liquidity variable pairs on the time series basis of individual firm. P_A is the quoted ask price, P_B being the bid price, P_M is the mid-quoted price. Q stands for quoted share quantity for the trading, subscripts A=ask and B=bid. When calculating the bi-dimensional liquidity measure, depth (D) is computed as $D_t = Log\{(\sum_{j=1}^{t}[DEP_j T_j])\sum_{j=1}^{t} T_j\}$ and IC is the immediacy cost according to Pascual, Escribano and Tapia (2004), defined as: $IC_t = Log\{(\sum_{j=1}^{t}[PQSPR_j T_j])\sum_{j=1}^{t} T_j\}$. There were 468 trading days and 113,960 stock-days in SHSE from July 2000 to June 2002. The proxies for each liquidity measure are averaged across all trades for each daily stock.

The absolute daily variations of liquidity measures are presented in Table 3.3. All the measures, except for the turnover rate and the measure of bi-dimensional liquidity, are consistently higher than the counterpart measures documented in similar studies of other markets. For example, I find that the mean of absolute daily variation for DQSPR is 5.1190 (0.8972 in SZSE), while it is 0.3302 in the Australian market as reported in Sujoto et al. (2005), 0.7282 in Fabre and Frino (2004) and 0.2396 in Chordia et al. (2000). The mean of absolute daily variation of DDEP is 8.3241 (7.3756 in SZSE), which contrasts with 0.5771 in Sujoto et al. (2005), 0.7886 in Fabre and Frino (2004), and 0.7828 in Chordia et al. (2000). These results show that liquidity on the Chinese stock market is relatively high but volatile, reflecting the institutional features of the Chinese stock market that is dominated by small but numerous investors.

My findings also show that the variation of depth is almost twice (7 times in the case of SZSE stocks) that of spread measures (except for the variation of PQSPR), which is in agreement with Sujoto et al. (2005), but different from Chordia et al. (2000). The variation of the turnover rate is substantially smaller than that of other liquidity measures, as is the bi-dimensional liquidity measure. This suggests the turnover rate and the bi-dimensional liquidity measure may reflect different aspects of liquidity, hence are interesting to investigating their behaviours when examining commonality in liquidity (Sujoto et al., 2005).

Table 3.3 Absolute Daily Percentage Changes in Liquidity Variables

Cross-sectional statistics for time series means (*SHSE*)	**Mean**	**Median**	**Standard Deviation**
Quoted Spread (| QSPR |)	5.1190	0.2594	48.3468
Percentage Quoted Spread (| PQSPR |)	13.8823	0.1864	592.1499
Depth (| DEP |)	8.3590	0.3361	64.0229
Dollar Depth (| VDEP |)	8.3241	0.3376	63.3598
Turnover Rate (| TR |)	0.5934	0.3535	1.2081
Bi-dimensional Liquidity Measure (| BLM |)	0.1354	1.21e-08	32.9917
Cross-sectional statistics for time series means (*SZSE*)	**Mean**	**Median**	**Standard Deviation**
Quoted Spread (| QSPR |)	0.8972	0.1765	5.9155
Percentage Quoted Spread (| PQSPR |)	43.7911	0.1771	3108.138
Depth (| DEP |)	7.3756	0.3269	59.8885
Dollar Depth (| VDEP |)	7.3575	0.3286	59.5470
Turnover Rate (| TR |)	0.5943	0.3503	1.5826
Bi-dimensional Liquidity Measure (| BLM |)	0.0007	2.82e-08	0.1488

Notes: This table presents the descriptive statistics of the absolute daily percentage change in that variable for each liquidity variable on the Chinese Stock Exchange between July 2000 and June 2002. The Chinese Stock Exchange includes the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE). QSPR is the quoted spread, PQSPR is the percentage quoted spread, DEP is depth. VDEP is Dollar Depth. TR is the Turnover Rate. BLM is the Bi-dimensional Liquidity Measure.

IV. Empirical Findings

I apply the methodology of Chordia et al. (2000), Fabre and Frino (2004) and Sujoto et al. (2005) to examine the co-variation of market liquidity. The regression equation is rendered as follows:

$$DL_{j,t} = \alpha_j + \beta_j DL_{M,t} + \varepsilon_{j,t} \qquad (3.1)$$

where D stuands for percentage changes (or the growth rate), so $DL_{j,t}$ is the percentage change in the liquidity measure (L) for stock j from day t -1 to t, and $DL_{M,t}$ is the contemporaneous growth of the market liquidity calculated by taking average of the same liquidity measure across the stocks. When taking the cross-sectional average to derive the market liquidity measure, stock j is excluded from the computation (Chordia, et al., 2000).

In examining association between the individual stock's liquidity measure and the market liquidity, contemporaneous changes in market liquidity as well as one lead and one lag of the market liquidity variable are included as the regressors. Following Chordia et al. (2000), I also include market return to control for possible spurious dependence between returns and bid-ask spread measures. The market return variable is also being led and lagged by one period to capture possible dynamics in commonality. In addition, the concurrent daily percentage change in the individual stock's squared return is deployed as a proxy for price volatility. However, I do not report the coefficients on the market returns and

squared stock returns because both are nuisance variables (Chordia, et al., 2000; Fabre and Frino, 2004; Sujoto, et al, 2005).

The residuals from individual regressions may not be normally distributed due to the discreteness in stock pricing. However, as argued by Chordia et al. (2000), the central limit theorem can slightly reduce the asymptotically normal distribution for the estimated coefficients. As a result, the cross-sectional mean of the estimated coefficients is close to Gaussian when the residuals of the individual regressions are independent (Chordia, et al., 2000).

Table 3.4 and Table 3.5 present the results of estimating equation (3.1). In the tables, the percentages of positive coefficients are shown in the 'Percentage+' row, while the 'Percentage+significant' row shows the percentages of the variables that have a t-statistic greater than + 1.645, the 5% critical level in an one-tailed test.

Table 3.4 Commonality in Liquidity (Value-weighted Market Liquidity)

SHSE	Quoted Spread (DQSPR)	Percentage Quoted Spread (DPQSPR)	Depth (DDEP)	Dollar Depth (VDEP)	Turnover Rate (DTR)	Bi-dimensional Liquidity Measure (BLM)
Concurrent	97.98 (20.38)	7.11 (5.97)	73.97 (12.35)	77.29 (15.84)	119.72 (3.00)	17.04 (0.25)
Median	78.72	1.28	75.51	74.92	14.27	1.54E-08
Percentage+	98.46	96.53	99.23	99.23	98.07	75.68
Percentage+significant	88.07	37.45	88.84	88.84	78.38	1.93
Lag	-41.60 (-0.29)	10.52 (1.04)	-40.37 (-0.36)	-32.00 (-0.25)	-96.21 (-1.56)	7.12 (0.12)
Median	-34.16	-0.45	-32.29	-23.46	-92.76	5.97E-09
Percentage+	23.94	9.27	3.86	6.56	3.86	67.57
Percentage+significant	1.16	3.86	0.39	0.39	0	0.77
Lead	-15.29 (-0.05)	4.66 (0.34)	-28.02 (-0.24)	-19.05 (-0.14)	-58.39 (-1.01)	-40.08 (-0.20)
Median	-0.65	-0.40	-25.78	-19.04	-66.71	6.287E-09
Percentage+	49.03	17.76	8.11	14.67	13.51	58.69
Percentage+significant	1.54	6.95	0.39	0.39	1.93	4.25
SUM	41.09 (6.68)	22.29 (1.53)	5.58 (3.92)	26.24 (5.15)	-34.88 (-0.14)	-15.92 (-0.19)
Adj R^2 Mean	0.32	0.13	0.26	0.36	0.17	0.01
Median	0.25	0.008	0.24	0.358	0.16	-0.005
SZSE	**Quoted Spread (DQSPR)**	**Percentage Quoted Spread (DPQSPR)**	**Depth (DDEP)**	**Dollar Depth (VDEP)**	**Turnover Rate (DTR)**	**Bi-dimensional Liquidity Measure (BLM)**
Concurrent	90.48 (8.01)	93.33 (6.31)	65.95 (5.47)	93.17 (5.75)	93.62 (2.98)	54.29 (0.71)
Median	87.75	3.98	16.03	36.87	68.63	-0.0006
Percentage+	94.14	92.76	98.97	98.97	98.28	37.59
Percentage+significant	93.10	11.38	47.93	63.45	82.41	6.90
Lag	-91.38 (-0.04)	-93.16 (-0.31)	-6.89 (-0.51)	-71.85 (-0.61)	-40.74 (-1.41)	80.11 (0.78)
Median	5.62	1.85	-12.54	-31.28	-44.37	0.0007
Percentage+	51.03	80.00	12.76	5.17	5.17	75.52
Percentage+significant	2.41	0.69	0	0	1.38	9.31
Lead	60.27 (0.37)	77.34 (0.29)	-11.62 (-0.02)	-11.62 (-0.90)	-43.27 (-0.32)	90.79 (0.66)
Median	11.83	1.20	-7.41	-17.26	-89.09	0.001
Percentage+	77.93	80	34.83	27.59	28.28	79.31
Percentage+significant	4.14	2.76	3.10	2.76	3.45	21.72
SUM	59.37 (2.78)	77.51 (2.31)	47.44 (1.66)	9.7 (1.41)	9.61 (0.42)	225.19 (0.25)
Adj R^2 Mean	0.18	0.12	0.13	0.13	0.13	0.08
Median	0.14	0.005	0.04	0.04	0.12	0.02

Notes: This table presents daily percentage changes in individual stocks' liquidity variables are regressed on the percentage changes of a value-weighted cross-sectional average of the liquidity variable on the time series basis for all stocks on the Chinese Stock Exchange between July 2000 and June 2002. The Chinese Stock Exchange includes the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE). QSPR is the quoted spread, PQSPR is the percentage quoted spread, DEP is depth. VDEP is Dollar Depth. TR is the Turnover Rate. BLM is the bi-dimensional Liquidity Measure. D denotes the daily percentage changes in that variable for each liquidity variable. The dependent variable stock is not included in the market average liquidity variables. 'Percentage+' is the percentage of positive coefficients. 'Percentage+significant' is the percentage of positive and significant coefficients. Both 'Percentage+' and 'Percentage+significant' are reported on concurrent liquidity variables as well as for the previous trading day (lag) and next trading day (lead).

Table 3.5 Commonality in Liquidity (Equal-weighted Market Liquidity)

SHSE	Quoted Spread (DQSPR)	Percentage Quoted Spread (DPQSPR)	Depth (DDEP)	Dollar Depth (VDEP)	Turnover Rate (DTR)	Bi-dimensional Liquidity Measure (BLM)
Concurrent	86.23 (16.00)	77.01 (5.94)	63.96 (12.45)	51.07 (10.30)	6.78 (2.61)	-80.30 (-0.25)
Median	87.95	1.32	53.73	41.84	6.50	1.10E-08
Percentage+	98.46	96.91	99.23	99.23	95.75	77.22
Percentage+significant	88.07	45.95	88.84	88.84	73.75	1.54
Lag	-1.96 (-0.33)	9.74 (1.07)	-1.27 (-0.27)	-0.77 (-0.18)	-4.01 (-1.37)	22.87 (0.11)
Median	-1.54	-0.48	-0.99	-0.61	-3.01	3.65E-09
Percentage+	11.20	9.65	4.25	13.51	6.95	65.64
Percentage+significant	1.54	4.25	0	0	0.39	0.39
Lead	-1.78 (-0.20)	4.73 (0.35)	-1.46 (-0.27)	-0.18 (-0.02)	-1.98 (-0.68)	-50.50 (-0.19)
Median	-0.79	-0.41	-1.34	-0.25	-2.03	3.62E-09
Percentage+	27.03	14.29	6.56	32.82	22.01	57.92
Percentage+significant	0.39	6.95	0.39	0.39	2.32	3.47
SUM	82.49 (5.16)	91.48 (1.50)	61.23 (3.97)	50.12 (3.37)	0.79 (0.19)	-107.93 (-0.18)
Adj R^2 Mean	0.38	0.11	0.26	0.20	0.15	0.006
Median	0.39	-0.001	0.24	0.18	0.14	-0.01
SZSE	**Quoted Spread (DQSPR)**	**Percentage Quoted Spread (DPQSPR)**	**Depth (DDEP)**	**Dollar Depth (VDEP)**	**Turnover Rate (DTR)**	**Bi-dimensional Liquidity Measure (BLM)**
Concurrent	30.61 (7.94)	78.45 (6.31)	18.00 (5.06)	19.88 (5.72)	5.66 (2.96)	29.31 (0.71)
Median	25.19	0.06	0.49	2.04	4.88	-9.66E-06
Percentage+	94.14	91.38	99.31	99.31	97.59	37.24
Percentage+significant	92.41	11.38	35.86	77.59	83.10	7.24
Lag	-1.68 (-0.18)	-0.88 (-0.26)	-2.06 (-0.47)	-2.86 (-0.85)	-2.54 (-1.57)	14.21 (0.77)
Median	-0.35	0.02	-0.08	-0.59	-2.55	1.06E-05
Percentage+	42.07	75.86	11.38	2.41	4.83	76.55
Percentage+significant	1.72	0.69	0	0.34	0.69	9.31
Lead	5.82 (3.06)	3.57 (0.22)	-0.67 (-0.13)	-2.41 (-1.85)	-1.70 (-0.86)	24.02 (0.62)
Median	5.92	0.01	-0.08	-0.74	-1.51	2.19E-05
Percentage+	90.34	72.41	27.59	10.69	12.76	77.59
Percentage+significant	45.17	2.07	2.41	1.72	1.72	19.31
SUM	34.75 (5.16)	81.14 (2.26)	15.27 (1.49)	14.61 (1.01)	1.42 (0.18)	67.54 (0.23)
Adj R^2 Mean	0.16	0.11	0.10	0.11	0.13	0.08
Median	0.12	-0.008	-0.0002	0.007	0.12	0.08

Notes: This table presents daily percentage changes in individual stocks' liquidity variables are regressed on the percentage changes of an equal-weighted cross-sectional average of the liquidity variable on the time series basis for all stocks on the Chinese Stock Exchange between July 2000 and June 2002. The Chinese Stock Exchange includes the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE). QSPR is the quoted spread, PQSPR is the percentage quoted spread, DEP is depth. VDEP is Dollar Depth. TR is the Turnover Rate. BLM is the bi-dimensional Liquidity Measure. D denotes the daily percentage changes in that variable for each liquidity variable. The dependent variable stock is not included in the market average liquidity variables. 'Percentage+' is the percentage of positive coefficients. 'Percentage+significant' is the percentage of positive and significant coefficients. Both 'Percentage+' and 'Percentage+significant' are reported on concurrent liquidity variables as well as for the previous trading day (lag) and next trading day (lead).

Both value-weighted and equal-weighted market liquidity variables are employed when conducting the regressions. Comparing the results in Tables 3.4 and 3.5, it is interesting to note that when the market liquidity measure is value weighted, the concurrent slope coefficients on the variable are greater than that when the measure is equal weighted. This is markedly different from what is reported in Chordia et al. (2000). This outcome is likely due to the fact that although the Chinese stock market is dominated by individual investors in number, big cap shares of the monopolistic state-owned firms could have stronger influence in value on the market. When examining the effect of the weighting schemes, market capitalisation at 30 June 2000 is used in my sample.

On the SHSE, the lowest cross-sectional mean of liquidity beta is -80 for BLM, and is 7 for DPQSPR, when the market liquidity measure is value-weighted. Also with this value weighted measure, the highest cross-sectional mean of liquidity beta is 86 for DQSPR, and 120 for DTR. The lowest proportion of stocks with positive β is 76% for BLM and 77% for BLM while the highest counterpart is 99% for DDEP and DVDEP.

Of the total 259 stocks, between 2% (for BLM) and 89% (for DDEP and DVDEP) have a significantly positive β at the 5% level, which is true for both equal- and value-weighted market liquidity measures.

On the SZSE, the lowest cross-sectional mean of liquidity beta is 6 for DTR and 54.29 for BLM with value-weighted market liquidity measure. Using this measure, the highest cross-sectional mean of liquidity beta is 79 for DPQSPR and 94 for DTR. The lowest proportion of stocks with positive β is 37% for BLM and 38% for BLM while the highest proportion of stocks with positive β is 99% for DDEP and DVDEP.

Of the total 291 stocks from the SZSE, between 7% stocks for BLM, 92% for DQSPR, and 93% for DQSPR have a significantly positive β at the 5% level for both value weighted and equal weighted market liquidity measures.

When compared with previous findings, my study provides much stronger evidence of the existence of liquidity commonality on the Chinese stock market (except for DPQSPR). The proportion of stocks that have positive and significant β coefficients for the spread measure and the depth measures in Table 3.4 and Table 3.5 is almost three times of that of comparable measures in Chordia et al. (2000). Furthermore, I also found a much higher proportion of Chinese stocks with positive and significant β in my sample: 89% in SHSE and 92%, on the SZSE compared with the less than 3% reported by Fabre and Frino (2004), 30% reported by Chordia et al. (2000) and more than 50% reported by Sujoto et al. (2005). This shows that commonality in liquidity in the Chinese order-driven market is higher than quote-driven markets such as the US stock market and also than other order-driven markets such as Hong Kong and Australian stock markets. One plausible reason for this is likely to be that the Chinese stock market is

dominated by institutional investors and both the best bid-ask spread and best depth are provided by them. However, normally these prices cannot reflect the real information in the market because many of the traders on the market are retail investors who only pursue short term profits. As a result, comparing with other order-driven markets, Chinese stock market with high commonality in liquidity cannot attract more liquidity suppliers to enter the market (Song and Tan, 2005).

However, my leading and lagged terms are not positive and significant. Most of the cross-sectional means of liquidity beta (β) on these terms are negative. Most results are quite small and quite a few are even zero. This implies the lead and lag effects of commonality are less significant and less pervasive on the Chinese stock market which perhaps suggests that there are no significant lead-and-lag structure in commonality in liquidity on the Chinese market.

Following Chordia et al. (2000), when calculating the cross-sectional t-statistic for the average liquidity β, it is assumed that the estimation errors in β are independent across regressions. The 'SUM' rows in the table present the combined effects of contemporaneous, lead, and lag coefficients. The outcome shows that in many cases the t-statistic is highly significant in the Chinese case. On the other hand, the average adjusted R^2 is less than two percent and the individual regression does not carry much explanatory power. These results suggest that there must be other significant influences, such as noise, on the changes in individual stock's liquidity (Chordia et al., 2000).

Overall, my results from traditional liquidity measures provide strong evidence for the existence of commonality in liquidity in Chinese stocks. However, regarding the claim in previous research on the subject of trading behaviour (Chordia, et al., 2000; Sujoto et al., 2005), my evidence suggests that, in response to common variations in liquidity, Chinese stock market participants tend to revise both their price and the quantity of shares in their orders.

Using the turnover rate as an alternative liquidity proxy, as suggested by Sujoto et al. (2005), I find even stronger evidence of commonality in liquidity. However, when employing another alternative liquidity measure, i.e. bi-dimensional liquidity, the cross-sectional mean of β is found to be not statistically significant and the proportion of stocks with significant and positive β is only 2% on the SHSE and 7% on the SZSE. These results suggest an absence of co-movements in this dimension of liquidity in my data sample. Given the evidence of the commonality in liquidity on the Chinese stock market in terms of many other liquidity proxies, it is likely that the bi-dimensional liquidity measure is not a suitable variable to be employed in investigating commonality in liquidity on the Chinese stock market.

V. Further Evidence

In order to examine the potential size effect of systematic liquidity, I divide the sample into five quintiles, based on market capitalisation at the beginning of the

sample period (Chordia, et al., 2000), and re-estimate equation (3.1) for each quintile.

The results are reported in Table 3.6 and Table 3.7. Previous studies have performed the same tests, but with varying results. Chordia et al. (2000) find that, while depth has little relation to size, the cross-sectional mean of "SUM" of the liquidity β on market liquidity proxied by the spread measures (DQSPR and DPQSPR) generally increases with size implying a size effect in this dimension of liquidity. Brockman and Chung (2002) find, when liquidity is measured in terms of spreads, there is the size effect in that the percentage of stocks with positively significant liquidity betas increases with firm size. Fabre and Frino (2004) do not report any significant size effects. Sujoto et al. (2005) find that, although in their sample, the proportion of significant and positive stocks increases with size quintile, no such size effect exists in the cross-sectional means of the liquidity beta. My study shows a somewhat different pattern on the Chinese stock market (see Tables 3.6 and 3.7 below).

Table 3.6 Commonality in Liquidity by Size Quintile (SHSE)

		Smallest N=51	2 N=52	3 N=52	4 N=52	Largest N=52
Quoted Spread (DQSPR)	Concurrent	30.49 (9.56)	89.61 (26.29)	68.28 (3.52)	114.92 (18.63)	165.40 (25.14)
	Median	30.43	90.51	66.80	116.29	164.46
	Percentage+	94.12	96.15	97.01	98.08	98.58
	Percentage+significant	90.20	96.15	97.01	98.08	98.58
	Adj R^2 Mean	0.25	0.62	0.15	0.44	0.59
Percentage Quoted Spread (DPQSPR)	Concurrent	1.99 (2.35)	112.21 (1.98)	114.93 (21.71)	14.96 (0.73)	5.93 (2.49)
	Median	1.8	49.22	113.26	7.20	5.22
	Percentage+	97.78	92.31	96.15	92.31	98.08
	Percentage+significant	86.67	19.23	63.46	21.15	26.92
	Adj R^2 Mean	0.03	0.01	0.55	0.04	0.03
Depth (DDEP)	Concurrent	32.88 (18.81)	69.69 (23.48)	99.26 (15.37)	88.23 (15.89)	22.56 (20.26)
	Median	28.77	67.82	101.17	85.53	22.89
	Percentage+	96.08	98.08	98.08	98.08	98.08
	Percentage+significant	94.12	97.08	97.15	98.02	98.08
	Adj R^2 Mean	0.54	0.56	0.33	0.35	0.47
Dollar Depth (VDEP)	Concurrent	22.75 (18.33)	69.10 (23.16)	101.24 (15.39)	22.52 (15.98)	22.78 (20.16)
	Median	28.65	67.31	103.50	21.89	23.15
	Percentage+	96.08	98.08	98.08	98.08	98.08
	Percentage+significant	94.12	97.08	97.15	98.02	98.08
	Adj R^2 Mean	0.52	0.56	0.34	0.35	0.47
Turnover Rate (DTR)	Concurrent	251.28 (1.22)	236.31 (0.90)	602.87 (2.22)	232.22 (0.79)	98.65 (1.61)
	Median	138.57	156.37	590.45	187.07	88.04
	Percentage+	86.27	96.15	98.08	96.15	96.15
	Percentage+significant	41.18	51.92	69.23	65.38	59.62
	Adj R^2 Mean	0.31	0.30	0.05	0.24	0.09
Bi-dimensional Liquidity Measure (BLM)	Concurrent	17.56 (4.54)	496.50 (1.83)	464.05 (1.29)	510.57 (0.58)	709 (-0.08)
	Median	15.80	271.13	153.90	34.04	-2.02E-07
	Percentage+	98.04	92.31	92.31	90.38	69.23
	Percentage+significant	86.27	69.23	76.92	76.92	66.53
	Adj R^2 Mean	0.06	-0.002	0.12	0.02	-0.006

Notes: This table presents daily percentage changes in individual stocks' liquidity variables are regressed on the percentage changes of a value-weighted cross-sectional average of the liquidity variable on the time series basis for all stocks on the Shanghai Stock Exchange (SHSE) by size quintile between July 2000 and June 2002. Column 3-7 are five quintiles, based on market capitalisation at the beginning of the sample period. QSPR is the quoted spread, PQSPR is the percentage quoted spread, DEP is depth. VDEP is Dollar Depth. TR is the Turnover Rate. BLM is the bi-dimensional Liquidity Measure. D denotes the daily percentage changes in that variable for each liquidity variable. The dependent variable stock is not included in the market average liquidity variables. 'Percentage+' is the percentage of positive coefficients. 'Percentage+significant' is the percentage of positive and significant coefficients. Both 'Percentage+' and 'Percentage+significant' are reported on concurrent liquidity variables.

Table 3.7 Commonality in Liquidity by Size Quintiles (SZSE)

		Smallest N=58	2 N=58	3 N=58	4 N=58	Largest N=59
Quoted Spread (DQSPR)	Concurrent	49.42 (12.41)	162.32 (13.35)	68.46 (11.72)	125.43 (60.67)	111.09 (22.93)
	Median	46.34	172.02	66.03	128.92	109.08
	Percentage+	94.83	98.28	98.21	98.28	98.31
	Percentage+significant	91.38	98.08	98.11	96.55	98.31
	Adj R^2 Mean	0.45	0.37	0.39	0.88	0.57
Percentage Quoted Spread (DPQSPR)	Concurrent	55.22 (0.08)	136.24 (9.16)	579.89 (0.46)	646.74 (22.82)	718.28 (6.45)
	Median	-0.010	148.56	3.20	1.26	1.22
	Percentage+	91.38	84.48	86.21	93.10	91.53
	Percentage+significant	8.62	10.34	8.62	32.76	18.64
	Adj R^2 Mean	0.03	0.30	-0.003	0.03	0.12
Depth (DDEP)	Concurrent	52.27 (18.29)	80.36 (12.06)	94.93 (42.60)	148.73 (21.31)	128.77 (17.16)
	Median	47.68	904.46	158.08	156.05	131.85
	Percentage+	98.28	98.28	96.55	98.28	98.31
	Percentage+significant	94.83	98.08	96.55	98.08	98.31
	Adj R^2 Mean	0.43	0.33	0.80	0.51	0.42
Dollar Depth (VDEP)	Concurrent	52.42 (18.62)	770.10 (11.92)	147.92 (41.79)	146.69 (21.23)	129.16 (17.11)
	Median	48.09	866.24	156.54	153.75	132.46
	Percentage+	96.55	98.28	96.55	98.28	98.31
	Percentage+significant	94.83	98.08	96.55	98.08	98.31
	Adj R^2 Mean	0.44	0.32	0.79	0.51	0.42
Turnover Rate (DTR)	Concurrent	496.84 (1.51)	163.17 (12.77)	85.81 (2.45)	89.74 (3.77)	29.05 (1.58)
	Median	357.18	185.05	78.86	91.19	12.62
	Percentage+	96.55	94.83	98.28	91.38	98.31
	Percentage+significant	51.72	70.69	62.07	51.72	55.93
	Adj R^2 Mean	0.08	0.50	0.08	0.17	0.15
Bi-dimensional Liquidity Measure (BLM)	Concurrent	483.96 (2.29)	-67.05 (0.44)	11.28 (-5.33)	13.02 (0.08)	13.14 (-0.22)
	Median	529.91	0.004	-0.02	0.11	-0.004
	Percentage+	84.48	51.72	41.38	58.62	25.42
	Percentage+significant	51.72	10.34	6.90	5.17	5.08
	Adj R^2 Mean	0.13	0.02	0.10	0.01	0.22

Notes: This table presents daily percentage changes in individual stocks' liquidity variables are regressed on the percentage changes of a value-weighted cross-sectional average of the liquidity variable on the time series basis for all stocks on the Shenzhen Stock Exchange (SZSE) by size quintile between July 2000 and June 2002. Column 3-7 are five quintiles, based on market capitalisation at the beginning of the sample period. QSPR is the quoted spread, PQSPR is the percentage quoted spread, DEP is depth. VDEP is Dollar Depth. TR is the Turnover Rate. BLM is the bi-dimensional Liquidity Measure. D denotes the daily percentage changes in that variable for each liquidity variable. The dependent variable stock is not included in the market average liquidity variables. 'Percentage+' is the percentage of positive coefficients. 'Percentage+significant' is the percentage of positive and significant coefficients. Both 'Percentage+' and 'Percentage+significant' are reported on concurrent liquidity variables.

From the tables, there is clear evidence of the size effect. In terms of liquidity beta on the concurrent market liquidity measure, it generally increases with size. On the Shanghai market for example, the concurrent slope coefficient on the market liquidity variable increases with size quintiles for DQSPR, DPQSPP, and BLM. Meanwhile, there is an inverted U shape of cross sectional means of the concurrent slope coefficient on the market liquidity for both DDEP and VDEP, but for both measures the proportion of stocks with a positively significant concurrent coefficient increases with size, which is consistent with the findings by Brockman and Chung (2002). Only for DTR, there is not any supportive evidence in terms of the slope coefficient, but the proportion of stocks with a positive and significant coefficient also varies with size.

The SZSE market shows a similar pattern. On that exchange, for all measures but BLM, the proportion of stocks with a positively significant concurrent coefficient varies with size. In terms of concurrent slope coefficient on the market liquidity measures, it increase with size for DQSPR and VDEP, and it has an inverted U pattern for DDEP and DPQSPR. For DTR and BLM, I find no evidence of a size effect.

On the other hand, the tables also show that that co-movement of liquidity exists for most of the quintiles. This means that, on the Chinese stock market, commonality in liquidity is driven by larger stocks in general, not just one or two quintiles. For liquidity measures of DQSPR, DDEP and VDEP on both markets, more than 90% of the stocks in every quintile have positively significant β.

On the whole, the outcome provides the evidence of the size effect in the liquidity commonality. The results that I record in the tables suggest that, in China, liquidity of large size stocks is more likely to move with liquidity of the market, hence suggesting that these stocks are more exposed to correlated trading. This facet of liquidity commonality in China might be caused by Chinese market participants' herding behaviour (Sujuto, et al., 2005; Fong, et al., 2004). But it is more likely that the Chinese investors' preference for large stocks is a reflection of these investors' "flight to quality", a strategy which these investors employ as a coping mechanism for problems resulting from under-development of the stock market in China.

It is possible that in systematic liquidity, there are both industry and market components (Chordia, et al., 2000, Brockman and Chung, 2002). To investigate the possibility of individual stock liquidity co-moves with liquidity of the industry to which a stock belongs and with liquidity of the market as a whole, I follow Sujoto, et al. (2005) to classify the sample firms into three categories based on Global Industry Classification Standard (GICS) code. These are: industrial (128 stocks for SHSE, 160 stocks for SZSE), resources (39 stocks for SHSE, 27 stocks for SZSE), and financial (84 stocks for SHSE, 79 stocks for SZSE). I then add an industry liquidity variable to Equation (3.1), which leads me to estimate the following formulation (leading and lagged variables are not shown):

$$DL_{j,t} = \alpha_j + \beta_{1,j} DL_{M,t} + \beta_{2,j} DL_{I,t} + \varepsilon_{j,t}, \qquad (3.2)$$

where $DL_{I,t}$ is the concurrent change in a cross-sectional mean of the liquidity measure of the industry to which stock j belong. When taking the average for all stocks in this industry, stock j is excluded.

Tables 3.8 and 3.9 present the results of estimating Equation (3.2). I find evidence of the existence of both market and industrial level commonality in terms of cross-sectional significance of liquidity coefficients, confirming that individual stock liquidity on the Chinese market is influenced by both market and industry-specific common factors, which is in agreement with Chordia, et al., (2000). Also, like Chordia et al. (2000), I find that, of all the liquidity measures, the cross sectional mean of the concurrent beta on market liquidity (β_1) is

Table 3.8 Market and Industry Commonality (SHSE)

	Market	Industry	Market	Industry	Market	Industry	Market	Industry	Market	Industry	Market	Industry
	Quoted Spread (DQSPR)		**Percentage Quoted Spread (DPQSPR)**		**Depth (DDEP)**		**Dollar Depth (VDEP)**		**Turnover Rate (DTR)**		**Bi-dimensional Liquidity Measure (BLM)**	
Concurrent	49.05 (3.19)	127.91 (18.31)	41.92 (4.01)	263.26 (6.20)	20.40 (3.41)	748.62 (11.71)	36.85 (4.22)	67.62 (8.58)	15.56 (2.39)	24.96 (0.65)	9.54E-06 (0.50)	0.01 (0.16)
Median	35.44	127.13	31.16	237.45	12.12	548.04	18.58	447.61	16.51	351.88	3.06E-06	5.92645E-05
Percentage +	73.80	92.86	92.21	60.58	80.55	98.48	86.09	86.09	91.54	70.24	75.13	75.13
Percentage +significant	61.90	90.48	80.09	53.10	60.55	90.12	70.34	86.02	82.09	10.90	13.65	10.90
Lag	27.18 (0.13)	-185.8 (-0.14)	98.10 (1.78)	64.15 (0.1)	-5.07 (-0.10)	33.43 (0.01)	-13.07 (-0.15)	71.11 (0.07)	-94.57 (-1.76)	220.12 (0.62)	-2.40E-06 (-0.21)	-2.60E-05 (-0.009)
Median	8.84	-99.07	150.35	-1547.26	-7.77	17.56	-13.26	42.56	-104.18	157.12	3.16E-07	7.21E-06
Percentage +	57.14	33.33	80.09	20.28	30.38	64.90	20.28	73.50	11.91	93.14	50.32	50.60
Percentage +significant	8.62	1.05	50.69	20.28	5.02	8.33	1.88	1.32	0.50	10.28	0.11	0.26
Lead	71.74 (0.35)	36.04 (0.14)	311.56 (2.65)	-268.77 (-2.55)	-5.11 (-0.10)	83.16 (0.12)	-11.29 (-0.14)	116.33 (0.17)	-82.43 (-1.35)	-0.38 (-0.006)	9.69E-06 (0.71)	-6.52898E-05 (-0.01)
Median	30.67	128.90	248.61	-985.21	-3.39	26.21	-8.96	37.57	-79.94	26.04	4.03E-06	4.07954E-05
Percentage +	73.81	59.52	60.14	42.14	42.14	80.09	40.03	80	7.05	65.66	72.59	65.66
Percentage +significant	4.76	2.38	50.08	40.05	2.32	0.96	2.20	1.94	0.04	10.28	27.20	1.52
SUM	147.97 (1.22)	-21.88 (-6.10)	451.58 (2.81)	58.64 (1.18)	10.22 (1.07)	865.21 (3.94)	12.49 (1.31)	255.06 (2.94)	-161.44 (-0.24)	244.7 (0.42)	1.68E-05 (0.47)	0.00022 (0.06)
Median	34.10	156.82	304.10	-14.60	0.46	99.11	-2.81	132.31	-72.86	137.50	1.70E-06	2.31403E-05
Adj R^2 Mean	0.70		0.70		0.41		0.42		0.18		0.04	
Median	0.75		0.98		0.46		0.49		0.15		0.03	

Notes: This table presents daily percentage changes in individual stocks' liquidity variables are regressed on the percentage changes of a value-weighted cross-sectional average of the liquidity. variable on the time series basis for all stocks on the Shanghai Stock Exchange (SHSE) and on the percentage changes of a value-weighted cross-sectional average of the liquidity variable on the time series basis for stock from special industries between July 2000 and June 2002. Market firms include all stocks we select on the SHSE. Industry firms include industrial stocks, resources stocks and financial stocks from Global Industry Classification Standard (GICS) code. QSPR is the quoted spread, PQSPR is the percentage quoted spread, DEP is depth. VDEP is Dollar Depth. TR is the Turnover Rate. BLM is the bi-dimensional Liquidity Measure. D denotes the daily percentage changes in that variable for each liquidity variable. The dependent variable stock is not included in the market average liquidity variables. 'Percentage+' is the percentage of positive coefficients. 'Percentage+significant' is the percentage of positive and significant coefficients. Both 'Percentage+' and 'Percentage+significant' are reported on concurrent liquidity variables as well as for the previous trading day (lag) and next trading day (lead).

Table 3.9 Market and Industry Commonality (SZSE)

	Market	Industry	Market	Industry	Market	Industry	Market	Industry	Market	Industry	Market	Industry
	Quoted Spread (DQSPR)		**Percentage Quoted Spread (DPQSPR)**		**Depth (DDEP)**		**Dollar Depth (VDEP)**		**Turnover Rate (DTR)**		**Bi-dimensional Liquidity Measure (BLM)**	
Concurrent	58.64 (4.72)	139.24 (20.14)	56.28 (6.63)	276.42 (7.61)	32.72 (6.94)	780.65 (12.62)	50.33 (5.73)	77.15 (11.83)	36.56 (2.51)	53.71 (0.76)	0.00045 (0.62)	2.01 (1.06)
Median	37.03	126.29	42.01	268.65	16.87	604.76	22.09	657.35	35.18	270.05	2.81E-02	0.91
Percentage +	78.83	94.37	92.42	61.32	82.21	98.16	88.06	87.98	93.77	72.78	78.85	70.93
Percentage +significant	61.28	91.45	82.02	56.09	67.92	90.90	70.82	80.74	81.59	10.57	14.61	10.61
Lag	22.23 (0.35)	-121.9 (-0.14)	98.89 (1.84)	64.74 (1.82)	-4.97 (-0.60)	58.75 (1.31)	-9.83 (-0.03)	104.79 (0.23)	-83.74 (-1.59)	409.81 (0.85)	-2.50E-05 (-0.92)	-1.32E-03 (-0.29)
Median	8.28	-27.43	155.32	-147.39	-8.08	20.05	-13.26	54.75	-5.19	368.78	0.02	0.12
Percentage +	57.52	34.26	80.54	22.40	33.26	68.37	20.27	75.59	15.52	90.49	56.50	58.51
Percentage +significant	2.21	2.74	50.31	20.21	7.13	10.10	0.98	2.24	0.17	12.18	0.19	0.23
Lead	85.83 (0.67)	36.04 (0.14)	581.28 (4.54)	-171.75 (-0.35)	-4.77 (-0.16)	102.34 (1.31)	0.48 (0.25)	139.25 (0.81)	-20.05 (-1.08)	2.81 (1.23)	3.91E-06 (1.29)	2.064E-05 (0.33)
Median	52.96	128.90	252.35	-345.62	-3.39	44.18	0.39	62.57	-5.62	4.02	0.006	5.124E-05
Percentage +	73.83	59.65	61.47	40.42	40.41	80.41	43.30	82.16	5.28	67.14	70.42	61.32
Percentage +significant	4.96	3.02	50.19	40.17	1.17	0.17	4.07	3.96	1.04	13.91	20.09	1.02
SUM	166.7 (2.31)	53.38 (8.20)	736.45 (3.06)	169.41 (3.74)	22.98 (2.88)	941.74 (3.32)	40.98 (1.62)	321.19 (2.62)	-67.23 (0.83)	466.33 (1.19)	0.000429 (0.47)	0.000201 (0.06)
Median	45.20	167.49	775	-9.80	5.08	71.41	0.25	455.61	-20.55	106.22	2.64E-03	1.574E-05
Adj R^2 Mean	0.82		0.88		0.72		0.51		0.20		0.01	
Median	0.85		0.85		0.49		0.56		0.13		0.003	

Notes: This table presents daily percentage changes in individual stocks' liquidity variables are regressed on the percentage changes of a value-weighted cross-sectional average of the liquidity variable on the time series basis for all stocks on the Shenzhen Stock Exchange (SZSE) and on the percentage changes of a value-weighted cross-sectional average of the liquidity variable on the time series basis for stock from special industries between July 2000 and June 2002. Market firms include all stocks we select on the SHSE. Industry firms include industrial stocks, resources stocks and financial stocks from Global Industry Classification Standard (GICS) code. QSPR is the quoted spread, PQSPR is the percentage quoted spread, DEP is depth. VDEP is Dollar Depth. TR is the Turnover Rate. BLM is the bi-dimensional Liquidity Measure. D denotes the daily percentage changes in that variable for each liquidity variable. The dependent variable stock is not included in the market average liquidity variables. 'Percentage+' is the percentage of positive coefficients. 'Percentage+significant' is the percentage of positive and significant coefficients. Both 'Percentage+' and 'Percentage+significant' are reported on concurrent liquidity variables as well as for the previous trading day (lag) and next trading day (lead).

generally smaller than the industry liquidity beta (β_2) on the Chinese market. This is also true for "SUM" coefficients of all liquidity measures. This finding is in opposition to Brockman and Chung (2002), and Sujoto, et al. (2005).

Further looking at the industry liquidity beta (β_2) as my main interest here, one can find that the cases where the proportion of stocks with significant and positive concurrent industry liquidity beta (β_2) is greater relative to market liquidity beta (β_1) are three out of six liquidity measures on both the SHSE and the SZSE (DQSPR, DDEP, and VDEP). However, after controlling for the industry effect, the proportion of positively significant beta on market liquidity becomes smaller for most of the liquidity measures than in the estimation where market liquidity is the only regressor. This may provide some further evidence of the industry effect.

Moreover, of the six liquidity proxies used in estimating Shanghai stocks, the spread-based proxy, i.e. DQSPR has the highest percentage of significantly positive industry liquidity beta (90.48%) while DTR and BLM have the lowest (both are 10.9%). For SZSE, again spread based liquidity proxy DQSPR (91.45%) has the highest percentage and DTR (10.57%) the lowest.

Commonality in liquidity may also vary on up and down markets. When examining this asymmetric effect, I follow the line of Sujoto et al. (2005) to define an up or down market based on the size of excess returns above the market, calculated by subtracting from the average of daily stock returns in the sample the risk free rate proxied by the 10-year Bank Accepted Bill (BAB) rate in China. On the SHSE, an up market day is when the day's extra return is greater than

–0.022995581 while a down market day is when it is less than -0.027055032. When it lies between -0.027055032 and –0.022995581, I call it a neutral market day. On the SZSE, the cut-off point for an up market is when the day's excess return is greater than –0.022929265 while a down market day appears when the excess return is less than -0.027070515. Between -0.027070515 and –0.022929265, it is a neutral market day. After splitting the sample evenly among up, down and neutral markets based on this approach, I estimate the asymmetric effect with the following equation:

$$DL_{j,t} = \alpha_j^n D_n + \alpha_j^u D_u + \alpha_j^d D_d + \beta_j^n D_n DL_{M,t} + \beta_j^u D_u DL_{M,t} + \beta_j^d D_d DL_{M,t} + \lambda_j DL_{j,t-1} + \varepsilon_{j,t} \quad (3.3)$$

where Ds are (1, 0) dummy variables with subscripts d, u and n indicating down, up and neutral market periods, respectively. The dummies are applied to both intercept and slope coefficients.

The inclusion in the equation of the lagged variable $DL_{j,t-1}$ is due to Sujoto et al. (2005) who believe this may improve the model's goodness of fit. The results of the estimation are presented in panel A of Table 3.10.

The outcome shows that the cross-sectional average of the slope dummy for up market, β_u, is positively significant only for DQSPR and DTR. On the SHSE, the lowest cross-sectional mean of coefficient β_u is -17.68 (for DDEP) and the highest cross-sectional mean of β_u is 15.46 (for DTR). On the SZSE, the lowest cross-sectional mean coefficient of β_u is -14.92 (for VDEP) and the highest

cross-sectional mean coefficient of β_u is 15.81 (for DTR). For DQSPR and DTR, over 10% of stocks have a positive and significant β_u.

On the down market, β_d is significant and positive only for DDEP and DTR. On the SHSE, β_d ranges from -35.96 (DQSPR) to 245.93 (DTR), while on the SZSE it lies between -31.43 (DQSPR) and 289.74 (DTR). Up to 18.19% of stocks for DDEP and up to 12.13% for DTR have a positive and significant β_d. Comparing the slope dummy coefficient on the DTR measure on respective up and down market, it seems that commonality in liquidity during the down market period is stronger (245.93) than that on the up market (15.46). This is likely due to the fact that, when market conditions decline, Chinese investors would become more concerned with macro news rather than the performance of individual firms. This phenomenon on one hand implies that during down markets Chinese investors are prone to contagion and herd behaviour, and on the other hand reflect the dominant influence of the government which is usually the source of macro event.

Panel B of Table 3.10 records the results of the Wald test with null hypothesis: $\beta_u = \beta_d$ to formally tests for whether liquidity commonality varies between up and down markets (Sujoto, et al., 2005). At the 10% level, depth related liquidity measures have the highest percentage of stocks that reject the null, e.g 35% of stocks for DDEP and 26% for VDEP on the SHSE. On the SZSE, the corresponding figures are 47% and 33%, respectively. At the 5% significance level, the null can be rejected for 17% and 13% of the stocks in terms of their association with depth related liquidity measures (DDEP and VDEP) on the SHSE, while on the SZSE the proportions are 10% and 15%.These findings provide some

evidence that commonality in liquidity varies in China between up and down markets.

Table 3.10 Asymmetric Commonality on Up and Down Markets

Panel A: Up and Down-market Commonality (SHSE)						
	Quoted Spread (DQSPR)	**Percentage Quoted Spread (DPQSPR)**	**Depth (DDEP)**	**Dollar Depth (VDEP)**	**Turnover Rate (DTR)**	**Bi-dimensional Liquidity Measure (BLM)**
β_u	1.98 (1.03)	-0.74 (-0.03)	-17.68 (-0.64)	-16.70 (-0.63)	15.46 (0.72)	-0.002 (-0.58)
Percentage+	40.85	30.93	15.48	10.40	20.26	6.28
Percentage+significant	16.11	2.61	1.31	1.21	12.13	0.04
β_d	-35.96 (-0.29)	-0.22 (-0.07)	14.50 (0.79)	5.98 (0.12)	245.93 (0.60)	-0.0004 (-0.92)
Percentage+	23.7	60.27	51.59	53.52	73.49	5.5
Percentage+significant	1.1	1.52	20.24	1.17	10.18	0.19
Adj R^2 Mean	0.177	0.161	0.148	0.134	0.394	0.215
DW	2.02	2.01	1.96	1.96	1.93	1.95
Panel B: Wald Test Results (SHSE)						
	Quoted Spread (DQSPR)	**Percentage Quoted Spread (DPQSPR)**	**Depth (DDEP)**	**Dollar Depth (VDEP)**	**Turnover Rate (DTR)**	**Bi-dimensional Liquidity Measure (BLM)**
χ^2	12.58	12.09	16.43	15.02	58.54	1.38
percentage_*	3.02	1.89	16.95	13.32	1.93	0.35
percentage_**	10	12.32	35	26.18	2.55	1.04
Panel C: Up and Down-market Commonality (SZSE)						
	Quoted Spread (DQSPR)	**Percentage Quoted Spread (DPQSPR)**	**Depth (DDEP)**	**Dollar Depth (VDEP)**	**Turnover Rate (DTR)**	**Bi-dimensional Liquidity Measure (BLM)**
β_u	2.46 (1.72)	-0.89 (-0.42)	-9.93 (-0.60)	-14.92 (-0.79)	15.81 (0.85)	-0.0013 (-0.93)
Percentage+	50.52	54.96	15.51	18.42	22.38	7.42
Percentage+significant	18.17	1.18	1.23	1.18	15.10	0.017
β_d	-31.43 (-0.27)	-0.14 (-0.12)	15.73 (0.93)	6.69 (0.23)	289.74 (1.77)	-0.0002 (-0.81)
Percentage+	26.49	66.50	60.47	62.35	80.39	6.41
Percentage+significant	1.18	2.19	18.19	1.09	12.13	0.109
Adj R^2 Mean	0.191	0.187	0.148	0.179	0.54	0.10
DW	2.21	2.13	1.98	1.94	1.96	1.92
Panel D: Wald Test Results (SZSE)						
	Quoted Spread (DQSPR)	**Percentage Quoted Spread (DPQSPR)**	**Depth (DDEP)**	**Dollar Depth (VDEP)**	**Turnover Rate (DTR)**	**Bi-dimensional Liquidity Measure (BLM)**
χ^2	11.09	14.28	18.77	19.16	69.05	1.02
percentage_*	5	1.21	10.13	15.43	2.43	0.75
percentage_**	14.01	10.17	47	33.12	3	0.94

Notes: This table presents the regression results of commonality in liquidity on up and down markets of the Chinese Stock Exchange. Mean coefficients, the percentage of positive coefficients and positive and significant coefficients and DW statistic are reported in Panel A and Panel C on the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE) respectively. 'Percentage+' is the percentage of positive coefficients. 'Percentage+significant' is the percentage of positive and significant coefficients. DW statistic is the cross-sectional average of the Durbin Watson test statistics. Panel B (Panel D) reports the results when using the Wald test. The null hypothesis is: H_0: β_u-B_d. χ^2 is the cross-sectional average of Chi-square statistics. The results that significantly reject the null hypothesis at the 5% level are reported in %_*. The results that significantly reject the null hypothesis at the 10% level are reported in %_**.

VI. Conclusion

This chapter examines to what extent liquidity is determined by common underlying factors in China which has adopted an order-driven trading system. Using a proprietary set of data from China, I selected a broad sample of stocks from two separate Chinese stock exchanges to measure and analyse market-wide movements in liquidity. This unique data set contains all intraday transactions of A-shares from July 2000 to June 2002 and provides rich information for the empirical estimation that follows the seminal work of Chordia et al. (2000). Evidence found in this study confirms that commonality in liquidity is present in China and seems more significant and pervasive. In parallel to a market-wide component in the commonality construct, I also found an industrial component.

In addition I found that the proportion of stocks with positively significant liquidity beta increases with the firm size, which is in agreement with other studies. Liquidity of large firms' stocks is found to be more likely to move with market liquidity. I also found that Chinese investors exhibit herding behaviour. In the face of shocks to market liquidity, Chinese market participants tend to adjust both the spread and the depth. In a down market, market liquidity moves more widely and commonality in liquidity becomes more significant. As arguably the most important emerging market, evidence from China may shed critical light on the property of commonality in liquidity of emerging markets. Findings regarding how liquidity co-moves can also promote a better understanding of the rapidly

growing Chinese capital market, which has attracted growing interest from international investors and national regulators.

Chapter 4

Sources of Liquidity Commonality on the Chinese Stock Market

I. Introduction

Given the empirical evidence confirming the existence of commonality in liquidity on the Chinese stock market, a question naturally arises as to why there is commonality in liquidity on the Chinese stock market. Essentially, this question is about the reasons for and causes of the existence of commonality in liquidity in China. In this chapter, I will tackle this problem by focusing my investigation on the sources of co-movement in liquidity with a variety of empirical methods.

In contrast to the rapidly growing body of literature that tests the existence of commonality in various markets, studies of what drives commonality have just begun to emerge. So far, three broad groups can be found in the nascent literature offering explanations of the sources of liquidity commonality: the microstructure approach, the market conditions approach, and order-driven market models. The first two are mainly concerned with quote-driven or specialist markets, while the

third has been developed for purely limited order markets. The microstructure approach conventionally views commonality in liquidity as being driven by factors that commonly affect the inventory cost and information asymmetry of individual stocks simultaneously (Chordia, Roll and Subrahmanyam, 2000). An alternative approach is in terms of common variations in market states. This market conditions approach attributes sources of commonality to common changes in the supply of and/or demand for liquidity (Fernando, 2003; Bauer, 2004; Coughenour and Saad, 2004; Domowitz, Hansch and Wang, 2005; Amihud, Mendelson and Pedersen, 2006). Although these strands of research have been developed in the context of quote-driven markets, they may also inform the research on commonality in liquidity of pure order-driven markets, including many in the emerging world. Indeed, the recently emerging studies of how commonality is determined in an order-driven market are mostly conducted along the same lines and offer the same reasons as researches on its counterpart trading system, i.e. the quote-driven market (Brockman and Chung, 2002).

Based on the previous literatures, I will adopt a synthetic approach to investigating sources of liquidity co-variation on the Chinese stock market. More specifically, I will use Chinese data to test for information asymmetry, market factors and macroeconomics factors as possible determinants of commonality in liquidity.

The Chinese stock market is experiencing extraordinary growth, increased risk and volatility, which are typical of an emerging economy. The situation is made

more complex by China's adoption of an order-driven market structure. Furthermore, in common with other order-driven markets, the Chinese stock market is characterised by high synchronicity of returns and poor protection of property rights, which deter risk arbitrage and cause more noise trading, leading to an increase in market-wide stock price variation. The underdevelopment of the Chinese market affords few alternative investments and therefore investors needing to liquidate may be unable to diversify their liquidity shocks among several asset classes, and this may lead to co-variation in liquidity. Therefore an exploration of the determinants of commonality in the Chinese context would improve the understanding of the sources of co-variation in liquidity with order-driven systems, and better the understanding of the functioning of those financial markets.

Several interesting findings have emerged from this study. Using transaction and quote data of every 15 minutes within a trading day during July 2000 to June 2002 for A- shares on two major Chinese stock exchanges, the SHSE and SZSE, I find that common factors are evident in measures of asymmetric information based on trading frequency in market-wide and industry-wide components, which, according to Brockman and Chung (2002), can be used as a reliable indicator of informed trading. As such, these results suggest at both market and industry levels asymmetric information is the source of commonality in liquidity. The empirical analysis also shows that on the Chinese stock market the common factors in market volatility and market liquidity are significantly related to commonality in liquidity. I find no evidence to suggest that the common factors in interest rate and

market returns are significantly related to commonality. Using VAR analysis, I also find that the relationship between market liquidity and macroeconomic factors varies over time, according to the prevailing macroeconomic conditions and monetary environment in China.

The rest of the chapter is organised as follows. Section II presents the background and literature review on the sources of commonality in liquidity; Section III provides empirical evidence of commonality in liquidity on the Chinese stock market from asymmetric information; Section IV explores whether and which market conditions variables can drive commonality in liquidity on the Chinese stock market; Section V proves the macroeconomic sources of commonality in liquidity; Section VI presents a summary and conclusions.

II. Literature Review

Existing literature usually treats liquidity as a property of an individual stock and so each security is expected to have its own liquidity. Conventional research on determination of liquidity is accordingly focused on factors that are unique to each stock. Influential factors identified as determinants of the liquidity of individual stocks include order flow, number of trades, trading volume, returns and volatility of individual stocks (Benston and Hagerman, 1974; Stoll, 1978a).

Recent research has suggested that it is not sufficient to examine the sources of individual securities in isolation, because securities are often related to one another and most investors trade in a portfolio of securities. New research has therefore been inspired to deal with the sources of liquidity in a market-wide context. This shift of research focus has led to the recent emergence of a burgeoning literature on the sources of commonality in liquidity.

The new theory of commonality in liquidity calls for attention to the facts that individual stock liquidity can be driven by common underlying determinants, which can generate market-wide effects. However, it is not known what precisely these common factors are. This means that the underlying economic drivers of this 'commonality in liquidity' are not well understood (Fujimto, 2004).

2.1 The Microstructure Approach

Chordia et al. (2000) are among the first to use a microstructure approach to offer an explanation for commonality. They suggest that two non-mutually exclusive influences, i.e. inventory risk and asymmetric information, can generate commonality in liquidity. This approach is justifiable from the perspective of three main drivers of costs for providing liquidity, i.e. costs of holding inventory, trading with informed traders, and processing orders, which are identified in Demsetz (1968), Stoll (1978a), Copeland and Galai (1983), Huang and Stoll (1997) and Mortal (2006). So, if there is a common component of the liquidity cost, changes in this common component will cause liquidity of individual stocks to vary over time and cross-sectionally, leading to the variation of liquidity being

correlated across securities, hence the existence of liquidity commonality (Huberman and Halka, 2001). Whereas common components of any of these drivers may cause commonality, Chordia et al. (2000), in a microstructure tradition, choose to examine the inventory effects and the asymmetric information effect on the adverse selection costs arising from trading with informed traders. However, they do not find evidence that asymmetric information itself has common determinants.

Examination of inventory effects by Chordia et al. (2000) follows the inventory paradigm of Demsetz (1968), Stoll (1978) and Ho and Stoll (1981). The examination looks into the factors informed by the inventory paradigm on which liquidity is dependent. They postulate that these determining factors often contain a market component. Through their effect on the risk of holding inventory, changes in these market components will induce a market-wide response of dealer inventory levels, and hence co-movements of liquidity across stocks. One example is the general price swings that tend to induce responses from market activity in terms of trading volume. Since trading volume is a principal determinant of dealer inventory, market-wide variations in trading volume tend to cause optical inventory levels of many dealers to change. Such co-movements in turn can result in co-movements in bid-ask spreads and other liquidity measures. Another example might be changes in market volatility. Thus, Chordia et al. (2000) argue that the risk of holding inventory can be increased by market-wide price movements and shocks to liquidity, and this in turn causes widening of the bid-ask spread and reduction of the quoted depth.

Chordia et al. (2002) further explore supply-side shocks to liquidity in terms of changes in the inventory levels caused by order imbalances. They find that order imbalances in either direction reduce liquidity.

Harford and Kaul (2005) also investigate such common effects in order flow, exploring both their causes and their implications. They focus on indexing, industry and market-wide influences on order flow, returns and trading costs. They control for own stock effects, and use membership of the S&P 500 to identify stocks that are subject to strong indexing effects. They also analyse the time-of-day and inter-temporal effects, bearing in mind that trading activity tends to be higher towards the end of the day, and has increased in recent years. Their results show powerful common effects in order flow and returns for S&P 500 stocks. As expected, the effects are stronger at the end of the day, and were greater in 1996 than in 1986. They also find common effects in order flow for non-index stocks, driven by industry and marketwide order flow and returns. Although economically small, these effects are nevertheless statistically significant. Like Hasbrouck and Seppi (2001), who also employ intraday frequencies, they find that common effects in trading costs are not as strong as those in order flow or returns. These findings conflict with Chordia et al. (2000), who record stronger common effects in changes in daily measures of trading costs.

In their 2006 study, Hughen and McDonald (2006) test their theory that retail investors are a source of commonality across securities. Their results show that

these investors may be uniquely sensitive to factors such as sentiment, which results in correlated order flow. Hughen and McDonald (2006) find that order flow commonality is strongest among medium trades, which, as earlier research has shown, have a large price impact.

According to Beltran-Lopez, Giot and Grammig (2006), the visible and hidden portions of the limit order book share some common dynamics, but also exhibit clear idiosyncracies. They argue that this is because an open order book market attracts a heterogeneous population of limit order traders, with a variety of trading strategies, trading needs, and asset valuations.

Another determining factor of commonality identified by Chordia et. al. (2000) is asymmetric information, which can exist at the industry or market level. Information asymmetry represents a potential trading cost for which market makers are to be compensated by the bid-ask spread. According to Glosten and Milgrom (1985) and Kyle (1985), the market consists of three types of traders: informed, uninformed and market makers. When a buyer comes across a potential seller who has private information that the company is failing, or a seller is met with a buyer who has private information that the company is about to show strong growth, the uninformed party would lose. This also applies to transactions that market makers conduct with their clients. Market makers are obliged to provide liquidity to maintain an orderly market but do not necessarily possess superior information. In their transactions, the clients are indistinguishable as to whether they are informed or uninformed traders. To require a fair return on their

capital and to avoid losing money consistently from such transactions, market makers charge a positive spread (Huberman and Halka, 2001). Along this line of reasoning one can extend the asymmetric information perspective to infer that, when there is a release of new information that has an impact beyond the individual stock level, co-movements of liquidity across stocks tend to ensue. One example of such co-movements due to changed information asymmetry is the emergence of a revolutionary new technology influencing many firms, as suggested in Chordia et al. (2000). To investigate the relationship between common variations in liquidity and the degree of asymmetric information, Chordia et al. (2000) test for the correlation between commonality and trading frequency and find that individual trading frequency positively affects spread, indicating that when informed traders become active, spread increases with the number of transactions. This is probably because informed traders attempt to conceal their activities by breaking trades into small units, thus increasing the number of transactions.

Like Chordia et al. (2000), Huberman and Halka (2001) also consider the determinants of the common movements in liquidity from the perspective of two basic factors. They argue that liquidity of individual stocks varies over time and cross-sectionally, and show that this variation has a common component. To statistically detect the presence of such a systematic component of liquidity, they estimate the autoregressive structure of each of the four liquidity proxies: spread, spread/price ratio, quantity depth, and dollar depth, to derive a series of the residuals of autoregressive processes. They find these innovations are positively

correlated for each liquidity proxy, indicating the presence of liquidity commonality. They find that variation in liquidity is positively correlated with return and negatively with volatility. However, they report that those variables do not capture the common component of the temporal variation in liquidity.

Although its theoretical underpinning is also derived from the microstructure approach, Fujimoto (2004) is a distinctive departure from previous researches that essentially estimate a single equation model in their empirical analyses. Rather than using cross-sectional modelling, Fujimoto (2004) applies the inventory and asymmetric information models to a time series analysis in a vector autoregression (VAR) representation. She assumes that, in the time series setting, asymmetric information can play only a limited role at the aggregate level and the inventory risk is the primary cause of commonality. The inventory risk and its determinants then become the primary concern of the empirical work and her modelling strategy is to focus on the factors that can simultaneously affect the inventory risks of many firms. In this light, macroeconomic fundamentals are the suitable candidates for such factors. She estimates the macroeconomic sources of time variation in liquidity, within the VAR framework. Having examined the dynamic relation between market liquidity and various macroeconomic factors over the past four decades, she finds that macroeconomic factors influence liquidity not only directly, but also indirectly through their effects on the market variables. So, macroeconomic fundamentals are significant determinants of the liquidity dynamics. Moreover, there are time-varying changes in this property since market makers' control of inventory levels is more responsive to macro

shocks when facing greater macroeconomic uncertainties. In periods when the economy is relatively stable, effects of the macro shocks on the movements of market liquidity are significantly smaller.

Mortal (2006), however, finds it surprising that existing research has mostly ignored the role of asymmetric information in explaining commonality. His paper is devoted solely to the role of information asymmetry in driving commonality in liquidity. He uses earnings surprises in the US market as a proxy for information asymmetry and finds that market liquidity contains an information asymmetry component. Evidence shows the existence of commonality in information asymmetry, which is time varying. In general, aggregate variations in information asymmetry are positively related to aggregate variations in liquidity. Aggregate variations in information asymmetry are also related to firm-level trading costs and trading activity. These outcomes suggest that commonality in information asymmetry helps to explain one important source of commonality in liquidity.

Huson and Ravi (2007) demonstrate the existence of asymmetric information about systematic factors. This finding is consistent with the fact that investors can face asymmetric information costs even when trading well diversified baskets of securities, although the size of such costs is inversely related to the degree of diversification. Huson and Ravi (2007) use the adverse selection component of the bid-ask spread (lambda) of Standard and Poor's Depository Receipts (SPDRs) as a measure of information asymmetry on the US equity market. Their results show that SPDR lambdas are both positively correlated with the lambdas of other

exchange traded funds and related to the lambdas of individual equity securities. Furthermore, the SPDR lambdas can be explained by measures of uncertainty about the aggregate market. Their results indicate that the SPDR lambda is more efficient than the measures proposed by Pastor and Stambough (2003) and Sadka (2006). Huson and Ravi (2007) conclude that there is commonality in the adverse selection component of liquidity.

Moreover, firm-level and industry-level information asymmetry explains only a small proportion of trading costs, whereas market wide information asymmetry explains the majority. This could be due to market makers requiring a high level of compensation for providing liquidity during periods of widespread market-wide information asymmetry.

2.2 Market Conditions Approach

The second group of research characterises commonality in liquidity in terms of common variation in market conditions, including the supply of, and/or demand for, liquidity. Much early research on the sources of commonality are actually concerned with the supply side of the liquidity concern, in that they examine commonality as a result of systematic variation in the cost of providing liquidity (Domowitz, Hansch and Wang, 2005). But intuitively, variation in a common factor might stimulate systematic variation in the desire to transact, thereby leading to demand-generated commonality in liquidity (Coughenour and Saad, 2004). Fernando (2003) argues that demand factors not only contribute to commonality in liquidity, but might even be more significant than supply factors.

This is because, on the demand side, idiosyncratic liquidity shocks are more important than systematic liquidity shocks since, through influencing variations of trading volume, they result in investor heterogeneity, which is the main source of the demand for liquidity. By recognising idiosyncratic liquidity shocks, investors might be better able to realise their different demands for different assets.

However, in reality, most systematic factors would alter both the demand for and the supply of liquidity. For example, an interest rate shock might induce a shared desire to rebalance portfolios and thus increase the demand for liquidity. On the other hand, such a shock would also alter the cost and risk of supplying liquidity (Coughenour and Saad, 2004).

In order to test whether commonality in liquidity is induced by market wide buying and selling pressure, Henker and Martens (2003) investigate how the proxies of commonality in liquidity (bid and ask prices) are affected by these pressures. In their empirical work, the regression results show that commonality in liquidity is influenced by both buying and selling pressure and by a common market maker. Coughenour and Saad (2004) further point out that liquidity co-variations are most likely to arise from a complex interplay among demanders of liquidity, market makers, and other liquidity suppliers, such as those placing public limit orders. From the fact that specialists of a firm share information and financial resources among themselves, they find the evidence that common sharing of information and capital causes commonality. Hence they infer that commonality in liquidity is induced by a common market maker.

Domowitz, Hansch and Wang (2005) claim that the source of commonality in liquidity is due to supply and demand co-movements. However, while investors tend to supply liquidity in a random manner, their demand for liquidity is often more intense and concentrated. This leads to the fact that liquidity commonality is asymmetric. Market liquidity is not easy to move up simultaneously across securities but is very easy to decrease at times of financial stress. Unfortunately, good times do not occur often, and as a result, in the event of a crash, we would see the breakdown of market liquidity.

Following on from research into whether commonality in liquidity is related to changes in market conditions, Hameed et al. (2006) formulate a funding constraint model in which they show that variation in market states can affect the funding ability of financial intermediaries, which in turn induces co-variation in these institutions' provision of liquidity. This is because, with large negative market returns, aggregate collateral of financial intermediaries fall and many investors are forced to liquidate; hence market liquidity falls and so financial intermediaries will find it difficult to provide liquidity. They find empirical evidence for the asymmetrical responses of liquidity to changes in stock market returns: large negative market returns induce a decrease in stock liquidity, but an increase in commonality in liquidity.

In addition, commonality in liquidity can be driven by demand factors, such as market volatility, market capitalisation indices, aggregate order imbalance, and equity holdings by institutional investors. In their research, Beaupain, Giot and

Petitjean (2006) examine liquidity co-movements within three market capitalisation indices, each comprising 100 NYSE stocks. They find that, on average, there is a positive relationship between the size of liquidity co-movements and the market capitalisation of the index, with the least intense co-movements found among small caps and the most intense among large caps. For large and mid caps, as the magnitude of spread-based liquidity co-movements is greater in quiet markets than in stressful markets, spread adjustments by liquidity providers may be more stock specific in stressful markets. On the other hand, since liquidity co-movements measured by the number of shares displayed at the best bid and offer (BBO) are larger during stressful markets, it is likely that liquidity providers may be able to adjust the size displayed at the BBO in a more systematic manner in stressful markets. Considering this result, Beaupain, Giot and Petitjean (2006) suggest that in stressful markets, liquidity providers react to an increased risk of information asymmetry in a given stock by individually adjusting the spread rather than the size displayed at the BBO, whereas in quiet markets they are more likely to adjust the size. Therefore long-run liquidity co-movements are quantified in each class and compared to short-run liquidity co-movements. In order to condition the analysis of systematic liquidity upon index volatility, Beaupain, Giot and Petitjean (2006) use the Markov-switching methodology to define three regimes of volatility. They find that, on average, there is a positive relationship between the magnitude of liquidity co-movements and the market capitalisation of the index. Their results show significant differences between short-run and long-run liquidity co-movements, and between

spread-based and depth-based measures. They also find that the volatility regime has a bearing on the liquidity co-movements relationships.

Sun (2007) investigates the role of institutional clienteles in commonality in liquidity. His definition of clienteles is based on the application of hierarchical clustering algorithms to institutional holdings. Using this approach, Sun (2007) finds that it is possible to cluster most institutional investors into a small number of clienteles. He demonstrates that funds within the same clientele appear to suffer correlated liquidity shocks, and these generate correlated order flow in the underlying stocks, inducing co-movement in liquidity. Therefore, it appears that clienteles play an important role in explaining commonality in liquidity.

These findings suggest that, in general, liquidity commonality is driven by changes in demand for liquidity, but the increase in liquidity commonality in down market states is related to adverse effects of a fall in the supply of liquidity (Hameed et al., 2006). Furthermore, there is strong evidence of a supply effect, which is reflected in the facts that the cost of providing liquidity is highest when the market substantially declines, and the effect of price reversal is strongest when a large price drop is accompanied by high liquidity commonality and large order imbalance (Madhavan, 2000).

2.3 Order-driven Market Models

The microstructure approach and the market conditions approach are primarily concerned with quote-driven markets. For the analysis of what drives

commonality in liquidity in order-driven markets, these approaches may not be directly applicable because of the fundamental difference in the market trading system. However, critical insights obtained by these approaches have proved useful for the study of order-driven markets, which are adopted by many emerging markets and are the main interest of this research. Many order-driven market models of commonality in liquidity have followed the line of reasoning that has been developed in quote-driven approaches, with the addition of their own innovations.

Following Chordia et al. (2000), Brockman and Chung (2002) view information asymmetry as a determinant of commonality in an order-driven market. They assume that the number of trades can be a sensible indicator of informed trading and so investigate the association between the numbers of trades and their informativeness by testing for market-wide and industry-wide commonality in order flow. Their results suggest that at both market and industry levels, trading frequency is shown to have common components, indicating that there is a common component in asymmetric information that is not specified in Chordia et al. (2000). By implication, this could suggest that such a common component in asymmetric information may be a source of commonality in liquidity.

While Brockman and Chung's (2002) research follows the spirit of the microstructure approach to look into the factors behind the risk that will affect the level of commonality, other researches follow the market conditions approach line of reasoning, to examine those broad factors that will affect market supply of and

demand for liquidity. Bauer (2004) uses data on a limit order market to explore sources of commonality in liquidity in such a market in terms of financial variables. Bauer finds that liquidity demand is more subject to common variation than is liquidity supply, and that the liquidity of individual stocks is sensitive to both market liquidity and market volatility, as measured by realised volatility. His research confirms that commonality in liquidity can be affected by some financial proxies, such as market returns, volatility, expected volume, unexpected volume, default yield, and term premium. Co-variation in the proxies listed might induce co-variation in the liquidity of individual stocks. Since these factors determine market uncertainty, I can assume that market uncertainty also drives market-wide co-movements in liquidity in order-driven markets.

In a similar fashion, Domowitz, Hansch and Wang (2005) postulate that liquidity commonality is induced by co-movements of supply and demand in different securities. To test this hypothesis, they measure liquidity in a limit-order market, where the basic factors of supply and demand are easily identified, and then try to find the relationship between order-type (market order or limit order), order flow (order direction and order size), and their impact on commonality in liquidity and returns. They find that co-movement of order-type determines commonality in liquidity, whereas co-movement of order-flow determines co-movement of returns.

Corwin and Lipson's (2005) research differs than others in the group in that it deals with the automated trading sector of NYSE, which has the nature of a

limited order market. Using a unique set of all electronic order flow data for a sample of 100 stocks listed on NYSE, Corwin and Lipson (2005) show that common factors are evident in measures of order flow, and that this reflects liquidity trading rather than informed trading. Furthermore, they find that such commonality in order flow is mainly due to program trading. Their result suggests that common factors also exist in liquidity measures, and that individual security liquidity is significantly related to own order flows and common factors in order flows. Given the fact that commonality in order flow is in turn driven by program traders, program trading is therefore an important source of commonality in liquidity on the NYSE.

Following the line of reasoning behind the notion that a common specialist is the cause of commonality in liquidity because specialists from the same firm share information and financial resources which consequently shape specialists' behaviour, Brockman, Chung and Pérignon (2006a) look for the common factor that traders and fund managers would share. They show that, for markets without any designated liquidity supplier, equity index inclusion is a significant source of commonality because many indexes are routinely traded in blocks by fund managers and arbitragers.

In short, different approaches have been developed to analyse the sources of commonality in liquidity under different market organisations. These studies essentially identify two major sets of determinants of commonality in liquidity, i.e. market risks intrinsic to the particular market trading mechanism, and the state

variables that characterise market conditions. For the purposes of this study, order-driven market models are instrumental since they offer critical insights on how commonality is driven under the trading system that China has adopted. However, existing models usually focus on only one factor, or particular aspect, of commonality determination, such as information asymmetry (Brockman and Chung, 2002), common trading rules (Brockman et al., 2006a), or financial variables (Bauer, 2004).

I argue that commonality in liquidity can be caused by changes in market risks as well as by market states. There is international evidence that, in an order-driven market, liquidity demand and supply in the marketplace is determined by factors within and outside the market. While in a fully automated order-driven market, liquidity is solely supplied by market participants placing limited orders, ultimately liquidity in such markets is created in the economy and demanded by all types of investors. It follows that, in the final analysis, general economic fundamentals will have a critical bearing on liquidity and hence liquidity commonality. In the meantime, market risks remain a factor that will affect the profitability of placing a limited order, and hence the supply of liquidity. However, conventional inventory effects are no longer valid since in an order-driven market there are no designated market makers or floor specialists. It is shown that information asymmetry could be a factor that drives commonality in liquidity (Brockman and Chung, 2002). The current research is therefore motivated to adopt a synthetic approach to investigating the determination of liquidity commonality in emerging markets. Specifically, this study seeks to examine the

determinants of commonality in liquidity in terms of the risk factors that are pertinent to the Chinese stock market, an important order-driven market, and the factors that will have a wider bearing on market states.

III. Commonality in Liquidity and Asymmetric Information

In view of the existence of time-varying information asymmetry and the evidence that information asymmetry is one of the drivers behind liquidity in order-driven markets (Brockman and Chung, 2002), I can infer that aggregate variations in information asymmetry might explain variations in market liquidity on the Chinese market. As such, there may be a market wide information asymmetry component which can explain variations in firm level information asymmetry and liquidity. Following the methodology of Brockman and Chung (2002), in what follows I first examine this effect.

3.1 Data and Methodology

The database provided by the China Stock Market & Accounting Research (CSMAR) comprises details of every transaction and related information for every working day, including data by bid and ask record. I obtained from CSMAR intra-day transactions and quote data for the period July 2000 to June 2002 for A-shares listed on the SHSE and the SZSE. Previous studies on the determination of commonality use data of only one year or less. The sample period chosen is

particularly interesting because of the variations in market states. The Chinese market was bullish in July 2000 and June 2001, while in July 2001 and June 2002 there was a bear market.

I set up the sample selection filter following the same method as Chordia et al. (2000). To be included in the sample a stock had to be listed constantly on the SHSE and the SZSE for 24 months in the sample period. To avoid possible bias due to trading units, no stocks which had paid dividends or been split during the sample period are selected and these stocks must have been traded at least once in at least ten trading days over the sample period of 24 months. To focus on normal trading activity during the continuous trading session, opening trades were deleted from the study. In addition, I deleted trades and transactions with ST and PT conditions to avoid eruptive movement of stock prices. Finally, observations of all shares for June 24th, 2002 are not included, because there was an unusually large market shock in China on that day due to the announcement by the government on the decision to shelf the state stock reduction program.

Barclay and Wamer (1993) examine informed investors' trade-size choices and report that informed trades concentrate their trades in medium size and tend to hide their identity by broking up their large accumulations (10,000 shares or more) into medium-size trades. From this, one may find a positive association between the numbers of trades and asymmetric information. Jones, Kaul, and Lipson (1994) show the evidence that it is the transactions per se, rather than their vulume, that generates volatility and that trade volume has no information beyond that

contained in the frequency of transactions. Based on these findings, Chordia, et al. (2000) and Brockman and Chung (2002) believe that the number of trades rather than the trade size can be used as an indicator of individual firm is asymmetric information and this indicator has been used in their studies of the sources of commonality. Following this line of research, I use the regression model developed by Brockman and Chung (2002) to test for sources of commonality at the market and industry levels:

$$\begin{aligned}\Delta NTrades_{J,t} = \alpha &+ \theta_1 \Delta NTrades_{M,t} + \theta_2 \Delta NTrades_{M,t+1} + \theta_3 \Delta NTrades_{M,t-1} \\ &+ \lambda_1 \Delta NTrades_{I,t} + \lambda_2 \Delta NTrades_{I,t+1} + \lambda_3 \Delta NTrades_{I,t-1} \\ &+ \delta_1 Return_{M,t} + \varepsilon_{J,t}, \qquad (4.1)\end{aligned}$$

where $NTrades_{J,t}$ is the total number of trades for firm J during the trading day t as a measure of transaction frequency. $NTrades_{M,t}$ is the equally weighted average on day t of the number of trades for all firms (but excluding firm J) in the sample. $Return_{M,t}$ is the equally weighted average of the daily return for all firms. Sample firms are classified into the three industry sectors designated by the Chinese securities authorities. $NTrades_{I,t}$ is the equally weighted average of the number of trades for all firms in the industry.

3.2 Empirical Results

The results for model (4.1) are presented in Table 4.1. On the SHSE, from the time-series regressions, the number of marketwide concurrent coefficient that is positive and significant accounts for 63.5% of the total estimates, which is twice that found by Brockman and Chung (2002). On the SZSE, 74.6% of the time-series regressions have a positive and significant concurrent coefficient for

the whole market. Both market and industry variables are positive and highly significant for the sum of concurrent, lag, and lead coefficients for the SHSE and the SZSE. Also in the time-series regressions, 45.8% of the concurrent industry-wide coefficient are positive and significant, which is much higher than the results from Brockman and Chung (2002). Given that the number of trades is a reliable indicator of informed trading, these results suggest, at both market and industry levels, there is a common component in the number of trades implying asymmetric information is likely a source of commonality in liquidity.

Despite the availability of information regarding market variables, at certain periods, especially during significant macro-economic changes, it may become difficult to value a firm. Traders who have more information about firm operations, and better communication channels with management, are better equipped to estimate how economic changes will affect firm value. This represents an informational advantage, which will motivate informed trading. Such an advantage will add up across firms and is non-diversifiable (Mortal, 2006).

Asymmetry of information is particularly severe in China. According to Wang (2002), the cost of asymmetric information represents about 80% of the cost of bid-ask spread. One reason for this is that Chinese firms tend not to fully disclose material changes in their business conditions, and published statements do not always meet international accounting standards. In addition, there is widespread share manipulation and insider trading, and little protection for investors (Chan,

Menkveld and Yang, 2008). In this environment, a shock of asymmetric information will induce systematic change in liquidity (Fernando and Herring, 2003). My empirical results support this hypothesis. Guo (2006) suggests that asymmetric information has an important role in the patterns for liquidity. My results expand their findings and provide evidence that asymmetric information may also critically impact the patterns of commonality in liquidity.

Table 4.1 Commonality and Asymmetric Information

Independent Variable (SHSE)		Mean (Median) of Est.	%+ and Sig.	%+ and inSig.	%- and inSig.	%- and Sig.	SUM_M and SUM_I Mean (median) [p-value]
$\Delta NTrades_{M,t}$	Θ_1	1.751 (1.061)	63.5%	35.2%	1.3%	0	0.695 (-0.312) [0.000]
$\Delta NTrades_{M,t+1}$	Θ_2	-0.164 (0.174)	1.9%	16.7%	80.1%	1.3%	
$\Delta NTrades_{M,t-1}$	Θ_3	-0.892 (-1.026)	2.6%	12.1%	84%	1.3%	
$\Delta NTrades_{I,t}$	Λ_1	0.522 (0.195)	51.3%	46.8%	1.9%	0	0.992 (-0.067) [0.000]
$\Delta NTrades_{I,t+1}$	Λ_2	0.677 (1.104)	0.6%	16.1%	80.7%	2.6%	
$\Delta NTrades_{I,t-1}$	Λ_3	-0.207 (-0.260)	2.6%	12.1%	84%	1.3%	
Independent Variable (SZSE)		**Mean (Median) Est. Coe.**	**%+ and Sig.**	**%+ and inSig.**	**%- and inSig.**	**%- and Sig.**	**SUM_M and SUM_I Mean (median) [p-value]**
$\Delta NTrades_{M,t}$	θ_1	4.850 (4.203)	74.6%	23.7%	1.7%	0	4.942 (0.381) [0.000]
$\Delta NTrades_{M,t+1}$	θ_2	-0.553 (-0.589)	2.8%	23.2%	72.3%	1.7%	
$\Delta NTrades_{M,t-1}$	θ_3	0.645 (1.009)	1.7%	41.8%	53.7%	2.8%	
$\Delta NTrades_{I,t}$	λ_1	1.440 (1.488)	45.8%	48%	6.2%	0	0.774 (-0.211) [0.000]
$\Delta NTrades_{I,t+1}$	λ_2	-0.387 (-0.348)	2.8%	10.2%	85.3%	1.7%	
$\Delta NTrades_{I,t-1}$	λ_3	-0.279 (-0.244)	2.3%	16.3%	78.6%	2.8%	

Notes: This table presents the regression results for commonality in liquidity is driven by asymmetric information on the Chinese Stock Exchange between July 2000 and June 2002. Asymmetric information is measured by the number of trades. The Chinese Stock Exchange includes the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE). *NTrades* is the total number of trades.

IV. Market Condition Determinants of Commonality in Liquidity

In this section, I examine whether and which market conditions variables can be identified as factors driving commonality in liquidity. My data filtering is as previously. Following Bauer (2004), I estimate the following time-series regressions for each stock j, 1, 2, . . . , 259 (291 stocks for the SZSE) by using the daily data from the high frequency database:

$$LIQ_{j,t} = \alpha_j + \beta_{MLIQ,j} MLIQ_t + \varepsilon_{j,t}, \qquad (4.2)$$

where LIQ_j is the liquidity proxy for individual stock j as a measure of individual liquidity and $MLIQ_t$ is a measure of market liquidity which is the average of the individual liquidity proxies excluding that of stock j. The results are presented in tables from Table 4.2 to Table 4.3. Reported figures in the tables are the averages of the estimated coefficients of the sample stocks. In each table, 'Sign' denotes the number of sample stocks with significant estimates, 'Pos' indicates the percentage of sample stocks with positive signs, and 'SPos' is the percentage of stocks with both positive and significant estimates.

As can be seen in Table 4.2 and Table 4.3, almost all estimated $\hat{\beta}_{MLIQ}$ are positive. For different proxies of market liquidity, all estimates are positive, 96% of

coefficients on QSPR[4] (98% for PQSPR) on the SHSE are significantly positive and 93% of QSPR (91% for PQSPR) on the SZSE are significantly positive. Also, all depth related liquidity proxies (DEP and VDEP) show a positive $\hat{\beta}_{MLIQ}$, with 99% of both variables being significantly positive. From adjusted R^2, the explanatory power is lower for the QSPR and PQSPR measures (27% and 20% on the SHSE) than for the depth measures (40% and 33% on the SHSE). Also, explanatory power of the liquidity measures in terms of bid-ask spread proxies is lower than that in the depth proxie.

[4] Here I also use different proxies of market liquidity in chapter 3. QSPR is the Quoted Spread. PQSPR is the Percentage Quoted Spread. DEP is Depth. VDEP is Dollar Depth. TR is the Turnover Rate. BLM is the Bi-dimentional Liquidity Measure.

Table 4.2 Sensitivity of Liquidity Proxies to Market Liquidity for Shanghai Market

$LIQ_{j,t} = \alpha_j + \beta_{MLIQ,j} MLIQ_t + \varepsilon_{j,t}$						
$\beta_{MLIQ,j}$					R^2	Adj. R^2
	Estim	Sign	Pos	SPos		
Quoted Spread (QSPR)	8.58	97	100	96	0.29	0.27
Percentage Quoted Spread (PQSPR)	6.44	98	99	98	0.22	0.20
Depth (DEP)	93.09	99	100	99	0.42	0.40
Dollar Depth (VDEP)	80.28	99	100	99	0.35	0.33
Turnover Rate (TR)	93.54	80	100	80	0.15	0.13
Bi-dimentional Liquidity Measure (BLM)	2.13	5	65	5	0.07	0.05

Notes: This table presents the time series regression results for commonality in liquidity is driven by market liquidity on the Shanghai Stock Exchange (SHSE) between July 2000 and June 2002. QSPR is the quoted spread, PQSPR is the percentage quoted spread, DEP is depth. VDEP is Dollar Depth. TR is the Turnover Rate. BLM is the bi-dimensional Liquidity Measure. 'Estim' is the estimated regression coefficients. 'Sign' is the percentage of significant coefficients. 'Pos' is the percentage of positive coefficients. 'SPos' is the percentage of significant and positive coefficients.

Table 4.3 Sensitivity of Liquidity Proxies to Market Liquidity for Shenzhen Market

$LIQ_{j,t} = \alpha_j + \beta_{MLIQ,j} MLIQ_t + \varepsilon_{j,t}$						
$\beta_{MLIQ,j}$					R^2	Adj. R^2
	Estim	Sign	Pos	SPos		
Quoted Spread (QSPR)	10.18	94	98	93	0.42	0.40
Percentage Quoted Spread (PQSPR)	8.74	91	96	91	0.22	0.20
Depth (DEP)	95.44	99	100	99	0.37	0.35
Dollar Depth (VDEP)	91.58	99	100	99	0.32	0.30
Turnover Rate (TR)	116.34	73	98	73	0.20	0.18
Bi-dimentional Liquidity Measure (BLM)	7.01	4	64	3	0.04	0.02

Notes: This table presents the time series regression results for commonality in liquidity is driven by market liquidity on the Shenzhen Stock Exchange (SZSE) between July 2000 and June 2002. QSPR is the quoted spread, PQSPR is the percentage quoted spread, DEP is depth. VDEP is Dollar Depth. TR is the Turnover Rate. BLM is the bi-dimensional Liquidity Measure. 'Estim' is the estimated regression coefficients. 'Sign' is the percentage of significant coefficients. 'Pos' is the percentage of positive coefficients. 'SPos' is the percentage of significant and positive coefficients.

From the low adjusted R^2 values hence the low explanatory power of the model with a single determinant of the liquidity level, one can reasonably suspect that there are other factors driving the daily changes in liquidity levels of individual stocks (Chordia, et al., 2000; Bauer, 2004). I now proceed to identify these possible contributing factors to commonality in liquidity in China and their effects.

Following Bauer (2004), I include several financial market variables in the estimation, including the market returns, price volatility of the market, the interest rate and the measure of market liquidity to form the variable space. For each of the measures of liquidity of individual stocks, the econometric formulation takes the following general form:

$$LIQ_{j,t} = \alpha_j + \beta_1 DIR_t + \beta_2 MRET_t + \beta_3 MVOL_t + \beta_4 MLIQ_t + \varepsilon_{j,t}, \quad (4.3)$$

The data sets used in the estimation are as follows. The one month overnight interest rate from CSMAR is used for the interest rate variable. Pre-tests show this interest rate variable (*DIR*) is not stationary and is integrated of I (1), so I take the first difference of the variable to make it stationary. In the model, the return variable *MRET* is the return on the comprehensive SHSE index and the comprehensive SZSE index, respectively. The volatility measure (*MVOL*) is realised volatility of the returns of all stocks in my sample. With an intention to reflect volatility of the stock prices during the day, I follow Bauer (2004) to construct this measure by first forming a large portfolio that is equally weighted

and includes all the stocks in my sample, then calculating the realised cumulated squared five minutes returns on this equally weighted portfolio in a trading day.

The regression results of each liquidity proxy as dependent variables are shown in Table 4.4 and Table 4.5. The highest explanatory power is found to be from *MLIQ* (24%), i.e. the market measure of liquidity. Of the market liquidity proxies, 83% have a positive coefficient, while 38% are significant.

Table 4.4 Multivariate Regression Results for Shanghai Market

$LIQ_{j,t} = \alpha_j + \beta_1 DIR_t + \beta_{2j} MRET_t + \beta_{3,j} MVOL_t + \beta_4 MLIQ_t + \varepsilon_{j,t}$

	B_1				B_2				B_3				B_4				R^2	Adj.
	Estim	Sign	Pos	SPos	Estim	Sign	Pos	SPos	Estim	Sign	Pos	SPos	Estim	Sign	Pos	SPos		
Quoted Spread (QSPR)	0.00		22		0.00	34	94	34	8.21	77	94	77	9.00	92	95	92	0.22	0.20
Percentage Quoted Spread (PQSPR)	0.00		17		0.00	22	76	22	6.01	47	95	47	8.18	82	94	82	0.23	0.21
Depth (DEP)	0.00		24		0.00	25	79	25	50.00	55	97	55	60.39	96	99	96	0.22	0.20
Dollar Depth (VDEP)	0.00		18		0.00	30	78	30	48.02	48	92	48	52.18	82	90	82	0.16	0.14
Turnover Rate (TR)	0.00		11		0.00	16	68	16	55.20	30	81	30	44.39	49	78	49	0.10	0.08
Bi-dimentional Liquidity Measure (BLM)	0.00		2		0.00	1	34	1	3.43	5	16	5	4.18	5	66	5	0.05	0.03

Notes: This table presents the time series regression results for commonality in liquidity is driven by interest rate, market return, volatility and market liquidity on the Shanghai Stock Exchange (SHSE) between July 2000 and June 2002. QSPR is the quoted spread, PQSPR is the percentage quoted spread, DEP is depth. VDEP is Dollar Depth. TR is the Turnover Rate. BLM is the bi-dimensional Liquidity Measure. 'Estim' is the estimated regression coefficients. 'Sign' is the percentage of significant coefficients. 'Pos' is the percentage of positive coefficients. 'SPos' is the percentage of significant and positive coefficients.

Table 4.5 Multivariate Regression Results for Shenzhen Market

$LIQ_{i,t} = \alpha_i + \beta_1 DIR_t + \beta_{2i} MKET_t + \beta_{3,i} MVOL_t + \beta_4 MLIQ_t + \varepsilon_{i,t}$

	B_1				B_2				B_3				B_4				R^2	Adj. R^2
	Estim	Sign	Pos	SPos	Estim	Sign	Pos	SPos	Estim	Sign	Pos	SPos	Estim	Sign	Pos	SPos		
Quoted Spread (QSPR)	0.00		17		0.00	26	74	26	7.37	68	85	68	10.01	83	93	83	0.22	0.20
Percentage Quoted Spread (PQSPR)	0.00		16		0.00	18	65	18	7.51	53	87	53	7.82	75	89	75	0.21	0.19
Depth (DEP)	0.00		29		0.00	8	65	8	80.24	47	96	47	88.77	96	97	96	0.22	0.20
Dollar Depth (VDEP)	0.00		15		0.00	10	60	10	65.02	49	86	49	75.27	94	95	94	0.22	0.20
Turnover Rate (TR)	0.00		11		0.00	9	56	9	66.31	23	86	23	69.32	50	81	50	0.13	0.11
Bi-dimentional Liquidity Measure (BLM)	0.00		8		0.00	1	18	1	6.89	12	24	12	4.13	2	55	2	0.05	0.03

Notes: This table presents the time series regression results for commonality in liquidity is driven by interest rate, market return, volatility and market liquidity on the Shenzhen Stock Exchange (SZSE) between July 2000 and June 2002. QSPR is the quoted spread, PQSPR is the percentage quoted spread, DEP is depth. VDEP is Dollar Depth. TR is the Turnover Rate. BLM is the bi-dimensional Liquidity Measure. 'Estim' is the estimated regression coefficients. 'Sign' is the percentage of significant coefficients. 'Pos' is the percentage of positive coefficients. 'SPos' is the percentage of significant and positive coefficients.

V. Macroeconomic Sources of Systematic Liquidity

In this section, I first construct two measures of monthly aggregate liquidity over the sample period of 78 months. They are: (i) the average monthly ratio of absolute return of stocks to their corresponding Yuan volume calculated from the daily data (Amihud, 2002), and (ii) The Pastor and Stambaugh (2003) liquidity factor that intends to capture the effect that there are greater possibilities of return reversals when liquidity is lower. These two measures of aggregate market liquidity are deployed in the following empirical formulation as the dependent variables when investigating the sources of commonality in liquidity in China.

The development of literature on commanality that was reviewed in the previous sections indicates that macroeconomic factors can critically influence co-movements of liquidity. Some popular measures of market liquidity have been constructed using high-frequency data. Chordia, Roll, and Subrahmanyam (2001) for example, study aggregate market spreads, depths, and trading activity for US equities from 1988 to 1998. They find that liquidity is influenced by several factors. The explanatory variables include short- and long- term interest rates, default spreads, market volatility and recent market movements. In another paper, Chordia, Sarkar, and Subrahmanyam (2005) study the dynamics of liquidity by estimating a VAR (vector autoregressive) model with a sample spanning from June 1991 to December 1998. In the interactions between liquidity and returns, return volatility and order flow, they find a link between macro liquidity and micro liquidity. Fujimoto (2004), however use a longer, 40 years sample to

identify the underlying sources of liquidity movement, in an effort to investigate broader macroeconomic influences on market liquidity.

5.1 Data and Methodology

In order to construct the monthly aggregate liquidity measures, I include in the sample listed shares on the SHSE and the SZSE. Again, the monthly stock files to form the sample are from the CSMAR database. The sample period is from January 1996 to June 2002. To ensure sufficient observations, stocks must be traded at least once on at least ten trading days over the 78 months. In order to focus on normal trading activity through continuous auction, opening first trades are deleted from the study. In order to maintain the stability of the stock prices, I also deleted trades and transactions with ST and PT conditions. Observations for June 24th 2002 are not included, because the Chinese stock market experienced a severe market shock on that day, resulting from the government decision to stop the program of reducing government holdings of state stocks. Since the Chinese stock market was re-opened in the early 1990s and during its early the market data were not particularly reliable, so the data available to this study is shorter than those of matured markets such as the US stock market or the UK stock market, I cannot apply the sub-sample analysis of the original model as did in Fujimoto (2004). This is largely constrained by the data availability due to institutional restrictions in China. However, in future research, interesting results may be found if longer datasets become available, which enables a meaningful analysis of sub-sample periods.

One index that may be used to measure the state of market liquidity is the illiquidity ratio which is based on the price impact of a trade. Brennan and Subrahmanyam (1996) show that the adverse selection due to the presence of informed investors is a primary cause of illiquidity in financial markets. Such illiquidity in turn creates significant costs for uninformed investors, and they find evidence confirming that the required rates of return of illiquid securities are higher. Based on these findings, Fujimoto (2004) use the illiquidity ratio as a proxy for the price impact of a trade in her study of the source of commonality in liquidity.

I follow this literature to use the illiquidity ratio, or the price impact of a trade to proxy the state of market liquidity (Amihud, 2002; Fujimoto, 2004; Martinez et al., 2005). In what follows, the price impact of a trade for stock *i* in month *t* is denoted as $pimp_{i,}$[5], which is given by the monthly ratio of absolute stock returns to their Yuan transaction volumes. The calculation is based on daily data using the following formula:

$$pimp_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \left| r_{i,d,t} \right| / v_{i,d,t}, \qquad (4.4)$$

where $r_{i,d,t}$ is stock i's return on day d in month t and $v_{i,d,t}$ being its transaction volume, and $D_{i,t}$ is the number of its observations in month *t*. I use a filter that

[5] This measure is the inverse of the Amivest measure which is the trading volume scaled by the security return, which is a measure of market depth, and so are widely used in the empirical microstructure as a measure of market liquidity. According to Becker-Blease and Paul (2006), the Amivest measure is calculated as the sum of daily trading volume divided by the sum of the absolute value of return for each stock, $LR_i = \Sigma_t VOL_{i,t} / \Sigma_t \mid R_{it} \mid$. $VOL_{i,t}$ and R_{it} are daily volume and daily stock returns, respectively, and the natural log of this variable is used in the empirical analysis.

allows only stocks with 15 observations on return and volume in a month to be included in the calculation of $pimp_{i,t}$.

.

Based on this daily illiquidity ratio of individual stocks, I construct the time series of the monthly market-wide liquidity measure by first calculating the cross-sectional average of the price impact of each stocks for each day and then taking average of these daily figures by the actual trading day in the month to form the monthly series (Eckbo and Norli, 2002; Fujimoto, 2004; Martinez et al., 2005; Sadka, 2006). To control for the possible instationarity which may exhibit in a normalised measure of illiquidity (Acharya and Pedersen, 2005 and Eckbo and Norli, 2002), I follow Fujimoto (2004) to multiply the above-caluculated illiquidity measure by a scaling factor, m_t/m_1, where m_t is the total Yuan value of sample stocks at the end of month t-1 and m_1 is the corresponding value for the base month, i.e. February 1996. Specifically, the scaled market-wide price impact for month t, $PIMP_t$, is given by:

$$PIMP_t = (m_t/m_1)\cdot(1/N_t)\sum_{i=1}^{N_t} pimp_{i,t}, \qquad (4.5)$$

N_t is the available stocks in month t for different stock exchanges in China. In the sample period, it ranges between 496 and 655 for the SHSE stocks and for the SZSE stocks it is between 477 and 502 stocks.

Another market liquidity measure that I construct for the empirical investigation in a VAR presentation in this section is the Pastor and Stambaugh's (2003)

liquidity factor. This market measure of liquidity is the equally weighted average of the liquidity measures of individual stocks using daily data within the month. The individual stock's liquidity in month t is proxied by $rrev_{i,t}$, which is obtained from its OLS estimate in the following regression:

$$r^{e}_{i,d+1,t} = \theta_{i,t} + \phi_{i,t} r_{i,d,t} + rrev_{i,t} \cdot sign(r^{e}_{i,d,t}) v_{i,d,t} + \varepsilon_{i,d+1,t}, \qquad (4.6)$$

Where $r_{i,d,t}$ is the return on stock i on day d in month t, is given by $r_{i,d,t}$ - $r_{m,d,t}$, with $r_{m,d,t}$ being the return on the value-weighted market return proxied by comprehensive Chinese stock market index on day d in month t, and $v_{i,d,t}$ being the Yuan trading volume for stock i on day d in month t. So the term of $r^{e}_{i,d,t}$ represents the excess return over the market (Pastor and Stambaugh, 2003). The filtration criteria for selecting the sample stocks are as those of the construction of *PIMP*.

The term is a proxy for order flow, which is of special importance in the construction of the Pastor and Stambaugh liquidity measure. According to Campbell, Grossman and Wang (1993), if a stock price drop is due to the arrival of negative public information inducing all investors to lower their market valuation, no change in the expected return would happen, nor the trading volume. However, if the price drop is caused by the desire of noninformational investors to sell stocks for exogenous reasons, the selling pressure by the noninformational investors would be reflected in unusual volume. On the other hand, other investors buying the stocks would ask for compensations for accommodating such liquidity

demands of the noninformational investors. The compensations may take the form of a lower stock price and a higher expected stock return. Therefore there will be contemporaneous price drops on the appearance of selling pressure, but on subsequent days price tend to increase (return reversal). This implies prices changes accompanied by high volume are more likely to be reversed in the future.

Following this line of reasoning, Pastor and Stambaugh (2003) use signed volume as a proxy for order flow (selling or buying pressure) and claim lower liquidity is reflected in stronger volume-related return reversals. The volume is given the same sign as the excess return of stocks above that of the market on the same day. Empirically, in the regressions of individual stock's return on the signed volume and other independent variables, Pastor and Stambaugh (2003) take the coefficient on the signed volume as the liquidity measure for individual stocks. The cross-sectional average of the individual liquidity measures of the sample stocks then is taken as the measure of the market liquidity. This is also followed in similar studies (Fujimoto, 2004, Martinez et al., 2005). According to Pastor and Stambaugh (2003), a stronger tendency for the return to be reversed after volume changes corresponds to lower liquidity.

To make the market liquidity measure stationary, I once again scale the time series of the aggregate market liquidity by a scaling factor of m_t/m_1, as in Pastor and Stambaugh (2003), Fujimoto (2004), among others. Specifically, I have:

$$RREV_t = (m_t/m_1)\cdot(1/N_t)\sum_{i=1}^{N_t} rrev_{i,t}, \qquad (4.7)$$

In the equation, N_t is the number of qualified stocks at month t, which is between 496 and 655 for the SHSE, and between 477 and 502 for the SZSE market.

Based on these two market liquidity measures, i.e. the illiquidity ratio (*PIMP*) and the Pastor - Stambaugh liquidity factor (*RREV*), I set up a four-variable VAR model in this section to estimate the macroeconomic sources of liquidity commonality. In addition to the liquidity measure which takes *PIMP* and *RREV* respectively, other variables of interest that are included in the variable space include market share turnover, market volatility, and market return. The market return variable (MRTN) in the estimation is the value-weighted monthly return for the Shanghai market and Shenzhen market. The return volatility variable (VOL) is the standard deviation of daily market return within each month for the Shanghai and Shenzhen markets, respectively. The market share turnover (STOV), or the ratio of the trading volume of the sample shares in the Shanghai and Shenzhen markets to the number of shares outstanding in the corresponding markets, is calculated as the cross-sectional average of individual shares' turnover.

Following Eckbo and Norli (2002) and Fujimoto (2004), I employ a scaling factor to make the time series of the market share turnover stationary. The factor is given by v_t/v_1, where v_t is the 3-month moving average of the original market turnover measure through months t-3 to t-1, while v_1 being the value of the market turnover for January 1996. Specifically, it is given by:

$$STOV_t = (v_t/v_1)\cdot(1/N_t)\sum_{i=1}^{N_t} stov_{i,t}, \qquad (4.8)$$

For the SHSE stocks, the number of stocks included in taking the average for month t, N_t, goes from 496 to 655, and for the SHSE market, the corresponding number for the averaging ranges from 477 to 502.

The estimation period finally chosen for the VAR modelling is from February 1996 to June 2002, after the use of the 3-month moving average of the scaling factor for the variable of the market share turnover (STOV). The descriptive statistics for the unscaled monthly time series of the liquidity measures are given in Table 4.6 (Panel A) and Table 4.7 (Panel A). During the sample period, the average unscaled illiquidity proxy (*PIMP)* is 0.032 for the SHSE stocks and the corresponding average value for the SZSE shares is 0.024.

For the SHSE stocks, the mean of the unscaled *RREV* is -0.021, and -0.027 for the SZSE market. The mean of the scaled *RREV* is -1.205 for Shanghai stocks and -1.698 for the SZSE market. The summary statistics are reported in Panel B of Table 4.6 and Panel B of Table 4.7. The results indicate that, on the SHSE market, for trading in 1 million Yuan worth of shares, the average cost is 0.021% of the transaction and in the SZSE market, the average cost is 0.027%. In terms of the scaled *RREV*, that the average cost of trading 1 million Yuan worth of shares at the first year of the sample (i.e. 1996), is 1.205% on the Shanghai market and is 1.698% in the SZSE. For the autocorrelation of these two liquidity measures, Table 4.6 and Table 4.7 show that, after scaling, the *PIMP* series are moderately persistent in both Shanghai and Shenzhen market, with one month autocorrelation being 0.776 on the SHSE and 0.730 on the SZSE. For the *RREV* series, the

autocorrelation shows the similar pattern in Shanghai. But on the SZSE, it is less persistent. Finally, the correlation between *PIMP* and *RREV* is negative, which is understandable given the fact that, by construction, a greater level of illiquidity is reflected in a higher value of *PIMP* but a lower value of *RREV*.

Table 4.6 Summary Statistics for Market Liquidity Measures of Shanghai Stocks

	Descriptive Statistics					Autocorrelations					Correlations	
	Mean	Median	Std.Dev.	Min	Max	1	2	3	4	5	Price Impact (PIMP)	Return Reversal (RREV)
A. Unscaled Liquidity Series												
Price Impact (PIMP)	0.032	0.028	0.344	0.002	18.364	-0.040	-0.190	0.038	-0.025	0.092	1.000	
Return Reversal (RREV)	-0.021	-0.028	6.215	-0.036	0.038	-0.402	0.274	0.305	0.179	0.143	-0.256	1.000
B. Scaled Liquidity Series												
Price Impact (PIMP)	0.014	0.009	0.266	0	20.003	0.776	0.746	0.604	0.536	0.485	1.000	
Return Reversal (RREV)	-1.205	-1.715	9.046	-3.162	4.162	-0.143	-0.006	-0.072	-0.013	-0.081	0.046	1.000

Notes: This table presents the descriptive statistics of the market liquidity measures in my VAR analysis on the Shanghai Stock Exchange (SHSE) during January 1996 to June 2002 period. Panel A is for unscaling the cross-sectional averages of *PIMP* and *RREV*. Panel B is for scaling the cross-sectional averages of *PIMP* and *RREV*. I use the ratio of the total Yuan value of the stocks based on the construction of the measures in that month to the corresponding value for February 1996.

Table 4.7 Summary Statistics for Market Liquidity Measures of Shenzhen Stocks

	Descriptive Statistics					Autocorrelations					Correlations	
	Mean	Median	Std.Dev.	Min	Max	1	2	3	4	5	Price Impact (PIMP)	Return Reversal (RREV)
A. Unscaled Liquidity Series												
Price Impact (PIMP)	0.024	0.022	0.136	0.001	3.088	0.442	0.336	0.343	0.303	0.258	1.000	
Return Reversal (RREV)	-0.027	6.17E-05	6.335	-0.100	0.065	-0.026	-0.159	-0.031	0.039	0.031	-0.258	1.000
B. Scaled Liquidity Series												
Price Impact (PIMP)	0.019	0.004	0.308	0.005	6.027	0.730	0.717	0.692	0.609	0.636	1.000	
Return Reversal (RREV)	-1.698	-9.343	2.238	-9.944	0.123	0.769	0.646	0.593	0.592	0.3614	-0.897	1.000

Notes: This table presents the descriptive statistics of the market liquidity measures in my VAR analysis on the Shenzhen Stock Exchange (SZSE) during January 1996 to June 2002 period. Panel A is for unscaling the cross-sectional averages of *PIMP* and *RREV*. Panel B is for scaling the cross-sectional averages of *PIMP* and *RREV*. I use the ratio of the total Yuan value of the stocks based on the construction of the measures in that month to the corresponding value for February 1996.

5.2 VAR Modelling of the Financial Market Variables

In order to investigate interactions between financial variables that are found to be important drives of liquidity commonality as indicated in the previous section and the other similar research including Bauer, 2004; Fujimoto, 2004; and Chordia, Sarkar, and Subrahmanyam, 2005, I follow Fujimoto (2004) to apply a VAR presentation to analyse the Chinese sources of liquidity commonality

To check for the stationarity of the variables in the VAR system, I test the unit roots in the time series of the variables with the augmented Dickey-Fuller method. A constant term is included in all the tests and the number of lags of the variables is based on the Schwarz Information Criterion (SIC). The null hypothesis of nonstationarity is rejected at a 5% significance level, suggesting that the variables in the system are stationary and so are suitable for the VAR estimation.

Based on SIC results, I chose one lag for the VAR system. The test results of this one-lag VAR system are presented in Table 4.8 and Table 4.9. As shown, significant causal relations can be found between aggregate liquidity and the market variables. Panel A of Table 4.8 shows that *STOV*, *VOL*, and *MRTN* can cause *PIMP* in Granger sense on the Shanghai stock market. However, in contrast to other similar studies (e.g. Fujimoto, 2004), *PIMP* does not Granger-cause any of the market variables. Panel B of Table 4.9 presents the results for the VAR (1) model with the market liquidity mesure being proxied by *RREV*. Again, one can observe that the three market variables affect *RREV* significantly and causally, but

there is no evidence of Granger-causality from *RREV* to the market variables. Outcome for VAR estimation with Shenzhen stocks shows a similar pattern.

Table 4.8 VAR Estimation for Shanghai Stocks

	Dependent Variables			
	Share Turnover ($STOV_t$)	***Market Volatility (VOL_t)***	***Market Return ($MRTN_t$)***	***Market Liquidity (LIQ_t)***
A. Market Liquidity (LIQ)=Price Impact (PIMP)				
Constant	1.654	0.011**	-0.023	-7.29E-09
$STOV_{t-1}$	0.529***	-0.004	0.014	2.75E-14***
VOL_{t-1}	-9.545***	0.105**	1.818*	2.10E-07***
$MRTN_{t-1}$	-1.135	0.003	0.023	1.66E-09***
LIQ_{t-1}	2.12E+12	2.217	4.279	0.638*
R^2	0.457	0.261	0.007	0.684
B. Market Liquidity (LIQ)=Return Reversal (RREV)				
Constant	1.677*	0.012***	0.028	-16.545
$STOV_{t-1}$	0.596***	-0.004	0.016	0.002***
VOL_{t-1}	5.063	0.295	2.419	1.992***
$MRTN_{t-1}$	-6.357	0.002	0.021	-203.477***
LIQ_{t-1}	-11.150	-2.372	31.943	-0.151*
R^2	0.692	0.185	0.008	0.052

Notes: This table presents the coefficient estimates of the VAR model, comprising market share turnover (STOV), market volatility (VOL), market return (MRTN) and market liquidity (LIQ), where *LIQ* is price impact (PIMP) and return reversal (RREV) on the Shanghai Stock Exchange (SHSE) during January 1996 to June 2002 period. Significance at 10% level is indicated by *, at 5% by **, and at 1% by ***.

Table 4.9 VAR Estimation for Shenzhen Stocks

	Dependent Variables			
	Share Turnover ($STOV_t$)	*Market Volatility (VOL_t)*	*Market Return ($MRTN_t$)*	*Market Liquidity (LIQ_t)*
A. Market Liquidity (LIQ)= Price Impact (PIMP)				
Constant	1.554	0.013***	-5.061	- 1.61E-08**
$STOV_{t-1}$	0.502***	1.13E-08	9.76E-07	7.87E-14***
VOL_{t-1}	-7.252***	0.148**	6.198*	2.49E-08***
$MRTN_{t-1}$	1.187	2.78E-05	-0.095	1.48E-12*
LIQ_{t-1}	2.92E+12	7.829	7.241	0.366*
R^2	0.696	0.228	0.013	0.707
B. Market Liquidity (LIQ)= Return Reversal (RREV)				
Constant	1.248*	0.012**	-5.023	3.583
$STOV_{t-1}$	0.696***	2.01E-08	-3.39E-07	-3.44E-05***
VOL_{t-1}	6.237	0.178*	5.959	8.485***
$MRTN_{t-1}$	1.644	3.06E-05	-0.096	-0.007***
LIQ_{t-1}	-2.069	5.32E-05	-0.060	0.266*
R^2	0.603	0.206	0.014	0.811

Notes: This table presents the coefficient estimates of the VAR model, comprising market share turnover (STOV), market volatility (VOL), market return (MRTN) and market liquidity (LIQ), where *LIQ* is price impact (PIMP) and return reversal (RREV) on the Shenzhen Stock Exchange (SZSE) during January 1996 to June 2002 period. Significance at 10% level is indicated by *, at 5% by **, and at 1% by ***.

Next I examined the effects of shocks in the variables in the VAR system by estimating their impulse response functions, which show the dynamic responses of an endogenous variable and other variables to an orthogonalised one-standard-deviation shock to the endogenous variable. The results are presented in Figure 4.1. Following the literature, the shocks are orthogonalise by using the Cholesky decomposition of the VAR residuals. Following Fujimoto (2004) and Chordia, Sarkar, and Subrahmanyam (2005), I order the variables in the sequence of *STOV, VOL*, *MRTN*, and *LIQ*, where the market liquidity variable *LIQ* will be proxied by either *PIMP* or *RREV*.

As shown in Figure 4.1, the impulse response functions of market liquidity in terms of *PIMP* and *RREV* indicate that shocks in various financial variables significantly influence market liquidity in the VAR system. It is shown that market liquidity may be significantly improved by a positive *STOV* shock and a negative *VOL* shock in the subsequent periods. In the Chinese case, a positive unit shock in *STOV* leads to a 6% decline in *PIMP* after a month and the impact remains significant for over 4 months. The similar magnitude of shock in *STOV* will cause a 20% increase in *RREV* in the following month and the significant impact would last for 10 months. In common with other studies e.g. Fujimoto, 2004, I find that shocks in *VOL* lead to higher *PIMP* and lower *RREV*. It is interesting to note that, on the Chinese stock market, a positive unit shock in *MRTN* improves liquidity, similar as those reported in Chordia, Roll, and Subrahmanyam (2001) and Fujimoto (2004). The outcome confirms the flight-to-quality phenomenon in that during up markets, market liquidity tends to

increase. I find a difference between *PIMP* and *RREV* to their own shocks: while *PIMP* shows a positive response to a unit shock to its own, *RREV* does not display a significant response in such occasions.

For impulse response functions of the market variables in the VAR system, I cannot find any significant relations, which is markedly different from the findings of Fujimoto (2004).

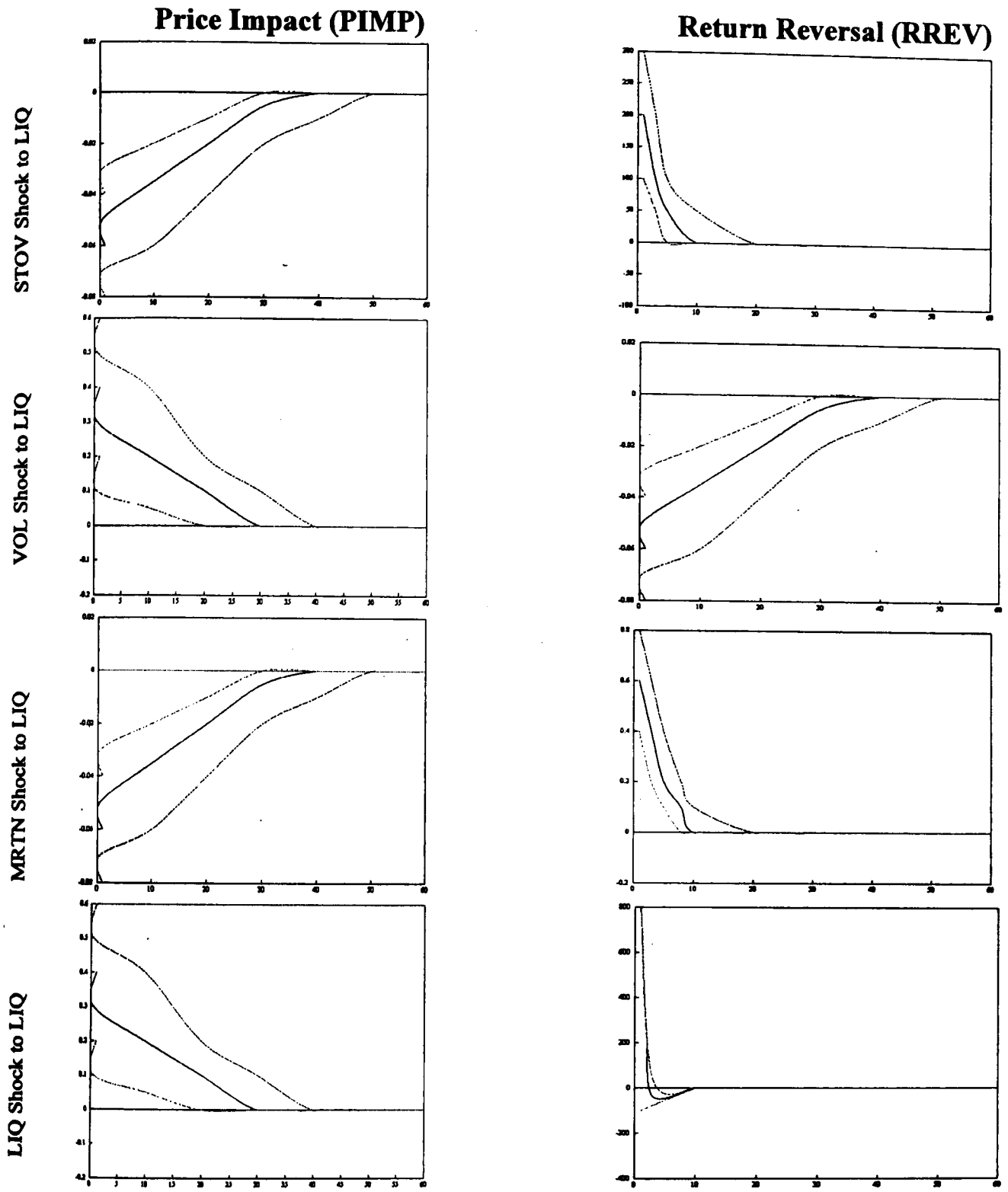


Figure 4.1: Impulse Responses of Market Liquidity. The figures show impulse responses of market liquidity to a unit change in the innovation of the variables in the VAR system during the sample period of 1996:Feb-2002:Jun. The variables are ordered in the sequence of market share turnover (*STOV*), market volatility (*VOL*), market return (*MRTN*), and market liquidity (*LIQ*). The chosen lag for the VAR system is one, with the market liquidity variable in the system being represented by the illiquidity measure (*PIMP*) and return reversal (*RREV*), respectively. The lines around the response path represent two-standard error bands.

To further examine the role of financial attributes in explaining the time variation in liquidity, I will apply variance decomposition analyses. Table 4.10 and Table 4.11 present the results. At all five forecast horizons (1, 3, 6, 12, and 24 months), although the majority of variations in liquidity are explained by the shocks to its own past, the financial market variables in the VAR system prove to be contributory. In the Chinese case, shocks in *STOV*, *VOL*, and *MRTN* can explain 0.83%, 6.64%, and 0.33%, respectively, of the error variance in forecasting *PIMP* on the SHSE at 1-month length. For *RREV*, the same market variables account for 2.54%, 7.89%, and 0.02% respectively. At longer forecast horizons say one year, shocks in *STOV*, *VOL*, and *MRTN* can explain 16.23%, 12.45%, and 0.12%, respectively, of the variations in *PIMP* on the SHSE. For *RREV*, the same market variables account for 3.52%, 7.49%, and 2.07%, respectively, of its variations. Of all these financial variables, on the Shanghai market, the most important shock turns out to come from volatility (*VOL*).

On the SZSE, shocks in *STOV*, *VOL*, and *MRTN* can explain, at 1-month horizon, 0.01%, 3.74% and 0.02% of the error variance in forecasting *PIMP*. The same variables respectively account for 7.63%, 5.54% and 0.03% variations in *RREV* at 1-month length. On the SZSE, shocks in *STOV*, *VOL*, and *MRTN* explain, at 1-year horizon, 44.26%, 1.67% and 0.60% of the error variance in forecasting *PIMP*. The same variables respectively account for 79.90%, 1.41% and 0.04% of variations in *RREV*. On the whole, on the Shenzhen market, although volatility is an important force driving changes in liquidity at the market level, the effect of the market turnover seems more important.

Table 4.10 Variance Decompositions of the VAR Model with Market Variables for Shanghai Stocks

Variable	Horizon	Share Turnover (STOV)	Market Volatility (VOL)	Market Return (MRTN)	Market Liquidity (LIQ)
Price Impact (PIMP)	1	0.83	6.64	0.33	92.20
	3	8.21	12.96	0.18	78.65
	6	13.76	12.73	0.14	73.37
	12	16.23	12.45	0.12	71.20
	24	12.65	12.40	0.12	70.83
Return Reversal (RREV)	1	2.54	7.89	0.02	89.55
	3	3.42	7.49	2.07	87.02
	6	3.51	7.49	2.07	86.93
	12	3.52	7.49	2.07	86.93
	24	3.51	7.49	2.07	86.93

Notes: This table presents the variance decomposition from the VAR model, comprising market share turnover (STOV), market volatility (VOL), market return (MRTN) and market liquidity (LIQ), where *LIQ* is price impact (PIMP) and return reversal (RREV) on the Shanghai Stock Exchange (SHSE) during January 1996 to June 2002 period. 'Variable' denotes the variable for which the variance decomposition is computed. 'LIQ' denotes the liquidity measure included in the VAR model. The results are given for the forecast horizons of 1, 3, 6, 12, and 24 months.

Table 4.11 Variance Decompositions of the VAR Model with Market Variables for Shenzhen Stocks

Variable	Horizon	Share Turnover (STOV)	Market Volatility (VOL)	Market Return (MRTN)	Market Liquidity (LIQ)
Price Impact (PIMP)	1	0.01	3.74	0.02	96.25
	3	29.62	2.60	0.40	67.78
	6	39.40	1.98	0.50	58.62
	12	44.26	1.67	0.60	54.07
	24	45.75	1.57	0.60	52.68
Return Reversal (RREV)	1	7.63	5.54	0.03	86.80
	3	8.84	2.32	0.04	88.80
	6	10.83	1.59	0.04	87.54
	12	11.45	1.41	0.04	87.10
	24	12.64	1.40	0.04	85.92

Notes: This table presents the variance decomposition from the VAR model, comprising market share turnover (STOV), market volatility (VOL), market return (MRTN) and market liquidity (LIQ), where *LIQ* is price impact (PIMP) and return reversal (RREV) on the Shenzhen Stock Exchange (SZSE) during January 1996 to June 2002 period. 'Variable' denotes the variable for which the variance decomposition is computed. 'LIQ' denotes the liquidity measure included in the VAR model. The results are given for the forecast horizons of 1, 3, 6, 12, and 24 months.

5.3 VAR Modelling of Effects of Macroeconomic Variables

Next, I extend the VAR modelling to investigate interactions among market liquidity, market variables and changes in macroeconomic conditions. As before, market variables comprise market return, volatility, and share turnover. Within a given economic system, these financial variables are inevitably subject to influences of economy-wide conditions. Thus, macroeconomic shocks may impact aggregate liquidity indirectly through their effect on the relative cost of placing limit or market orders in an order driven environment. In the meantime, macroeconomic conditions may directly impact market liquidity on these financial market variables. The VAR representation is particularly suitable for modelling such interactions (Fujimoto, 2004).

Following the literature, five macroeconomic variables are deployed for the VAR analyses (Fujimoto, 2004). The variables and their data sources are explained below:

IP: The industrial production's monthly growth rate.

CPI: The monthly inflation rate from the consumer price index.

RMP: The rate of monthly change in the index of raw material prices.

OIR: The overnight interest rate as an indicator of China's monetary policy.

M2: This variable includes money and quasi-money. It is used as a measure of the monetary condition in China.

I use the first log difference of the data series to calculate the growth rates of the variables. The original data on *IP*, *CPI*, *RMP*, *OIR* and *M2* are from the People's Bank of China (http://www.pbc.gov.cn) and the database of CSMAR. Summary statistics are given in Table 4.12. The one-lag VAR model, comprising macroeconomic variables *IP*, *CPI*, *RMP*, *OIR*, *M2* and financial market variables *STOV*, *VOL*, *MRTN*, and the liquidity measure (*LIQ*, which may be either *PIMP* or *RREV*), covers the sample period from March 1996 to June 2002. Before formed VAR estimation, the variables are tested for their stationarity using the augmented Dickey-Fuller method, which do not reject the null of nonstationarity.

To analyse impulse responses of market liquidity to shocks in macroeconomic shocks, I arrange the macroeconomic variables to be ahead of the financial market variables. The macroeconomic conditions variables are ordered in this sequence: *IP*, *CPI*, *RMP*, *OIR*, *M2*. The order of the financial market variables is as before. However, when examining the effect of monetary conditions (*M2*) on *LIQ*, I follow Fujimoto (2004) to place *M2* ahead of *OIR*.

Table 4.12 Summary of Descriptive Statistics for Macroeconomic Variables

(March 1996 – June 2002)

	Descriptive Statistics		Correlations				
	Mean	Std.Dev	IP	CPI	RMP	OIR	M2
IP	0.148	0.143	1.000				
CPI	-0.554	0.002	-0.122	1.000			
RMP	-0.428	0.002	0.109	0.243	1.000		
OIR	4.519	3.777	-0.085	-0.362	-0.336	1.000	
M2	0.006	0.006	0.105	-0.028	0.061	0.084	1.000

This table gives descriptive statistics for the industrial production growth (IP), CPI inflation (CPI), growth in the index of sensitive material prices (RMP), the first difference in the overnight interest rate (OIR), and the money and quasi-money (M2) as well as their pairs correlations on the Chinese Stock Exchange during March 1996 to June 2002 period.

Figure 4.2 graphically presents the results of the impulse response functions. It is shown that macroeconomic factors are important forces driving the changes in market liquidity. It is shown that, within one month and in the subsequent periods, market liquidity can be significantly improved by a negative *ORI* shock or a positive *M2* shock. A positive unit shock in *M2* causes an immediate improvement in liquidity and the impact remains significant for up to 8 months for *PIMP,* and 10 months for *RREV*. An *ORI* shock on *PIMP* becomes significant 8 months after the shock and remains significant for another 10 months, while the impact of its shock on *RREV* becomes significant after 5 months and remains significant for another 3 months. The outcome shows the particular importance of monetary policy in terms of its impact on aggregate liquidity of the Chinese stock market. Other macroeconomic shocks are less significant. For example, the inflation shock, either *CPI* inflation or *RMP* inflation, does lower market liquidity in the following months, but the influence is insignificant. However, they do have significant effect on the return reversal tendency (*RREV*). These results show that these macroeconomic factors have some direct impacts on market liquidity of the Chinese stock market where individual investors are the dominant investment customers and they are prone to shocks in macroeconomic events.

Somehow unexpectedly, I do not find evidence that macroeconomic shocks would exert a significant effect on financial market variables such as market share turnover, volatility, and return.

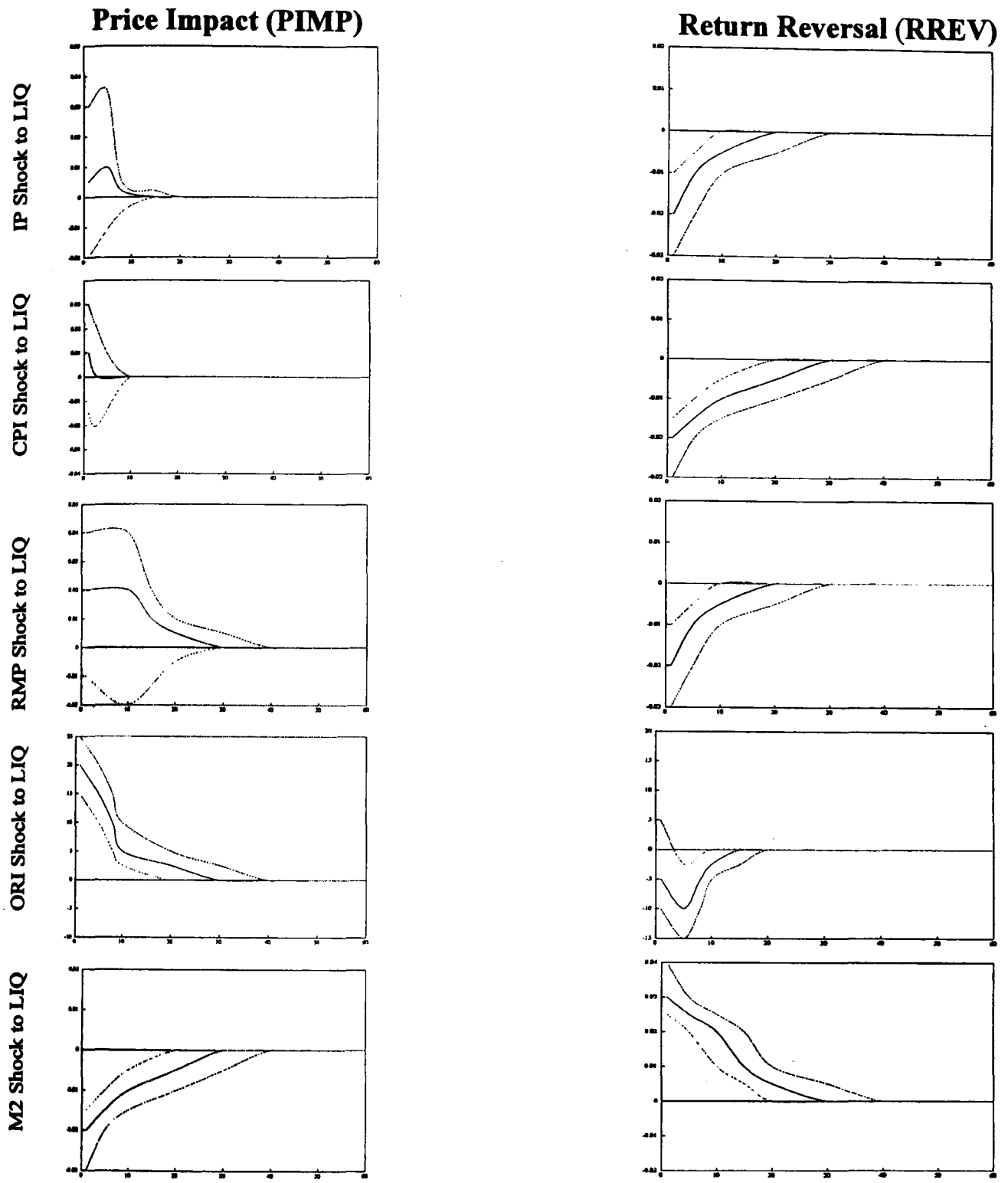


Figure 4.2: Impulse Responses of Market Liquidity to Macroeconomic Shocks. The figures show impulse responses of market liquidity to a unit change in the innovation of the macroeconomic variables in the VAR system during the sample period of Mar: 1996-Jun: 2002. The variables are ordered in the sequence of the industrial production growth (*IP*), CPI inflation (*CPI*), the change rate of Raw Material Price index (*RMP*), changes in the interest rate (*ORI*), the broad money (*M2*), market share turnover (*STOV*), market volatility (*VOL*), market return (*MRTN*), and the market liquidity measure in either *PIMP* or *RREV*. The chosen lag for the VAR system is one. The lines around the response path represent two-standard error bands.

Next, I again apply the variance decomposition analysis to the VAR system with macroeconomic conditions. The results are reported in Table 4.13 and Table 4.14. At all five forecast horizons (1, 3, 6, 12, and 24 months), I find a large proportion of variations in the specific measure of market liquidity is due to shocks in financial market variables and also the macroeconomic shocks in *CPI*, *RMP*, *ORI*, and *M2*. During the sample period, the total contribution of financial variables to the variations in *PIMP* is about 12% at the one month horizon on the Shanghai market, while the sum of effects of macroeconomic shocks accounts for 8%. At longer time horizons, the sum contribution at one year horizon due to shocks in market variables is 25.5 % and the macro shocks' sum contribution is 19.3 %. At the two year horizon, the corresponding percentages change to 25.6 % and 19.4 %. For *RREV*, the proportion of the forecast error variance arising from the financial market shocks increases from about 16.2 % at the 1-month horizon to about 16.4 % at the 1-year horizon and the sum contribution from macro economic shock ranges from 6.3 % at one month horizon to 14.8 % at 1-year horizon. On the Shenzhen market, the pattern of relative contributions is similar. These results once again show that macroeconomic factors are critical contributors to the changes in market liquidity.

Table 4.13 Variance Decompositions (Macroeconomic Variables) for Shanghai Stocks

Variable	LIQ	Horizon	IP	CPI	RMP	OIR	M2	Sum Macro	STOV	VOL	MRTN	Sum Mkt	LIQ
Price Impact (PIMP)		1	0.59	3.49	1.05	0.03	2.60	7.78	4.52	6.41	0.85	11.78	79.39
		3	2.45	3.85	4.87	2.13	1.39	14.69	5.78	13.31	1.10	20.19	65.11
		6	2.96	3.58	7.55	3.13	1.11	18.33	7.40	16.04	0.85	24.29	57.37
		12	3.07	3.53	8.29	3.41	1.03	19.33	7.82	16.89	0.78	25.49	55.18
		24	3.08	3.52	8.35	3.43	1.02	19.40	7.86	16.97	0.78	25.61	54.98
Return Reversal (RREV)		1	0.02	0.13	5.81	0.32	0.02	6.30	3.26	12.91	0.01	16.18	77.52
		3	0.06	3.47	5.40	4.70	0.52	14.15	3.54	11.18	1.48	16.20	69.65
		6	0.07	3.45	5.60	5.00	0.56	14.68	3.74	11.12	1.48	16.34	68.99
		12	0.07	3.46	5.63	5.08	0.55	14.79	3.81	11.11	1.48	16.40	68.80
		24	0.07	3.46	5.63	5.09	0.55	14.80	3.82	11.11	1.47	16.40	68.79

Notes: This table presents the variance decomposition from the VAR model, comprising the industrial production growth (IP), CPI inflation (CPI), growth in the index of sensitive material prices (PCOM), the first difference in the overnight interest rate (OIR), and the money and quasi-money (M2), market share turnover (STOV), market volatility (VOL), market return (MRTN), and market liquidity (LIQ) on the Shanghai Stock Exchange (SHSE) during March 1996 to June 2002 period. 'Variable' denotes the variable for which the variance decomposition is computed. 'LIQ' denotes the liquidity measure included in the VAR model. 'Sum Macro' denotes the total variance in liquidity explained by macro variables. 'Sum Mkt 1' denotes the total variance in liquidity explained by market variables. 'Sum Mk2' denotes the corresponding statistics from the VAR models with macro and market variables. The results are given for the forecast horizons of 1, 3, 6, 12, and 24 months.

Table 4.14 Variance Decompositions (Macroeconomic Variables) for Shenzhen Stocks

Variable	LIQ	Horizon	IP	CPI	RMP	OIR	M2	Sum Macro	STOV	VOL	MRTN	Sum Mkt	LIQ
Price Impact (PIMP)		1	0.09	0.05	0.65	1.43	1.17	3.39	0.02	1.70	0.16	1.88	94.78
		2	0.52	1.67	7.92	3.46	2.41	15.98	20.57	0.90	0.36	21.83	62.20
		3	0.90	1.48	10.94	5.99	1.63	20.94	25.58	1.64	0.43	21.83	51.41
		4	1.01	1.39	11.98	7.30	1.35	23.03	27.32	1.99	0.40	24.86	47.26
		5	1.03	1.37	12.14	7.53	1.31	23.38	27.58	2.05	0.39	26.58	46.59
Return Reversal (RREV)		1	1.54	0.02	3.20	0.69	3.79	9.24	4.95	3.94	0.02	8.91	81.85
		2	2.31	2.66	13.26	1.15	3.40	22.78	45.79	1.82	0.05	47.66	29.55
		3	2.41	2.68	17.34	0.77	2.75	25.95	50.92	2.36	0.11	53.39	20.66
		4	2.39	2.70	18.30	0.69	2.58	26.66	52.10	2.64	0.11	54.85	18.49
		5	2.39	2.70	18.38	0.68	2.57	26.72	52.19	2.66	0.10	54.95	18.32

Notes: This table presents the variance decomposition from the VAR model, comprising the industrial production growth (IP), CPI inflation (CPI), growth in the index of sensitive material prices (PCOM), the first difference in the overnight interest rate (OIR), and the money and quasi-money (M2), market share turnover (STOV), market volatility (VOL), market return (MRTN), and market liquidity (LIQ) on the Shenzhen Stock Exchange (SZSE) during March 1996 to June 2002 period. 'Variable' denotes the variable for which the variance decomposition is computed. 'LIQ' denotes the liquidity measure included in the VAR model. 'Sum Macro' denotes the total variance in liquidity explained by macro variables. 'Sum Mkt 1' denotes the total variance in liquidity explained by market variables. 'Sum Mk2' denotes the corresponding statistics from the VAR models with macro and market variables. The results are given for the forecast horizons of 1, 3, 6, 12, and 24 months.

VI. Conclusion

Given the evidence of commonality in liquidity discovered in the previous chapter on the Chinese stock market, this chapter tackles the question that naturally arises as to why such liquidity commonality would be present. While conventional research mainly documents the sources of individual stock's liquidity, the new literature on liquidity commonality has investigated various common factors causing movements of liquidity across stocks under different market organisations. These studies essentially identify two broad sources of commonality in liquidity, i.e. market risks intrinsic to the particular market trading mechanism, and the state variables that characterise market conditions. This chapter studies the Chinese case in an order-driven market environment.

Commonality in liquidity can be caused by changes in market risks, market states and macroeconomic factors. Consequently, I adopted a synthetic approach to investigating the determination of liquidity commonality in China, which involved examining the risk factors that are pertinent to the Chinese stock market, and the factors that have a wider bearing on the marketplace. Specifically, in this chapter I research into the sources of Chinese commonality in liquidity by examining the effects that are related to adverse selection, financial market variables and macroeconomic influences.

The literature on order-driven market models suggests adverse selection due to asymmetric information is a critically important source of commonality in

liquidity. Following this line of research, I test the sources of commonality at the market and industry levels using the number of trades as an indicator of informed trading. The results for the sum of concurrent, lagged, and leading coefficients on such a variable show that the asymmetric information proxy is positive and highly significant for stocks from the SHSE and the SZSE. Given that the number of trades is a reliable indicator of informed trading, this outcome suggests that asymmetric information is a significant source of liquidity commonality in China. This finding sheds critical light on the working of the Chinese stock market. Asymmetric information is a particularly severe problem in China. Chinese firms tend to disclose only incomplete or even biased information on their business and in the marketplace share manipulation and insider trading are pervasive. In this environment a shock of asymmetric information tends to induce systematic change in liquidity across the market. My empirical results give evidence to the importance of asymmetric information as a determining factor causing liquidity commonality which is a vital attribute of the Chinese stock market.

In testing for the effects of financial market variables as determinants of liquidity commonality, I find that, on the Chinese stock market, in addition to market liquidity, market volatility is the most important factor driving co-movements of liquidity across individual stocks. It has the highest percentage of positively significant coefficient of all stocks in my sample, than that of other financial variables such as the interest rate and market returns. This also provides supportive empirical evidence of the important relationship between volatility and commonality in liquidity. A 'flight to quality' explanation is from Brunnermeier

and Pedersen (2007). They mention high-volatility securities are more affected by speculator wealth shocks.

I further examine the effects of financial market variables on commonality in a VAR modelling presentation. This time I follow the literature to use two new measures of aggregate liquidity, i.e. the illiquidity ratio or the monthly average ratio of absolute return of stocks to their corresponding volume and the Pastor and Stambaugh liquidity factor. The VAR analysis of dynamic responses of variables in the system to an impulse shock indicates that the two market liquidity measures are significantly influenced by financial variables such as market share turnover, market volatility and share returns.

The VAR analysis then is extended to investigate into the effects of macroeconomic conditions such as growth of the economy, inflation, the interest rate and monetary policy. The analysis of impulse functions suggest that macroeconomic factors can directly cause co-movements of liquidity on the Chinese stock market. Of these macroeconomic determinants, the Chinese monetary policy is found to be particularly influential in affecting aggregate liquidity. In response to a positive shock in money supply *M2* and a negative shock in the overnight interest rate, market liquidity will be improved significantly for an extended period of time. Other macroeconomic shocks such as the inflationary shock may have the significant effect on the alternative market liquidity measure, i.e. the Pastor and Stambaugh liquidity factor. Meanwhile, the variance decomposition analysis show that, at all forecast horizons adopted in this

study, a large proportion of variations in aggregate liquidity is due to shocks in both financial market variables and macroeconomic conditions. On the SHSE, the sum contribution due to shocks in financial market variables at one year horizon is about 26% of the total variation and the macro shocks' sum contribution is 19%. On the SZSE, this pattern is similar. These findings confirm that macroeconomic conditions are an important source of commonality in liquidity in China.

This chapter has performed an empirical analysis of the determinants of commonality in liquidity on the Chinese stock market. The next chapter will explore the impacts of such commonality with a view to fully understanding the commonality phenomenon and the functioning of the Chinese stock market.

Chapter 5

Commonality in Liquidity as a Priced Risk on the Chinese Stock Market

I. Introduction

I have provided theoretical underpinning and empirical evidence of the presence and sources of commonality in liquidity on the Chinese stock market. In this chapter I will address the question of whether commonality in liquidity is regarded as a systemic risk factor by Chinese investors and so is priced on the Chinese stock market. In other words, I will empirically investigate into whether or not the liquidity risk premium exists on the Chinese stock exchanges.

Understanding the impacts of liquidity commonality is important for investment strategies and financial stability. For example, if an investor holds assets with higher sensitivities to aggregate liquidity, but he needs to liquidate some assets for cash, liquidations of the assets that are sensitive to aggregate liquidity would be costly to the investor. Furthermore, such liquidations are more likely to occur when liquidity is low, since drops in his overall wealth are then more likely to

accompany drops in liquidity (Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005). This effect is costlier when market liquidity is lower, wealth already decreased and marginal utility of wealth higher. For assets that react strongly to changes in market-wide liquidity crises these effects will be even more pronounced, and investors are likely to require a systematic liquidity premium (Martinez, et al., 2005).

In addition, a number of researchers have shown that variations in systematic and total liquidity volatility affect traders' arbitrage behaviour. It has been shown that less liquid stocks tend to be more severely overpriced. Since increases in aggregate market liquidity accelerate the convergence of such stocks' prices to fundamentals, returns of these overpriced stocks are more negatively correlated with the aggregate market liquidity (Kamara, 1988; Amihud and Mendelson, 1991; Pontiff, 1996; Mitchell and Pulvino, 2001; Lesmond, Schill, and Zhou, 2004; and Sadka and Scherbina, 2007; Korajczyk and Sadka, 2008). Furthermore, Longstaff (2001) and Longstaff (2005) demonstrate that investors facing liquidity constraints behave very differently from unconstrained investors. A liquidity-constrained investor endogenously acts as if facing borrowing and short-selling constraints, and illiquidity may limit his investment opportunity sets so that it may not be feasible for him to purse diversification for his investment. This means that it is crucial for investment managers to understand changes in systematic liquidity including their sources and possible consequences.

Finally, as shown by O'Hara (2003), the liquidity provision and price discovery processes can affect the systematic and idiosyncratic volatility of stock returns. Therefore, research into systematic liquidity can have relevance for understanding the pricing of idiosyncratic return volatility (Goyal and Santa-Clara, 2003; Ghysels, Santa-Clara, and Valkanov, 2005; and Ang, Hodrick, Xing, and Zhang, 2006).

My empirical work in chapter analyses whether, on the Chinese stock market, expected returns in the sample period of 1993 to 2003 are associated cross-sectionally with liquidity risks. Comparing with previous results, I will test whether there is a linear relation between the aggregate wealth return and state variables and whether a measure of aggregate illiquidity risk affects expected stock returns in China.

In terms of studies of asset pricing in China, a number of authors have explored the relative pricing of A-shares (held by Chinese locals) versus B-shares (held by foreign investors). See for example, Fung, Lee, and Leung, 2000; Sun and Tong, 2000; Fernald and Rogers, 2002; Chan, Menkveld and Yang, 2008. However, in contrast to other countries, China does not officially require foreign investors to pay a premium above the price paid by local investors. Although in real transactions, B-shares trade at a substantial discount relative to A-shares, only less than 10 percent of companies listed in China have both B- and A-shares (Eun and Huang, 2007). So this will virtually makes it impossible to investigate the differential pricing effect between A-shares and B-shares due to the illiquidity

effect. However, Chen and Xiong (2001) investigate the differential pricing between public A-shares and the restricted legal entity shares of the same companies, which can only be traded through private transfers and occasional auctions. They find that the restricted shares are discounted by almost 80% relative to the exchange-traded public shares. This suggests that the price of illiquidity is very high.

Other studies have addressed different areas. Eun and Huang (2007) utilise data from the first 10-year period of Chinese stock trading to investigate how public A-shares are priced on the Shanghai and Shenzhen stock exchanges. Meanwhile, in their investigations of the cross-sectional determinants of Chinese stock returns, Bailey et al. (2003), Drew et al. (2003), Wang and Xu (2004) and Cui and Wu (2007) seek to determine whether the size and value premium exists in China.

The Chinese market is still emerging, and as such it suffers from unsatisfactory corporate governance, dubious accounting practice, market manipulation, and problems of insider trading. It lacks institutional investors, and what investors there are tend to trade speculatively with very short holding periods. This leads to a high turnover ratio, with investors more interested in short term gains rather than long term investment objectives. This is the ideal environment in which to study asset pricing questions while avoiding the data snooping problem (Wang and Xu, 2004). The question I will address is whether common risk of market liquidity is significantly priced on the Chinese stock market based on dynamic versions of asset pricing models that are augmented with the liquidity effect. The research

findings will help us understand whether commonality in liquidity is a useful factor that is related to fundamentals and will impact emerging markets' pricing behaviour.

In this chapter, my investigation into the pricing impacts of market-wide liquidity will follow the microstructure approach. Several interesting findings have emerged from this study. Using transaction and quote data for A- shares on two major Chinese stock exchanges, i.e. the SHSE and the SZSE, from CSMAR, I find that both the market-wide measures, SMB and HML, exhibit relatively large abnormality. The market risk-adjusted average returns on the Chinese stock market are significantly different than that of returns on the portfolios that are sorted according to the liquidity betas as the priced liquidity risk factors. Finally, evidence shows that the liquidity premium in relation to ILLQ is also significant, but the liquidity premium associated with OFL is marginally significant only in the conditional models.

The rest of the paper is organised as follows. Section II presents the literature review. Section III briefly discusses the data used in this work. Section IV describes the liquidity risk factors to be used in the estimation. These include both the market-wide measure of liquidity proposed by Pastor and Stamburgh (2003) and the aggregate illiquidity measure of Amihud (2002). General characteristics of the portfolios employed in the research are also reported. Section V contains the empirical results on asset pricing with market-wide liquidity risk factors, and Section VI gives my conclusions.

II. Literature Review

Previous research has highlighted economic consequences of liquidity variability, especially its role in asset pricing. Amihud and Mendelson (1986) believe that when valuing a security, a risk-neutral investor will take into account the transaction costs. Since the buyer will do the same, the investor will also have to consider the entire future stream of transaction costs that will be paid on the security. Therefore, the price discount due to illiquidity is the present value of the expected stream of transaction costs through its lifetime. They then find that the required return on a security that is costly to trade is the return that would be required on a similar security that is perfectly liquid, plus the expected trading cost per period.

Recently, a number of authors have developed theoretical or empirical arguments for rationalising the study of the consequences of commonality and the impact of aggregate liquidity shocks on asset pricing (Holmstrom and Tirole, 2001; Lustig, 2001; Amihud, 2002; Pastor and Stambaugh, 2003; Sadka, 2004; Acharya and Pedersen, 2005; Domowitz, Hansch and Wang, 2005; Martinez, Nieto, Rubio, and Tapia, 2005; Piqueira, 2005; Ericsson and Renault, 2006).

2.1 Commonality in Liquidity as a Risk Factor

In conventional microstructure theory, liquidity is a deterministic factor. As such, it is a risk only in a very limited sense. Liquidity is a risk because it is an important factor in investment plans and instruments and by implication lack of

liquidity would be problematic. It is only in this limited sense that the level of liquidity usually enters conventional asset pricing models as an additional risk factor (Constantinides, 1986; Vayanos and Vila, 1999).

The recent research on commonality in liquidity views liquidity as a random process, hence the notion of stochastic liquidity. Therefore, the variability of liquidity in the market at large represents a systematic risk. The systematic risk is from shocks to common liquidity factors. The systematic liquidity variation is non-diversifiable, and so is a priced risk factor. Thus, investors holding such assets will demand a systematic liquidity premium to bear the risk. The evidence for the presence of commonality in liquidity risk is a prerequisite before one can explore channels through which liquidity may affect asset pricing (Stahel, 2005a).

Chordia et al. (2001) in their study suggest that it seems to be reasonable to assume that the second moment of liquidity should be positively related to asset returns, if agents care about the risk associated with fluctuations in liquidity. However, when analysing the relation between expected equity returns and the level as well as the volatility of liquidity using trading activity as a proxy, they find investors' behaviour to be contradictory to this hypothesis. A negative and surprisingly strong relationship exists between risk-adjusted stock returns and the variability of liquidity measures in terms of dollar trading volume (as in Brennan et al., 1998) and in terms of share turnover (as in Datar et al., 1998). They believe this finding could suggest a possibility that a previously unknown risk factor may have caused such an effect. Vayanos (2004) also links the illiquidity risk to the

volatility of the market. Chen (2005) points out that liquidity risk differs from volatility effects. Using the Ang, Hodrick, Xing, and Zhang (2004) aggregate volatility measure, Chen finds that the liquidity effect is robust in controlling a volatility effect. This implies that despite being intimately related to each other, liquidity and volatility have different pricing effects. Furthermore, stock market liquidity risk is shown to be priced in the bond market as well, due to perhaps the "flight to quality effect". The results suggest that liquidity risk is a pervasive risk factor.

Coughenour and Saad (2004) claim the degree of liquidity co-variation to be positively related to the risk of providing liquidity. To prove the hypothesis, they use three tests. The first two are about specialist firm size and the third test is based on the direction of market returns.

Their first finding is that there is an inverse relation between specialist firm size and degree of liquidity co-variation because the larger specialist firms tend to use lower cost capital and have greater diversification benefits. This suggests larger specialist firms will have a lesser degree of commonality. Next, they test for the same relation in specialist firm mergers. When estimating specialist and market portfolio commonality jointly, the degree of liquidity co-variation with the market portfolio decreases significantly after the mergers, though it is not significant for the degree of commonality with the specialist firm (Coughenour and Saad, 2004).

These two tests are based on the hypothesis that stocks handled by larger

specialist firms will display less commonality because individual liquidity shocks have less influence on larger specialist firms as they have low cost capital and handle more stocks. The outcome from the two size-based tests confirms the hypothesis (Coughenour and Saad, 2004).

Kamara, Lou and Sadka (2007) also find a significant (positive) relationship, particularly for larger firms, between time variations in systematic risk and time variations in systematic liquidity. They examine the relation between the degree of commonality and the sign and magnitude of market returns. They observe that the mean degree of co-variation is lower in the upper three quartiles when they use return quartile. Also, individual stock liquidity co-varies with specialist portfolio liquidity and this commonality is significantly greater during periods with relatively large negative market returns. As a result, they conclude that there is a negative relation between the degree of specialist portfolio liquidity and market returns. They believe that increases in institutional ownership are associated with increases in the stock's sensitivity to systematic liquidity shocks and this has significant implications for expected returns. According to their analysis, changes in the structure of the American equity market have caused an increase in the exposure of large stocks to common liquidity shocks. As a result, it has become more difficult in recent years to diversify systematic risk and aggregate liquidity shocks by holding large-cap stocks. The US equity market has become less able to withstand unanticipated events.

For the relationship between commonality in liquidity and market returns, the results from Vayanos' (2004) model, where the risk facing the investors due to illiquidity is time-varying and increasing with volatility, show the compensation for illiquidity varies with time as well. They demonstrate that during volatile times, assets' liquidity premiums increase; investors become more risk averse; assets become more negatively correlated with volatility, assets' pairwise correlation increase, and illiquidity assets' market betas increase.

Following the research from Coughenour and Saad (2004) and Vayanos (2004), Domowitz, Hansch and Wang (2005) make a good ease for liquidity co-movement being a separate risk. They distinguish two types of commonality: commonality in returns and commonality in liquidity. They are caused by different sources and so they may not move in the same direction all the time. It is therefore possible for stocks to have negative or small return correlations, which are good for portfolio diversification, but strong positive liquidity correlations, which could bring risk to the portfolio. This means commonality in liquidity is a separate risk that needs to be minimised. Where there is failure to realise this, choosing stocks to form a portfolio solely on small or negative return correlations would not necessarily diversify away the liquidity risk if these shares have a high degree of liquidity commonality.

In their 2006 research, Chollete, Næs and Skjeltorp construct fundamental liquidity measures in order to study the pricing implications of shared variation in a large set of high frequency liquidity measures. They use a common factor

analysis to estimate three orthogonal, market-wide liquidity variables that statistically capture time series variations in liquidity. In addition, they test for differential explanatory power of trade-based and order-based factors. Their results indicate that two of the common liquidity factors are significantly related to cross-sectional differences in returns. Both of these factors are related to the time and quantity dimensions of liquidity, while neither is related to price. The result is robust to various model specifications. Chollete, Næs and Skjeltorp (2006) also find that differences in returns cannot be explained by order-based liquidity measures, but that common factors estimated from trade-based liquidity measures are significantly related to cross-sectional variation in realised returns. This indicates that realised, rather than expected, liquidity may be a fundamental driver in asset returns.

Acharya and Pedersen (2005) refer liquidity risk to random variability of liquidity over time. Specifically, they suggest that liquidity risk may exist in three forms: commonality in an individual asset's liquidity with the market liquidity; return sensitivity to market liquidity; and liquidity sensitivity to market returns. Therefore, they explicitly treat commonality in liquidity as a risk factor. This essentially creates the concept of market liquidity risk that includes the volatility of liquidity as well as the co-variance between returns and liquidity.

With the exception of the relationship between commonality in liquidity as a risk factor and volatility, size effects and market return, Chen (2005) constructs a measure of pervasive liquidity risk and its associated risk premium. In her

examination of seven market-wide liquidity proxies, she uses Principal Component analysis to extract the first principal component, which captures 62% of the standardised liquidity variance. The first common factor attracts a significant premium in cross-sectional asset pricing tests. The remaining principal components are not priced in the cross-section of stock returns. Her results indicate that although the different liquidity proxies differ greatly in theory, they share a common source of variation. This common source of liquidity can be used as a unique liquidity risk measure. Between 1971 and 2002, a difference in liquidity risk contributes 3.7% to the difference in annualised expected return between high liquidity beta and low liquidity beta stocks. Stock market liquidity risk is also priced in the bond markets. According to Chen, this is evidence for a 'flight to quality' effect, consistent with Pastor and Stambaugh's (2003) findings. She also finds a significant negative relation between liquidity and the conditional variance of monthly stock returns, and the liquidity measure subsumes traditional GARCH coefficients in the conditional variance.

Saar (2006) puts forward a rationale for systematic liquidity and links liquidity to time variation in the risk premium. In this model endogenous liquidity is driven by uncertainty about the preferences and endowments of investors. Since order flow provides clues to these preferences and endowments, information about the risk premium gives rise to the price impact of trades. Saar's model suggests that sudden unexpected increases in uncertainty about the risk premium would harm liquidity. Even between such shocks, however, the risk premium and liquidity are time-varying, reflecting the fact that transaction prices incorporate current beliefs

about the investor population, and these beliefs change according to the information provided by order flow. Saar's model suggests an important link between market microstructure and asset pricing. He shows that where there is more uncertainty about investors' aversion to risk, the liquidity of risky assets would be lower; where there is less uncertainty, liquidity would be higher. This could explain common factors and intertemporal patterns in liquidity. In this framework, therefore, liquidity is related to the risk premium because it is the means by which the market learns about the risk premium.

Using data from 1963 to 2005, Kamara, Lou and Sadka (2007) show that cross-sectional variation of liquidity commonality increased over that period. They use Chordia et al.'s (2000) market model of liquidity to estimate each firm's sensitivity to variations in market liquidity. The daily change in (the log of) Amihud's (2002) measure of firm's illiquidity is used as proxy for the changes in liquidity. Their findings indicate that patterns in institutional ownership over the sample period can explain the divergence of systematic liquidity, and the authors believe that the systematic risk of different size groups when estimated with a market model of stock returns exhibits similar time trends to their respective systematic liquidity.

Keene and Peterson (2007) examine liquidity as a risk factor affecting stock returns. Their proxies for liquidity are dollar volume of shares traded, share turnover, standard deviation of dollar volume, standard deviation of share turnover, coefficient of variation of dollar volume, and coefficient of variation of

share turnover. They estimate the time-series regressions using monthly data from July 1963 to December 2002. While their basic model is similar to the one employed by Fama and French (1993), Keene and Peterson (2007) add a liquidity-mimicking portfolio and include a market portfolio and mimicking portfolios for size, book-to-market equity, and momentum. They find that liquidity is an important factor affecting portfolio returns, even after the effects of market, size, book-to-market equity, and momentum are taken into account. However, the continued presence of non-zero intercepts indicate that some risk factors are missing.

Nguyen and Puri (2007) examine whether market liquidity risk can provide an explanation for the traditional characteristic liquidity premium. Their results show that after adjusting for the Pastor and Stambaugh market liquidity factor, the level of traditional liquidity remains priced. In common with previous studies, they find no evidence to suggest that the impact of liquidity level on stock return is determined by stock characteristics or Fama-French factors. This suggests that stock-specific liquidity cannot be accounted for by the market liquidity factor. Nguyen and Puri (2007) conclude that after controlling for stock characteristics, the dollar volume is statistically significant and negatively correlated with stock returns. They also show that the size-return relationship might be no more than a proxy for the liquidity-return relationship. Nguyen and Puri's (2007) results are consistent in time series and cross-sectional frameworks, and robust in both the NYSE-AMEX and the Nasdaq exchanges.

2.2 Commonality in Liquidity as a Priced Source of Risk

Given that commonality in liquidity represents a separate risk, whether it is priced naturally is important. Chordia, Subrahmanyam and Anshuman (2001) find a significant cross-sectional relation between stock returns and the variability of liquidity in terms of dollar trading volume and share turnover. However, Pastor and Stambaugh (2003) differ from that of Chordia, Subrahmanyam and Anshuman (2001). They report that stocks with more volatile liquidity have lower expected returns, implying a negative relationship between liquidity and expected returns, which is against the expectations derived from the framework of Chordia, et al. (2001). In the paper of Chordia, Subrahmanyam and Anshuman (2001), liquidity risk is measured as firm-specific variability in liquidity. Recent studies focus on systematic liquidity risk in returns and find that stocks more exposed to market liquidity fluctuations tend to have higher expected returns (Pastor and Stambaugh, 2003).

In an influential paper, Pastor and Stambaugh (2003) investigate whether market liquidity is a state variable for pricing financial assets. Their investigation uses a measure of market liquidity that is constructed as the equal-weighted average of the liquidity measures of individual stocks on NYSE and AMEX, which is based on daily price reversals. The derived measure of market liquidity is monthly time series based on daily data within the month.

In their initial analysis, the sharpest drops in the market liquidity correspond to economic or financial crises such as the oil embargo in early 1973, the 1987 stock

market crash, the 1997 Asian financial melt-down and the LTCM drama of 1998. However, Gibson and Mougeot (2004) find that systematic liquidity risk dominates market risk and is not affected by extreme liquidity events such as the stock market crash in October 1987. Moreover, in months of large liquidity drops, stock returns are negatively correlated with fixed-income returns, in contrast to other months. Also, significant commonality across stocks is found in their monthly liquidity measure. These findings increase the likelihood that market liquidity is a priced state variable.

The authors then formally test how liquidity risk is priced. To this end, they first form 10 portfolios. The assignment of stocks to each decile portfolio is based on the stocks' predicted liquidity betas at the end of each year. A single return series for each of these 10 portfolios is then derived by joining together the post-formation returns on these portfolios during the next 12 months during 1965 to 1999. According to the authors, if the liquidity risk factor is priced, one would see systematic differences in the average returns of the beta-sorted portfolios. Evidence is found in their extensive empirical inquiries confirming the pricing of liquidity risk (Gibson and Mougeot, 2004).

They show that, from 1966 through 1999, stocks with high sensitivity to fluctuations in the liquidity factor earn higher returns than stocks with low sensitivity. Their estimate suggests that liquidity risk, on average, earns a premium of 7.5% annually, after controlling for exposures to the markets return and other factors including size, value, and momentum effect. Their findings

strongly support the hypothesis that the liquidity risk factor is priced and this risk requires a positive premium. The intuition is that decrease in aggregate liquidity is undesirable to investors, so they will require compensation for holding stocks with greater exposure to this risk. As a result, stocks with higher sensitivity to aggregate liquidity shocks offer higher expected returns (Gibson and Mougeot, 2004).

That commonality in liquidity and hence liquidity risk is priced is also reported in Acharya and Pedersen (2005). Based on the measure of illiquidity developed by Amihud (2002), they show that a security's expected return is a function of expected stock illiquidity, and the co-variation of its own return and liquidity with overall market return and liquidity. In their model setting, they find evidence of a liquidity risk premium. Specifically, they show that the required return of a security is an increasing function of the co-variance between its illiquidity and the market illiquidity, or commonality in liquidity. Meanwhile, it is a decreasing function of the co-variance between the security's return and the market illiquidity, and is also decreasing in the co-variance between its illiquidity and market returns.

Results show that the impact of changes in liquidity is weaker than that of levels of liquidity. Within a classic consumption-investment framework, He and Kryzanowski (2003) propose a reformulated asset pricing model. Three components are used to explain cross-sectional expected returns: the interest rate, market risk and firm specifics. In the model, the illiquidity premium comes from a

non-diversifiable co-variance term caused by common liquidity and a diversifiable firm-specific characteristic term due to above or below average transaction costs. Using monthly data from the Canadian market, they estimate the model to determine the relative importance of the two terms.

Their empirical results indicate that the fundamental beta plays a predominant role and the co-variance liquidity seems unlikely to explain gross, before-cost expected returns. Moreover, the static channel of liquidity (level of liquidity) turns out to be more material than the dynamic channel of liquidity (change of liquidity), a finding different from that of Chordia, et al. (2000). They attribute the difference to the fact that they use monthly time series of liquidity obtained by averaging inter-day bid and ask quotes for each stock, while Chordia et al. (2000) use intra-day data within a year. They also stress that their model is not a liquidity model per se (He and Kryzanowski, 2003).

Following He and Kryzanowski (2003), Sadka (2004) makes the distinction between liquidity level per se and liquidity risk. Evidence shows that liquidity varies across assets and over time. He finds that systematic liquidity risk, rather than the level of liquidity, proves important in explaining cross-sectional variation of expected returns.

Using intra-day data, Sadka (2004) develops unique measures of liquidity to test the hypothesis that a significant part of the anomaly represents a compensation for liquidity risk. Following the fundamental microstructure approach, he first

constructs unique measures of firm-level liquidity. These are then used to derive an economy-wide liquidity factor. Such a liquidity factor can be interpreted as the ratio of informed trading against noise trading transactions.

Gibson and Mougeot (2004) confirm that the risk of systematic liquidity shocks is priced and is important in the stock market, but investors would not be able to diversify this risk by trading. They use a bivariate Garch-in-mean model to test whether systematic liquidity risk is priced and its sin. The test is based on the data of monthly excess returns of the S&P 500 Index for 1973-1997.

In their tests, the aggregate liquidity is proxied by the number of shares traded in the S&P 500 per month. Their findings suggest that liquidity risk is priced on the US stock market during the period under examination. The liquidity risk premium is negatively signed and time-varying.

Piqueira (2005) uses a standard three-factor asset pricing model to re-investigate the importance of liquidity as an additional priced risk factor. In line with previous studies he defines liquidity risk as the sensitivity of portfolio returns to market liquidity fluctuations. Using Glosten and Harris's (1988) microstructure models of trading costs, estimated with intra-day data, he constructs a time-series of market liquidity innovations (liquidity factor). He tests a standard factor model specification including the liquidity factor, for 25 portfolios sorted by size and book-to-market. His results show that for these portfolios, liquidity risk cannot provide a significant explanation for the cross-sectional variation in returns. There

is a weak improvement in the fit, but the liquidity risk premium is not significant, either statistically or economically.

From the relationship between the priced risks of commonality in liquidity, Pastor and Stambaugh (2003) set up a multiple regression function that includes the aggregate liquidity term plus other factors considered important for asset pricing as in Fama and French (1993): Where there is asset excess return, MKT denotes the excess return on a broad market index, and the other two factors, SMB and HML, are payoffs on long-short spreads constructed by sorting stocks according to market capitalisation and book-to-market ratio. In such a model setting, what is captured is the co-movement of the asset's excess return with aggregate liquidity, not captured by other determinants of asset price.

Under three different specifications, i.e. the CAPM, the Fama-French three factor model, and the four-factor model, they estimate the alphas for the decile portfolios that are value-weighted. The results are that all three alphas are significant and positive. For alphas when the decile portfolios are equally-weighted, the results are even slightly stronger (Pastor and Stambaugh, 2003).

From Sadka (2004), it is reported that the correlations of this liquidity factor with the Fama-French model is low, which is important to justify its inclusion as an orthogonal factor in asset-pricing models. In a variety of model specifications such as the CAPM, the Fama and French three-factor model, and a four-factor model, they carry out cross-sectional regressions to test the importance of

liquidity for asset pricing. The results indicate that liquidity risk is a priced factor, which strongly corroborates the conclusions in other research.

The results of Gibson and Mougeot (2004) imply that, if systematic liquidity risk was ignored, the traditional asset pricing models may be biased. It is therefore necessary to develop asset pricing models that incorporate inter-temporal systematic liquidity shocks to account for the pricing of systematic liquidity risk so that some empirical anomalies can be explained within a rational asset pricing framework.

However, when applied to specific countries, different empirical results are reported. Chan and Faff (2003) employ a cross-sectional regression framework to explore whether liquidity is priced on the Australian market. They use monthly data for the period 1990 to 1999, and consider share turnover as the proxy for liquidity. Their findings indicate that turnover is negatively related to stock returns, even after controlling for book-to-market, size, stock beta and momentum, and regardless of seasonality effects and potential non-linearities.

In their study of the relationship between liquidity and stock returns in Australia's pure order-driven market, comparing with Chan and Faff (2003), Marshall and Young (2003) use bid–ask spread, turnover rate, and amortised spread as proxies for liquidity. They also widen their study to consider other factors known to influence stock returns, for example beta and size. Their research methodology is based on seemingly unrelated regressions (SUR) and the cross-sectionally

correlated timewise autoregressive (CSCTA) model. The negative relationship identified between bid-ask spread and spread may be because inaccurate estimation of beta means that spread is acting as a proxy for a risk variable associated with the reciprocal of a price variable. The negative relationship between return and turnover remains statistically significant throughout the year, indicating the presence of a positive liquidity premium. In the case of amortised spread, the lack of any significant relationship between liquidity and stock returns also indicates a small liquidity premium, present throughout the year. There is also strong evidence of a negative size effect (Marshall and Young, 2003).

Martinez, Nieto, Rubio, and Tapia (2005) apply the analysis of whether commonality in liquidity is priced to Spain. They analyse the cross-sectional relation between expected returns and betas estimated on the Spanish stock market during the 1990s, in terms of two competing liquidity risk factors. They define market-wide liquidity factor to be the difference between returns highly sensitive to changes in relative bid-ask spread minus returns with low sensitivity to those changes. The other liquidity risk factor is *a la* Pastor and Stambaugh (2003), which is associated with the strength of volume-related return reversals as mentioned above. They find that none of the systematic liquidity risks carries a premium on the Spanish market.

Bekaert et al. (2007) study the pricing of liquidity risk in nineteen emerging markets. Using a model that extends Acharya and Pedersen (2005), they test for the effects of liquidity factors - a country and a global (US-based) factor, and a

country and a global (US) return factor. They allow for different prices for the two risks, market and liquidity. Their model also allows them to study the differences in the effects on expected return of segmented and integrated markets, both with and without the risks due to the global return and liquidity factors. They find that the price of the local market risk is not significant, but the price of local liquidity risk is positive and significant. In a mixed model that allows for both segmentation and integration, the positive and significant effect of the local liquidity risk is preserved, while the price of global liquidity risk and the pricing of the global return factor is positive but only marginally significant. The best fitting model assumes a locally-segmented market and estimates a compensation for local liquidity risk of 85 basis points per month. These findings suggest that the effect of local liquidity risk remains the most important priced factor, even after opening up the local market to foreign investors.

In their study of the pricing of liquidity in relatively young financial markets, Moor and Sadka (2006) show that liquidity is a fundamentally priced determinant of asset returns. Employing a unique data set of securities traded on the Madrid Bolsa and the Zürich Börse between 1902 and 1925, they consider liquidity level, ie. the pricing of liquidity as a characteristic of a stock, together with the pricing of systematic liquidity risk. Their findings show that while liquidity level is an important determinant of the cross-sectional variation of returns, the return sensitivity of securities to market-wide liquidity shocks or price movements plays no such role. They also find that securities with least liquidity earn the highest returns. In the case of the Madrid Bolsa, which has a high number of frequently

traded securities, it appears that Spanish investors are mainly concerned with how quickly they can buy or sell a particular security. For the Zürich Börse, liquidity levels do seem to influence investors' behaviour, but the evidence here is not so clear. This might be because, with more than twice the number of securities listed than in Madrid, investors on the Zurich exchange have a greater range of options with regard to diversifying their low liquidity holdings. Moor and Sadka's (2006) results indicate that liquidity is a more fundamental determinant of asset returns than is systematic risk, and thus differ from the results of He and Kryzanowski (2003) and Sadka (2004).

In a recent study, implementing an empirical test on the float-adjusted return model, Zhang, Tian and Wirjanto (2007) investigate whether systematic liquidity risk is priced. Using an appropriate empirical measure of liquidity beta based on Chinese stock market data, and after controlling for market risk, size, and book-to-market equity, they find that systematic liquidity risk is priced with an annual premium of 6.7 percent. Their results also offer some explanation for cross-sectional variations in Chinese stock returns after controlling for liquidity risk, size and book-to-market equity.

2.3 Liquidity Commonality and Asset Pricing Models

Conventional microstructure theory typically views liquidity as deterministic. Within this framework, the role of liquidity in asset pricing is studied in terms of the level of liquidity, which was pioneered by Amihud and Mendelson (1986). The authors point out that an investor often faces a trade off in capital markets:

She may either wait for a favourable price to appear to execute her trade or immediately execute at the current bid or ask price. The quoted ask price is therefore a premium for instant buying while the bid price is a concession needed for a quick sale. In this sense, the level of liquidity, or more accurately the lack of it, becomes an argument of asset pricing equation. Amihud and Mendelson (1986) show that expected asset returns are interesting in the level of liquidity. But traditional microstruture theory usually regards the effect of the level of liquidity on asset pricing as second order (Constantinides, 1986; Vayanos and Vila, 1999). The novelty of the new research since Chordia et al. (2000) is its focus on changes in liquidity. The commonality literature highlights that, for asset pricing, not only the first moment of liquidity but also its second moment, i.e. variance and co-variance of liquidity, is important (Domowitz, Hansch and Wang, 2005). The existence of commonality in liquidity therefore broadens the concept of liquidity risk and calls for exploration of channels through which liquidity may affect asset pricing.

Domowitz, Hansch and Wang (2005) argue that, granted that commonality in liquidity exists, then when liquidity of one stock dries up, other stocks may suffer the same, leading to a plunge in liquidity in the whole market, as we have witnessed in recent financial crises. Or, for an investor who takes a long position, if under a liquidity shock she is forced to sell some securities of a diversified portfolio while liquidity of these securities in the market happen to decline, she would be unable to unload these securities.

Consequently, liquidity commonality may affect asset pricing through two channels. First, investors would require a liquidity premium for bearing the risk of commonality in liquidity. This means, in terms of investors' optimisation problems, one has to modify the standard constraint so that the desired return of the portfolio now includes the expect return as well as a liquidity premium. Second, because liquidity commonality is a separate risk, investors would naturally seek to keep it to a minimum. The investor's objective function now also needs to change accordingly, i.e. in addition to the risk of portfolio returns, the investor must also minimise liquidity. In short, the presence of commonality in liquidity will change the structure of constraint and the object functions in a mean-variance framework. This sheds critical light on possible refinement of the conventional asset pricing model (Domowitz, Hansch and Wang, 2005).

Following the point made by Domowitz, Hansch and Wang (2005), that liquidity commonality may affect asset pricing, Goyenko (2005) shows that in addition to the illiquidity premium of the stock market identified in other literature, stock returns also contain an illiquidity premium of the bond market. A difference of 10 percentage points between two stocks in their exposure to bond liquidity risk translates into a difference of 7 to 9 percent in their expected returns per year. Illiquidity premiums of both the stock and bond markets are also found in bond returns.

In their investigation of the liquidity effect in asset pricing, Chan, Hong and Subrahmanyam (2006) study the liquidity-premium relationship of an American

Depositary Receipt (ADR) and its underlying share in the home market. By considering how the same asset is traded in multiple markets, it is possible to test both the pure liquidity effect in each market, and the transmission of liquidity from one market to another. Therefore, they use the multiple markets setting to test whether variations in liquidity across markets affect the pricing of assets traded in multiple markets. In this way, they seek to determine whether differences in liquidity between markets is a contributory factor to differences in price between otherwise identical assets traded in those markets. Following Amihud (2002), they use turnover ratio and trading infrequency as proxies for liquidity. They find that a higher ADR premium is associated with higher ADR liquidity and lower home share liquidity. When the levels of and changes to the premium and liquidity variables are measured, it is found that the liquidity effects remain strong, even after controlling for firm size and country characteristics such as exchange rate changes, market performance, and degree of openness and transparency of the market.

Liu (2006) differs from previous studies by using a factor-mimicking stock portfolio that reflects the liquidity premium, constructed in a similar way to the Fama-French SMB and HML factors. Stock illiquidity for each month is measured as the sum of the number of non-trading days and the average reciprocal of daily turnover (scaled) over the prior 250 trading days. Illiquid stocks have more non-trading days and a higher value of the reciprocal of turnover, and this proxies the stock's holding period (Amihud and Mendelson, 1986; Datar et al., 1998). Using this illiquidity measure, stocks are sorted into 10 portfolios. The

sample includes NYSE, AMEX and Nasdaq stocks over 41 years, 1963–2003. Results show that return alphas from the Fama–French model increase almost monotonically in the rank of illiquidity, with significant difference in alphas between high and low illiquidity. By showing that liquidity risk is priced, Liu's innovative factor-mimicking portfolio of high-minus-low illiquidity reinforces earlier results. Liu's second model has only two factors: excess market return and the illiquidity factor. The alphas from this model are not significantly related to stock size or to book-to-market ratio, and this supports the adequacy of the liquidity-based two-factor asset pricing model. After adjusting for trading costs, this model also renders the momentum effect insignificant (Liu, 2006).

In their 2005 research, Brunetti and Caldarera investigate the effects of aggregate illiquidity on asset prices, volatilities and correlations. They build a new asset pricing framework, consistent with empirical studies on the effects of illiquidity on asset returns, volatilities and correlations, in which the Black-Scholes economy is obtained as the limiting case of perfectly liquid markets. After considering the qualitative properties of this model, Brunetti and Caldarera (2005) then use nine years data for 24 randomly sampled stocks traded on the NYSE to estimate stocks' sensitivities to aggregate liquidity. The degree of sensitivity determines the effect of aggregate illiquidity on expected returns, volatilities, correlations, CAPM-betas and Sharpe ratios. Brunetti and Caldarera (2005) identify clear patterns for liquidity according to capitalisation and sector. Consumer Discretionary, Industrials and Utilities exhibit a β that decreases in capitalisation, while for IT stocks, the opposite is the case. IT has by far the highest liquidity βs,

and Utilities the lowest. This indicates that small caps stocks are more sensitive to market-wide liquidity.

In an overlapping-generations model, Acharya and Pedersen (2005) explore how risk averse agents trade securities with stochastic liquidity variability. Solving the model explicitly, they derive a liquidity-adjusted capital asset pricing model. They claim that their model is capable of providing a unified theoretical framework that can offer an integrated explanation for existing empirical findings in relation to the effect of the level and changes of liquidity, including implications of commonality in liquidity for asset pricing.

They consider empirically the total and relative economic effects of liquidity level and the three liquidity risks in a variety of specifications. In evaluating contribution of each liquidity risk to cross-sectional return differences, they find that the return premium due to commonality in liquidity is 0.08%. This implies that while investors require a return premium for a security that is illiquid when the market as a whole is illiquid, the effect of commonality with liquidity however seems not particularly sizable (Acharya and Pedersen, 2005).

Lee's (2005) study spans the period 1988 to 2004, and takes in 25,000 individual stocks from 48 developed and emerging countries. He employs an equilibrium asset pricing model with liquidity risk at the global level. Lee (2005) finds no evidence to support the use of Acharya and Pedersen's liquidity adjusted capital asset pricing model in international financial markets. Lee (2005) also shows the

importance of the US market as a driving force of world-market liquidity risk. This evidence is considered to be consistent with an intertemporal capital asset pricing model in which stochastic shocks to global liquidity serve as a priced state variable.

Goyenko (2005) examines the implications for asset pricing of the liquidity linkage between the stock and Treasury bond markets. His finding that liquidity risk is not represented by size and book-to-market factors supports previous work by Brennan and Subrahmanyam (1996) and by Chordia, Subrahmanyam and Anshuman (2001). His results also suggest that bond market liquidity is a source of systematic risk which is not captured by Fama-French factors or stock liquidity in the equity market, thus supporting the hypothesis of the existence of a cross-market liquidity effect. He shows that the liquidity risk of the stock market and/or unexpected shock to the liquidity of the bond market dominate the momentum factor in Carhart's (1997) four-factor model. Goyenko introduces a five-factor model, which gains an improvement of 6% in explanatory power as compared to Carhart's four-factor model. The unexpected shock to bond market liquidity, obtained as the residual term from the first order autoregression of the bond liquidity time series, has a stronger effect on stock returns than does the level of bond liquidity. Goyenko then tests the cross-market liquidity effect within an arbitrage-free affine joint stock and bond pricing model with stock and bond market liquidity included in the vector of state variables, and finds support for the model. Under the restrictions imposed by the model a change of 10 percentage

points in the illiquidity of the stock leads to a change of 1.4% in the risk free rate per year.

In Fujimoto and Watanabe's (2005) study, they propose that the effects of liquidity – both level and risk – on stock returns vary over time across identifiable states. They estimate the liquidity beta - analogous to that in Pastor and Stambaugh (2003) and to β^{L2} in Acharya and Pedersen (2005) - from a regression of portfolio return on a liquidity index (the negative of the residuals of an AR(2) model of modified ILLIQ) by a regime-switching model. They find that, regardless of the size of firms in the portfolios, the liquidity betas are higher when investors may expect liquidity needs, especially when turnover is abnormally high. They identify the high liquidity-beta states as during 43–47 months (depending on the portfolio sorting method) out of the 480 months of the study period, 1965–2004. They go on to find that where there is high liquidity beta, the level of liquidity and the price of liquidity risk (measured by the coefficients of the liquidity betas) have a greater effect on stock returns.

Martinez et al.'s (2005) work is an important research on this issue. Their empirical analysis examines whether Spanish average returns vary cross-sectionally with betas estimated relative to three competing liquidity risk factors. First, as in Pastor and Stambaugh (2003), they examine temporary price fluctuation reversals induced by order flow. Second, they define the market-wide liquidity factor as the difference between returns highly sensitive to changes in the relative bid–ask spread and returns with low sensitivities to those changes. Finally,

as suggested by Amihud (2002), they employ the aggregate ratio of absolute stock returns to euro volume. They find that systematic liquidity risk is significantly priced on the Spanish stock market only when betas are measured relative to the illiquidity risk factor based on the price response to one euro of trading volume on either unconditional or conditional versions of liquidity-based asset pricing models. My research in this chapter will follow their methodology.

Fernando (2003), however, considers that the risk of idiosyncratic liquidity shocks is more important than the risk of systematic liquidity shocks. He develops a model of liquidity trading in which liquidity shocks cause investors to alter their personal valuations of the market liquidity condition. According to him, such shocks can have both systematic (i.e., common across investors) and idiosyncratic components. So he makes a critical distinction between the risk of systematic liquidity shocks and the risk of idiosyncratic liquidity shocks.

He shows that systematic liquidity shocks do not cause commonality in trading volume and this risk is always priced in the secondary market irrespective of market liquidity. However, idiosyncratic liquidity shocks give rise to investor heterogeneity that creates demand for liquidity. Meanwhile, demand for liquidity is manifested in trading volume. Therefore, idiosyncratic liquidity shock will create liquidity demand and volume. Investors can diversify this risk by trading, but pricing of the risk of idiosyncratic liquidity shocks depends on market liquidity. In a perfectly illiquid market, the idiosyncratic liquidity risk will be fully priced. He also shows that, in asset pricing models, volume is induced by

idiosyncratic liquidity shocks and price volatility is induced by systematic liquidity shocks (Fernando, 2003).

Furthermore, he emphasises the implications of these findings for practical investment. Shifting the focus away from that of the traditional literature on factors related to the supply of liquidity, to the notion that liquidity is the outcome of both demand and supply factors, he argues that the demand side has a much more fundamental impact than previously thought in the literature. Since investors are likely to have varied liquidity demand, it is important for companies to take this into consideration when targeting their securities to different groups of investors and markets (Fernando, 2003).

Furthermore, both cross-sectional and time-series tests from Lee (2005) indicate that liquidity risks that arise from the co-variances between the return and liquidity of individual stocks, and local and global market factors, are priced.

2.4 Commonality in Liquidity and Investment Strategies

The existence of commonality in liquidity also has profound implications for investment plans and strategies. Domowitz, Hansch and Wang (2005) point out that conventional Markowitz mean-variance portfolio theory assumes a frictionless world in which investors choose securities that can cancel out in returns to gain diversification benefits. But it ignores how these benefits might be realised. In a real world, the difficulty with realising the diversification benefit can come from market frictions including transaction cost and the lack of liquidity. On

top of these, Domowitz, Hansch and Wang (2005) show that liquidity commonality makes the diversification benefit hard to realise and therefore poses a hazard to practical investment.

The benefits of diversification critically rely on the stocks that have few or negative return interactions. Commonality in liquidity implies that liquidity of one asset will co-move with that of the others. If liquidity of one stock dries up, other stocks may face the same situation. Therefore, a general liquidity plunge may happen regardless of the property of stocks in a portfolio that the investor forms to gain diversification benefits, as happened in recent financial crises. In addition to such systematic risk in extreme cases, it is more likely that individual investors may face the eventuality that she is unable to unload some of her securities when she is under a liquidity shock. This is because liquidity of these securities in the market will also have declined (Domowitz, Hansch and Wang, 2005).

On the other hand, commonality in liquidity can also be a factor affecting momentum profiles. Pastor and Stambaugh (2003) show that momentum returns are related to liquidity risk. Momentum strategies are typically conducted in a short time space and their returns are short-lived. But liquidity, measured for example as bid-ask spreads, may change over time. So, when conducting momentum strategies, an investor faces the risk that her future profits may vary with the changes in liquidity. This uncertainty creates the liquidity risk.

Pastor and Stambaugh (2003) report that the liquidity risk factor in their model, which incorporates the effect of liquidity commonality, explains half of the profits to a momentum strategy in the overall sample period of 34 years. Although it is not conclusive that liquidity risk provides a partial explanation for momentum, the authors believe it can be observed that liquidity risk induces spreads, the addition of which to investors' costs will in turn affect the importance of momentum in investment.

Sadka (2004) views the existence of the momentum anomaly as compensation for holding liquidity risk and focuses on the effect of liquidity risk on the momentum anomaly. He defines liquidity as price impact induced by trades, and constructs his liquidity measures based on Glosten and Harris (1988) and recent empirical findings in the literature.

Sadka (2004) argues that, for asset pricing, it is the systematic liquidity, rather than the absolute level risk, that matters. Decomposing liquidity into permanent and transitory effect and using the estimated price impacts, he shows that what is priced is the permanent component of liquidity risk, not the transitory component. Furthermore, the permanent component of liquidity risk explains a substantial part of the cross-sectional variation of expected momentum returns. So momentum profits can be partially attributed to compensation for liquidity risk. Furthermore, seemingly profitable momentum strategies are mostly associated with stock which has low levels of liquidity with high-volume. As for liquid firms, momentum strategies are more profitable among the low-volume stocks. Therefore, he

believes the liquidity level is a possible limit to arbitrage. These results emphasise that investors must take the liquidity risk into consideration in momentum trading. On the other hand, achieving momentum profits in practice may be viewed as superior trading ability in avoiding high transaction cost, etc.

2.5 Implications for Market Stability

As a source of systematic risk, commonality in liquidity may impact on the stability of financial markets, which could be a serious concern. The papers discussed so far study the effects of liquidity costs which result in part from asymmetric information (Amihud, Mendelson and Pedersen, 2006). Easley et al. (2002) hypothesise that, because asymmetric information exposes uninformed investors to the risk of being unable to infer information from prices, and because this risk is priced, therefore, information risk affects asset returns. Following Easley et al. (1997), they test this hypothesis on the cross-section of asset returns, employing PIN, the probability of informed trading, estimated by maximum likelihood from a structural model. PIN is an estimate of the fraction of information-based orders, based on the imbalance between buy and sell trades. Their findings show that across stocks, PIN is negatively correlated with size and positively correlated with the bid–ask spread. Employing the methods of Fama and MacBeth (1973) and Litzenberger and Ramaswamy (1979), they use data for NYSE stocks for the years 1983–1998 to examine the effect of PIN in a cross section regression of stock returns with controls for beta, size and book-to-market ratio. They find that PIN has a positive and significant coefficient. This positive effect survives when bid–ask spread, return standard deviation, turnover and the

coefficient of variation of turnover are included in the equation. Although in a multiple regression the liquidity measures have the expected signs (positive for the bid–ask spread, negative for turnover), the positive and significant effect of PIN means that it contains information beyond other liquidity-related variables. (The paper does find some puzzling results for the spread in certain specifications.) These results indicate that the risk of informed trading is priced (Easley et al., 2002).

Fernando and Herring (2003) see more serious consequences of commonality on financial stability. They argue that commonality in liquidity could be one reason leading to the collapse of financial markets. In the conventional literature, markets can collapse for two reasons. The first is the bursting of a bubble of an asset's price and the other concerns substantial information asymmetry about market fundamentals. But they point out the possibility of market collapse even in the absence of these two conditions.

In a theoretical model that relates liquidity to asset prices, and using an illustration of the collapse of the market for perpetual floating-rte notes (perps), they show that market collapse has nothing to do with fundamentals, but is solely due to the shift of investors' beliefs about market liquidity. Such a shift can in turn be triggered by a common liquidity shock. This research therefore provides serious new insights into the implication of the existence of commonality in liquidity for the stability of financial markets (Fernando and Herring, 2003).

O'Hara (2004) points out that there two aspects to this. First, commonality may cause investors to "flight to quality", i.e. to move their capital from riskier to safer investment vehicles in times of financial market uncertainty or fear. But as long as investors remain in the market, the instability caused by the commonality will not be global. On the other hand, the existence of commonality may instead induce investors to enter the market. This will increase the number of buyers and sellers in the market, thereby enhancing stability.

Thus, researchers have developed diverse approaches to analyse the impacts of commonality in liquidity in the different types of market. They have looked in particular at the effects of commonality in liquidity in the conventional asset pricing models and on whether or not systematic liquidity risks are priced. However, most of the existing models focus on quote-driven markets, such as the NYSE (Amihud, Mendelson and Pedersen, 2006). I argue the effects of commonality in liquidity in the conventional asset pricing models, both conditional and unconditional, and investigate whether systematic liquidity risk is significantly priced on the Chinese stock market, an important order-driven market. The absence of market makers, and the high level of noise trading mean that the Chinese market is an ideal environment in which to study questions relating to systematic liquidity.

III. Data and Some Preliminary Empirical Evidence

The data is collected from the China Stock Market & Accounting Research (CSMAR) database. This is the most reliable and most widely used security database in China, and includes both trading and financial statement data of all listed Chinese companies since their IPOs (Wang and Xu, 2004). I use individual daily and monthly returns for all stocks traded on the Chinese continuous market from January 1993 to December 2003.

The return of the market is an equally weighted portfolio comprising all sample stocks available in a given month or on a particular day. For the risk-free rate of return I use the Chinese 1-year Time Deposit Rate. Using all the individual stocks I follow Martinez et al. (2005) to construct 20 portfolios, i.e. 10 portfolios for each alternative liquidity measures. In addition, I form 10 traditional portfolios according to market value. To form the portfolios, monthly returns are calculated. Other data that are deployed include the number of shares traded and the Yuan trading volume of the common stocks in the portfolios.

Following the methods proposed by Martinez et al. (2005), several proxies are used for risk factors, which will be included in different asset pricing models. For the size variable in the Fama–French three-factor model, it is proxied by the market value using the number of shares of each firm in December multiplied by their price at the end of each month in the following year. The BM ratio for each firm is directly from the CSMAR data base. The SMB and HML variables for the

Fama–French portfolios are calculated according to the market value of each firm based on its total capitalisation value in the precious month. In the conditional asset pricing models, the arithmetic mean of the BM ratios is used as the aggregate BM ratio as a proxy for the state variable.

Two thirds of the individual stocks have a price jump of over 50% during the IPO month. This is because IPO prices were determined by the CSRC (the China Securities Regulatory Commission) according to P/E ratios being set between 15 and 20, an IPO P/E ratio much lower than the prevailing market level. Therefore, I exclude the first month return data of individual stocks (Wang and Xu, 2004).

In order to have a necessary minimum number of observations, sample stocks needed to have a return history of at least 36 months to the end of 2003 (Eun and Huang, 2007). Therefore I only include stocks with a minimum of 36 monthly return observations so that the test period can be at least 12 months. This means that my sample stocks originally listed in 2001, 2002 and 2003 are omitted. Some of the parameters, for example the total risk, are estimated using returns on a 24-month rolling window (Eun and Huang, 2007).

From 1999, changes in accounting procedures and regulations caused some listed companies to experience negative book value of equity. These companies are excluded after their book value turns negative (Wang and Xu, 2004).

The descriptive statistics of the variables are reported in Table 5.1. In it, I report the mean value, volatilities and other related characteristics of market returns, the Fama–French factors. In addition, the table also records the descriptive statistics of two liquidity-based risk proxies. They are the Pastor and Stambaugh Factor (OFL) and the Illiquidity Factor (ILLQ)[6]. As can be seen, these liquidity-based risk factors exhibit

[6] They are the same as the RREV and PIMP variable which are used in Chapter 4. For their calculations, see that Chapter. I use OFL and ILLQ here for ease of comparison with the empirical results from Martinez et al. (2005).

Table 5.1 Descriptive Statistics for Risk Factors

(A) (***Shanghai Stock Market***)

Risk factor	Average return	Volatility	Skewness	Excess kurtosis	
Market Returns (RM)	0.13	0.86	0.903	1.488	
Small – Big Factor (SMB)	-0.66	0.41	-1.598	8.373	
High – Low Factor (HML)	-0.25	0.55	-0.917	3.870	
Order Flow based Liquidity (OFL)	0.12	0.91	1.150	3.548	
Illiquidity Measure (ILLQ)	0.14	0.93	1.216	3.612	

(B) Correlation coefficients (***Shanghai Stock Market***)

	RM	SMB	HML	OFL	ILLQ
Market Returns (RM)	1.000	0.040	-0.132	0.093	-0.091
Small – Big Factor (SMB)		1.000	0.208	0.046	0.019
High – Low Factor (HML)			1.000	-0.108	-0.153
Order Flow based Liquidity (OFL)				1.000	0.192
Illiquidity Measure (ILLQ)					1.000

(C) (***Shenzhen Stock Market***)

Risk factor	Average return	Volatility	Skewness	Excess kurtosis	
Market Returns (RM)	0.17	0.11	1.668	4.833	
Small – Big Factor (SMB)	-0.10	0.04	-0.429	0.800	
High – Low Factor (HML)	-0.20	0.08	1.720	23.202	
Order Flow based Liquidity (OFL)	0.11	0.10	1.474	4.918	
Illiquidity Measure (ILLQ)	0.16	0.11	1.455	4.272	

(D) Correlation coefficients (***Shenzhen Stock Market***)

	RM	SMB	HML	OFL	ILLQ
Market Returns (RM)	1.000	-0.040	-0.240	0.112	-0.167
Small – Big Factor (SMB)		1.000	0.161	0.142	-0.042
High – Low Factor (HML)			1.000	0.213	-0.073
Order Flow based Liquidity (OFL)				1.000	-0.086
Illiquidity Measure (ILLQ)					1.000

Notes: This table presents the descriptive statistics of the liquidity risk factors on the Chinese Stock Exchange during the 1993 to 2003 period. Panel A and Panel B report the average statistics and correlation coefficients of relevant variables on the Shanghai Stock Exchange (SHSE). Panel C and Panel D report the average statistics and correlation coefficients of relevant variables on the Shenzhen Stock Exchange (SZSE).

relatively large abnormality. The SMB and HML market-wide measures have left-skewed distributions on the SHSE, while in the SZSE only SMB market-wide measures have left-skewed distributions. In general, correlation coefficients are low. In contrast to Martinez et al. (2005) and Liu (2006), I do not find a relatively high positive correlation between ILLQ and HML. (Liu's (2006) measures of systematic liquidity are not the same as mine, and his measure is based on ILLQ from Amihud (2002).) More in line with my expectations, I find that market returns are positively correlated with OFL, and negatively related to ILLQ, which is in agreement with the results from Liu (2006). In the SZSE, there is a negative and small correlation between OFL and ILLQ, but on the SHSE the correlation is positive while small. Both of the results are disturbing. Should these factors be able to correctly capture market-wide liquidity, one would expect a negative correlation. Thus, while my results for the SZSE coincide with previous results, those for the SHSE are different.

Next, based on the year-end market value of each stock, I construct 10 portfolios, sorted out according to their size and the portfolios ranging from MV1 (smallest) to MV10 (largest). In addition, another 20 portfolios are constructed based on two liquidity betas, 10 portfolios for each liquidity measure. Table 5.2 and Table 5.3 present the average descriptive statistics of these portfolios. Returns on these portfolios are to be used in the next section to test the asset pricing models with liquidity. The volatilities of these portfolios' returns are more or less in line with expectations, with the greatest volatility exhibited in the stocks with smallest capitalisations. On the SZSE, I find that for MV portfolios, large stocks tend to

have lower volatility. However, for OFL and ILLQ portfolios, the opposite pattern applies. Furthermore, in line with the findings reported by Martinez, et al. (2005), I also find from the results that on the SHSE, stocks with a greater possibility of return reversals when the level of liquidity declines, i.e. the OFL1 factor, have higher average returns than do the OFL10 stocks that are prone to return reversals when liquidity is greater. My results for the SZSE are different from that of Martinez et al. (2005), but are consistent with those of Pastor and Stamburgh (2003).

Table 5.2 Summary Statistics for Portfolios of Stocks on the Shanghai Market

Portfolios	Average return	Volatility	OFL beta (t statistic)	ILLQ beta (t statistic)
Portfolio based on Order Flow Liquidity (OFL1)	0.13	1.04	-0.082 (-5.13)	-
Portfolio based on Order Flow Liquidity (OFL2)	0.15	0.98	-0.075 (-4.40)	-
Portfolio based on Order Flow Liquidity (OFL3)	0.12	0.91	-0.069 (-3.73)	-
Portfolio based on Order Flow Liquidity (OFL4)	0.13	0.89	-0.066 (-3.10)	-
Portfolio based on Order Flow Liquidity (OFL5)	0.14	0.91	-0.062 (-3.35)	-
Portfolio based on Order Flow Liquidity (OFL6)	0.11	0.90	-0.057 (-3.39)	-
Portfolio based on Order Flow Liquidity (OFL7)	0.13	0.88	-0.056 (-3.41)	-
Portfolio based on Order Flow Liquidity (OFL8)	0.12	0.95	-0.038 (-1.85)	-
Portfolio based on Order Flow Liquidity (OFL9)	0.06	0.70	0.021 (1.97)	-
Portfolio based on Order Flow Liquidity (OFL10)	0.02	0.75	0.046 (2.66)	-
Portfolio based on Illiquidity Measure (ILLQ1)	0.30	1.06	-	-0.341 (-9.91)
Portfolio based on Illiquidity Measure (ILLQ2)	0.10	0.76	-	-0.880 (-12.60)
Portfolio based on Illiquidity Measure (ILLQ3)	0.14	1.00	-	-0.567 (-11.22)
Portfolio based on Illiquidity Measure (ILLQ4)	0.14	1.05	-	-0.343 (-9.52)
Portfolio based on Illiquidity Measure (ILLQ5)	0.12	0.92	-	-0.157 (-4.65)
Portfolio based on Illiquidity Measure (ILLQ6)	0.11	0.89	-	0.375 (4.42)
Portfolio based on Illiquidity Measure (ILLQ7)	0.11	0.93	-	0.879 (4.33)
Portfolio based on Illiquidity Measure (ILLQ8)	0.14	0.96	-	1.613 (4.34)
Portfolio based on Illiquidity Measure (ILLQ9)	0.13	0.87	-	3.454 (6.10)

Portfolio based on Illiquidity Measure (ILLQ10)	0.13	0.84	-	10.520 (6.83)
Portfolio based on Market Value (MV1)	0.26	1.06	-0.064 (-3.65)	-0.181 (0.52)
Portfolio based on Market Value (MV2)	0.15	0.95	-0.059 (-3.23)	-0.069 (-0.33)
Portfolio based on Market Value (MV3)	0.12	0.93	-0.050 (-2.75)	-0.436 (-0.89)
Portfolio based on Market Value (MV4)	0.11	0.88	-0.045 (-2.44)	-1.213 (-1.56)
Portfolio based on Market Value (MV5)	0.11	0.92	-0.051 (-2.81)	-1.036 (-2.32)
Portfolio based on Market Value (MV6)	0.12	0.86	-0.049 (-2.67)	-0.866 (-2.14)
Portfolio based on Market Value (MV7)	0.12	0.92	-0.049 (-2.64)	-0.714 (-1.90)
Portfolio based on Market Value (MV8)	0.07	0.85	-0.048 (-2.68)	-3.102 (-2.32)
Portfolio based on Market Value (MV9)	0.05	0.84	-0.046 (-2.57)	-4.220 (-1.93)
Portfolio based on Market Value (MV10)	0.08	0.88	0.878 (-1.93)	-13.809 (-2.83)

Notes: This table presents the descriptive statistics of the portfolios of the stocks on the Shanghai Stock Exchange (SHSE). The table is based on the monthly data of relevant variables from January 1995 to December 2003.

Table 5.3 Summary Statistics for Portfolios of Stocks on the Shenzhen Market

Portfolios	Average return	Volatility	OFL beta (t statistic)	ILLQ beta (t statistic)
Portfolio based on Order Flow Liquidity (OFL1)	0.04	0.83	-0.157 (-10.78)	
Portfolio based on Order Flow Liquidity (OFL2)	0.03	0.83	-0.515 (-14.97)	
Portfolio based on Order Flow Liquidity (OFL3)	-0.01	0.81	-0.470 (-5.03)	
Portfolio based on Order Flow Liquidity (OFL4)	0.06	0.85	-0.004 (-0.79)	
Portfolio based on Order Flow Liquidity (OFL5)	0.15	1.09	0.002 (2.72)	
Portfolio based on Order Flow Liquidity (OFL6)	0.13	1.04	0.003 (3.33)	
Portfolio based on Order Flow Liquidity (OFL7)	0.14	1.14	0.004 (5.62)	
Portfolio based on Order Flow Liquidity (OFL8)	0.19	1.23	0.005 (6.52)	
Portfolio based on Order Flow Liquidity (OFL9)	0.17	1.15	0.006 (6.61)	
Portfolio based on Order Flow Liquidity (OFL10)	0.17	1.08	1.032 (6.22)	
Portfolio based on Illiquidity Measure (ILLQ1)	0.16	0.99		-0.235 (-9.84)
Portfolio based on Illiquidity Measure (ILLQ2)	0.20	1.06		-0.103 (-11.51)
Portfolio based on Illiquidity Measure (ILLQ3)	0.10	0.91		-0.072 (-12.15)
Portfolio based on Illiquidity Measure (ILLQ4)	0.14	1.08		-0.047 (-12.22)
Portfolio based on Illiquidity Measure (ILLQ5)	0.15	1.08		-0.032 (-12.91)
Portfolio based on Illiquidity Measure (ILLQ6)	0.18	1.23		-0.001 (0.53)
Portfolio based on Illiquidity Measure (ILLQ7)	0.17	1.19		0.143 (5.20)
Portfolio based on Illiquidity Measure (ILLQ8)	0.18	1.14		0.239 (6.17)
Portfolio based on Illiquidity Measure (ILLQ9)	0.15	1.09		0.429 (6.58)

Portfolio based on Illiquidity Measure (ILLQ10)	0.13	1.00		1.56 (6.99)
Portfolio based on Market Value (MV1)	0.25	1.28	-0.072 (-4.10)	-0.562 (-0.31)
Portfolio based on Market Value (MV2)	0.22	1.21	-0.070 (-3.59)	-0.426 (-0.29)
Portfolio based on Market Value (MV3)	0.18	1.19	-0.069 (-3.07)	-0.357 (-3.54)
Portfolio based on Market Value (MV4)	0.14	1.01	-0.056 (-2.93)	-1.524 (-0.73)
Portfolio based on Market Value (MV5)	0.17	1.21	-0.032 (-2.62)	-1.007 (-0.22)
Portfolio based on Market Value (MV6)	0.16	1.15	-0.029 (-2.61)	-0.745 (-3.08)
Portfolio based on Market Value (MV7)	0.11	1.10	-0.021 (-2.02)	-0.709 (-2.05)
Portfolio based on Market Value (MV8)	0.16	1.27	-0.014 (-1.97)	-0.312 (-2.39)
Portfolio based on Market Value (MV9)	0.10	1.07	-0.009 (-1.33)	-3.964 (-1.64)
Portfolio based on Market Value (MV10)	0.08	1.09	0.624 (-1.04)	-11.230 (-3.52)

Notes: This table presents the descriptive statistics of the portfolios of the stocks on the Shenzhen Stock Exchange (SZSE). The table is based on the monthly data of relevant variables from January 1995 to December 2003.

For the ILLQ betas, my results differ from that of both Martinez et al. (2005) and Liu (2006) in that I do not find a large difference in average returns between ILLQ1 and ILLQ10. However, there is a clear monotonic relation in my results between the average returns and the sensitivity of returns to the ILLQ factor. On both the SHSE and the SZSE markets, average returns of the stocks that are negatively sensitive to ILLQ are higher than the average returns of the stocks that are positively sensitive to ILLQ. But the differences are much smaller than that reported in Martinez et al. (2005) and Liu (2006). The similar monotonic pattern can also be found in the relations between the average returns and volatility. In addition, on both the SHSE and the SZSE, I find significant liquidity betas only for extreme portfolios and in response to shocks to market liquidity, ILLQ1 stocks moves in opposite directions than do the ILLQ10 stocks. This is also confirmed in Martinez et al. (2005).

IV. Empirical Evidence

In testing for whether liquidity commonality is a priced risk factor on the Chinese stock market, I follow Martinez et al. (2005) which postulate that if the pricing effect of market liquidity exists, there would be systematic difference in average returns (alpha) of the portfolios that are sorted according to their sensitivity to measures of liquidity. So, in the asset pricing models that are to be deployed, the average return of a portfolio with higher sensitivity to liquidity changes should be

significantly higher than that of the portfolio with lower sensitivity. As such, it makes sense to test for the significance of the alphas, after adjustment for risk. For example, when there is a significant liquidity premium related to aggregate liquidity risk, the difference between the average returns on ILLQ10 and ILLQ1 portfolios should be significantly negative, when taking consideration of market risks (Martinez et al., 2005). This testing strategy can also be found in Pastor and Stamburgh (2003) and Chen (2005).

Following Martinez et al. (2005), four alternative pricing models are used for the tests. They are the traditional CAPM model, the two modified CAPM models that incorporate the aggregate liquidity effect constructed by adding the two liquidity measures (OFL and ILLQ) respectively to the standard CAPM model, and the Fama–French three-factor model. However, due to data availability, I do not test CAPM liquidity-based models with HLS which is included in Martinez et al. (2005), I report different alphas for each year between January 1995 and December 2003. Table 5.4 reports the estimation results.

In all the models, I find the Pastor and Stambaugh factor (OFL), which measures the possibility of return reversal in the face of liquidity changes, to be not significant. This is in agreement with Martinez et al. (2005) but differs from the outcome of Pastor and Stamburgh (2003) which find that, after controlling for the market return, size, value and momentum effects, the average returns on stocks highly sensitive to liquidity exceeds that on stocks with low sensitivities by 7.5 percent annually during the sample period. Interestingly, in my estimation, only

significant liquidity risk premium is the liquidity measure of ILLQ, which is also reported in Martinez et al. (2005).

Table 5.4 Alphas of Extreme Portfolios in Four Asset Pricing Models

(A) Portfolios based on Aggregate Liquidity Measures (***Shanghai Stock Market***)

	Alpha of Portfolio OFL10 Minus Alpha of Portfolio OFL1			Alpha of Porfolio ILLQ 10 Minus Alpha of Portfolio ILLQ1		
	Value	χ^2 Test	P value	Value	χ^2 Test	P value
CAPM Model	-0.02	-0.338	-0.158	0.04	1.676	-0.030
Fama-French Three Factor Model	0.01	-0.150	-0.248	0.01	1.198	0.407
CAPM Model with Order Flow Liquidity Measure	-0.01	0.271	-0.074	0.03	2.024	-0.004
CAPM Model with Illiquidity Measure	-1.31	-0.338	-0.158	1.45	1.676	-0.023

(B) Portfolio based on Market Values (***Shanghai Stock Market***)

	Alpha of Portfolio MV10 Minus Alpha of Portfolio MV1		
	Value	χ^2 Test	P value
CAPM Model	-0.16	0.587	-0.151
Fama-French Three Factor Model	-0.03	-1.696	0.210
CAPM Model with Order Flow Liquidity Measure	-0.22	2.154	-0.145
CAPM Model with Illiquidity Measure	-2.21	0.817	-0.173

(C) Portfolios based on Aggregate Liquidity Measures (***Shenzhen Stock Market***)

	Alpha of Portfolio OFL10 Minus Alpha of Portfolio OFL1			Alpha of Porfolio ILLQ 10 Minus Alpha of Portfolio ILLQ1		
	Value	χ^2 Test	P value	Value	χ^2 Test	P value
CAPM Model	0.02	0.670	0.122	-0.01	-0.299	-0.035
Fama-French Three Factor Model	0.04	2.692	-0.006	0.03	-1.363	0.186
CAPM Model with Order Flow Liquidity Measure	0.03	0.244	-0.042	-0.04	-0.868	-0.123
CAPM Model with Illiquidity Measure	0.02	0.670	0.120	-0.01	-0.299	-0.030

(D) Portfolio based on Market Values (***Shenzhen Stock Market***)

	Alpha of Portfolio MV10 Minus Alpha of Portfolio MV1		
	Value	χ^2 Test	P value
CAPM Model	-0.43	0.630	0.343
Fama-French Three Factor Model	-0.08	0.172	-0.052
CAPM Model with Order Flow Liquidity Measure	-0.21	1.088	0.036
CAPM Model with Illiquidity Measure	-0.20	0.630	0.165

Notes: This table presents the averages of returns, volatilities, and factor betas of four differently sorted portfolios according to relevant variables from January 1995 to December 2003 on the time series basis. Panel A and Panel B report the portfolio results from liquidity measures and portfolio results from liquidity measures from market values on the Shanghai Stock Exchange (SHSE). Panel C and Panel D report the portfolio results from liquidity measures and portfolio results from liquidity measures from market values on the Shenzhen Stock Exchange (SZSE).

It is therefore that OFL turns out to be an insignificant pricing factor in the CAPM models when one wants to capture the liquidity risk effect by adding it to the models. In my tests, the average returns on OFL10 and OFL1 for the Shanghai market differ by -0.02 (0.02 on the SZSE) in the traditional CAPM model. After adding the OFL factor to the model, the difference becomes -0.01 (0.03 on the SZSE) and the differences are not statistically significant. However, in contrast to Martinez et al. (2005), when I rank the portfolios according to the size of the OFL factor, I do not find significant negative difference between the alphas of the extreme portfolios. But this on the other hand is consistent with Pastor and Stamburgh (2003).

The results for the 10 portfolios that are sorted by betas on the ILLQ factor show a strong significant liquidity premium for each of the portfolios in all the models. For the liquidity based CAPM model which includes the ILLQ factor, which has the highest absolute value of the liquidity premium in Martinez et al. (2005) as compared to the liquidity premium in other models under study, I can also obtain a higher value. But the difference between the liquidity premium (the negative alpha) in this model and other liquidity based models is not as high as in the case of Martinez, et al. (2005). However, this will draw the conclusion that, on the Chinese stock market, there is significant evidence of liquidity premium using ILLQ as a measure of aggregate, or market-wide liquidity. This finding that the ILLQ is a priced liquidity risk factor is in line with Martinez et al. (2005) for the Spanish stock market and Liu's (2006) results for the American NYSE/AMEX markets.

Next, I apply the cross-sectional analysis in the Martinez et al. (2005) framework by testing for the pricing effect of the liquidity risk using the two measures of aggregate liquidity. According to Martinez et al. (2005), the fundamental asset pricing model can be written as:

$$E_{t-1}\{[\delta_0 + \delta_{01}bm_{t-1} + \delta_1 R_{mt} + \delta_{11}(bm_{t-1}R_{mt}) + \delta_2 L_t + \delta_{21}(bm_{t-1}L_t)](1 + R_{jt})\} = 1, \quad (5.1)$$

If written in the traditional multi-beta representation, Equation (5.1) can also be expressed as

$$E(R_j) = \gamma_0 + \gamma_1\beta_{jm} + \gamma_2\beta_{jbm} + \gamma_3\beta_{jmbm} + \gamma_{4(6)}\beta_{jL} + \gamma_{5(7)}\beta_{jLbm}, \qquad (5.2)$$

In this basic model, the pricing effect of the aggregate liquidity risk is to be captured by OFL in γ_4 and γ_5, and ILLQ in γ_6 and γ_7 to ILLQ. I will empirically test their significance in different models.

Table 5.5 and Table 5.6 present the test results for the portfolios on the SHSE and the SZSE, respectively. Following Martinez et al. (2005), I employ the monthly returns on the 10 size-sorted portfolios, and monthly returns on the 10 portfolios constructed on the basis of sensitivity to aggregate liquidity risks as my dependent variable in the standard Fama–MacBeth model. In both tables, the cross sectional results for the OFL, ILLQ, and MV sorted portfolios are recorded in Panels A, B and C.

As in the previous test results reported in Table 5.4, the Pastor and Stamburgh factor has the wrong sign and is not significant. This gives further confirmation that the Pastor and Stamburgh measure of liquidity risk is not a priced risk factor on the Chinese stock market. On the other hand, the results for ILLQ (Panel A and Panel C) show a consistent pattern regardless of the other endogenous variables used in the models. In all the estimations, significant and favourable evidence is found for the pricing effect in terms of the liquidity beta associated with ILLQ. Due to the fact that the Chinese stock market was not re-opened until 1990 which imposes serious data availability problems on this research, the evidence of the pricing effect for the ILLQ factor can be said as approving.

The results in Table 5.5 and Table 5.6 also show that, in the case of the returns on OFL portfolios, addition of liquidity factors causes the aggregate liquidity premium to become positive and significant. This is, however not the case in the models with ILLQ or size-sorted portfolios.

It is also interesting that, as in Martinet et al. (2005), the liquidity premium associated with the OFL factor is both significant and positive in the conditional model but not in the unconditional model, confirming the importance of adding dynamics in modelling asset pricing behaviour in the Chinese context which may be crucial for future research.

In Panel B of both Table 5.5 (for the Shanghai market) and Table 5.6 (for the Shenzhen market), assets are classified according to their sensitivity to the ILLQ

factor. According to Amihud (2002) and Martinez, et al. (2005), an adverse shock to aggregate liquidity

Table 5.5 Cross-sectional Test Results for Asset Pricing Models (Shanghai Stock Market)

γ_0	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	γ_7	R^2
(A) 10 Prtfolios based on Order Flow Based Liquidity Measure								
0.0627 (3.02) (2.54)	-0.0524 (-1.27) (-1.18)	-	0.0323 (0.82) (1.36)	-	-	-	**0.0249** (2.05) (2.03)	0.8
0.0132 (0.61) (2.04)	0.0008 (0.05) (-0.10)	-	0.0138 (0.31) (0.57)	-0.0059 (-0.16) (-0.26)	-0.0011 (-0.05) (0.02)	-	0.0051 (0.10) (-0.14)	0.6
0.0229 (-0.36) (0.01)	0.0210 (0.20) (0.22)	-	0.0085 (0.08) (0.03)	0.0087 (0.35) (0.36)	0.0014 (0.18) (0.32)	-	0.0036 (0.08) (0.16)	0.5
0.0455 (1.83) (2.35)	-0.0139 (-0.06) (0.03)	-	0.0004 (0.07) (0.10)	-0.0088 (0.10) (0.41)	-0.0036 (-0.18) (-0.05)	-	0.0137 (0.17) (-0.26)	0.5
-0.0068 (-0.39) (-0.88)	0.0013 (0.04) (0.14)	**-0.0167** (-1.47) (-2.20)	0.0045 (0.22) (0.55)	0.0056 (0.17) (0.48)	-	**0.0587** (1.47) (2.92)	0.0025 (-0.04) (-0.02)	0.5
-0.0060 (-0.71) (-1.46)	-0.0069 (-0.20) (-0.40)	**-0.0142** (-2.70) (-3.91)	0.0017 (0.35) (0.31)	0.0066 (-0.18) (-0.97)	-	**0.0317** (1.47) (2.92)	0.0018 (-0.20) (-0.77)	0.6

-0.0095 (-0.49) (-0.81)	-0.0099 (-0.33) (-0.78)	**-0.0137** (-0.98) (-2.08)	-0.0122 (-0.19) (-0.36)	-0.0093 (-0.15) (0.06)	-	-	-0.0017 (0.06) (0.60)	0.5
(B) 10 Prtfolios based on Illiquidity Measure								
0.0732 (3.90) (6.59)	**-0.0692** (-1.85) (-2.76)	-	-0.0020 (-0.06) (-0.07)	-	-	-	**0.0190** (1.73) (2.64)	0.8
0.0189 (1.16) (0.72)	0.0066 (0.29) (0.62)	-	0.0252 (0.74) (1.33)	0.0240 (0.14) (0.23)	0.0045 (0.23) (0.43)	-	0.0009 (0.41) (0.86)	0.6
0.0267 (-1.33) (-2.73)	0.0087 (-0.06) (0.04)	-	0.0156 (0.31) (0.56)	0.0033 (0.13) (0.10)	0.0005 (0.01) (0.01)	-	**0.0116** (1.34) (2.48)	0.4
0.0338 (1.70) (1.97)	0.0046 (0.48) (1.09)	-	-0.0144 (-0.11) (0.02)	-0.0101 (-0.16) (-0.15)	-0.0045 (-0.14) (-0.08)	-	-0.0006 (-0.36) (-0.54)	0.6
-0.0004 (0.27) (0.67)	-0.0019 (-0.34) (-0.99)	-0.0244 (-1.39) (-1.63)	-0.0151 (-0.62) (-0.99)	-0.0010 (0.40) (0.88)	-	**0.0304** (0.84) (1.97)	-0.0193 (-0.54) (-0.68)	0.6
-0.0029 (0.03) (0.08)	-0.0060 (0.01) (-0.25)	**-0.0151** (-0.93) (-1.64)	-0.0046 (0.11) (0.19)	-0.0071 (-0.19) (-0.60)	-	**0.0164** (0.84) (1.98)	-0.0117 (-0.18) (-0.38)	0.5

-0.0039 (0.01) (-0.11)	-0.0302 (-0.43) (-0.58)	**-0.0787** (-1.55) (-2.13)	-0.0231 (-0.52) (-1.09)	-0.0229 (-0.26) (-0.90)	-	-	-0.0158 (-0.55) (-0.91)	0.5
(C) 10 Portfolios based on Market Values								
0.0593 (2.54) (2.22)	-0.0794 (-1.42) (-1.49)	-	0.0109 (0.29) (0.22)	-	-	-	0.0038 (0.30) (0.25)	0.8
0.0341 (1.95) (1.38)	-0.0352 (-0.69) (-0.46)	-	0.0296 (1.01) (0.57)	0.1544 (-0.23) (-0.33)	0.0344 (0.38) (0.12)	-	0.3982 (0.15) (0.07)	0.6
0.0281 (-0.27) (-0.24)	-0.0009 (0.11) (-0.02)	-	0.0102 (0.52) (0.43)	-0.0040 (-0.27) (-0.27)	-0.0009 (-0.39) (-0.33)	-	-0.0092 (-0.86) (-0.50)	0.5
0.0469 (4.65) (3.15)	-0.0496 (0.01) (0.07)	-	-0.0124 (0.46) (0.75)	-0.0096 (-0.03) (-0.13)	-0.0041 (0.14) (0.15)	-	0.0097 (0.62) (0.62)	0.6
-0.0007 (-0.08) (0.11)	-0.0097 (-0.15) (-0.10)	**-0.0150** (-1.19) (-1.86)	0.0010 (0.08) (-0.02)	-0.0015 (-0.02) (0.29)	-	0.0170 (0.71) (0.33)	-0.0063 (-0.21) (-0.31)	0.5
-0.0015 (0.12) (0.13)	0.0002 (-0.13) (-0.17)	**-0.0172** (-1.39) (-2.76)	-0.0042 (-0.08) (0.16)	-0.0056 (-0.04) (-0.22)	-	0.0094 (0.73) (0.34)	0.0030 (0.22) (0.23)	0.6

-0.0091 (-0.51) (-1.05)	0.0203 (0.41) (0.42)	-0.0231 (-1.98) (-1.43)	-0.0186 (-0.42) (-0.63)	**-0.0568** (-1.77) (-3.47)	-	-	-0.0050 (-0.31) (-0.90)	0.6

Notes: This table presents the average monthly coefficients from asset pricing tests using standard Fama–MacBeth methodology on the Shanghai Stock Exchange (SHSE) from January 1995 to December 2003. The Fama–MacBeth t statistics are in parentheses. Below the t statistics are the robustness test results to serially correlated gammas. Results in bold indicate they are significantly different from zero.

Table 5.6 Cross-sectional Test Results for Asset Pricing Models (Shenzhen Stock Market)

γ_0	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	γ_7	R^2
(A) 10 OFL portfolios								
0.0416 (2.16) (5.33)	-0.0405 (-0.75) (-1.24)	-	0.0154 (0.32) (0.41)	-	-	-	0.0095 (0.60) (0.84)	0.4
-0.0014 (-0.09) (-0.07)	0.0301 (0.82) (0.80)	-	0.0207 (0.66) (0.79)	-	-0.0001 (-0.56) (-0.85)	0.0001 (0.28) (0.63)	0.0033 (0.24) (0.44)	0.4
-0.0103 (-0.72) (-0.55)	-0.0068 (-0.16) (-0.14)	-	-0.0011 (-0.03) (-0.03)	0.0213 (0.66) (0.66)	0.0109 (0.58) (0.66)	-	0.0213 (0.88) (1.07)	0.7
0.1325 (3.63) (2.67)	0.0217 (0.14) (0.18)	-	0.0249 (0.25) (0.32)	-0.0106 (-0.33) (-0.78)	-0.0063 (-0.33) (-0.78)	-	-0.0191 (-0.43) (-1.05)	0.2
-0.0024 (-0.07) (-0.09)	-0.0030 (-0.10) (-0.20)	**0.0072** (0.65) (1.80)	0.0251 (0.49) (0.80)	**0.0098** (0.70) (1.97)	-	-	-0.0078 (-0.11) (-0.20)	0.5
-0.1352 (-19.20) (-33.17)	-0.0103 (-0.64) (-1.07)	**-0.0001** (-1.53) (-3.92)	**-0.0242** (-1.76) (-2.60)	-	-	-	0.0003 (0.10) (0.25)	0.7

0.0973 (7.71) (6.57)	0.0051 (0.17) (0.15)	**0.0016** (1.21) (2.53)	-0.0088 (-0.38) (-0.63)	**0.0028** (1.16) (2.35)	-	-	0.0105 (0.70) (1.15)	0.7
(B) 10 ILLQ portfolios								
0.0309 (2.13) (1.65)	0.0317 (0.78) (1.19)	-	**0.0237** (0.66) (1.61)	-	-	-	0.0029 (0.24) (0.38)	0.3
-0.0122 (-0.89) (-0.69)	**0.0609** (1.96) (3.52)	-	0.0213 (0.80) (1.28)	-	-0.0040 (-0.39) (-0.47)	-0.0092 (-0.13) (-0.21)	**0.0114** (0.98) (2.57)	0.8
-0.0286 (-5.21) (-6.68)	**-0.0183** (-1.02) (-1.69)	-	**0.0138** (1.11) (1.91)	-	**0.0001** (1.18) (1.61)	-	0.0090 (0.75) (0.95)	0.7
0.1060 (0.38) (2.56)	0.0374 (0.29) (0.52)	-	-0.0021 (-0.02) (-0.06)	0.0129 (0.48) (1.45)	0.0078 (0.48) (1.46)	-	0.0148 (0.39) (1.09)	0.4
-0.0350 (-2.83) (-3.25)	**-0.0406** (-3.41) (-8.80)	**0.0132** (3.13) (5.80)	**-0.0830** (-4.24) (-5.91)	**0.0172** (3.16) (6.07)	-	-	**-0.0771** (-2.78) (-3.72)	1.0
-0.1251 (-3.67) (-4.26)	-0.0467 (-0.60) (-0.91)	0.0001 (0.33) (0.51)	**-0.0523** (-0.78) (-1.69)	-	-	-	-0.0078 (-0.50) (-1.24)	0.4

0.1186 (7.13) (7.13)	0.0079 (0.20) (0.31)	**-0.0010** (-0.56) (-2.51)	**0.0243** (0.80) (1.67)	**-0.0016** (-0.51) (-2.30)	-	-	-0.0117 (-0.59) (-1.45)	0.6
© 10 MV portfolios								
0.0513 (5.32) (12.62)	**-0.0400** (-1.48) (-2.58)	-	0.0046 (0.19) (0.29)	-	-	-	-0.0056 (-0.70) (-0.90)	0.8
0.0484 (1.78) (1.05)	-0.0898 (-0.78) (-0.76)	-	-0.0088 (-0.13) (-0.22)	0.7069 (0.61) (1.41)	0.3754 (0.61) (1.41)	**8.8673** (0.62) (2.55)	**4.7152** (0.62) (2.57)	0.4
0.0050 (0.46) (0.54)	-0.0241 (-0.74) (-0.56)	-	0.0095 (0.35) (0.31)	0.0020 (0.07) (0.07)	0.0010 (0.07) (0.07)	-	0.0005 (0.03) (0.02)	0.6
0.1310 (4.98) (13.97)	0.0406 (0.37) (1.04)	-	0.0447 (0.62) (0.83)	-0.0088 (-0.38) (-0.79)	-0.0053 (-0.38) (-0.80)	-	-0.0213 (-0.66) (-1.32)	0.6
-0.0276 (-1.02) (-2.58)	0.0042 (0.16) (0.18)	-0.0026 (-0.29) (-0.47)	-0.0075 (-0.17) (-0.43)	-0.0037 (-0.31) (-0.51)	-	-	0.0059 (0.10) (0.19)	0.3
-0.1427 (-4.67) (-3.93)	0.0374 (0.54) (0.68)	0.0000 (0.07) (0.17)	-0.0247 (-0.41) (-0.71)	-	-	-	0.0086 (0.61) (1.30)	0.4

0.1118 (10.40) (17.52)	0.0236 (0.94) (1.26)	**-0.0033** (-2.83) (-7.37)	**0.0554** (2.81) (4.61)	**-0.0059** (-2.86) (-7.69)	-	-	**-0.0363** (-2.84) (-8.13)	0.9

Notes: This table presents the average monthly coefficients from asset pricing tests using standard Fama–MacBeth methodology on the Shenzhen Stock Exchange (SZSE) from January 1995 to December 2003. The Fama–MacBeth t statistics are in parentheses. Below the t statistics are the robustness test results to serially correlated gammas. Results in bold indicate they are significantly different from zero.

will lead to an increase in ILLQ and assets with negative liquidity betas need to offer an extra return in this period of restricted liquidity resulting from adverse liquidity shocks. Therefore, if a liquidity risk premium is to be present, the gamma coefficient on the ILLQ beta should be negative (Martinez et al., 2005). In my empirical estimation, in all the asset pricing models that include the liquidity effect, I have found significant negative coefficients of the betas associated with the ILLQ factor. This is the most important and crucial result regarding the pricing effect of commonality in liquidity in China. Together with the findings in the previous section where I found significant average returns in alphas for different ILLQ portfolios, this evidence confirms that commonality in liquidity is a priced risk factor on the Chinese stock market.

V. Further Tests

To check for the robustness of my findings regarding the pricing effect of commonality in liquidity in the Chinese stock market, here I further test a dynamic model that developed and applied by Avramov and Chordia (2006). The results in the previous sections are based on a standard CAMP model with cross section estimates. Recently, Avramov and Chordia (2006) develop a dynamic model in which the effect of liquidity on excess stock returns may be analysed.

Although the main focus of their investigation is whether asset pricing models can explain financial anomalies including the effects of size, value, and momentum strategies, one model under their consideration, i.e. the Fama and French model augmented by the Pastor-Stambaugh liquidity factor, is estimated to test for the impact of the level of liquidity on returns. The inclusion of the Pastor-Stambaugh measure is to capture the impact of liquidity risk. This is pretty similar to what the current research has attempted to examine, i.e. the pricing effect of liquidity commonality in the Chinese context. It is therefore interesting to see whether new findings can be drawn following their modeling approach. In particular, this may enable us to check for the robustness of my previous modeling outcome that provides confirmative evidence of liquidity commonality being a priced risk factor in the Chinese stock market.

While the CAPM is widely regarded as the cornerstone of modern asset pricing theory, there is evidence in the literature that the cross-sectional difference in average returns are determined not only by the market risk. A number of researchers have pointed out that the cross-sectional difference in returns may also be caused by firm level characteristics such as market capitalisation, book-to-market, and prior returns (Basu, 1977; Jegadeesh, 1990; Fama and French, 1992; Fama and French, 1993; Fama and French, 1996). To Avramov and Chordia (2006), the static CAPM may fail to provide a complete description of factors driving asset prices and so the use of dynamic asset pricing models is warranted.

Avramov and Chordia (2006) develop and apply a pricing framework which uses single securities in cross-sectional tests that allow risk and expected return to vary with conditioning information. Within this framework, they test whether factors in conditional asset pricing model may vary with firm-specific market capitalization, book-to-market and business cycle-related variables (a macroeconomic predictor). They purse the research to find out whether beta in a single equity can explain financial market anomalies which include size, book-to-market, turnover and momentum effects on expected returns. The null hypothesis for the cross-sectional regression is the independent variables should be insignificant and the R^2 should be low.

The two-stage Fama-MecBeth method is adopted by Avramov and Chordia (2006) in estimating their models. In this approach, the first stage is time series regression. Given the importance of modeling beta variation, factor loadings in this first-pass time series regressions are allowed to change with firm size, book-to-market and business conditions. Four specifications are attempted for modeling the betas in the regression. The first specification is unconditional under which all betas except intercept are zero. The next three are conditional ones with some of the betas are restricted to zero or all betas are allowed to depart from zero, depending on the model specification. The second stage is cross-sectional regression. The dependent variables are risk-adjusted returns obtained from the

first-pass regressions and the independent variables are financial market anomalies which include size, book-to-market, turnover and lagged returns. The research idea is if the predictive power of these variables is explained by asset pricing models, then such firm-level characteristics variables should not be statistically significant in the second-pass cross-sectional regressions (Avramov and Chordia, 2006).

They choose to use the Fama-MecBeth method because it can measure additional risks of beta in the CAPM. Methods proposed by Shanken (1992) and Janannathan and Wang (1998) then are applied to adjust the bias of the standard errors in the estimated coefficients because the Fama-MacBeth method is known to overstate the accuracy of betas. A distinctive feature of Avramov and Chordia (2006) is that they use individual stocks in their empirical tests while previous studies tend to use portfolio data.

Their results show that, when betas are constant, none of the models can capture size, book-to-market, turnover and other variables relative to past return since these financial market anomalies are very significant in the cross-sectional regressions. However, allowing beta to vary with equity characteristics and business conditions is found to have substantially improved the pricing abilities of the models. But they find no model can capture the impact of liquidity or momentum on the cross-section of individual stock returns. They therefore

conclude that time-varying beta versions of multifactor models can capture the size and book-to-market effects. But for capturing the impacts of turnover and momentum, no model is satisfactory.

Following Avramov and Chordia (2006), I use the Fama and French model augmented by the liquidity factor of Pastor and Stambaugh (2003) to test for the pricing effect of commonality in liquidity in the Chinese context. The Pastor and Stambaugh liquidity factor is formulated on the basis of the commonality in liquidity argument. This market liquidity measure is claimed by Pastor and Stambaugh (2003) to be able to reflect the effect of lower liquidity in stronger volume-related return reversals. I still use individual daily and monthly returns for all stocks on the Chinese stock market from January 1995 to December 2003.

The null hypothesis for the cross-sectional regression is as that of Avramov and Chordia (2006), i.e. coefficients on the firm characteristics variables should be insignificant in the second-pass cross-sectional regressions. Also following Avramov and Chordia (2006), the estimation of the model uses single securities, rather than portfolios, to guards against the data-snooping biases.

Table 5.7 reports descriptive statistics of the stocks from the SHSE. These statistics include the average of the cross-sectional means, median, and standard

deviations of excess return, firm size, book-to-market ratio, turnover rate, and return2-3, return4-6, and return7-12 on the time-series basis.

In the table, both firm size and turnover rate are the logarithm of respective individual firm characteristics. Return2-3 is the cumulative sum of the returns between the second and third months before the current month. Return4-6 is the sum of the returns between the fourth and sixth months before the current month. Return7-12 is the sum of the returns between the seventh and twelfth months before the current month. The mean (median) of excess returns, book-to-market ratio, and turnover rate are -0.68 (-0.64), 0.25 (0.23) and 2.92 (1.88). These results, in absolute value, are lower than the results found by Avramov and Chordia (2006). The mean (median) for return2-3, return4-6, and return7-12 are -2.47 (-2.45), -4.33 (-4.28) and -8.07 (-8.06). These results, in absolute value, are higher than the NASDAQ results found by Avramov and Chordia (2006).

Table 5.7 Descriptive Statistics of Stocks from the SHSE

	Mean	Median	Standard deviation
Excess return	-0.68	-0.64	0.14
Firm size	0.64	0.64	0.03
Book-to-market ratio	0.25	0.23	0.15
Turnover rate (%)	2.92	1.88	3.06
Return2-3	-2.47	-2.45	0.23
Return4-6	-4.33	-4.28	0.34
Return7-12	-8.07	-8.06	0.50

Notes: This table presents the descriptive statistics of the stock characteristics on the Shanghai Stock Exchange (SHSE) from January 1995 to December 2003. The results include the average of the cross-sectional means, median, and standard deviations of excess return, firm size, book-to-market ratio, turnover rate, and return2-3, return4-6, and return7-12 on the time-series basis. Firm size is the logarithm of the market capitalisation in billions of Chinese Yuan. Turnover rate is the logarithm of the monthly share trading volume divided by shares outstanding. Return2-3 is the sum of the returns between the second and third months before the current month. Return4-6 is the sum of the returns between the fourth and sixth months before the current month. Return7-12 is the sum of the returns between the seventh and twelfth months before the current month.

Avramov and Chordia (2006) develop and apply a dynamic framework using two-pass regressions. Following this approach, the econometric formulation that I deploy in the first pass time series regression is in the following form (see Avramov and Chordia, 2006):

$$r_{jt} = \alpha_j + \beta_{j1} r_{mt} + \beta_{j2} c_{t-1} r_{mt} + \beta_{j3} Size_{jt-1} r_{mt} + \beta_{j4} c_{t-1} Size_{jt-1} r_{mt} + \beta_{j5} BM_{jt-1} r_{mt} + \beta_{j6} c_{t-1} BM_{jt-1} r_{mt} + \beta_{j7} SMB_{jt} + \beta_{j8} HML_{jt} + \beta_{j9} OFL_{jt} + \mu_{jt}, \quad (5.3)$$

where r_{mt} is the excess market return based on a value-weighted market index on the SHSE. c_{t-1} is a single macroeconomic predictor, which is the yield differential between 10-year national bond rates and 10-year corporate bond rates during the sample period under investigation. $Size_{jt-1}$ is the market capitalisation for stock j at time $t-1$, and BM_{jt-1} is the book-to-market ratio for stock j at time $t-1$. c_{t-1}, $Size_{jt-1}$ and BM_{jt-1} are all scaling factors. SMB_{jt} is the returns of small-size portfolios minus returns of big-size portfolios at time t, and HML_{jt} represents the returns of high book-to-market portfolios minus the returns of low book-to-market portfolios at time t. OFL_{jt} is the liquidity factor of Pastor and Stambaugh (2003).

Table 5.8 shows the time series regression results. These include both means and medians of intercept, stock characteristics, SMB, HML, commonality in liquidity factors, residuals, and adjusted R^2.

Table 5.8 Fama MacBeth Time Series Regression Estimates

	Mean	Median
α_j (intercept)	0.14	0.01
β_{j1} (excess return)	14.76	0.86
β_{j2} (excess return and macroeconomic predictor)	-11.26	0.02
β_{j3} (firm size and excess return)	-1.79	0.02
β_{j4} (macroeconomic predictor, firm size and excess return)	1.46	-0.006
β_{j5} (book-to-market ratio and excess return)	-3.66	-0.04
β_{j6} (macroeconomic predictor, book-to-market ratio and excess return)	3.06	0.008
β_{j7} (SMB)	0.11	0.17
β_{j8} (HML)	-0.12	-0.09
β_{j9} (Pastor and Stamburgh measure)	0.008	0.006
μ_{jt}	0.001	-0.002
adjusted R^2	0.70	0.73

Notes: This table summarises the time series OLS regression coefficient estimates. The results of relevant variables are from the Shanghai Stock Exchange (SHSE) between January 1995 and December 2003.

The next stage is a cross-sectional regression. The econometric formulation is:

$$R_{jt} = \gamma_{0t} + \gamma_{1t}Size_{jt\text{-}1} + \gamma_{2t}BM_{jt\text{-}1} + \gamma_{3t}TURN_{jt\text{-}1} + \gamma_{4t}RET2\text{-}3_{jt\text{-}1} + \gamma_{5t}RET4\text{-}6_{jt\text{-}1} + \gamma_{6t}RET7\text{-}12_{jt\text{-}1} + e_{jt}, \qquad (5.4)$$

where $R_{jt} = \alpha_j + \mu_{jt}$, $Size_{jt\text{-}1}$ is stock j's logarithm of firm capitalisation at time $t\text{-}1$ and $BM_{jt\text{-}1}$ is stock j's book-to-market ratio at time $t\text{-}1$. $TURN_{jt\text{-}1}$ is stock j's turnover rate at time $t\text{-}1$. $RET2\text{-}3_{jt\text{-}1}$ is the sum of the returns between the second and third months before the current month. $RET4\text{-}6_{jt\text{-}1}$ is the sum of the returns between the fourth and sixth months before the current month. $RET7\text{-}12_{jt\text{-}1}$ is the sum of the returns between the seventh and twelfth months before the current month. The size of the firm, book-to-market ratio, turnover, and different lagged return variables are all equity characteristics in the sample.

Table 5.9 records the estimation results. Its first two columns show the means and medians of the estimated coefficients of the financial-market anomalies. The third column shows t-statistics by using standard errors from Shanken (1990), and the fourth column shows t-statistics by using standard errors from Jagannathan and Wang (1998).

Following Avramov and Chordia (2006), I adjusted my t-statistics in absolute value by using standard errors from Jagannathan and Wang (1998), which produced results higher than the t-statistics in absolute value using standard errors from Shanken (1990).

In general, the outcome here is different from what Avramov and Chordia (2006) has reported in their paper. The estimated coefficients for the turnover rate and past returns in absolute value are lower and less significant than those from Avramov and Chordia (2006) when a commonality in liquidity factor is included. In addition, the adjusted R^2 is lower than the results from Avramov and Chordia (2006). This shows that the null hypothesis for the cross-sectional regression cannot be rejected and that adding commonality in liquidity factor into the model can capture the impact of turnover rates and past returns in individual stock returns when the beta varies with the firm size, book-to-market, and business-cycle-related variables.

Avramov and Chordia (2006) report that the liquidity factor in their model does not capture the impact of turnover and past returns in the cross-section of individual stock returns. This difference can be explained by differences in trading systems. The NYSE-AMEX and NASDAQ are quote-driven markets, while the Chinese Stock Market is an order-driven one, which has been proven to be more suitable for the study of commonality in liquidity and asset-pricing models in my previous discussions.

Table 5.9 Fama-MacBeth Cross Sectional Regression Estimates

	Mean	Median	t-statistics by Shanken	t-statistics by Jagannathan and Wang
γ_{0t} (intercept)	-1.75	-0.56	-0.23	-1.02
γ_{1t} (firm size)	0.06	0.06	0.25	0.94
γ_{2t} (book-to-market ratio)	-0.15	-0.02	-0.09	-1.03
γ_{3t} (turnover rate)	-0.06	0.03	-0.02	-0.79
γ_{4t} (the sum of the returns between the second and third months before the current month)	0.20	0.04	0.47	0.97
γ_{5t} (the sum of the returns between the fourth and sixth months before the current month)	0.18	0.17	0.46	0.89
γ_{6t} (the sum of the returns between the seventh and twelfth months before the current month)	-0.34	-0.32	-0.13	-0.93
adjusted R^2	0.27	0.24		

Notes: This table summarises the average of the cross-sectional OLS regression coefficient estimates on the time-series basis. The results of relevant variables are from the Shanghai Stock Exchange (SHSE) between January 1995 and December 2003.

VI. Conclusion

This chapter presents a liquidity risk premium is priced and it can explain the cross-section of average returns in China following the methodology of Martinez et al. (2005). A liquidity risk premium exists on the Chinese stock market. These results are robust for the recent empirical findings from US market and Spanish market which contain the large size of market-wide liquidity.

According to my empirical work, first, I find that the liquidity-based factors exhibit relatively large abnormality. The SMB and HML market-wide measures have left-skewed distributions on the SHSE, while on the SZSE only SMB market-wide measures have left-skewed distributions. In general, correlation coefficients are low. In contrast to Martinez et al. (2005) and Liu (2006), I do not find a relatively high positive correlation between ILLQ and HML. These results show book-to-market ratio on the Chinese stock market are quite different from that on the US stock market and the Spanish stock market because it will be affected by the difference between priority stock and normal stocks (Yang and Jiang, 2004). More in line with my expectations, I find that market returns are positively correlated with OFL, and negatively related to ILLQ, which is in agreement with the results from Liu (2006). On the SZSE, there is a negative and small correlation between OFL and ILLQ, but on the SHSE the correlation is positive while small. This reflects the difference in the liquidity between SHSE and SZSE. There are more speculations on the SZSE (Xu, Liu and Wu, 2004). This can cause the movement between order flows, returns and trading volume

with more noise. OFL1 factor have higher average returns than do the OFL10 stocks that are prone to return reversals when liquidity is greater. My results for the SZSE are different from that of Martinez et al. (2005), but are consistent with those of Pastor and Stamburgh (2003). For the ILLQ betas, my results differ from that of both Martinez et al. (2005) and Liu (2006) in that I do not find a large difference in average returns between ILLQ1 and ILLQ10.

Second, I follow Martinez et al. (2005) which postulate that if the pricing effect of market liquidity exists, there would be systematic difference in average returns (alpha) of the portfolios that are sorted according to their sensitivity to measures of liquidity. So, in the asset pricing models that are to be deployed, the average return of a portfolio with higher sensitivity to liquidity changes should be significantly higher than that of the portfolio with lower sensitivity. I use four alternative pricing models: the traditional CAPM model, the two modified CAPM models that incorporate the aggregate liquidity effect constructed by adding the two liquidity measures (OFL and ILLQ) respectively to the standard CAPM model, and the Fama–French three-factor model, I report different alphas for each year between January 1995 and December 2003. My results show that the ILLQ is a priced liquidity risk factor.

Third, using the model of Martinez et al. (2005), the liquidity premium associated with the OFL factor is both significant and positive in the conditional model but not in the unconditional model, confirming the importance of adding dynamics in modelling asset pricing behaviour in the Chinese context which may be crucial for

future research. Also, in my empirical estimation, in all the asset pricing models that include the liquidity effect, I have found significant negative coefficients of the betas associated with the ILLQ factor. This is the most important and crucial result regarding the pricing effect of commonality in liquidity in China. Thus, together with the findings in the last paragraph where I found significant average returns in alphas for different ILLQ portfolios, this evidence confirms that commonality in liquidity is a priced risk factor on the Chinese stock market.

Chapter 6

Summary and Concluding Remarks

Liquidity is important to individual investors, institutions and regulators. An adequate level of liquidity is generally regarded as crucial to the proper functioning of financial markets. A lack of liquidity can have serious adverse effects on the value of individual assets, investment returns, and stability of the financial system as a whole. It is therefore vital to understand the properties of liquidity, including its determination and its role in asset pricing.

Liquidity is conventionally studied as an attribute of an individual stock. In a quote-driven market, liquidity is believed to be determined mainly by inventory costs and asymmetric information. In an order-driven architecture, market makers do not exist and the trading mechanism is fundamentally different from that of a quote-driven market. In such order-driven markets, limit orders provide liquidity while market orders demand liquidity. The main determinants of liquidity in an order-driven market are adverse selection and other factors that can be broadly characterised as the market microstructure effect and the macroeconomic conditions effect.

Liquidity is however difficult to measure. In the literature, the major proxies of liquidity are bid-ask spread and depth. In addition, the measures of liquidity also relate to the trading volume, volatility, and price of the individual stock. In an order-driven marketplace, the main measure of liquidity, the bid-ask spread, is calculated slightly differently than its quote-driven market counterpart. It is given by the difference between the lowest ask price of a sell order and the highest price of the buy order that was not executed. This measure is also adopted in this study.

Previous research has been concerned mainly with liquidity of individual assets. The burgeoning of the commonality literature highlights the growing research consensus on the overwhelming importance of liquidity co-movements caused by common determinants across securities. Existing research work has generally confirmed that at least part of the change in an individual stock's liquidity is determined by market-wide factors. Therefore, commonality in liquidity is a systematic factor that is to be priced, and securities should be characterised with liquidity, in addition to risk and returns. The research on commonality, with its evidence, sources and impacts, represents a very important development of finance theory.

The existing literature, however, leaves a critical void in our knowledge, because little research has been conducted on liquidity commonality in emerging markets. This is despite the fact that one major concern triggering the development of the commonality literature was the conviction that shocks to liquidity were a

contributing factor to financial crises in emerging economies during 1997-98. This study fills the gap by studying the case of China.

Another fact that has motivated this research is that most previous research focus on commonality in liquidity in the context of quote-driven markets. Sources of common changes in the supply of and/or demand for liquidity of this market are predominantly related to market makers, which are non-existent in order-driven markets. Trading mechanisms and traders' choice between the order types are also fundamentally different in an order-driven environment from those in a quote-driven market. This poses a challenge to an adequate understanding of liquidity as an essential element of financial markets. It is even more imperative to research into liquidity in the emerging world where order-driven markets are the main platform of stock market transactions.

As perhaps the most important emerging market, China provides a weighty case for the study of liquidity commonality in an emerging order-driven market. Typical of an emerging economy, the Chinese stock market is experiencing extraordinary growth as well as increased risk and volatility. The adoption of an order-driven market structure makes the situation more complex. Research into how liquidity responds to shocks under this regime can shed critical light on the determination of liquidity on the Chinese stock market, hence enhancing our understanding of the functioning of financial markets there.

This study examines liquidity commonality in two main exchanges in China, i.e. the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE). Now the second largest in Asia after Japan in terms of capitalisation, the Chinese stock market has some unique features compared to the markets in the developed countries such as the US and Britain. The market is segmented in many ways, including segmentation of A-shares and B-shares, tradable shares and non-tradable shares, and domestic and international investors. It is also isolated from other major world financial markets. In addition to the requirement that all companies' shares must be listed, most of the listed companies are state-owned.

The Chinese trading system has a modern infrastructure that includes a computer based automated trading regime. After the pre-opening call session, a continuous, discriminating auction session takes place, during which market and limit orders may be placed. Matching of the orders is according to a price-time priority scheme and stocks are allowed to trade within plus or minus 10% of their closing price on the previous day.

The Chinese market does not have market makers to stabilise stock prices by trading on their own accounts. Therefore, the inventory holding costs do not exist as a determinant of bid-ask spread and hence liquidity. In addition, other institutional details and market conditions prove to have important bearing on the liquidity of the Chinese market. It is found that asymmetric information is widespread in China and plays a crucial role in the determination of liquidity. Other factors will enhance this effect or, on their own, affect levels and changes of

liquidity. From the current literature, institutional factors can enhance the level of asymmetric information among investors. The existence of non-tradable shares is the case. From an empirical perspective, adverse selection, the market microstructure including some institutional details, and the macroeconomic effect prove to be the main driving forces behind the supply of and demand for liquidity in the Chinese order-driven market.

However, there are unanswered questions about the common factors that cause liquidity changes in China. This research looks beyond the determinants of liquidity of individual assets to examine the questions of liquidity commonality in China. I endeavour to solve the questions that govern this research. These questions include: To what extent does commonality exist in China? What are the causes of this existence? How is commonality in liquidity as a systematic risk priced on the Chinese market?

Following the basic model of Chordia et al. (2000), I first examine to what extent liquidity is determined by common underlying factors on the Chinese stock market. Using a proprietary set of data that contains all intraday transactions of A-shares from July 2000 to June 2002, I find evidence that commonality in liquidity is present in the Chinese stock market. Moreover, this evidence is much stronger than in previous research. The magnitude of liquidity beta for the spread measure and the depth measure is almost three times that of comparable measures in Chordia et al. (2000). I also find a much higher proportion of stocks with positive and significant liquidity beta. This implies that commonality in liquidity

is likely to be more significant and more pervasive in an emerging market as evidenced in the Chinese case.

To further detect the existence of commonality in China, the sample is portioned into five quintiles. The results show that commonality exists in most of the quintiles in both exchanges. It is also found that the percentage of stocks that have a positively significant liquidity beta increases with the firm size, which is in agreement with other studies. That the liquidity of large stocks is more likely to move with market liquidity, suggests that large stocks might be more exposed to correlated trading. This can be due to the herding behaviour of Chinese investors, but it is more likely that, due to market imperfection, Chinese investors tend to "flight to quality" by concentrating their investment on larger funds, especially in the down market period.

The concept of 'flight to quality' suggests that investors will tend to escape to the market with more liquidity in financial turmoil. Thus, the sudden evaporation of liquidity on the Chinese Stock Exchange is a major policy concern for central banks and regulators, which means commonality in liquidity is a critical element to be monitored for the maintenance of financial stability. A key policy for regulators and central banks is to enhance the liquidity provision to attract investors. Disclosure rules, greater transparency, insider trading laws and lower transaction costs are all important factors for achieving the goal (O'Hara, 2004).

Significant commonality has also been found for all liquidity proxies in the models in this study. This indicates that, when responding to shocks to systematic liquidity, Chinese market participants tend to revise both the spreads (i.e. prices) and depth (the quantity of shares they are willing to trade) in their orders.

To investigate into the possibility of individual stock liquidity co-moves with liquidity of the industry to which a stock belongs and with liquidity of the market as a whole, respectively, the sample firms are classified into three categories: industrial, resources and financial. Cross-sectional evidence confirms that the liquidity constructed of individual stocks can be influenced by market-wide common factors as well as by industry specific common factors.

Commonality is found to be present in both up and down markets. However, there are significant differences of liquidity co-movements between the two markets. In the up market, commonality is relatively moderate and less volatile. In contrast, during the down market period the range of co-movements of liquidity is wider and the evidence of significant commonality in liquidity is stronger.

In short, by observing the influences of the size, industry, and up and down markets effects, the empirical evidence of the existence of commonality in China is robust.

It is not fully understood in the literature what precisely the common factors driving liquidity commonality are. In the current research three strands of the

sources of commonality in liquidity can be identified: the microstructure approach, the market conditions approach, and order-driven market models. This research contributes to the literature by investigating the sources of commonality in liquidity on the Chinese market.

The literature on order-driven market models suggests adverse selection due to asymmetric information is a critically important source of commonality in liquidity. Following this line of research, I test the sources of commonality at the market and industry levels using the number of trades as an indicator of informed trading. The results for the sum of concurrent, lagged, and leading coefficients on such a variable show that the asymmetric information proxy is positive and highly significant for stocks from the SHSE and the SZSE. Given that the number of trades is a reliable indicator of informed trading, this outcome suggests that asymmetric information is a significant source of liquidity commonality in China. This finding sheds critical light on the working of the Chinese stock market. Asymmetric information is a particularly severe problem in China. Chinese firms tend to disclose only incomplete or even biased information on their business and in the marketplace share manipulation and insider trading are pervasive. In this environment, a shock of asymmetric information tends to induce systematic change in liquidity across the market. My empirical results give evidence to the importance of asymmetric information as a determining factor causing liquidity commonality which is a vital attribute of the Chinese stock market.

As a result, above evidence shows commonality in liquidity can also affect the risk management of investment funds and other financial institutions. Shocks to liquidity may expose these institutions to insolvency risk, hence decrease the value of their net worth. Given the importance of, the relationship between capital and liquidity, especially during the financial crisis period, liquidity risk is a necessary aspect of risk management in funds and other financial institutions (Acharya and Schaefer, 2006). In addition to this, the commonality in liquidity literature shows liquidity of individual stocks may co-move across the board, so liquidity commonality embodies a type of systematic risk. For example, during the time of market-wide financial turmoil, funds and financial institutions will receive less capital from firms than that during the time of non-systematic risk because firms will turns to a market with high liquidity for their funds (Brunnermeier and Pedersen, 2007). So, the short-term cash inflows of Chinese financial institutions will decline. Thus, their ability of providing liquidity to the market will be constrained. This 'flight to quality' phenomenon is likely to cause liquidity across stocks to vary. The phenomenon of commonality in liquidity therefore adds a new dimension to risk management in China.

In testing for the effects of financial market variables as determinants of liquidity commonality, I find that, on the Chinese stock market, in addition to market liquidity, market volatility is the most important factor driving co-movements of liquidity across individual stocks. It has the highest percentage of positively significant coefficient of all stocks in my sample, than that of other financial variables such as the interest rate and market returns.

I further examine the effects of financial market variables on commonality in a VAR modelling presentation. This time I follow the literature to use two new measures of aggregate liquidity, i.e. the illiquidity ratio or the monthly average ratio of absolute return of stocks to their corresponding volume and the Pastor and Stambaugh liquidity factor. The VAR analysis of dynamic responses of variables in the system to an impulse shock indicates that the two market liquidity measures are significantly influenced by financial variables such as market share turnover, market volatility and share returns.

The VAR analysis then is extended to investigate the effects of macroeconomic conditions such as growth of the economy, inflation, the interest rate, and monetary policy. The analysis of impulse functions suggest that macroeconomic factors can directly cause co-movements of liquidity on the Chinese stock market. Of these macroeconomic determinants, the Chinese monetary policy is found to be particularly influential in affecting aggregate liquidity. In response to a positive shock in money supply *M2* and a negative shock in the overnight interest rate, market liquidity will be improved significantly for an extended period of time. Other macroeconomic shocks such as the inflationary shock may have the significant effect on the alternative market liquidity measure, i.e. the Pastor and Stambaugh liquidity factor. Meanwhile, the variance decomposition analysis show that, at all forecast horizons adopted in this study, a large proportion of variations in aggregate liquidity is due to shocks in both financial market variables and macroeconomic conditions. On the SHSE, the sum contribution due to shocks in financial market variables at a one year horizon is about 26% of the total variation

and the macro shocks' sum contribution is 19%. On the SZSE, this pattern is similar. These findings confirm that macroeconomic conditions are an important source of commonality in liquidity in China.

The relationship between commonality in liquidity and asset returns is remarkable using my empirical results. The impacts of commonality in liquidity showed the cross-section of average returns in China derived from a priced liquidity risk factor. The liquidity-based factors exhibit relatively large abnormality. The SMB and HML market-wide measures have left-skewed distributions on the SHSE, while on the SZSE only SMB market-wide measures have left-skewed distributions. In general, correlation coefficients are low. In contrast to Martinez et al. (2005) and Liu (2006), I do not find a relatively high positive correlation between ILLQ and HML. More in line with my expectations, I find that market returns are positively correlated with OFL, and negatively related to ILLQ, which is in agreement with the results from Liu (2006). On the SZSE, there is a negative and small correlation between OFL and ILLQ, but on the SHSE the correlation is positive while small. OFL1 factor have higher average returns than do the OFL10 stocks that are prone to return reversals when liquidity is greater. My results for the SZSE are different from that of Martinez et al. (2005), but are consistent with those of Pastor and Stamburgh (2003). For the ILLQ betas, my results differ from that of both Martinez et al. (2005) and Liu (2006) in that I do not find a large difference in average returns between ILLQ1 and ILLQ10.

If the pricing effect of market liquidity exists, there would be systematic difference in average returns (alpha) of the portfolios that are sorted according to their sensitivity to measures of liquidity. So, in the asset pricing models that are to be deployed, the average return of a portfolio with higher sensitivity to liquidity changes should be significantly higher than that of the portfolio with lower sensitivity. I use four alternative pricing models: the traditional CAPM model, the two modified CAPM models that incorporate the aggregate liquidity effect constructed by adding the two liquidity measures (OFL and ILLQ) respectively to the standard CAPM model, and the Fama–French three-factor model, I report different alphas for each year between January 1995 and December 2003. My results show that the ILLQ is a priced liquidity risk factor.

According to the investigation by Martinez et al. (2005), the liquidity premium associated with the OFL factor is both significant and positive in the conditional model but not in the unconditional model. This highlights the importance of adding dynamics in modelling asset pricing behaviour in relation to liquidity co-movements, which may also be crucial for future research in the Chinese context. Furthermore, in my empirical estimation, in all the asset pricing models that include the liquidity effect, I have found significant negative coefficients of the betas associated with the ILLQ factor. This is the most important and crucial result regarding the pricing effect of commonality in liquidity in China. Thus, together with the findings of significant average returns in alphas for different ILLQ portfolios, this evidence confirms that commonality in liquidity is a priced risk factor on the Chinese stock market. The additional importance of this finding

is that it may facilitate further research on the relation between asset pricing and microstructure, since it now becomes possible to avoid detailed microstructure data, which are not always available for long enough sample periods.

Further research may also explore new trading strategies of institutional investors on the Chinese stock market in the light of the existence of commonality in liquidity. As a priced factor, commonality in liquidity should be an important consideration when institutional investors choose individual assets for their portfolios and make asset allocation decisions. It is therefore necessary for further research into how to measure covariance between liquidity of individual stock and market liquidity in a dynamic model. Also, the research in commonality in liquidity can be extended to cover the bond market in China, and possibly to Chinese derivative market. It will be very interesting to see whether and to what extent liquidity co-moves among the Chinese stock market, bond market and derivative market.

Bibliography

Acharya, V.V. and S. Schaefer, 2006, Liquidity risk and correlation risk: implications for risk management, Working Paper, London Business School.

Acharya, V.V. and L.H. Pedersen, 2005, Asset pricing with liquidity risk, *Journal of Financial Economics* 77, 375-410.

Admati, A. and P. Pfleiderer, 1988, A theory of intraday patterns: Volume and price variability, *Review of Financial Studies* 1, 3-40.

Ahn, H., K. Bae, and K. Chan, 2001, Limit orders, depth, and volatility: Evidence from the Stock Exchange of Hong Kong, *Journal of Finance* 56, 767-788.

Ahn, H., J. Cai, Y. Hamao, and R.Y.K. Ho, 2002, The components of the bid-ask spread in a limit-order market: Evidence from the Tokyo Stock Exchange, *Journal of Empirical Finance* 9, 399-430.

Ahn, H. and Y. Cheung, 1999, The intraday patterns of the spread and depth in a market without market makers: The Stock Exchange of Hong Kong, *Pacific-Basin Finance Journal* 7, 539–556.

Aitken, M. and C. Comerton-Forde, 2003, How should liquidity be measured? *Pacific-Basin Finance Journal* 11, 45-59.

Amihud, Y., 2002, Illiquidity and stock returns: Cross-section and time-series effects, *Journal of Financial Markets* 5, 31-56.

Amihud, Y. and H. Mendelson, 1980, Dealership market: Market making with inventory, *Journal of Financial Economics* 8, 31-53.

Amihud, Y. and H. Mendelson, 1986, Asset pricing and the bid-ask spread, *Journal of Financial Economics* 17, 223-249.

Amihud, Y. and H. Mendelson, 1991, Liquidity, maturity and the yields on U.S. government securities, *Journal of Finance* 46, 1411–1425.

Amihud, Y., H. Mendelson, and B. Lauterbach, 1997, Market microstructure and securities values: Evidence from the Tel Aviv Stock Exchange, *Journal of Financial Economics* 45, 365-390.

Amihud, Y., H. Mendelson, and L.H. Pedersen, 2006, Liquidity and asset prices, *Foundations and Trends in Finance* 1, 269-364.

Andersen, T.G., T. Bollerslev, and F.X. Diebold, 2002, Parametric and nonparametric volatility measurement, in L.P. Hansen and Y. Ait-Sahalia (eds.), Handbook of Financial Econometrics. Amsterdam: North-Holland.

Andersen, T.G., T. Bollerslev, F.X. Diebold, and P. Labys, 2001, The distribution of realized exchange rate volatility, *Journal of the American Statistical Association* 96, 42–55.

Andersen, T.G. and T. Bollerslev, 1997, Intraday periodicity and volatility persistence in financial markets, *Journal of Empirical Finance* 4, 115–158.

Andersen, T.G. and T. Bollerslev, 1998, Answering the skeptics: Yes, standard volatility models do provide accurate forecasts, *International Economic Review* 39, 885–905.

Ang, A., B. Hodrick, Y. Xing, and X. Zhang, 2006, The cross-section of volatility and expected returns, *Journal of Finance* 61, 259-299.

Angel, J., 1997, Tick size, share prices, and stock splits, *Journal of Finance* 52, 655-681.

Annals of Chinese Securities Regulatory Commission, various issues, Beijing, PRC.

Annals of Shanghai Stock Exchange, Shanghai, PRC.

Annals of Shenzhen Stock Exchange, Shenzhen, PRC.

Avramov, D. and T. Chordia, 2006, Stock return predictability, *Journal of Financial Economics* 82, 387-415.

Bacidore, J., R.H. Battalio, and R.H. Jennings, 2003, Order submission strategies, liquidity supply, and trading in pennies on the New York Stock Exchange, *Journal of Financial Markets* 6, 337-362.

Bagehot, W., 1971, The only game in town, *Financial Analysts Journal* 27, 12-17.

Bailey, W., J. Cai, Y. Cheung, and F. Wang, 2006, Stock returns, order imbalances, and commonality: Evidence on individual, institutional, and proprietary investors in China, Working Paper, Cornell University.

Bailey, W., J. Cai, Y. Cheung, and Z. Zheng, 2003, The cross-sectional determinants of stock returns in China: Further evidence on characteristics, factor, and momentum, Working Paper, Cornell University.

Baker, M. and J.C. Stein, 2004, Market liquidity as a sentiment indicator, *Journal of Financial Markets* 7, 271-299.

Bank for International Settlements (BIS) Paper 34, 1-34, 1999.

Barclay, M. and J. Warner, 1993, Stealth trading and volatility: Which trades move prices? *Journal of Financial Economics* 34, 281-306.

Barth, M.J., E.M. Remolina, and P.D. Wooldridge, 2002, Changes in market functioning and central bank policy: An overview of the issues, BIS paper 12, 1-24.

Basu, S., 1977, Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis, *Journal of Finance* 32, 663-682.

Bauer, W., 2004, Commonality in liquidity in pure order-driven markets, Working Paper, The National Centre of Competence in Research 'Financial Valuation and Risk Management'.

Beaupain, R., P. Giot, and M. Petitjean, 2006, Market-wide liquidity co-movements, volatility regimes and market cap sizes, CORE Discussion Paper 2006/102.

Becker-Blease, J.R. and D.L. Paul, 2006, Stock liquidity and investment opportunities: Evidence from index additions, *Financial Nanagement* 35, 35-51.

Bekaert, G., C.R. Harvey, and C. Lundblad, 2007, Liquidity and expected returns: Lessons from emerging markets, *Review of Financial Studies* 20, 1783-1831.

Beltran-Lopez, H., P. Giot, and J. Grammig, 2006, Commonalities in the order book, Working Paper, Universite catholique de Louvain.

Beltratti, A. and B. Bortolotti, 2006, The nontradable share reform in the Chinese stock market, Working Paper, Bocconi University.

Benston, G. and R. Hagerman, 1974, Determinants of bid-asked spreads in the over-the-counter market, *Journal of Financial Economics* 1, 353-364.

Berkman, H. and V.R. Eleswarapu, 1998, Short-term traders and liquidity: A test using Bombay Stock Exchange data, *Journal of Financial Economics* 47, 339-355.

Bernanke, B.S. and A.S. Blinder, 1992, The federal funds rate and the channel of monetary transmission, *American Economic Review* 82, 901-921.

Bernanke, B.S. and I. Mihov, 1998, Measuring monetary policy, *Quarterly Journal of Economics* 113, 869-902.

Bernanke, B.S. and M. Gertler, 1995, Inside the black box: The credit channel of monetary policy transmission, *Journal of Economic Perspectives* 9, 27-48.

Bessembinder, H., 1994. Bid-ask spreads in the interbank foreign exchange markets, *Journal of Financial Economics* 35, 317-348.

Biais, B., L. Glosten, and C. Spatt, 2005, Market microstructure: A survey of microfoundations, empirical results, and policy implications, *Journal of Financial Markets* 8, 217-264.

Biais, B., P. Hillion, and C. Spatt, 1995, An empirical analysis of the limit order book and the order flow in the Paris Bourse, *Journal of Finance* 50, 1655-1689.

Bloomfield, R., M. O'Hara and G. Saar, 2005, The "make or take" decision in an electronic market: Evidence on the evolution of liquidity, *Journal of Financial Economics* 75, 165-199.

Brands, S., D.R. Gallagher and A. Looi, 2002, Active investment manager portfolios and preferences for stock characteristics: Australian evidence, Working Paper, University of New South Wales and Security Industry Research Centre of Asia Pacific.

Breen, W.J., L.S. Hodrick, and R.A. Korajczyk, 2002, Predicting equity liquidity, *Management Science* 48, 470-483.

Brennan, M. and A. Subrahmanyam, 1996, Market microstructure and asset pricing: On the compensation for illiquidity in stock returns, *Journal of Financial Economics* 41, 441-464.

Brennan, M., T. Chordia, and A. Subrahmanyam, 1998, Alternative factor specifications, security characteristics, and the cross-section of expected stock returns, *Journal of Financial Economics* 49, 345-373.

Brockman, P., D.Y. Chung, and C. Pérignon, 2006a, Commonality in liquidity: A global perspective, Working Paper, University of Missouri – Columbia.

Brockman, P., D.Y. Chung, and C. Pérignon, 2006b, Multinational firm liquidity: A migration toward global commonality, Working Paper, University of Missouri – Columbia.

Brockman, P. and D.Y. Chung, 1999, Bid-ask spread components in an order-driven environment, *Journal of Financial Research* 22, 227-246.

Brockman, P. and D.Y. Chung, 2000, Informed and uniformed trading in an electronic, order driven environment, *Journal of Financial Review* 35, 125-46.

Brockman, P. and D.Y. Chung, 2002, Commonality in liquidity: Evidence from an order-driven market structure, *Journal of Financial Research* 4, 521-539.

Brockman, P. and D.Y. Chung, 2006, Index inclusion and commonality in liquidity: Evidence from the Stock Exchange of Hong Kong, *International Review of Financial Analysis* 15, 291-305.

Brown, P., N. Thompson, and D. Walsh, 1999, Characteristics of the order flow through an electronic open limit order book, *Journal of International Financial Markets, Institutions & Money* 9, 335-357.

Brunetti, C. and A. Caldarera, 2005, Asset prices and asset correlations in illiquid markets, Working Paper, Johns Hopkins University.

Brunnermeier, M. and L.H. Pedersen, 2007, Market liquidity and funding liquidity, Working Paper, Princeton University.

Campbell, J.Y., S.J. Grossman, and J. Wang, 1993, Trading volume and serial correlation in stock returns, *Quarterly Journal of Economics* 108, 905-939.

Carhart, M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57-82.

Chalmers, J.M.R. and G.B. Kadlec, 1998, An empirical examination of the amortized spread, *Journal of Financial Economics* 48, 159-188.

Chan, H.W. and R.W. Faff, 2003, An investigation into the role of liquidity in asset pricing: Australian evidence, *Pacific-Basin Finance Journal* 11, 555-572.

Chan, J.S.P., D. Hong, and M.G. Subrahmanyam, 2006, Liquidity and asset prices in multiple markets, Working Paper, Lee Kong Chian School of Business, Singapore Management University.

Chan, K., A. Menkveld, and Z. Yang, 2008, Information asymmetry and asset prices: evidence from the China foreign share discount, *Journal of Finance* 63, 159-196.

Chan, Y-C, 2000, The price impact of trading on the Stock Exchange of Hong Kong, *Journal of Financial Markets* 3, 1-16.

Chen, J., 2005, Pervasive liquidity risk and asset pricing, Working Paper, Columbia University.

Chen, L., D.A. Lesmond, and J. Wei, 2007, Corporate bond liquidity and its effect on bond yield spreads, *Journal of Finance* 62, 119-149.

Chen, N., R. Roll, and S.A. Ross, 1986, Economic forces and the stock market, *Journal of Business* 59, 383-403.

Chen, N., 1991, Financial investment opportunities and the macroeconomy, *Journal of Finance* 46, 529-554.

Chen, Z. and P. Xiong, 2001, Discounts on illiquid stocks: Evidence from China, Working Paper, Yale University.

Cheung, W.M. and F.M. Song, 2005, Liquidity, size and cycle of order flow: Evidence from Hong Kong Stock Exchange, Working Paper, University of Hong Kong.

China Securities Regulatory Commission, 2005, Circular on issues relating to the pilot reform of listed companies split share structure, www.crsc.gov.cn.

Choi, W.G. and D. Cook, 2005, Stock market liquidity and the macroeconomy: Evidence from Japan, IMF Working Paper.

Chollete, L., 2004, Asset pricing implications of liquidity and its volatility, Job Market Paper, Columbia Business School.

Chollete, L., R. Næs, and J.A. Skjeltorp, 2006, Pricing implications of shared variance in liquidity measures, Working Paper, Norwegain Scool of Economics and Business Administration.

Chordia, T., A. Sarkar, and A. Subrahmanyam, 2005, An empirical analysis stock and bond market liquidity, *Review of Financial Studies* 18, 85-129.

Chordia, T., R. Roll, and A. Subrahmanyam, 2000, Commonality in liquidity, *Journal of Financial Economics* 56, 3-28.

Chordia, T., R. Roll, and A. Subrahmanyam, 2001, Market liquidity and trading activity, *Journal of Finance* 56, 501-530.

Chordia, T., R. Roll, and A. Subrahmanyam, 2002, Order imbalance, liquidity and market returns, *Journal of Financial Economics* 65, 111-130.

Chordia, T., R. Roll, and A. Subrahmanyam, 2003, Determinants of daily fluctuations in liquidity and trading activity, *Cuadernos de Economia* 40, 728-751.

Chordia, T., A. Subrahmanyam, and V. Anshuman, 2001, Trading activity and expected stock returns, *Journal of Financial Economics* 59, 3-32.

Chow, E.H., Y.L. Hsu and I. Tso, 2002, Liquidity providers on an electronic order-driven market, Working Paper, National Chengchi University.

Chowdhry, B. and V. Nanda, 1991, Multi-market trading and market liquidity, *Review of Financial Studies* 4, 483-511.

Christiano, L.J., M. Eichenbaum, and C.L. Evans, 1996, The effects of monetary policy shocks: Some evidence from the flow of funds, *Review of Economics and Statistics* 78, 16-34.

Christiano, L.J., M. Eichenbaum, and C.L. Evans, 1998, Monetary policy shocks: What have we learned and to what end? NBER Working Paper No. 6400.

Chuhan, P., 1992, Are institutional investors and important source of portfolio investment in emerging markets? World Bank Working Paper No. 1243.

Chung, K.H., B.F. Van Ness, and R.A. Van Ness, 1999, Limit orders and the bid-ask spread, *Journal of Financial Economics* 53, 255-287.

Chung, K.H., B.F. Van Ness, and R.A. Van Ness, 2004, Trading costs and quote clustering on the NYSE and Nasdaq after decimalization, *Journal of Financial Research* 32, 309–328.

Cochrane, J., 2001, Asset pricing, NJ: Princeton University Press, Princeton.

Comerton-Forde, C. and J. Rydge, 2003, Equity market microstructure review, Working Paper, Security Industry Research Centre of Asia Pacific.

Constantinides, G.M., 1986, Capital market equilibrium with transaction costs, *Journal of Political Economy* 94, 842-862.

Cooper, S.K., J.C. Groth, and W.E. Avera, 1985, Liquidity, exchange listing, and common stock performance, *Journal of Economics and Business* 37, 19-33.

Copeland, T. and D. Galai, 1983, Information effects on the bid-ask spread, *Journal of Finance* 38, 1457-1469.

Corwin, S.A. and M.L. Lipson, 2005, Order flow, trader type, and the determinants of commonality in prices and liquidity, Working Paper, University of Notre Dame.

Coughenour, J.F. and M.M. Saad, 2004, Common market makers and commonality in liquidity, *Journal of Financial Economics* 73, 37-69.

Cui, R., and Y. Wu, 2007, Disentangling liquidity and size effects in stock returns: Evidence from China, Working Paper, EFMA 2007 Vienna Meetings.

Datar, V., N. Naik, and R. Radcliffe, 1998, Liquidity and stock returns, *Journal of Financial Markets* 1, 203-219.

Datar, V., R.W. So, and Y. Tse, 2006, Liquidity commonality and spillover in the US and Japanese markets: An intraday analysis using the exchange-traded funds, Working Paper, Chinese University of Hong Kong.

De Jong, F. and A. Mentink, 2006, Commonality in liquidity in Euro security markets, Working Paper, University of Amsterdam.

Demsetz, H., 1968, The cost of transacting, *Quarterly Journal of Economics* 82, 33-53.

Domowitz, I., O. Hansch, and X. Wang, 2005, Liquidity commonality and return co-movement, *Journal of Financial Markets* 8, 351-376.

Drew, M.E., T. Naughton, and M. Veeraraghavan, 2003, Firm size, book-to-market equity and security returns: Evidence from the Shanghai Stock Exchange, *Australian Journal of Management* 28, 118-141.

Easley, D. and M. O'Hara, 1997, Price, trade size, and information in securities markets, *Journal of Financial Economics* 19, 69-90.

Easley, D., N.M. Kiefer, and M. O'Hara, 1997, One day in the life of a very common stock, *Review of Financial Studies* 10, 805-835.

Easley, D., S. Hvidkjaer, and M. O'Hara, 2002, Is information risk a determinants of asset returns? *Journal of Finance* 58, 2185–2210.

Eckbo, B.E. and Ø. Norli, 2002, Pervasive liquidity risk, Working Paper, Tuck School at Dartmouth and Rotman School of Management, University of Toronto.

Eichenbaum, M., 1992, Comment on interpreting the macroeconomic time series facts: The effects of monetary policy, *European Economic Review* 36, 1001-1011.

Eleswarapy, V., 1997, Cost of transacting and expected returns in the Nasdaq market, *Journal of Finance* 52, 2113-2127.

Eleswarapy, V. and M. Reinganum, 1993, The seasonal behaviour of liquidity premium in asset pricing, *Journal of Financial Economics* 34, 373-386.

Ericsson, J. and O. Renault, 2006, Liquidity and credit risk, *Journal of Finance* 61, 2219-2250.

Eun, C.S. and W. Huang, 2007, Asset pricing in China's domestic stock markets: Is there a logic? *Pacific-Basin Finance Journal* 15, 452-480.

Fabre, J. and A. Frino, 2004, Commonality in liquidity: Evidence from the Australian Stock Exchange, *Accounting and Finance* 44, 357-368.

Fama, E. and J. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607-636.

Fama, E. and K. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427-465.

Fama, E. and K. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Fama, E. and K. French, 1996, Multifactor explanations of asset pricing anomalies, *Journal of Finance* 51, 55-84.

Fang, J., 1991, Shanghai: Stock market re-established, *Beijing Review* 34, 38-40.

Fernald, J. and J.H. Rogers, 2002, Puzzles in the Chinese stock market, *Review of Economics and Statistics* 84, 416-432.

Fernando, C.S., 2003, Commonality in liquidity: Transmission of liquidity shocks across investors and securities, *Journal of Financial Intermediation* 12, 233-254.

Fernando, C.S. and R.J. Herring, 2003, Commonality in liquidity and market collapse: Theory and application to the market for perps', Working Paper, AFA 2002 Atlanta Meetings, Wharton Financial Inst. Centre.

Fernando, C.S., R.J. Herring, and A. Subrahmanyam, 2006, Ownership concentration and common liquidity risk: A clinical study of the market for perps*, Working Paper, AFA 2002 Atlanta Meetings, Wharton Financial Inst. Centre.

Fong, K., D.R., Gallagher, P. Gardner, and P.L. Swan, 2004, A closer examination of investment manager herding behaviour, Working Paper, University of New South Wales and Security Industry Research Centre of Asia Pacific.

Foster, F.D. and S. Viswanathan, 1990, A theory of the intraday variations in volume, variance and trading costs in securities markets, *Review of Financial Studies* 3, 593-624.

Foucault, T., 1999, Order flow composition and trading costs in a dynamic limit-order market, *Journal of Financial Markets* 2, 193–226.

Foucault, T., O. Kadan, and E. Kandel, 2005, Limit order book as a market for liquidity, *Review of Financial Studies* 18, 1171-1217.

Frey, S. and J. Grammig, 2006, Liquidity supply and adverse selection in a pure limit order book market, *Empirical Economics* 30, 1007-1033.

Friedman, D., 1993, How trading institutions affect financial market performance: Some laboratory evidence, *Economic Inquiry* 21, 410-435.

Frino, A., D. Gerace, and A. Lepone, 2007, Bid-ask spreads surrounding earnings announcements: Evidence from the Italian bourse, Working Paper, EFMA 2007 Vienna Meetings.

Fujimoto, A., 2003, Liquidity and expected market returns: An alternative test, Working Paper, Yale University.

Fujimoto, A., 2004, Macroeconomic sources of systematic liquidity, Working Paper, Yale University.

Fujimoto, A. and M. Watanabe, 2005, Time-varying liquidity risk and the cross-section of stock returns, Working Paper, University of Alberta and Rice University.

Fung, H., W. Lee, and W.K. Leung, 2000, Segmentation of the A and B Chinese equity markets, *Journal of Financial Research* 2, 179-195.

Galariotis, E.C. and E. Giouvris, 2007, Liquidity commonality in the London Stock Exchange, *Journal of Business Finance and Accounting* 34, 374-388.

Gao, S., 2002, China stock market in a global perspective, Research Report of Dow Jones Indexes.

Garman, M., 1976, Market microstructure, *Journal of Financial Economics* 3, 257-275.

George, T., G. Kaul, and M. Nimalendran, 1991, Estimation of the bid-ask spread and its components: A new approach, *Review of Financial Studies* 4, 623-656.

Ghysels, E., P. Santa-Clara, and R. Valkanov, 2005, There is a risk-return tradeoff after all, *Journal of Financial Economics* 76, 509–548.

Gibson, R. and N. Mougeot, 2004, The pricing of systematic liquidity risk: Empirical evidence from the US stock market, *Journal of Banking & Finance* 28, 157-178.

Giouvris, E., 2003, Systematic liquidity and expected returns: Evidence from the London stock exchange, Working Paper, EFMA 2003 Helsinki Meetings.

Giouvris, E., 2007, Determinants of the components of the bid-ask spreads on the London stock exchange, Working Paper, EFMA 2007 Vienna Meetings.

Girardin, E. and Z. Liu, 2003, The Chinese stock market: A casino with 'buffet zones'? *Journal of Chinese Economic and Business Studies* 1, 57-70.

Glosten, L.R., 1994, Is the electronic open limit-order book inevitable? *Journal of Finance* 49, 1127–1161.

Glosten, L.R. and L.E. Harris, 1988, Estimating the components of the bid-ask spread, *Journal of Financial Economics* 21, 123-142.

Glosten, L.R. and P.R. Milgrom, 1985, Bid, ask and transaction prices in a specialist with heterogeneously informed traders, *Journal of Financial Economics* 14, 71-100.

Gordon, R.H. and W. Li, 2003, Government as a discriminating monopolist in the financial market: The case of China, *Journal of Public Economics* 87, 283–312.

Goyal, A. and P. Santa-Clara, 2003, Idiosyncratic risk matters? *Journal of Finance* 58, 975–1007.

Goyenko, R., 2005, Stock and bond pricing with liquidity risk, Working Paper, Indiana University.

Grammig, J., A. Heinen and E. Rengifo, 2004, Trading activity and liquidity supply in a pure limit order book market, Working Paper, Center of Operations Research and Econometrics, Catholic University of Louvain.

Green, S., 2003, China's stock market: A guide to its progress, players and prospects, The Economist, London.

Greene, J.T., 1996, The impacts of limit order execution on trading costs in New York Stock Exchange stocks, Working Paper, Georgia State University.

Grossman, S. and M. Miller, 1988, Liquidity and market structure, *Journal of Finance* 43, 617-633.

Gu, L., 1997, The liquidity of legal person shares of listed companies and its benefits to the state owned assets, *The Journal of Finance and Economics* 8, 15-22, (in Chinese).

Gul, F.A., 1999, Government share ownership, investment opportunity set and corporate policy choices in China, *Pacific-Basin Finance Journal* 7, 157-172.

Guo, M., 2006, Intraday return, volatility and liquidity: An investigation of the market microstructure of the Chinese stock market, PhD Thesis, University of Western Sydney.

Hameed, A., W. Kang, and S. Viswanathan, 2006, Stock market decline and liquidity, Working Paper, Duck University.

Han, D., C. Wang, and H. Yue, 2006, An analysis of the components of bid-ask spread on Chinese stock market: An empirical study based on order driven markets, *Journal of Beijing Institute of Technology (Social Sciences Edition)* 8, 82-85, (in Chinese).

Handa, P., R.A. Schwartz, and A. Tiwari, 1997, The ecology of an order-driven market, *Journal of Portfolio Management* 24, 47-55.

Handa, P., R.A. Schwartz, and A. Tiwari, 1998, Determinants of the bid-ask spread in an order-driven market, Working Paper, University of Iowa.

Handa, P., R.A. Schwartz, and A. Tiwari, 2003, Quote setting and price formation in an order-driven market, *Journal of Financial Markets* 6, 461-489.

Handa, P. and R.A. Schwartz, 1996a, How best to supply liquidity to a securities market, *Journal of Portfolio Management* 22, 44-51.

Handa, P. and R.A. Schwartz, 1996b, Limit order trading, *Journal of Finance* 51, 1835-1861.

Harford, J. and A. Kaul, 2005, Correlated order flow: Pervasiveness, sources, and pricing effects, *Journal of Financial and Quantitative Analysis* 40, 29-55.

Harris, L., 1991, Stock price clustering and discreteness, *Review of Financial Studies* 4, 389-415.

Harris, L., 1994, Minimum price variations, discrete bid-ask spreads, and quotation size, *Review of Financial Studies* 7, 149-178.

Harris, L., 2003, Trading & exchanges: Market microstructure for practitioners, Financial Management Association Survey and Synthesis Series, Oxford University Press.

Harris, L. and J. Hasbrouck, 1996, Market vs. limit orders: The SuperDOT evidence on order submission strategy, *Journal of Financial and Quantitative Analysis* 31, 213-232.

Hasbrouck, J., 1991, Measuring the information content of stock trades, *Journal of Finance* 46, 179-207.

Hasbrouck, J., 2004, Trading costs and returns for US equities: The evidence from daily data, Working Paper, New York University.

Hasbrouck, J. and D. Seppi, 2001, Common factors in prices, order flows and liquidity, *Journal of Financial Economics* 59, 383-411.

Hasbrouck, J. and R. Schwartz, 1988, Liquidity and execution costs in equity markets, *Journal of Portfolio Management* 14, 10-16.

He, Z.L. and L. Kryzanowski, 2003, A reformulated asset pricing model of risk, liquidity and returns, Working Paper, 2004 Meeting Programme, Midwest Finance Association.

Hendershott, T., P.C. Moulton, and M.S. Seasholes, 2006, Capital constraints and stock market liquidity, Working Paper, University of California, Berkeley.

Henker, T. and M. Martens, 2004, Spread decomposition and commonality in liquidity, Working Paper, School of Banking and Finance, University of New South Wales.

Hmaied, D.M., O.B. Sioud and A. Grar, 2003, Order placement strategy on an order-driven market: Evidence from the Tunis stock market, Working Paper, Department of Finance, Institut des Hautes Etudes Commercials.

Ho, T. and H. Stoll, 1981, Optimal dealer pricing under transactions and return uncertainty, *Journal of Financial Economics* 9, 47-73.

Ho, T. and H. Stoll, 1983, The dynamics of dealer markets under competition, *Journal of Finance* 38, 1053-1074.

Hollifield, B., R.A. Miller, P. Sandas and J. Slive, 2001, Liquidity supply and demand: Empirical evidence from the Vancouver Stock Exchange, Working Paper, The Rodney L. White Centre for Financial Research.

Holmstrom, B. and J. Tirole, 2001, LAPM: A liquidity-based asset pricing, *Journal of Finance* 56, 1837–1867.

Huang, F. and C. Yang, 2007, A study of liquidity of Chinese stock market based on transaction demand of institutional investors, *Economic Theory and Economic Management* 2, 54-59, (in Chinese).

Huang, M., 2002, Liquidity shocks and equilibrium liquidity premia, *Journal of Economics Theory* 109, 104-129.

Huang, R.D. and H.R. Stoll, 1997, The components of the bid-ask spread: A general approach, *Review of Financial Studies* 10, 995-1034.

Huberman, G. and D. Halka, 2001, Systematic liquidity, *Journal of Financial Research* 24, 161-178.

Hughen, J.C. and C.G. McDonald, 2006, Does order flow commonality extend across trade sizes and securities? *Financial Management* 35, 107-128.

Huson, M.R. and R. Ravi, 2007, Commonality in liquidity: Is there asymmetric information about systematic factors? Working Paper, University of Alberta.

Instefjord, N., 1999, A simple model of market liquidity, *Economics Letters* 64, 329-337.

Jagannathan, R. and Z. Wang, 1998, An asymptotic theory for estimating beta-pricing models using cross-sectional regression, *Journal of Finance* 53, 1285-1309.

Jegadeesh, N., 1990, Evidence of predictable behaviour in security returns, *Journal of Finance* 45, 881-898.

Ji, Y. and W. Yang, 2002, An empirical analysis of determinants of liquidity in the Shanghai stock market, *Journal of Financial Research* 6, 12-21, (in Chinese).

Jiang, T., 2005, The research of liquidity in Chinese stock market, Report of Shenyin Wanguo Security Ltd, PRC, (in Chinese).

Jingu, T. and S. Ri, 2006, Reform to Chinese nontradable shares, Nomura Securities Economic Research, 11 April.

Jones, C., 2002, A century of market liquidity and trading costs, Working Paper, Columbia University.

Jones, C., G. Kaul, and M. Lipson, 1994, Transactions, volume, and volatility, *Review of Financial Studies* 7, 631-651.

Judge, G., W. Griffiths, R. Hill, H. Lutkepohl, and T. Lee, 1985, The theory and practice of econometrics, Wiley, New York.

Jun, S.G., A. Marathe, and H.A. Shawky, 2003, Liquidity and stock returns in emerging equity markets, *Emerging Markets Review* 4, 1–24.

Kamara, A., 1988, Market trading structures and asset pricing: Evidence from the treasury-bill markets, *Review of Financial Studies* 1, 357–375.

Kamara, A., X. Lou, and R. Sadka, 2007, The divergence of systematic liquidity and the cross-section of stock returns, Working Paper, University of Washington Business School.

Kavajecz, K.A., 1999, A specialist's quoted depth and the limit order book, *Journal of Finance* 54, 747-771.

Keene, M.A. and D.R. Peterson, 2007, The importance of liquidity as a factor in asset pricing, *Journal of Financial Research* 30, 91-109.

Kempf, A. and D. Mayston, 2005, Commonalities in the liquidity of a limit order book, Working Paper, Department of Finance and Centre for Financial Research, University of Cologne, Germany.

Kempf, A. and D. Mayston, 2008, Liquidity commonality beyond best prices, *Journal of Financial Research* 31, 25-40.

Korajczyk, R.A. and R. Sadka, 2004, Are momentum profits robust to trading costs? *Journal of Finance* 59, 1039–1082.

Korajczyk, R.A. and R. Sadka, 2008, Pricing the commonality across alternative measures of liquidity, *Journal of Financial Economics* 87, 45-72.

Krinsky, I. and J. Lee, 1996, Earnings announcements and the components of the bid-ask spread, *Journal of Finance* 51, 1523-1535.

Kumar, S. and A. Shah, 2006, Commonality in liquidity of an open electronic limit order book market, Conference Paper, Microstructure of International Financial Markets Winter Research Conference, India.

Kyle, A., 1985, Continuous auctions and insider trading, *Econometrica* 53, 1315-1335.

La Porta, R., F. Lopez-de-Silanes, A. Shleifer, and R.W. Vishny, 1997, Legal determinants of external finance, *Journal of Finance* 52, 1131-1150.

La Porta, R., F. Lopez-de-Silanes, A. Shleifer, and R.W. Vishny, 1998, Law and finance, *Journal of Political Economy* 106, 1113-1155.

Lan, Y., 1997, The stock market in China: Problems and prospects for domestic and foreign investment, Working Paper, Chinese Economies Research Centre, University of Adelaide.

Lee, B., 1992, Causal relations among stock returns, interest rates, real activity, and inflation, *Journal of Finance* 47, 1591-1603.

Lee, C. and M. Ready, 1991, Inferring trade direction from intraday data, *Journal of Finance* 46, 733-746.

Lee, C., B. Mucklow, and M. Ready, 1993, Spreads, depths, and the impact of earnings information: An intraday analysis, *Review of Financial Studies* 6, 345-374.

Lee, C.J. and S. Xue, 2002, Earnings management of loss-firms in China, Working Paper, A.B. Freeman School of Business, Tulane University, New Orleans, USA., and School of Economics and Management, Tsinghua University, Beijing, China.

Lee, K.H., 2005, The world price of liquidity risk, Working Paper, Ohio State University.

Leggett, K., 1999, Foreign investors get a new bridge to Chinese shares, Wall Street Journal. P. C1.

Lehmann, B.N. and D.M. Modest, 1994, Trading and liquidity on the Tokyo Stock Exchange: A bird's eye view, *Journal of Finance* 48, 1595-1628.

Lei, J. and Y. Zheng, 2006, Component analysis of bid-ask spread in the Shanghai stock market, *Systems Engineering* 24, 74-80, (in Chinese).

Lesmond, D.A., 2005, Liquidity of emerging markets, *Journal of Financial Economics* 77, 411 – 452.

Lesmond, D.A., M.J. Schill, and C. Zhou, 2004, The illusory nature of momentum

profits, *Journal of Financial Economics* 71, 349–380.

Lettau, M. and S. Ludvigson, 2001, Consumption, aggregate wealth, and expected stock returns, *Journal of Finance* 56, 815-849.

Li, D.D., 2001, Beating the trap of financial repression in China, *Cato Journal* 21, 77-91.

Li, K., 1994, Financial repression and economic reform in China, Westport: Praeger.

Li, X., 1999, The study on the liquidity of state owned shares and corporate owned shares, *Journal of Economic Research* 1, 53-59, (in Chinese).

Litzenberger, R.H. and K. Ramaswamy, 1979, The effect of personal taxes and dividends on capital asset prices: Theory and empirical evidence, *Journal of Financial Economics* 7, 163-195.

Liu, H., L. Zhong, and C. Wu, 2002, The changes of liquidity between A-shares and B-shares caused by the opening of B-shares for local investors, *Journal of Systems Engineering* 17, 417-423, (in Chinese).

Liu, H., C. Wu, W. Wu, and Z. Chen, 2004, The study on price limits and stock market liquidity, *Systems Engineering Theory Methodology Applications* 13, 20-26, (in Chinese).

Liu, T. and S. Green, 2003, China's informal stock market: How it developed, how it works and how it might grow, Working Paper, Asia Programme, The Royal Institute of International Affairs, London, UK.

Liu, W., 2006, A liquidity-augmented capital asset pricing model, *Journal of Financial Economics* 82, 631-671.

Lo, A. and J. Wang, 2000, Trading volume: Definitions, data analysis, and implications of portfolio theory, *Review of Financial Studies* 3, 257-300.

Longstaff, F.A., 2001, Optimal portfolio choice and the valuation of illiquid securities, *Review of Financial Studies* 14, 407–431.

Longstaff, F.A., 2005, Asset pricing in markets with illiquid assets, UCLA Finance Working Paper 11-04.

Lustig, H., 2001, The market price of aggregate risk and the wealth distribution, Working Paper, Stanford University.

Madhavan, A., 1992, Trading mechanisms in securities markets, *Journal of Finance* 47, 607-641.

Madhavan, A., 2000, Market microstructure: A survey, *Journal of Financial Markets* 3, 205-258.

Madhavan, A., M. Richardson, and M. Roomans, 1997, Why do security prices change? a transaction level analysis of NYSE stocks, *Review of Financial Studies* 10, 1035-1064.

Madhavan, A. and S. Smidt, 1993, An analysis of changes in specialist quotes and inventories, *Journal of Finance* 48, 1595-1628.

Marshall, B.R. and M. Young, 2003, Liquidity and stock returns in pure order-driven markets: Evidence from the Australian stock market, *International Review of Financial Analysis* 12, 173-188.

Martinez, M.A., B. Nieto, G. Rubio, and M. Tapia, 2005, Asset pricing and systematic liquidity risk: An empirical investigation of the Spanish stock market, *International Review of Economics and Finance* 14, 81–103.

Massimb, M.N. and B.D. Phelps, 1994, Electronic trading, market structure and liquidity, *Financial Analysts Journal* 50, 39-50.

McInish, T.H. and R.A. Wood, 1992, An analysis of intraday patterns in bid/ask spreads for NYSE stocks, *Journal of Finance* 47, 753-764.

Mendelson, H., 1982, Market behavior in a clearinghouse, *Econometrica* 50, 1505-1524.

Menyah, K. and K. Paudyal, 2000, The components of bid-ask spreads on the London Stock Exchange, *Journal of Banking and Finance* 24, 1767-1785.

Merton, R.C., 1973, An intertemporal capital asset pricing model, Econometrica 41, 867–887.

Merton, R.C., 1987, A simple model of capital market equilibrium with incomplete information, *Journal of Finance* 42, 483-510.

Mitchell, M. and T. Pulvino, 2001, Characteristics of risk and return in risk arbitrage, *Journal of Finance* 56, 2135–2175.

Mookerjee, R. and Q. Yu, 1995, Capital market reform on the road to a market-oriented economy: The case of stock markets in China, *Journal of Developing Areas* 30, 23-40.

Moore, L. and R. Sadka, 2006, How fundamental is the pricing of liquidity, Working Paper, Northwestern University.

Mortal, S., 2006, Commonality in information asymmetry & its relation to liquidity, Working Paper, Missouri University.

Mu, Q., C. Wu, and H. Liu, 2004, Component analysis of bid-ask spread in the Shenzhen Stock Exchange, *Systems Engineering Theory Methodology Applications* 13, 239-249, (in Chinese).

Mu, Q., H. Liu, C. Wu, and T. Liu, 2004, Costs of liquidity in an order-driven market and analysis of the factors affecting them, *Journal of Shanghai Jiaotong University* 38, 321-325, (in Chinese).

Nam, S.K., K.S. Park, and Y.-K. Kim, 1999, Agenda for capital market reforms in the PRC, in ADB, *A Study of Financial Markets*, Vol. 4: People's Republic of China. Manila: ADB, 68–98.

Newey, W. and K. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703-708.

Nguyen, D., S. Mishra, A. Prakash, and D. Ghosh, 2007, Liquidity and asset pricing under the three-moment CAPM paradigm, *Journal of Financial Research* 30, 379-398.

Nguyen, D. and T.N. Puri, 2007, Systematic liquidity, characteristic liquidity and asset pricing, Working Paper, University of Massachusetts Dartmouth.

O'Hara, M., 1995, Market microstructure theory, Blackwell Publishers: Cambridge.

O'Hara, M., 2003, Presidential address: Liquidity and price discovery, *Journal of Finance* 58, 1335-1354.

O'Hara, M., 2004, Liquidity and financial market stability, Working Paper, Cornell University.

O'Hara, M. and G. Oldfield, 1986, The microeconomics of market making, *Journal of Financial and Quantitative Analysis* 21, 361-376.

Pan, D. and D. Shi, 2004, A comparative study of order aggressiveness between individual and institutional investors, *Management Review* 16, 16-22, (in Chinese).

Park, K.H., Van Agtmael, A.W. (eds.) 1993, The world's emerging stock markets: Structure, developments, regulations and opportunities, Probus Publishing, Chicago, 243-262.

Parker, E., 2000, Firm governance and the Chinese stock market, Working Paper, http://unr.edu/homepage/elliottp/wp/parkerstock2000.pdf.

Pascual, R., A. Escribano, and M. Tapia, 2004, On the bi-dimensionality of liquidity, *The European Journal of Finance* 10, 542 – 566.

Pastor, L. and R. Stambaugh, 2003, Liquidity risk and expected stock returns, *Journal of Political Economy* 111, 642-685.

Patelis, A.D., 1997, Stock return predictability and the role of monetary policy, *Journal of Finance* 52, 1951-1972.

Persand, A., 2000, The puzzling decline in financial market liquidity, in BIS (eds), Market Liquidity: Proceedings of a workshop held at the BIS, BIS Paper 2, 152 – 159.

Piqueira, N.S., 2005, Market liquidity and another look at liquidity risk, Working Paper, Princeton University.

Pistor, K. and C. Xu, 2005, Governing stock markets in transition economics lessons from China, *American Law and Economics Review* 7, 184-210.

Pontiff, J., 1996, Costly arbitrage: Evidence from closed-end funds, *Quarterly Journal of Economics* 111, 1135–1151.

Qin, Y., 2006, Liquidity and commonality in emerging markets, Doctoral Thesis Proposal, Department of Finance and Accounting, School of Business, National University of Singapore, Singapore.

Qu, W., 2006, Properties of stock market microstructure: Current situations in China in international comparison, *Financial Research*, General No. 311, 23-32, (in Chinese).

Qu, W. and S. Wu, 2002, An empirical analysis of the characters in market microstructure of Chinese stock market-the pattern and impacts of bid-ask spread, *Journal of Economics Research* 1, 56-63, (in Chinese).

Rouwenhorst, K.G., 1999, Local return factors and turnover in emerging stock markets, *Journal of Finance* 4, 1439-1464.

Saad, M.M., 2002, Common market makers and commonality in liquidity, PhD Thesis, University of Dalaware.

Saar, G., 2006, Systematic liquidity and learning about the risk premium, Working Paper, Cornell University.

Sadka, R., 2004, Liquidity risk and asset pricing, Working Paper, University of Washington Business School.

Sadka, R., 2006, Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk, *Journal of Financial Economics* 80, 309–349.

Sadka, R. and A. Scherbina, 2007, Analyst disagreement, mispricing, and liquidity, *Journal of Finance* 27, 2367-2403.

Sandas, P., 2001, Adverse selection and competitive market making: Empirical evidence form a limit order market, *Review of Financial Studies* 14, 705-734.

Shanken, J., 1990, Intertemporal asset pricing: An empirical investigation, *Journal of Econometrics* 45, 99-120.

Shi, D. and P. Sun, 2003, Market microstructure: Theory and experience from China, Shanghai Sanlian Bookshop, (in Chinese).

Shleifer, A. and R.W. Vishny, 1997, A survey of corporate governance, *Journal of Finance* 52, 737-783.

Sims, C.A., 1992, Interpreting the macroeconomic time series facts: The effects of monetary policy, *European Economic Review* 36, 975-1000.

Sims, C.A. and T.A. Zha, 1998, Does monetary policy generate recessions? Working Paper, Federal Reserve Bank of Atlanta.

Smidt, S., 1971, Which road to an efficient stock market: Free competition or regulated monopoly, *Financial Analysts Journal* 27, 18-20, 64-69.

Song, F., 2002, The development of the Chinese stock markets, Working Paper, Centre for China Financial Research & School of Economics and Finance, University of Hong Kong.

Song, F. and H. Tan, 2005, Commonality in liquidity on an order-driven market: An empirical study on Chinese stock market, *Collected Essays on Finance and Economics* 3, 63-69, (in Chinese).

Song, F. and J. Tang, 2002, Information transmission and liquidity demand in the Chinese stock market, *Economic Science* 2, 46-57, (in Chinese).

Stahel, C.W., 2005a, Is there a global liquidity factor? Working Paper, George Mason University.

Stahel, C.W., 2005b, Liquidity across developed and emerging markets? Working Paper, George Mason University.

Stoll, H., 1978a, The supply of dealer services in securities markets, *Journal of Finance* 33, 1133-1151.

Stoll, H., 1978b, The pricing of security dealer services: An empirical study of NASDAQ stocks, *Journal of Finance* 33, 1153-1172.

Strongin, S., 1995, The identification of monetary policy disturbances: Explaining the liquidity puzzle, *Journal of Monetary Economics* 35, 463-497.

Su, D., 2003, Chinese stock markets: A research handbook, World Scientific Publishing Co. Pre. Ltd.

Su, D., 2004, The research for the liquidity and execution costs in Chinese stock market, *Science of Economics* 2, 44-54, (in Chinese).

Sujoto, C., P.S. Kalev, and R.W. Faff, 2005, An examination of commonality in liquidity: New evidence, long-run effects and non-linearities, Working Paper, Department of Accounting and Finance, Monash University.

Sun, P. and C. Yang, 2002, Liquidity, trading activities and bid-ask spread: An empirical study based on the Shanghai stock market, *Shanghai Management Science* 26-28, (in Chinese).

Sun, P. and D. Shi, 2002, Market microstructure, liquidity and bid-ask spread: An empirical study based on the Shanghai Stock Exchange, *International Economics* 4, 69-72, (in Chinese).

Sun, Q. and W.H.S. Tong, 2000, The effect of market segmentation on stock prices: The China syndrome, *Journal of Banking and Finance* 24, 1875-1902.

Sun, Y., 2006, An analysis of components of bid-ask spread in order-driven markets, *Commercial Research* 19, 141-144, (in Chinese).

Sun, Z., 2007, Clustered institutional holdings and stock comovement, Working Paper, New York University.

Tan, L., 2005, Empirical analysis of Chinese stock market behaviour: Evidence from dynamic correlations, herding behaviour, and speed of adjustment, PhD Thesis, Drexel University.

Tenev, S. and C. Zhang, 2002, Corporate governance and enterprise reform in China: Building the institution of modern market, World Bank and International Finance Corporation, Washington D.C.

The Chinese Securities and Futures Statistical Year Book, 2001.

Theissen, E., 2000, Market structure, informational efficiency and liquidity: An experimental comparison of auction and dealer markets, *Journal of Financial Markets* 3, 333-363.

Thorbecke, W., 1997, On stock market returns and monetary policy, *Journal of Finance* 52, 635-654.

Tian, G. and M. Guo, 2006, Interday and intraday volatility: Additional evidence from the Shanghai Stock Exchange, *Review of Quantitative Finance and Accounting* 28, 287-306.

Tinic, S.M., 1972, The value of time preferences and the behaviour of liquidity costs in the New York Stock Exchange, PhD Thesis, Cornell University.

Tinic, S.M. and R. West, 1972, The economics of liquidity services, *Quarterly Journal of Economics* 86, 79-83.

Tkac, P.A., 1999, A trading volume benchmark: Theory and evidence, *Journal of Financial and Quantitative Analysis* 34, 89-114.

Trading Rules of Shanghai Stock Exchange, Shanghai, PRC, 2006.

Vayanos, D., 2004, Flight to quality, flight to liquidity and the pricing of risk, Working Paper, LSE.

Vayanos, D. and J.L. Vila, 1999, Equilibrium interest rate and liquidity premium with transaction costs, *Economic Theory* 13, 509-539.

Vayanos, D. and T. Wang, 2007, Search and endogenous concentration of liquidity in asset markets, *Journal of Economic Theory* 136, 66-104.

Veldkamp, L.L., 2006, Information markets and the comovement of asset prices, *Review of Economic Studies* 73, 823-845.

Wan, G., C. Yuan, and S. Ha, 2005, Non-tradable to tradable-reforming the stock markets in the PRC, Linklaters, September.

Wan, S., 2006, Measurement of liquidity of the Shanghai stock market and analysis of its determinants, *Theory and Practice of Systems Engineering* 2, 1-9, (in Chinese).

Wang, F. and Y. Xu, 2004, What determines Chinese stock returns? *Financial Analysts Journal* 60, 65-77.

Wang, M., L. Zu, and C. Kuo, 2007, Anatomy of bid-ask spread: Empirical evidence from an order-driven market, Working Paper, National Sun Yat-Sen University.

Wang, T., 2002, The asymmetric information in Chinese stock market, Working Paper, Renmin University, China, (in Chinese).

Wang, Z. and P. Chen, 2006, An estimation and analysis of the adverse selection component of bid-ask spread in the Shengzhen market, *Herald of Securities Market* 2, 65-70, (in Chinese).

Wang Z, Y. Zeng, and P. Li, 2005, The analysis of the price behavior under periodic auction and continuous auction trading mechanism, *Systems Engeneering Theory Methodology Applications* 14, 17-22, (in Chinese)

White, H., 1980, A heteroscedasticity consistent covariance matrix estimator and a direct test of heteroscedasticity, *Econometrica* 48, 817–838.

Wong, S.M.L., 2005, A marriage of capitalism and socialism: The case of China's stock market development, Working Paper, Hong Kong Institute of Economics and Business Strategy, Faculty of Business and Economics, The University of Hong Kong, Pokfulam Road, Hong Kong.

World Bank, 1995, China: The emerging capital market I and II, New York.

Wu, C., Y. Feng, H. Liu, W. Wu, R. Xu, L. Zhong, and Q. Mu, 2003, The research for the liquidity in Shenzhen stock market, Research report of Shenzhen Stock Exchange, Shenzhen, PRC, (in Chinese).

Wu, W. and Y. Wang, 2005, Investment with restricted stock and the value of information, *Applied Mathematics and Computation* 163, 811-824.

Wugler, J., 2000, Financial markets and the allocation of capital, *Journal of Financial Economics* 58, 187-214.

Xie, J., 2006, New development in the study of market microstructure theories, *Journal of Chongqing University (Social Science Edition)* 12, 34-39, (in Chinese).

Xu, B. and J. Chen, 2004, An analysis of determinants of liquidity of stock markets, *Today's Science and Technology* 7, 24-26, (in Chinese).

Xu, C.K., 2000, The microstructure of the Chinese stock market, *Chinese Economic Review* 11, 79-97.

Xu, R., 2006, Price formation mechanism in order-driven markets, *Systems Engineering: Theoretical Methodology Applications* 15, 519 – 523, (in Chinese).

Xu, R., Y. Feng, and C. Wu, 2004, Policies and factors affecting liquidity of Chinese A-share market, *Journal of Shanghai Jiaotong University* 38, 362-367, (in Chinese).

Xu, R., H. Liu, and C. Wu, 2004, The statistical characteristic and trend of liquidity in Chinese A share market, *Theory and Practice of Systems Engineering* 3, 26-32, (in Chinese).

Xu, Y., 1993, China, in Keith K.H. Park & Antoine W. Van Agtmael (eds.), The world's emerging stock market: Structure, developments, regulation and opportunities, Probus Publishing Co., Chicago, 243-262.

Yang, C., P. Sun, and D. Shi, 2002, Microstructure, market depth, and asymmetric information, *World Economy* 11, 53 – 58, (in Chinese).

Yang, J. and F. Jiang, 2002, An empirical study of the explanatory factors to the cross-sectional expected returns in China's stock market, *Journal of Shanghai Jiaotong University* 38, 326-329, (in Chinese).

Yang, Z., Z. Li, and F. Liu, 2002, Ownership structure, bid-ask spreads, and market liquidity: Evidence from Chinese stock markets, Working Paper, Tsinghua University.

Ying, Z., 2001, The research for market liquidity in Chinese stock market, *The Newspaper of Security Market* 7, 63-68, (in Chinese).

Yuan, C., 2005, New proposals on the desegregation of shares, Linklaters, May.

Zabel, E., 1981, Competitive price adjustment without market clearing, *Econometrica* 49, 1201-1221.

Zhang, F., Y. Tian, and T.S. Wirjanto, 2007, Liquidity risk and cross-sectional returns from the Chinese stock markets, Working Paper, University of British Columbia.

Zheng, X. and Z. Zhang, 2006, Commonality in liquidity in emerging markets: Evidence from the Chinese stock market, Working Paper, University of Durham.

Zhou, W. and D. Sornette, 2004, Antibubble and prediction of China's stock market and real-estate, *Physica A: Statistical and Theoretical Physics* 337, 243-268.

Zhuang, X. and Y. Liu, An empirical analysis of liquidity of the Chinese stock market, *Southern Economy* 2, 71-79, (in Chinese).