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ABSTRACT

In this paper, using data for the period January 1995 to May 2009 for the Shanghai stock exchange (SHSE), we show that aggregate illiquidity is a priced risk factor. We develop the relationship between the illiquidity factor, asymmetric information, and market collapse. Our empirical results show that while the illiquidity factor is a source of asymmetric information on the SHSE, asymmetric information does not trigger a market collapse.

Keywords: Illiquidity Factor; Asymmetric Information; Market Collapse.

1. Introduction

The literature on the illiquidity or liquidity situation of a firm has mainly examined its impact on stock returns (Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005; Martinez *et al*., 2005). For assets that react strongly to changes in market-wide liquidity crises, illiquidity will lead to higher extra expected returns from investors, and investors are likely to require a systematic liquidity premium (Amihud, 2002; Huang and Wang, 2009).

Another group of studies has focused on the impact of illiquidity directly on share prices (Amihud and Mendelson, 1986; Vayanos, 2004). Amihud and Mendelson (1986), for instance, argue that liquidity-based spread is a transaction cost for traders. When liquidity increases, transaction costs (spread) decrease, so share prices will increase as a result. On the other hand, illiquidity will decrease share prices because it causes the price discount, which is the present value of the expected stream of transaction costs through its lifetime.

Vayanos (2004) establishes the link between illiquidity and share prices, and argues that illiquidity, by virtue of increasing volatility of share prices, decreases share prices. He demonstrates that during volatile times, assets' liquidity premium increases; as a result, investors become more risk averse.

Despite the relevance of illiquidity in understanding stock market performance, the literature on the illiquidity factor and stock market collapse is limited. Three studies stand out in this regard. Persand (2000) argues that 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.

Fernando and Herring (2008) posit that markets can collapse for two reasons. The first is the bursting of a bubble of an asset's price and the other concerns the substantial information asymmetry about market fundamentals. However, they point out the possibility of a market collapse even in the absence of these two conditions. They show that common liquidity shocks may precipitate a shift in investors' beliefs about the market, which in turn could lead to a market collapse.

Huang and Wang (2009) use a general equilibrium model to link stock market liquidity and its impacts on asset prices. They find that if there are complete matching agents' trading needs in the market, then endogenous order imbalances and the need for liquidity will increase. The endogenous liquidity needs will cause excessive selling in the market, which can lead to market collapse.

One feature of the three studies discussed here is that they are all theoretical in nature. In other words, none of the studies in this literature have empirically examined the relationship between asymmetric information and market collapse. In light of the dearth of research on this topic, our paper makes three contributions to this literature. First, our research question: Is the illiquidity factor a priced risk factor in the Chinese stock market? is new, and thus provides fresh insights from the Chinese stock market. We find that the illiquidity factor is a priced risk factor in the Chinese stock market. Second, we specifically explore the empirical relationship between asymmetric information (proxied by the number of trades)

and the illiquidity factor based on the asset pricing model. We find that the illiquidity factor is a source of asymmetric information on the Chinese stock market.

Third, this is the first paper in this literature which provides a direct test for the relationship between asymmetric information and market collapse, where the latter is proxied by stock returns. To achieve this, we use the Fama-French three factor model and find that asymmetric information only has a statistically significant negative effect on stock returns in around 11% of cases. This implies very weak evidence of asymmetric information causing market collapse on the Chinese stock market. We explain why this is likely to be the case.

The rest of the paper is organised as follows. Section 2 briefly discusses the data used in this paper and considers some preliminary empirical evidence. Section 3 contains the empirical results showing that the illiquidity factor is a priced risk factor on the Chinese stock market. Section 4 describes the conceptual relationship between market collapse, the illiquidity factor, and asymmetric information, while section 5 provides some concluding remarks.

2. Data and Some Preliminary Empirical Evidence

The data is collected from the China Stock Market and Accounting Research (CSMAR) database. We use individual daily and monthly returns for all stocks traded on the Chinese continuous market from January 1995 to May 2009. The data series relate to the Shanghai Stock Exchange (SHSE), which is the main

stock exchange in China.

The market return variable is an equally weighted portfolio comprising of all sample stocks available in a given month or on a particular day. For the risk-free rate of return, we use the Chinese 1-year Time Deposit Rate. Using all the individual stocks, we follow Martinez *et al*. (2005) to construct 20 portfolios, i.e. 10 portfolios for liquidity measure. In addition, we form 10 traditional portfolios according to market value.

Following the methods proposed by Martinez *et al*. (2005), several proxies are used for risk factors, which we include in different asset pricing models. For the size variable in the Fama–French three-factor model, risk is proxied by the market value, based on the number of shares of each firm in December multiplied by their price at the end of each month in the following year. The SMB (returns of small-size portfolios minus returns of big-size portfolios) and HML (returns of high book-to-market portfolios minus returns of low book-to-market portfolios) variables for the Fama-French portfolios are calculated according to the market value of each firm, based on its total market capitalisation value in the previous month. We divide our sample stocks into three groups based on the total market capitalisation value in the previous month. These are the smallest 30% of stocks (S); 30% of stocks in the middle range (M); and the largest 30% of stocks (B). The sample stocks are also divided into two groups, namely largest 50% (H) and lowest 50% (L), based on the book-to-market ratio in the last month of the previous year. This leads to six different portfolios: (S, L), (S, H), (M, L), (M, H),

(B, L) and (B, H), and the average returns for these portfolios are denoted as P1, P2, P3, P4, P5, and P6, respectively. So, now SMB = (P1 + P2)/2 - (P5 + P6)/2 and HML = (P2 + P4 + P6)/3 - (P1 + P3 + P5)/3. We use the arithmetic mean of the BM ratio as the state variable in the conditional asset pricing model.

In order to have a necessary minimum number of observations, sample stocks need to have a return history of at least 36 months to the end of May 2009 (Eun and Huang, 2007). Therefore, we only include stocks with a minimum of 36 monthly return observations so that the test period can be at least 12 months. Some of the parameters, for example, the total risk, are estimated using returns on a 24-month rolling window, following the approach adopted by Eun and Huang (2007)[1].

The descriptive statistics of the variables are reported in Table 1. In particular, we report the mean value, volatilities, and other related characteristics of market returns, including the Fama–French factors. In addition, the table also contains the descriptive statistics of liquidity-based risk proxy, which is the Illiquidity Factor (ILLQ)—estimated using the approach suggested by Amihud (2002).

INSERT TABLE 1

From Amihud (2002), the price impact for stock i in month t, $illq_{i,t}$, is given by the average daily ratio of absolute return to Yuan volume over the month:

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[1] 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.

$$illq_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} |r_{i,d,t}| / V_{i,d,t} \quad (1)$$

$r_{i,d,t}$ and $V_{i,d,t}$ are the return and the Yuan volume (in millions of Yuans) for stock i on day d in month t. $D_{i,t}$ is the number of observations for stock i in month t. $illq_{i,t}$ is computed for stocks with at least 15 observations on return and volume during the month.

In order to make the series stationary, we multiply the original measure by a scaling factor which is from Acharya and Pedersen (2005), m_t/m_1, where m_t is the total Yuan value at the end of month t-1 of the stocks included in the cross-sectional average in month t and m_1 is the corresponding value for January 1995. The scaled market-wide price impact for month t, $ILLQ_t$, is given by:

$$ILLQ_t = (m_t/m_1) \cdot (1/N_t) \sum_{i=1}^{N_t} illq_{i,t} \quad (2)$$

N_t is the number of available stocks at month t.

As can be seen, these liquidity-based risk factors exhibit relatively large abnormalities. The SMB and HML market-wide measures have left-skewed distributions on the SHSE. In general, correlation coefficients are low. In contrast to Martinez *et al*. (2005) and Liu (2006), we do not find a relatively high positive correlation between ILLQ and HML. More in line with our expectations, we find that market returns are negatively related to ILLQ, which is consistent with the

findings from Liu (2006).

Next, based on the year-end market value of each stock, we construct 10 portfolios, sorted according to their size. The portfolios range from MV1 (smallest) to MV10 (largest). Table 2 presents the average descriptive statistics of these portfolios. Returns on these portfolios are to be used to test the asset pricing models with illiquidity factor. The volatilities of these portfolios' returns are more or less consistent with expectations: the greatest volatility is experienced by stocks with smallest capitalisations. Furthermore, consistent with the findings of Martinez *et al*. (2005), we also find that on the SHSE, stocks with a greater possibility of return reversals increase when the level of liquidity declines.

INSERT TABLE 2

For the ILLQ betas, our results differ from that of both Martinez *et al*. (2005) and Liu (2006), in that we do not find a large difference in average returns between ILLQ1 and ILLQ10. However, there is a clear monotonic relation in our results between the average returns and the sensitivity of returns to the ILLQ factor. Moreover, average returns of stocks that are negatively sensitive to ILLQ are higher than the average returns of stocks that are positively sensitive to the ILLQ. But the differences are much smaller than that reported in Martinez *et al*. (2005) and Liu (2006).

In addition, we find significant liquidity betas only for extreme portfolios and in response to shocks to market liquidity. The ILLQ1 stocks move in opposite directions compared with the ILLQ10 stocks. This is similar to the findings of

Martinez *et al*. (2005).

3. Pricing Illiquidity Factor

In testing for whether the illiquidity factor is a priced risk factor on the Chinese stock market, we follow Martinez *et al*. (2005). They 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 we employ, 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 average returns on ILLQ10 and ILLQ1 portfolios should be significantly positive, when market risks are accounted for (Martinez *et al*., 2005). This testing strategy can also be found in Pastor and Stamburgh (2003) and Chen (2005).

Following Martinez *et al*. (2005), three alternative pricing models are used for the tests. They are the traditional CAPM model, the modified CAPM model that incorporates the illiquidity factor, and the Fama–French three-factor model. In Table 3, we report different alphas for each year between January 1995 and May 2009.

INSERT TABLE 3

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 models. The liquidity based CAPM, which includes the ILLQ factor, contains the highest absolute value of the liquidity premium. This finding, we notice, is consistent with Martinez *et al*. (2005). We, however, notice that the difference between the liquidity premium (the positive alpha) in the CAPM and other liquidity-based models is not as high as in the case of Martinez *et al*. (2005). The implication of this is 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 consistent with Martinez *et al*. (2005) for the Spanish stock market and Liu (2006) for the American NYSE/AMEX markets.

4. Market Collapse: Conceptual Framework and Motivation

It is now well established that a market will not function properly if information about asset price is not homogenous among investors; that is, there exists asymmetric information about asset prices. This can be seen from the models of Glosten and Milgrom (1985) and Bhattacharya and Spiegel (1991). Glosten and Milgrom (1985) show that the bid-ask price will increase with an increase in information asymmetry and the degree of uncertainty regarding the 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 the volume.

Bhattacharya and Spiegel (1991) argue that the main reason for the market

collapse is that outsiders refuse to trade with insiders because the high asymmetric information potentially gives insiders more opportunities for hedging, which can result in losses for outsiders.

Asymmetric information prompts traders to use different dynamic trading strategies to measure market conditions. But uninformed traders often cannot detect that price changes are caused by insider trading. Informed traders hold the private information and they always make profits earlier than uninformed traders (Kyle, 1985). Even market makers will lose money from informed traders. Actually, informed traders split their insider information behind noise traders across time, which can ensure long-run profits. It follows that the price goes up initially, but as the level of asymmetric information increases, price correction will occur, leading to compensations from the uninformed traders. The relatively large price changes have a higher probability of inducing a market collapse.

In the event of a bad news, the price of the stock will decline. In this case, investors will be more risk averse and will refrain from holding risky stocks. They will sell their stocks, which will reduce prices. Due to the price reduction, the market lacks the capacity to provide funds for submitting new orders; as a result, a market collapse will eventuate (Grossman, 1988).

Before we discuss the relationship between asymmetric information and bubbles, let us define a bubble. A bubble will eventuate when an asset price is larger than its fundamental value. Large changes in prices are caused by shifts in the

fundamental values (LeRoy and Porter, 1981; Shiller, 1989). Normally, the fundamental value of an asset is difficult to determine but it can be sorted out by the asymmetric information. Gennotte and Leland (1990) point out that the price drop is a bad signal for the fundamental value of a stock because traders hold asymmetric information for the value of the stock. When this happens, there are more uncertainties for dynamic hedging strategies because uninformed traders perceive that the insider information has been combined into the fundamental value, which thus does not reveal the real price of assets. As a result, they will sell their assets quickly, which will reduce the price of assets. The market position can worsen when other market participants begin to sell their shares because more and more traders perceive that due to insider information, asset prices are distorted.[2]

In addition, Allen *et al.* (1993) find strong presence of bubbles if each trader has private information; that is, if information is heterogeneous. In other words, strong bubbles will not arise if there is common knowledge in the market. On the other hand, a bursting bubble can cause a market collapse. A bursting bubble means an excessive asset price rise before the crash. It seems all market traders have the common knowledge in the market and they believe they can sell assets at a very high price but others cannot. Each trader will have a different level of asymmetric information; in other words, among traders heterogeneity will exist in terms of the degree of asymmetric information. When this asymmetric information is aggregated (that is for the market as a whole), the effect on asset price can be

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[2] Michayluk and Neuhauser (2008) point out that the bubble can be observed in internet trading. Asymmetric liquidity can be estimated during the peak of internet bubble as well as before and after the bubble.

relatively more severe, sufficient to cause the market to crash. In this sense, bursting bubbles can cause market collapse with asymmetric information rather than bubbles themselves; for related discussion, see Allen *et al*. (1993), Allen and Gale (1994) and Brunnermeier (2001).

In view of the important relationship between time-varying information asymmetry and the liquidity (Brockman and Chung, 2002), there may be asset price bubbles based on market-wide information asymmetry component, which can explain firm level information asymmetry and illiquidity. Barclay and Warner (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 number of trades and asymmetric information.

Jones *et al*. (1994) show that it is the transactions *per se*, rather than their volume, that generate 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) argue that the number of trades rather than the trade size can be used as an indicator of asymmetric information.

Based on the discussion so far, in formulating our empirical model, we use the number of trades as the measure of asymmetric information. Essentially, our empirical objective is to model the impact of a priced liquidity risk factor (ILLQ)

on the number of trades (our measure of asymmetric information). It follows that our main hypothesis here is that the liquidity risk factor increases asymmetric information. To control for market volatility, we also include the market returns variable in our proposed model. The estimable model has the following form:

$$NTrades_{J,t} = \alpha + \theta ILLQ + \delta Return_{M,t} + \varepsilon_{J,t} \quad (3)$$

where $NTrades_{J,t}$ is the total number of trades for firm J during the trading day t as a measure of transaction frequency. $ILLQ$ is the priced factor of liquidity in the sample. $Return_{M,t}$ is the equally weighted average of the daily return for all firms which can control the volatility in the market; similar control variables have been used by Chordia $et\ al.$ (2000). The results for model are presented in Table 4. On the SHSE, from the time-series regressions, the number of market-wide concurrent coefficient that is positive and significant accounts for 63.5% of total estimates. Given that the number of trades is a reliable indicator of informed trading, as argued earlier, these results suggest that there is a common component in the number of trades, implying the illiquidity factor is an important factor for explaining asymmetric information.

INSERT TABLE 4

So far, we have ascertained an indirect relationship between the illiquidity factor and market collapse through the asymmetric information channel. However, the direct impact of asymmetric information on market collapse is of the main interest. Alas, this relationship has not been tested in this literature so far. In what follows,

we make a first attempt at testing the direct relationship between asymmetric information and market collapse. We have already defined asymmetric information, now in order to model its impact on market collapse (or survival), we need to define market collapse. This is simple: we define market collapse by the stock returns. It follows that if asymmetric information (that is, the number of trades) has a statistically significant negative effect on stock returns, then this implies market collapse. On the other hand, if asymmetric information has a statistically significant positive effect on stock returns, then this can be perceived as asymmetric information-led growth in stock returns. In order to test this relationship, we augment the conventional Fama-French model with our asymmetric information proxy variable. We, thus, propose the following model:

$$Return_{J,t} = \alpha + \gamma_1(Return_{M,t} - Return_f) + \gamma_2 SMB_{J,t} + \gamma_3 HML_{J,t} + \gamma_4 NTrades_{J,t} + \varepsilon_{J,t\,t} ,(4)$$

where $Return_{M,t}$ is the market return of SHSE at time t; $Return_f$ is the risk free rate which is the Chinese 1-year Time Deposit Rate; $SMB_{J,t}$ is the returns of small-size portfolios minus returns of big-size portfolios at time t; $HML_{J,t}$ is the returns of high book-to-market portfolios minus the returns of low book-to-market portfolios at time t; and $NTrades_{J,t}$ is the total number of trades, our proxy for asymmetric information, for firm J during the trading day t.

The null hypothesis is that asymmetric information has a statistically significant negative effect on stock returns. A statistically significant and negative relationship provides direct evidence of market collapse induced by asymmetric information. Our interest is only on this relationship; hence, to conserve space, we

only report results relating to this hypothesis. The results are presented in Table 5[3].

We find the coefficient on the asymmetric information variable to be negative and statistically significant for 11.40% of the time and positive and statistically significant in 6.96% of cases. This low number of significant (and negative) cases implies that asymmetric information has weak effects for market returns when we control for the Fama-French three factors. On the basis of this result, we can conclude that on the Chinese stock market, asymmetric information does not contribute to a market collapse. There are several reasons for this, as we explain next. It seems that the Chinese stock markets impressive growth has been achieved against this backdrop of a market exposed to asymmetric information. Some sources of asymmetric information are as follows. First, Chinese firms do not 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 *et al*., 2008).

Second, for a significantly long period of time, A-shares could only be purchased and traded by domestic investors. A feature of these investors was that they possessed very weak knowledge and experience in investments. They also likely suffer from imperfect information (Chen *et al*., 2007). Beginning in 2002, China launched a program of Qualified Foreign Institutional Investors (QFII) under which overseas investors could invest in and trade Chinese A-shares through qualified institutional investors. This marked an important step towards opening

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[2] We only report the results for the asymmetric information. The results for Fama-French three factors are available upon request.

the Chinese share market and reducing market segmentation.

Third, foreign investors in China pay much less than domestic investors for intrinsically identical shares (Gordon and Li, 2003). This implies price asymmetry. Fourth, trading on the Chinese stock market is restricted to the local currency, the Renminbi (RMB) (Tan et al., 2008). This implies that sources of asymmetry emanating from the Chinese exchange rate market, for instance, could transmit to the financial market (see, for instance, Feng and Alon, 2007).

Fifth, in a recent study, Tan *et al*. (2008) test the herding behavior by A-share investors on the SHSE. They find that the market displays strong asymmetric characteristics; that is, herding behavior is higher when (a) stock markets are performing well, (b) trading volume is high, and (c) market volatility is high.

Sixth, on average, individual hold only one-third of outstanding shares, while two-thirds are held by government entities. This greater market power enables government entities to act as controlling insiders, making corporate decisions that could possibly infringe upon the rights of individual shareholders (Eun and Huang 2007: 454). A common institutional weakness of the Chinese stock market is that shareholders rights are not well established in China, reflecting in large part opaque corporate governance and weak legal enforcement (Eun and Huang, 2007). China did not have well established securities laws until 1999, while a code of corporate governance for listed firms only came into effect in 2002 (Fong, 2009).

5. Concluding Remarks

This paper attempts to investigate three related issues: (a) whether liquidity risk premium is priced in the Chinese stock market, (b) the role of the illiquidity factor in generating asymmetric information, and (c) whether asymmetric information causes market collapse. We consider these empirical issues by utilizing data for the period January 1995 to May 2009 relating to the Shanghai stock exchange (SHSE).

Our main findings can be summarized as follows. First, we find systematic differences in the market risk-adjusted average returns of our liquidity-beta-sorted portfolios because the liquidity risk factors are priced in the Chinese market. Using three alternative pricing models: the traditional CAPM, Fama-French model, and the CAPM liquidity-based models constructed by augmenting the with the liquidity factor (ILLQ), we find differences in alphas for each year between January 1995 and May 2009. Our results show that the liquidity risk premium only exists for the ILLQ factor.

Second, the literature suggests that asymmetric information is an important determinant of asset price bubbles. Following this line of research and based on the priced common liquidity (ILLQ), we directly test the hypothesis that commonality in liquidity induces asymmetric information, and find this to be the case on the SHSE. Since theoretically it has been shown that the greater the level of asymmetric information, the greater the probability of a market collapse, in the final exercise we, for the first time in this literature, test the relationship between

asymmetric information and market collapse. We find that, contrary to the theoretical conjecture, asymmetric information has a very weak effect on market returns on the SHSE: we find that in only around 11% of cases asymmetric information has a statistically significant negative effect on market returns. This finding sheds critical light on the working of the Chinese stock market, in that asymmetric information is a particularly severe problem in China. Chinese firms tend to disclose only incomplete or even biased information about their business. Moreover, in the marketplace share manipulation and insider trading are pervasive. In this environment, while our results show that the illiquidity factor is a source of asymmetric information, asymmetric information does not induce the market collapse.

REFERENCES

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

Allen, F. and D. Gale, 1994, Financial innovation and risk sharing, MIT Press, Cambridge, MA.

Allen, F., S. Morris, and A. Postlewaite, 1993, Finite bubbles with short sale constraints and asymmetric information, *Journal of Economic Theory* 61, 206-229.

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

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

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'.

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

Bhattacharya, U. and M. Spiegel, 1991, Insiders, outsiders and market breakdowns, *Review of Financial Studies* 4, 255-282.

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

Brunnermeier, M.K., 2001, Asset pricing under asymmetric information, Oxford University Press, New York.

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.

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

Chen, G.M., A.K. Kim, J.R. Nofsinger and O.M. Rui, 2007, Trading performance, disposition effect, overconfidence, representativeness bias, and experience of emerging market investors, *Journal of Behavioral Decision Making*, 20, 425-451.

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

Coughenour, J.F. and M.M. Saad, 2004, Common market makers and commonality in liquidity, *Journal of Financial Economics* 73, 37-69.

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.

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.

Feng, X., and I. Alon, 2007, Chinese RMB exchange rate and local currency price stability in ASEAN trade, *China Economic Review* 18, 417-424.

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., R.J., Herring and A., Subrahmanyam, 2008, Common liquidity shocks and market collapse: Lessons from the market for perps*, *Journal of Banking and Finance* 32, 1625-1635.

Fong, W.M., 2009, Speculative trading and stock returns: A stochastic dominance analysis of the Chinese A-share market, *Journal of International Financial Markets, Institutions and Money* 19, 712-727.

Gennotte, G. and H. Leland, 1990, Market liquidity, hedging, and crashes, *American Economic Review* 80, 999-1021.

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.

Grossman, S.J., 1988, An analysis of the implications for stock and futures price volatility of program trading and bynamic hedging strategies, *Journal of Business* 61, 275-298.

Huang, J. and J. Wang, 2009, Liquidity and market crashes, *Review of Financial Studies* 22, 2607-2643.

Jones, C.M., G. Kaul and M.L. Lipson, 1994, Transactions, volume and volatility, *Review of Financial Studies* 7, 631-651.

Komáromi, G., 2004, Was there a stock market bubble in Hungary? *Competitio* 3, 169-178.

Kyle, A., 1985, Continuous auctions and insider trading, *Econometrica* 53, 1315-1335.

LeRoy, S.F. and R.D. Porter, 1981, The present value relation: Tests based on implied variance bounds, *Econometrica* 64, 555-574.

Lipson, M.L., 2003, Market microstructure and corporate finance, *Journal of Corporate Finance* 9, 377-384.

Liu, W., 2006, A liquidity-augmented capital asset pricing model, *Journal of Financial Economics* 82, 631-671.

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.

Michayluk, D. and K. Neuhauser, 2008, Is liquidity symmetric? A study of newly listed internet and technology stocks, *International Review of Finance* 8, 159–178.

Mortal, S., 2006, Commonality in information asymmetry & its relation to liquidity, Working Paper, Missouri University.

Newey, W. and K. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703-708.

Pastor, L. and R. Stambaugh, 2003, Liquidity risk and expected stock returns, *Journal of Political Economy* 111, 642-685.

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.

Shiller, R.J., 1989, Market volatility, MIT Press, Cambridge, MA.

Tan, L., T.C. Chiang, J.R. Mason and E. Nelling, 2008, Herding behavior in Chinese stock markets: An examination of A and B shares, *Pacific Basin Finance Journal* 16, 61-77.

Vayanos, D., 2004, Flight to quality, flight to liquidity and the pricing of risk, Working Paper, LSE.

White, H., 1980, A heteroscedasticity consistent covariance matrix estimator and a direct test of heteroscedasticity, *Econometrica* 48, 817–838.

Table 1: Descriptive Statistics for Risk Factors

Risk factor	Average return	Volatility	Skewness	Excess kurtosis
Market Returns (RM)	0.23	0.96	0.903	1.588
Small – Big Factor (SMB)	-0.76	0.51	-1.698	8.473
High – Low Factor (HML)	-0.35	0.65	-0.917	3.970
Illiquidity Measure (ILLQ)	0.24	0.93	1.316	3.712
	RM	SMB	HML	ILLQ
Market Returns (RM)	1.000	0.040	-0.132	-0.091
Small – Big Factor (SMB)		1.000	0.208	0.019
High – Low Factor (HML)			1.000	-0.153
Illiquidity Measure (ILLQ)				1.000

Notes: This table presents the descriptive statistics of the liquidity risk factors on the Chinese Stock Exchange during the January 1995 to May 2009 period.

Table 2: Summary Statistics for Portfolios of Stocks on the Shanghai Market

Portfolios	Average return	Volatility	ILLQ beta (t statistic)
Portfolio based on Illiquidity Measure (ILLQ1)	0.40	1.16	-0.341 (-9.91)
Portfolio based on Illiquidity Measure (ILLQ2)	0.20	0.86	-0.880 (-12.60)
Portfolio based on Illiquidity Measure (ILLQ3)	0.24	1.10	-0.567 (-11.22)
Portfolio based on Illiquidity Measure (ILLQ4)	0.24	1.15	-0.343 (-9.52)
Portfolio based on Illiquidity Measure (ILLQ5)	0.22	0.92	-0.157 (-4.65)
Portfolio based on Illiquidity Measure (ILLQ6)	0.21	0.89	0.375 (4.42)
Portfolio based on Illiquidity Measure (ILLQ7)	0.21	0.93	0.879 (4.33)
Portfolio based on Illiquidity Measure (ILLQ8)	0.24	0.96	1.613 (4.34)
Portfolio based on Illiquidity Measure (ILLQ9)	0.23	0.87	3.454 (6.10)
Portfolio based on Illiquidity Measure (ILLQ10)	0.23	0.84	10.520 (6.83)
Portfolio based on Market Value (MV1)	0.36	1.16	-0.181 (0.52)
Portfolio based on Market Value (MV2)	0.25	0.95	-0.069 (-0.33)
Portfolio based on Market Value (MV3)	0.22	0.93	-0.436 (-0.89)
Portfolio based on Market Value (MV4)	0.21	0.88	-1.213 (-1.56)
Portfolio based on Market Value (MV5)	0.21	0.92	-1.036 (-2.32)
Portfolio based on Market Value (MV6)	0.22	0.86	-0.866 (-2.14)
Portfolio based on Market Value (MV7)	0.22	0.92	-0.714 (-1.90)
Portfolio based on Market Value (MV8)	0.17	0.85	-3.102 (-2.32)
Portfolio based on Market Value (MV9)	0.15	0.84	-4.220 (-1.93)
Portfolio based on Market Value (MV10)	0.18	0.88	-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 May 2009.

Table 3: Differences between Alphas of Extreme Portfolios sorted on Aggregate Liquidity and Market Value January 1995-May 2009

(A) Liquidity-sorted portfolios			
	Alpha ILLQ10-alpha ILLQ1		
	Value	χ² Test	P value
CAPM alpha	0.04	1.676	0.030
Fama-French alpha	0.01	1.198	0.407
CAPM+ILLQ alpha	1.45	1.676	0.023

(B) Size-sorted portfolios			
	Alpha MV10-alpha MV1		
	Value	χ² Test	P value
CAPM alpha	-0.16	0.587	-0.151
Fama-French alpha	-0.03	-1.696	0.210
CAPM+ILLQ alpha	-2.21	0.817	-0.173

The summary statistics represent the time-series-annualised averages of returns, volatilities, and factor betas of two differently sorted portfolios according to: (i) the sensitivity of returns to the monthly average across days of the absolute percentage price change per Yuan of trading volume (ILLQ); and (ii) market capitalisation (MV). ILLQ1 includes stocks negatively sensitive to market-wide illiquidity, and MV1 has small market value stocks. Data are from January 1995 to May 2009.

Table 4: Asymmetric Information and illiquidity factor

Firm-by-firm time-series regressions are based on:

$$NTrades_{J,t} = \alpha + \theta ILLQ_{J,t} + \delta Return_{M,t} + \varepsilon_{J,t}, (3)$$

where $NTrades_{J,t}$ is the total number of trades for firm J during the trading day t. $ILLQ_{J,t}$ is the sensitivity of returns to the monthly average across days of the absolute percentage price change per Yuan of trading volume. $Return_{M,t}$ is the equally weighted average of the daily return for all firms in the market. This table presents regression results on the estimated the illiquidity coefficients of the market variables only.

Independent Variable (SHSE)		Mean (Median) of Est. Coe.	%+ and Sig.	%+ and inSig.	%- and inSig.	%- and Sig.
$ILLQ_{J,t}$	θ	1.751 (1.061)	63.5%	35.2%	1.3%	0
$Return_{M,t}$	δ	0.522 (0.195)	51.3%	46.8%	1.9%	0

Table 5: Market Collapse and Asymmetric Information from Fama French Three Factors Model

Firm-by-firm time-series regressions are based on:

$$Return_{J,t} = \alpha + \gamma_1 Size_{J,t} + \gamma_2 SMB_{J,t} + \gamma_3 HML_{J,t} + \gamma_4 NTrades_{J,t} + \varepsilon_{J,t\,t}, \ (4)$$

where $Size_{J,t}$ is firm size which is the logarithm of the market capitalisation in billions of Chinese Yuan. $SMB_{J,t}$ is the returns of small-size portfolios minus returns of big-size portfolios at time t, and $HML_{J,t}$ is the returns of high book-to-market portfolios minus the returns of low book-to-market portfolios at time t. $NTrades_{J,t}$ is the total number of trades for firm J during the trading day t. This table presents regression results on the asymmetric coefficients only.

Independent Variable (SHSE)		Mean (Median) of Est. Coe.	%+ and Sig.	%+ and inSig.	%- and inSig.	%- and Sig.
$\Delta NTrades_{M,t}$	γ_4	0.212 (0.273)	6.96%	34.06%	47.58%	11.40%