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Liquidity and Stock Returns: Evidence from the Chinese Stock Market*

Keith S. K. Lam,[1] Lewis H. K. Tam,[2] and Liang Dong[3]

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Abstract

We investigate the role of liquidity in explaining stock returns in China's stock market. We construct a new liquidity measure by capturing four liquidity dimensions. Our results show that liquidity is an important factor in pricing returns in China, after taking other well-documented asset-pricing factors into consideration. We compare alternative factor models and find that the model including the factors of market, size, value, and liquidity outperforms the other factor models in explaining stock returns in China. Our results are validated in both time-series and cross-sectional tests. They are also robust to adding portfolio residuals, higher moments, monthly seasonality, and conditional-market tests.

Keywords: Asset Pricing, Liquidity Four-Factor Model, Fama and French Three-Factor Model, High Moments, China Stock Market

JEL classification: G12, G15

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1 Corresponding author. Department of Finance and Business Economics, Faculty of Business Administration, University of Macau. Av. Padre Tomas Pereira, S.J. Taipa, Macao SAR, China. E-mail: keithlam@umac.mo.

2 Department of Finance and Business Economics, Faculty of Business Administration, University of Macau. E-mail: lewistam@um.edu.mo.

3 Department of Finance and Business Economics, Faculty of Business Administration, University of Macau. E-mail: dong.sophie@hotmail.com.

流动性与股票收益率：中国股票市场的实证研究

摘要

本文构建一个可以捕获四个不同流动性维度的新型流动性指标，并基于该指标研究了流动性对于中国股票市场中股票收益率变动的影响。研究结果证明流动性是中国股市收益率的一个重要影响因子，且其定价作用无法被多个文献中已被充分证明定价因子所取代。通过比较几个多因子定价模型在实证分析中的表现，我们发现一个包含市场因子、市值因子、市值账面比因子与流动性风险因子的模型在解释股票收益率变动方面的表现胜过了其他多因子模型。该研究结果在时间序列测试与横截面测试中都得到了证实，也通过了一系列包括增加残差变量、增加高阶市场因子变量、月度季节性测试及条件性市场测试在内的稳健性测试。

I. Introduction

The Chinese stock market has experienced phenomenal growth since its inception. Since 2007, it has consistently been ranked among the top five stock markets in the world in terms of market capitalisation. Given its unique features, many studies have explored the pricing mechanisms in the Chinese stock market (e.g. Wong *et al.*, 2006; Eun and Huang, 2007; Chen *et al.*, 2011; Morelli, 2012). Such studies have focused on identifying the factors that are important for explaining the cross-sectional variations in stock returns in China. Although these studies have documented strong evidence concerning the pricing impact of size and book-to-market ratio, their findings regarding the role of liquidity have been rather mixed (e.g. Wang and Iorio, 2007; Chen *et al.*, 2010; Narayan and Zheng, 2011). Furthermore, none of them have focused on constructing a systematic liquidity risk factor (with a factor-mimicking portfolio) or examining the performance of asset-pricing models augmented with such a liquidity factor in China's stock market. This research gap motivates us to investigate whether liquidity risk serves as an important factor for stock returns on the Chinese stock market. In particular, we examine the performance of various multifactor models involving the proposed liquidity risk factor and other well-known asset-pricing factors, such as the Fama and French (1992, 1993, 1996) three-factor model and the momentum factor model.

Stock liquidity is a more important concern for investors in China than in the US. First, China's stock market is order driven, without market makers to provide liquidity. Furthermore, it is known for the dominating influence of small retail investors,[4] who are unlikely to act as stable providers of liquidity. Therefore, we expect the stock market liquidity in China to be volatile. Second, previous studies have extensively documented that China has significant commonality in stock liquidity. Indeed, of the 40 countries examined by Karolyi *et al.* (2012), China has the highest commonality in liquidity. If stock liquidity in China has a large systematic component, it should be priced by investors. Third, with strict capital controls and little participation from foreign investors, China's stock market liquidity is largely affected by the Chinese government's economic and financial policies.

Any single liquidity proxy used in the literature captures only one dimension of liquidity. Thus, we propose and construct a new proxy for liquidity that is based on the common components extracted from single liquidity proxies using the asymptotic principal components (APC) method. This new proxy incorporates four established liquidity proxies representing the four cost dimensions of liquidity.[5] These dimensions are trading quantity

[4] In 2013, retail investor trading accounted for 82% of all trading on the Shanghai Stock Exchange (Shanghai Stock Exchange Statistics Annual, 2013).

[5] Several other liquidity classifications have been used in the literature. For example, Kyle (1985) suggests that market liquidity is a slippery and elusive concept encompassing three transactional properties of stock markets. These properties are tightness, depth, and resiliency. Tightness is the cost of turning a position around in a short period, which is close to the trading cost component. Depth is the size of an order flow innovation that is required to change prices by a given amount, which is similar to the price impact component. Resiliency is the speed with which prices recover from a random, uninformative

(Datar *et al.*, 1998), price impact (Amihud, 2002), trading speed (Liu, 2006), and trading cost (Corwin and Schultz, 2012).[6] We then estimate liquidity risk as the sensitivity of stock returns to the extracted common component. Finally, we construct the systematic liquidity risk factor through buying stocks with lower factor loadings and selling stocks with higher factor loadings.

We test the performance of our liquidity risk factor by regressing stock returns on the capital asset pricing model (CAPM), the Fama-French three-factor asset-pricing (FF3F) model, the momentum four-factor (WML4F) model, and the liquidity augmented factor model. We form three sets of portfolios sorted by size, book-to-price ratio, and liquidity. We also form eight sets of anomaly-sorted portfolios as the testing portfolios. Our results show that the liquidity risk factor plays an important asset-pricing role in China's stock market. This role remains clear even after we account for the other well-documented asset-pricing factors. We check the robustness of liquidity risk as an asset-pricing factor by performing cross-sectional tests, examining higher-moment (coskewness and cokurtosis) effects that may indicate missing factors, and conducting seasonality and conditional-market tests. We also perform multivariate regressions on all of the related factors. We find that the liquidity four-factor (LIQ4F) model that includes excess market return, size, value, and liquidity factors outperforms the other factor models. However, unlike the patterns seen in the US market, the momentum factor is weakly priced in China's stock market.

We contribute to the literature in three ways. First, we shed light on the asset-pricing mechanism in China's stock market by proposing a new liquidity risk factor that uses the APC approach to capture the four dimensions of liquidity. Studies have demonstrated that when different one-dimensional liquidity measures are used as proxies for liquidity, inconsistent results are obtained concerning the pricing effect of liquidity (e.g. Narayan and Zheng, 2011; Ho and Chang, 2015). Therefore, we propose incorporating multiple dimensions of liquidity in a single common liquidity factor. By doing so, our results are less subject to arbitrary choices of liquidity proxies.[7]

Second, unlike previous studies, which have mainly examined the cross-sections of stock returns in China (e.g. Wong *et al.*, 2006; Eun and Huang, 2007; Narayan and Zheng, 2010; Morelli, 2012), our time-series tests allow us to evaluate the performance of asset-pricing models by examining the regression intercepts. If the proposed risk factors capture all of the systematic risks that affect stock returns, the intercepts of a set of stock portfolios, formed by a certain sorting criterion, should be jointly equal to zero. By comparing

shock, which resembles the trading speed component.

[6] We draw three of the liquidity dimension proxies (trading quantity, price impact, and trading speed) from Lam and Tam (2011). We take the fourth proxy (trading costs) from Corwin and Schultz (2012). Appendix A describes the construction of these liquidity proxies.

[7] For example, Lam and Tam (2011) construct nine liquidity measures based on different proxies for liquidity in the Hong Kong stock market. They find that although most liquidity measures produce consistent results, some measures do not work well.

the regression intercepts of different models, we can identify the sets of risk factors that are most relevant for asset pricing in China. Our cross-sectional test also confirms that liquidity risk serves as a risk factor (not only as a firm characteristic) that helps explain stock returns.

Third, we provide out-of-sample evidence regarding liquidity and other multifactor models in a highly volatile stock market (i.e. China). Lo and MacKinlay (1990) point out that gathering out-of-sample evidence beyond the US market is important for avoiding the data-snooping problem. Therefore, it is worthwhile to study an important, volatile emerging market, such as China's, which is not highly correlated with the data used in previous research.

The rest of this study is organised as follows. Section II reviews and summarises the risk-return literature and provides background information on China's stock market. Section III describes the research methodologies and the data collected. Section IV presents and analyses the empirical results. Section V concludes the study.

II. Literature Review

Sharpe (1964), Lintner (1965), and Black *et al.* (1972) first introduced the CAPM in the 1960s and 1970s. A large body of research has since evaluated the validity of this model, with early empirical tests mainly supporting it (e.g. Black *et al.*, 1972; Fama and MacBeth, 1973). A number of firm-level characteristics, such as size (Banz, 1981; Reinganum, 1981, 1982) and book-to-market ratio (Rosenberg *et al.*, 1985; Chan *et al.*, 1991), are found to be linked with strong return patterns after 1980. This indicates that aside from market beta, many firm-specific characteristics have significant explanatory power regarding average returns.

This body of evidence strongly suggests that the single factor (beta) in the CAPM is insufficient for explaining stock returns, a finding that has motivated researchers to search for new multifactor asset-pricing models that can better explain the return patterns. In a series of papers, Fama and French (1992, 1993, 1996) propose the FF3F model, which includes a market factor (excess market return, MP), a size factor (SMB), and a book-to-market (BM) factor (HML). The size and BM factors also have significant explanatory power for stock returns in Asia. These factors have significant influence in the stock markets of Singapore (Wong and Lye, 1990), Korea (Mukherji *et al.*, 1997), Malaysia (Chui and Wei, 1998; Lau *et al.*, 2002), Hong Kong (Ho *et al.*, 2000; Lam, 2002), the Philippines (Drew and Veeraraghavan, 2003), Taiwan (Shum and Tang, 2005), and China (Wang and Iorio, 2007; Morelli, 2012). Following Fama and French (1996), Carhart (1997) proposes the WML4F model by adding the momentum factor (WML)[8] to the FF3F model. However, only a few studies provide evidence supporting the profitability of momentum strategies in specific

[8] The momentum factor involves the effect that past winners (losers) continue to perform well (poorly). Momentum strategies for buying stocks with high returns and selling stocks with low returns over the previous 3 to 12 months generate significant abnormal returns in most equity markets.

Asian markets (e.g. Chan *et al.*, 2000; Grundy and Martin, 2001; Fong *et al.*, 2005).

In addition to these well-documented pricing factors, researchers have paid much attention to liquidity. For example, Amihud (2002) finds a significant relation between liquidity and expected stock returns. Amihud (2002) also documents a positive relation between returns and illiquidity, even in the presence of size, beta, and momentum. Pastor and Stambaugh (2003) propose a liquidity risk measure based on assessing price reversals that arise due to the temporary effects of trading volumes on prices. They find that this measure accounts for prices in the US market. Several studies show that liquidity works well in the US market (Acharya and Pedersen, 2005; Avramov and Chordia, 2006; Liu, 2006) and in European markets (Martinez *et al.*, 2005; Antoniou *et al.*, 2007). Using Pastor and Stambaugh's (2003) price-reversal liquidity risk measure, Liang and Wei (2012) find that both local and global liquidity risks are priced in 11 developed markets. In Asia, Lam and Tam (2011) document a significant liquidity–return relation in the Hong Kong stock market.

Studies of the liquidity-return relation in the Chinese market can be classified into two groups. The first group analyses the role of liquidity as one firm-level characteristic along with others, such as size and book-to-market ratio. For example, Eun and Huang (2007) use the monthly turnover ratio as a firm-level liquidity proxy and find that it is significantly priced in a cross-sectional test in China. Wang and Iorio (2007) use the 12-month average turnover ratio as a proxy for firm liquidity in their cross-sectional tests and report a weak liquidity pricing effect. Chen *et al.* (2010) include 18 firm characteristics in their cross-sectional regressions, among which firm illiquidity is represented by the percentile rank of the 12-month average Amihud (2002) ratio. They find illiquidity to be a significant stock return predictor in the univariate test but not in the multivariate tests.

The second group of studies examines the liquidity-return relation through the risk channel, using various approaches to estimate the liquidity risk. Chen *et al.* (2011) use a liquidity beta (i.e. the covariance between stock level liquidity and market level liquidity) as a proxy for liquidity risk. They show that this factor plays an important role in explaining the cross-sectional variations in portfolio returns. Narayan and Zheng (2011) examine the pricing effect of the liquidity beta (i.e. the covariance between stock returns and market level liquidity) and find that liquidity risk is not consistently priced when differing liquidity proxies are used. Zhang *et al.* (2007) propose a liquidity risk measure based on the free float proportion and demonstrate that this factor is priced with a considerable premium. These studies offer mixed evidence on the role of liquidity risk as their proposed liquidity risk measures differ.

No study has investigated the impact of liquidity risk on stock returns in China using a liquidity proxy that embodies the various dimensions of liquidity. China's stock market is among the most volatile markets in the world and is well known for being dominated by small firms. Thus, liquidity is likely to be an important factor for many firms listed in China's stock exchanges. Furthermore, unlike the US market, China's market is order driven. With an absence of market makers, investors in an order-driven market can freely enter and exit the market, causing the stock exchanges to operate more like perfect competitive markets (Brockman and Chung, 2002). Therefore, China's stock market is an ideal out-of-sample testing ground for the liquidity–return relation. Motivated by the lack of previous studies on this subject in China, we examine whether the liquidity risk factor is important for explaining both the time-series and cross-sectional variations in stock returns on China's stock market. We also compare the results of the liquidity-augmented pricing model with those of alternative pricing models, such as the FF3F and WML4F models.

III. Data and Methodologies

3.1 Data

China has two stock exchanges, namely the Shanghai Stock Exchange and the Shenzhen Stock Exchange, which opened in 1990 and 1991, respectively. Both exchanges have the same listing requirements. The listed firms' shares are usually divided into tradable and non-tradable shares.[9] Both state-owned shares and legal entity shares were non-tradable and non-transferrable[10] until the split-share structure was reformed between 2005 and 2007. All non-tradable shares were gradually transformed into tradable shares after this reform. Table 1 summarises the key statistics of the Chinese stock market.

We collect all of the data used in this study from the China Stock Market and Accounting Research (CSMAR) database. We use value-weighted market returns (with cash dividends reinvested) as a proxy for market returns.[11] As the stock exchanges provide separate Shanghai and Shenzhen composite index data, we compute the market-return proxy from the value-weighted average of the two composite indexes using the corresponding month-end index values as weights. For the risk-free rate, we use the 1-year deposit rate of the People's Bank of China as a proxy.[12]

In line with previous studies, we adopt four data selection criteria. First, we include only monthly return data on non-financial companies, with appropriate adjustments for capital changes. Second, we exclude financial firms, firms with negative book equity, and

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[9] Proceeds from the sale of A-shares are subject to foreign exchange control and cannot be repatriated, but foreign tradable shares can be freely repatriated. Foreign tradable shares can be listed on two local exchanges as B-shares or on overseas exchanges, such as the Hong Kong Exchange or the New York Stock Exchange.

[10] Legal entity shares have been tradable among qualified institutions on a special market since August 1992.

[11] We also conduct our tests using equal-weighted market returns. We find similar results to those of tests using value-weighted market returns. These results are available upon request.

[12] The Shanghai Interbank Offer Rate should be a more appropriate proxy for the risk-free rate because it reflects the true market movement. However, this rate has only been recorded since January 2007. Thus, the period is too short for our sample set. The 3- and 6-month deposit rates are not available in the CSMAR database.

firms in the growth enterprise market (GEM).[13] Third, we remove stocks with more than 3 months of consecutive missing returns; this serves to rule out extremely thin-trading stocks that are likely to have very irregular return characteristics. Last, following Wang and Xu (2004), we exclude the first-month IPO returns on individual stocks as first-month IPO stock returns are unusually high in China's stock market (with most returns being over 50%). Hence, excluding the first month's IPO returns on individual stocks can help rule out extreme return observations, which may seriously bias our test results. Finally, the selected data consist of firms with monthly individual stock returns and with data on dividend reinvestment, market capitalisation, book-to-market ratio, and monthly trading volume. After applying the screening criteria, our data comprise 1,310 listed firms from the Shanghai and Shenzhen stock exchanges for the period July 1994 to June 2014.[14]

Table 1 Summary Statistics of Chinese firms (July 1994–June 2014)

This table presents the number of listed firms, market values, and tradable and non-tradable share percentages for the whole sample period (1994–2014), the first sub-period before the share reform (1994–2004) and the sub-period after the share reform (2005–2014). The table provides information pertaining to both A- and B- share stocks in China. All numbers are as of the last trading day of the year. For consistency, the market value is converted to US$ by using the exchange rate at the end of each month in each year. The numbers are obtained from the China Stock Market Trading Database (CSMAR) and the China Securities Regulatory Commission website (www.csrc.gov.cn).

	1994–2014			**1994–2004**			**2005–2014**		
	Mean	**Max**	**Min**	**Mean**	**Max**	**Min**	**Mean**	**Max**	**Min**
Combined market									
Number of listed stocks -total	1310.33	2190.00	338.00	899.00	1382.00	338.00	1762.80	2190.00	1412.00
Number of listed stocks -A	1225.81	2087.00	283.00	825.45	1302.00	283.00	1666.20	2087.00	1283.00
Number of listed stocks -B	172.00	1003.00	56.00	75.27	85.00	56.00	278.40	1003.00	83.00
Total market value in US$ (billion)	1174.65	3198.06	39.22	295.29	536.52	39.22	2141.95	3198.06	480.49
Tradable Shares (%)	60.90	100.00	5.26	37.50	100.00	8.48	69.18	100.00	5.26
Non-tradable Shares (%)	39.10	92.19	0.00	62.50	87.16	0.00	30.82	92.19	0.00
Shanghai Stock Exchange									
Number of listed stocks -total	685.76	967.00	199.00	504.82	843.00	199.00	884.80	967.00	843.00
Number of listed stocks -A	642.38	914.00	168.00	466.91	801.00	168.00	835.40	914.00	787.00
Number of listed stocks -B	44.33	53.00	32.00	38.91	44.00	32.00	50.30	53.00	43.00
Total market value in US$ (bil)	763.63	1896.85	29.14	183.06	319.38	29.14	1402.26	1869.82	336.15
Tradable Shares (%)	57.40	100.00	5.26	36.93	100.00	8.48	68.28	100.00	5.26
Non-tradable Shares (%)	42.50	92.19	0.00	63.07	87.16	0.00	31.72	92.19	0.00
Shenzhen Stock Exchange									
Number of listed stocks -total	624.57	1223.00	139.00	394.18	539.00	139.00	878.00	1223.00	559.00
Number of listed stocks -A	583.33	1173.00	115.00	358.55	501.00	115.00	830.60	1173.00	496.00
Number of listed stocks -B	41.95	51.00	24.00	36.36	42.00	24.00	48.10	50.00	39.00
Total market value in US$ (bil)	411.02	1328.25	10.09	112.23	246.13	10.09	739.69	1328.25	336.15
Tradable Shares (%)	58.30	100.00	10.39	38.41	80.20	14.93	64.50	100.00	10.39
Non-tradable Shares (%)	41.60	88.36	0.00	61.59	85.00	0.00	35.50	88.36	0.00

[13] China's GEM was launched in March 2009. As its history is short and the average firm size is relatively small, we exclude GEM firms from this study.

[14] Too few firms were listed before 1994 for consideration in this study. Only 13 firms were listed in 1991, and the figure increased to just 140 in 1993. However, the number of firms increased sharply to 232 firms in 1994 and continued to increase steadily afterwards. Therefore, we choose to start the study from 1994.

3.2 Methodologies

We use a time-series test to examine whether the asset-pricing models (which include size, book-to-market, momentum, and liquidity risk factors) can explain the time-series variations in stock returns. In doing this, we focus on investigating whether the liquidity risk factor plays an important role in explaining time-series variations. If liquidity risk and other pricing factors can sufficiently capture the stock return variations, we expect the intercepts of the time series to be jointly equal to zero (after controlling for the factors). Following Nguyen *et al.* (2007) and Gu and Huang (2010), we use the GRS *F*-test (Gibbons *et al.*, 1989) to determine whether the intercepts are jointly equal to zero.[15] In addition to the time-series tests, we conduct cross-sectional tests to check the robustness of the time-series results in Section 4.3.2.

To compute the new liquidity proxy, we select one proxy from each of the four daily liquidity measures (TO, LM, ILLIQ, and HL) which represent the four cost dimensions of liquidity (i.e. trading quantity, trading speed, price impact, and trading costs). The trading-quantity component is related to the amount of stock trading. Higher (lower) trading-quantity stocks may signal lower (higher) liquidity risk. Datar *et al.* (1998) recommend using the turnover ratio (TO) to proxy for the trading-quantity component of liquidity. The trading-speed component is related to how quickly stocks are traded, with faster and more frequent trading indicating more liquidity. Liu (2006) proposes a liquidity measure (LM) to represent the trading frequency of stocks. According to Liu (2006), the LM measure captures "multiple dimensions of liquidity such as trading speed, trading quantity, and trading cost, with particular emphasis on trading speed, that is, the continuity of trading and the potential delay or difficulty in executing an order" (p. 632). Stocks with higher continuity of trading (higher trading speed) are considered to be more liquid. Amihud (2002) proposes an illiquidity stock return measure (ILLIQ) to capture this price-impact aspect. The illiquidity measure is the ratio of the absolute value divided by the trading volume.[16] The trading cost component can be measured by the bid-ask spread of stock prices. Higher trading costs may indicate that stocks have less liquidity because investors ask for higher spreads to compensate for the illiquidity risk. Traditionally, intraday measures have been used to proxy for trading costs. However, Corwin and Schultz (2012) show that using the

[15] Studies have used a variety of tests to determine whether the intercepts of time-series portfolio return regressions were all zero. Gibbons *et al.* (1989) find that standard tests (e.g. the Wald, likelihood ratio, and Lagrange multiplier tests) are asymptotically distributed by using a chi-square test with N (the number of portfolios) degrees of freedom as the number of periods and T (which approaches infinity). However, these tests produce biased statistics because N is close to T. Therefore, Gibbons *et al.* provide an *F*-test with a tractable small-sample property. Essentially, their test statistics compare (1) the Sharpe ratio of the *ex-post* optimal portfolio (as generated by the market proxy plus all of the 25 stock portfolios) and (2) the Sharpe ratio of the market proxy alone. Gibbons *et al.* (1989) then extend their tests to multifactor models.

[16] In Amihud (2002), the 1% upper tail of the illiquidity measure distribution is eliminated. We set the threshold to a 0.5% upper tail to reserve as much data as possible. We also test eliminating the 1% upper tail of the illiquidity ratio. We do not find a significant difference in the results.

daily high-low price ratio yields empirical results similar to those resulting from using the intraday bid-ask spread to measure trading costs. We use daily liquidity proxies in this study. Thus, we use the daily high-low ratio (HL) as our proxy for the trading cost component, as proposed by Corwin and Schultz (2012).

We use Korajczyk and Sadka's (2008) APC approach to extract the systematic component of the combined liquidity proxy from the four liquidity measures.[17] Appendix A provides a brief discussion of the individual proxies. Next, we estimate the sensitivity of stock returns to the systematic liquidity measure as the stock's liquidity factor beta (Fβeta), using 36-month rolling estimation windows that contain at least 12 months of non-missing stock returns. We then form the new liquidity risk factor (LIQ) as the difference in returns between the low-Fβeta portfolio and the high-Fβeta portfolio. Appendix C provides details.[18]

We construct 25 portfolios for each year using China's stock market data. We form three sets of portfolios which are based on (1) the liquidity ratio and size (Fβeta-size), (2) the liquidity ratio and the book-to-price ratio (Fβeta-B/P), and (3) the liquidity ratio (Fβeta) only. In forming the second set of 25 portfolios, we use the book-to-price ratio (i.e. the book equity per share divided by market price) as the measure of a firm's book-to-market value ratio. Calculating the book-to-market ratio (the total book equity divided by the total market value of an A share) yields incorrect results for firms that list both A shares and other classes of shares on foreign markets (Xu and Zhang, 2014; Hou and Zhang, 2019). To form the 25 Fβeta-size portfolios (at the end of June every year), we calculate the respective factor beta (Fβeta) for each stock in the sample and then assign each stock to one of five liquidity portfolios. Independently, we rank the stock data yearly by market capitalisation and divide the sample into five equally sized portfolios. We form 25 portfolios by taking the intersection between the Fβeta and the size groups and then repeat the portfolio-formation procedure using the Fβeta and the book-to-price ratio. To form the 25 liquidity portfolios at the end of June every year, we calculate the annual respective Fβeta for each stock in the sample and then assign the stock to one of the 25 equal portfolios according to its Fβeta rank. After forming three sets of portfolios, we compute each portfolio's value-weighted monthly return. We calculate the excess portfolio return by taking the difference between the portfolio monthly return and the risk-free rate. We rebalance the portfolios at the end of June every year from 1995 to 2014.

To check the robustness of our results, we test and compare the results from various asset-pricing models, such as the FF3F, WML4F, LIQ4F, and momentum-liquidity

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[17] We do not use liquidity measures based on high-frequency intraday data (e.g. bid-ask spreads or signed order flows) because high-frequency data are available only for a much shorter period.

[18] We use the alternative liquidity measure constructed in this study (LIQ) instead of the combined liquidity factor extracted by the APC method (F_t in Appendix C). However, we also perform tests using both measures and find that our alternative liquidity measure performs better than the APC-extracted measure.

five-factor (LIQ5F) models. We estimate ordinary least squares (OLS) time-series regressions for each of the 25 portfolios onto the factor models. These factor models are presented in the following equations:

$$R_{pt} - R_{ft} = a_p + b_p MP_t + \varepsilon_{pt} \quad (1)$$
$$R_{pt} - R_{ft} = a_p + b_p MP_t + s_p SMB_t + h_p HML_t + \varepsilon_{pt} \quad (2)$$
$$R_{pt} - R_{ft} = a_p + b_p MP_t + s_p SMB_t + \psi_p LIQ_t + \varepsilon_{pt} \quad (3)$$
$$R_{pt} - R_{ft} = a_p + b_p MP_t + s_p SMB_t + h_p HML_t + \psi_p LIQ_t + \varepsilon_{pt} \quad (4)$$
$$R_{pt} - R_{ft} = a_p + b_p MP_t + s_p SMB_t + h_p HML_t + w_p WML_t + \varepsilon_{pt} \quad (5)$$
$$R_{pt} - R_{ft} = a_p + b_p MP_t + s_p SMB_t + h_p HML_t + w_p WML_t + \psi_p LIQ_t + \varepsilon_{pt}, \quad (6)$$

where ($R_{pt} - R_{ft}$) is the portfolio's excess returns, MP_t is the market's excess returns, SMB_t is the size factor, HML_t is the book-to-market factor, WML_t is the momentum factor, LIQ_t is the liquidity risk factor, and p_t is an error term that is assumed to have a zero mean. This error term is also assumed to be uncorrelated with any of the other explanatory variables or with the factor sensitivities or loadings. Finally, b_p, s_p, h_p, w_p, and ψ_p are the slope coefficients for the MP, SMB, HML, WML, and LIQ factors, respectively. We use Newey and West's (1987) approach in the *t*-tests to adjust for possible heteroscedasticity or autocorrelation problems.

We construct the three Fama and French asset-pricing factors and the momentum factors (MP, SMB, HML, and WML) following Fama and French (1993) and L'her *et al.* (2004). Appendix B explains how the non-liquidity measures are formed. We construct the liquidity risk factor (LIQ) as follows. At the end of each June, we sort the firms by size (i.e. by market capitalisation) and separate them into two portfolios: small (*S*) and big (*B*). We independently sort the same stocks into three portfolios according to their Fβeta. The top 30% of the stocks belong to the high-Fβeta *L1* portfolio and the bottom 30% belong to the low-Fβeta *L3* portfolio. The middle 40% of the stocks represent the *L2* portfolio. Next, we form six portfolios (*S/L1*, *S/L2*, *S/L3*, *B/L1*, *B/L2*, and *B/L3*) based on the intersections of the size and Fβeta ratings. The value-weighted monthly returns on these six portfolios are calculated for each month over the 12 months following the portfolio formation. Repeating this procedure every year yields 228 value-weighted monthly returns (from July 1995 to June 2014) for each of the six portfolios. LIQ is the simple average of the returns on the *L3* portfolios (with higher expected portfolio returns) minus the returns on the *L1* portfolios (with lower expected portfolio returns):

$$LIQ = [(S/L3 - S/L1) + (B/L3 - B/L1)]/2$$

We conduct a time-series test to examine whether liquidity risk affects the expected stock returns. If liquidity risk has an important pricing effect, we expect the intercepts from the regressions of the factor models without liquidity factors or without liquidity risk factors (e.g. the CAPM, FF3F, or WML4F models) to be positive for the low-Fβeta stocks and negative for the high-Fβeta stocks. Furthermore, the intercepts should be jointly different from zero. However, this difference is reduced after controlling for the liquidity risk factor in these time-series regressions. Furthermore, by comparing the relative performance of the factor models with and without a liquidity factor, we are able to search for a more suitable asset-pricing model for China's stock market.

IV. Empirical Results

4.1 Descriptive Statistics of Explanatory Variables

Table 2 presents the summary statistics and correlations of the explanatory variables. Panel A shows that the mean market premium (MP) in China is positive, at 0.59% per month. This exceeds the MP observed in the US market, which is 0.41% according to Keene and Peterson (2007). However, the MP's standard deviation (8.5%) in China is almost twice that in the US, which is 4.5% according to Keene and Peterson (2007). Although we find both the mean SMB and HML to be positive, only the SMB is significant at the 5% level. The magnitude of the SMB (0.98%) is 3.5 times greater than that in the US market, which is 0.28% according to Keene and Peterson (2007). However, the magnitude of the HML (0.20%) is approximately half that of the US market, which is 0.43% according to Keene and Peterson (2007). The mean WML is insignificant and small, at -0.02%. This differs from the 0.91% that Keene and Peterson (2007) find in the US market. The magnitude of the LIQ is 0.29% per month, which is significant at the 5% level (*t*-value = 2.19). This indicates preliminarily that liquidity risk is priced with a positive premium in the Chinese stock market.

Panel B reports the correlations between variables. No obviously high correlations are found between pairs of variables, and most of the values are below 0.30. The largest correlation is between the MP and the LIQ (0.3193). The middle part of Panel B reports the correlations between the four firm-level liquidity components. These four components have low correlations, with the TO and HL (Hi-Low ratio) demonstrating the highest correlation (0.2651). These correlations indicate that the four liquidity components represent the four dimensions of liquidity quite independently. The bottom row of Panel B reports the correlations between the firm-level factor beta ratio (Fβeta), the four liquidity components, and the LIQ factor. All of these correlations are low (between -0.2412 and 0.0567). We do not expect these low correlations to cause a serious multicollinearity problem in our regression tests.

Hou *et al.* (2015) claim that a factor model has greater explanatory power if the efficient combination of the factors in the model has a higher Sharpe ratio. Panel C reports the Sharpe ratios of the LIQ factor and the three-factor models that include the LIQ factor (LIQ3F, LIQ4F, and LIQ5F). We compare the Sharpe ratios based on the LIQ factor formed from the APC approach with those formed from each of the four single liquidity measures. The first row shows that the LIQ factor formed from the APC approach has a higher Sharpe ratio than those

Table 2 Descriptive Statistics of Variables (Explanatory Factors, Liquidity Ratios, and Factor Beta) (July 1994–June 2014)

The table presents the descriptive statistics of the model variables (explanation factors, liquidity ratios, and factor beta). Panel A presents the summary statistics, while Panel B displays the correlations between variables. Monthly time-series statistics are reported for the variable returns. MP is the value-weighted monthly market excess return, SMB is the monthly return of a hedging portfolio formed by buying small stocks and selling large stocks, HML is the monthly return of a hedging portfolio formed by buying high B/P stocks and selling low B/P stocks, and WML is the monthly return of a hedging portfolio formed by buying past winners and selling past losers. The construction of these factors follows those of Fama and French (1992) and L'her *et al.* (2004). LIQ is the monthly return of a hedging portfolio formed by buying low factor beta (Fβeta) stocks and selling high factor beta stocks. Fβeta is the firm-level sensitivity factor by performing a time-series regression for each stock's excess return on the AR(2) fitted extracted common factor (^F_t) constructed by taking the first principal component of turnover ratio (TO), trading speed (LM), price impact (ILLIQ) and trading cost (HL) using the asymptotic principal components analysis approach (APC) of Connor and Korajczyk (1986). TO is the turnover ratio of Datar *et al.* (1998), LM is the trading speed ratio of Liu (2006), ILLIQ is the illiquidity ratio of Amihud (2002), and HL is the high-low trading cost ratio of Corwin and Schultz (2012). Refer to Appendix A for the exact definitions. *T-statistic* indicates the Newey West adjusted *t*-statistic. Panel B reports the correlation coefficients. Panel C reports the Sharpe ratios.

Panel A1: Summary Statistics for Time-Series Variables					
Variable	**Mean**	**Standard Deviation**	**t-statistic**	**Maximum**	**Minimum**
MP	0.0059	0.0850	1.00	0.3646	-0.2702
SMB	0.0098	0.0405	3.44	0.1188	-0.1308
HML	0.0020	0.0286	0.99	0.1035	-0.0930
WML	-0.0002	0.0304	-0.10	0.0841	-0.1055
LIQ	0.0029	0.0191	2.19	0.0579	-0.0524
Panel A2: Summary Statistics for Firm-Level Variables					
TO	0.4345	0.3540	660.90	7.4475	0.0000
LM	6.0518	10.0447	314.56	208.9123	0.0006
ILLIQ	0.0323	0.1157	149.71	3.4393	0.0000
HL	0.0095	0.0040	1267.74	0.1115	0.0000
Fβeta	-3.2190	4.3728	-387.28	7.1870	-15.6161

Panel B: Correlations between Variables									
Correlation	**MP**	**SMB**	**HML**	**WML**	**LIQ**	**TO**	**LM**	**ILLIQ**	**HL**
MP	1.0000								
SMB	0.1642	1.0000							
HML	0.0528	-0.1296	1.0000						
WML	0.0700	-0.2428	-0.2516	1.0000					
LIQ	0.3193	-0.0365	0.1523	0.0264	1.0000				
TO	0.0624	0.1006	-0.0513	-0.0679	0.0708	1.0000			
LM	0.1103	0.0076	0.0106	-0.0218	0.0023	0.0954	1.0000		
ILLIQ	-0.0072	-0.0292	0.0145	0.0122	-0.0042	-0.1701	0.0981	1.0000	
HL	0.0820	0.0994	-0.0370	-0.1058	0.0348	0.2651	0.1726	0.0816	1.0000
Fβeta	-0.0966	-0.0711	0.0496	0.0823	-0.0471	-0.2412	-0.1934	0.0567	-0.1813

Note: All correlations are significant at the 5% level.

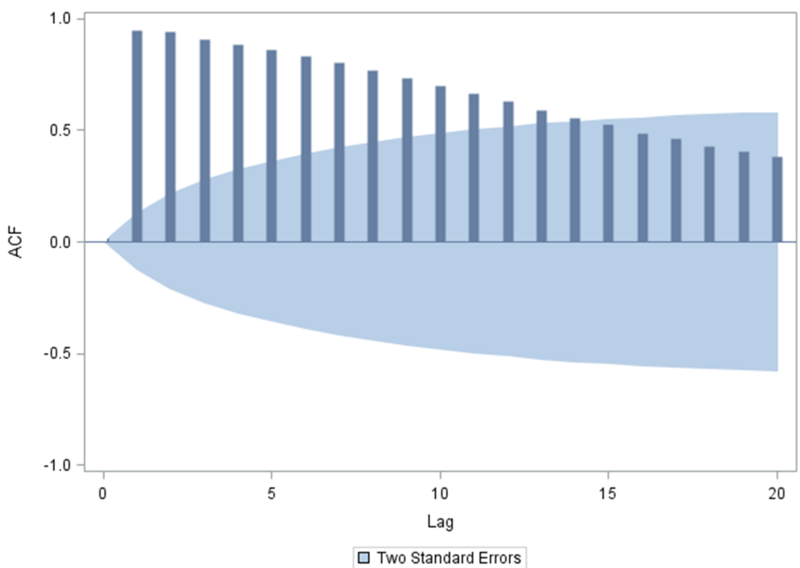
Panel C: Maximum Sharpe Ratios					
	LIQ-APC	LIQ-TO	LIQ-ILLIQ	LIQ-LM	LIQ-HL
LIQ factor	0.15	0.13	-0.06	0.04	0.10
LIQ3F	0.29	0.25	0.25	0.26	0.27
LIQ4F	0.30	0.26	0.27	0.27	0.28
LIQ5F	0.31	0.28	0.28	0.28	0.29

formed from the four liquidity components. Moreover, the Sharpe ratios of all three-factor models with the APC-based LIQ factor are constantly higher than those based on individual liquidity measures. Overall, the results shown in Panel C suggest that the LIQ factor constructed using the APC approach is a better choice than the LIQ factors constructed using the four individual liquidity measures.

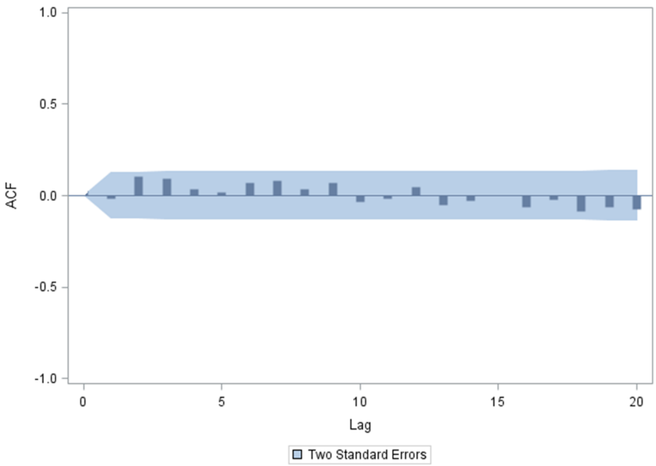
Figure 1 Autocorrelations of Common Factor LIQ, Fβeta, and LIQ

The figure plots the autocorrelations of common factor LIQ, Fβeta, and LIQ factor. The common factor LIQ is the first principal component extracted from the four liquidity proxies. Fβeta is the firm-level sensitivity factor by performing a time-series regression for each stock's excess return on the AR(2) fitted extracted common factor ($\hat{F}_t$) constructed by taking the first principal component of turnover ratio (TO), trading speed (LM), price impact (ILLIQ), and trading cost (HL) extracted by the asymptotic principal components analysis approach (APC) of Connor and Korajczyk (1986). TO is the turnover ratio of Datar *et al.* (1998), LM is the trading speed ratio of Liu (2006), ILLIQ is the illiquidity ratio of Amihud (2002), and HL is the high-low trading cost ratio of Corwin *et al.* (2012). Refer to Appendix A for the exact definitions. Panel A plots the autocorrelation of the common factor LIQ. Panel B plots the autocorrelation of the AR(2) common factor LIQ, which is the AR(2) regression residual of the common factor LIQ. Panel C plots the autocorrelation of Fβeta, which is the monthly mean Fβeta over firms. Panel D plots the autocorrelation of LIQ, where LIQ is the monthly return of a hedging portfolio formed by buying high Fβeta stocks and selling low Fβeta stocks.

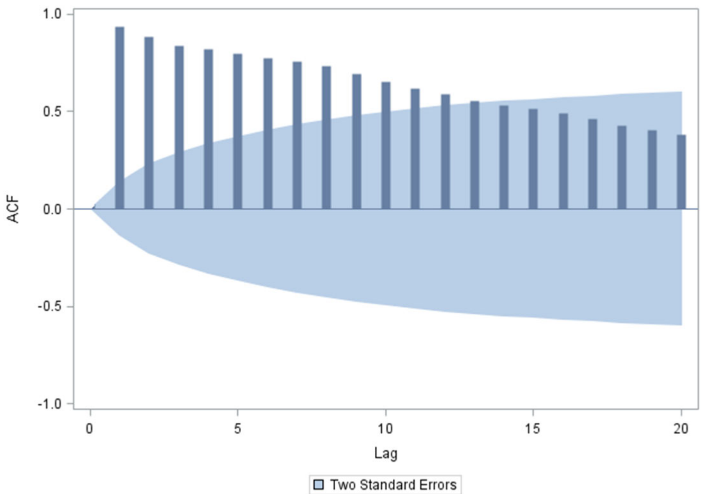
Panel A: Common factor LIQ autocorrelation



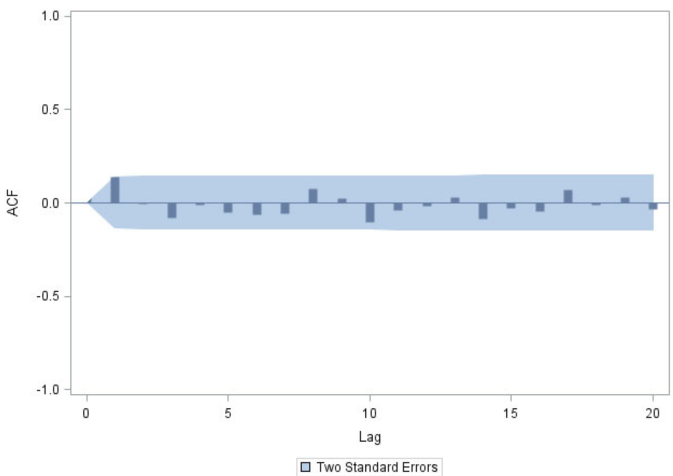
Panel B: AR(2) common factor LIQ autocorrelation



Panel C: Fβeta autocorrelation



Panel D: LIQ factor autocorrelation



We also investigate the shock effect and the persistence of the liquidity factors. We first investigate the autocorrelations in factors by plotting the autocorrelation function of the Fβeta and LIQ factors along with the confidence intervals, as shown in Figure 1. Fβeta is constructed from the common first principal component (common factor) of the four individual liquidity proxies. Thus, we also plot the autocorrelation function of the common factor and the residual of the AR(2) regression of the common factor. As Fβeta is a firm-level ratio, we use the monthly average Fβeta ratio in our computation. The common liquidity factor exhibits significant autocorrelations, as shown in Panel A. As expected, the AR(2) common factor residual, which represents the innovation in liquidity, shows very low autocorrelation (Panel B). The Fβeta also exhibits significant autocorrelations (Panel C), but the LIQ factor shows very little autocorrelation (Panel D).

Table 3 Persistence of Aggregate Liquidity

Within-measure common factors are extracted separately for different measures of liquidity using the APC method. In addition, across-measure common factors are extracted for all the liquidity measures jointly. Then, for each first principal component, we apply an AR(2) model (coefficients Ro1 and Ro2 along with t-statistics in brackets below). The common factor is the first principal component extracted from four liquidity proxies by the asymptotic principal components analysis approach (APC) of Connor and Korajczyk (1986). The four liquidity measures analysed are turnover ratio (TO), trading speed (LM), price impact (ILLIQ), and trading cost (HL). TO is the turnover ratio of Datar *et al.* (1998), LM is the trading speed ratio of Liu (2006), ILLIQ is the illiquidity ratio of Amihud (2002), and HL is the high-low trading cost ratio of Corwin *et al.* (2012). Refer to Appendix A for the exact definitions. Fβeta is the firm-level sensitivity factor obtained by performing a time-series regression for each stock's excess return on the AR(2) fitted extracted common factor ($\hat{}F_t$). The 6- and 12-month values of the impulse response function applied to each time series are also reported.

			Shock after	
Variables	**Ro1**	**Ro2**	**6 months**	**12 months**
TO	1.80	-0.80	2.87	2.61
	[46.72]	[-20.86]		
ILLIQ	0.58	0.34	0.52	0.38
	[9.59]	[5.53]		
LM	1.56	-0.57	2.10	1.94
	[29.42]	[-10.76]		
HL	0.59	0.37	0.62	0.54
	[9.29]	[5.75]		
Common Factor	0.53	0.45	0.66	0.60
	[9.11]	[7.65]		
Fβeta	0.82	0.12	0.64	0.47
	[11.78]	[1.76]		

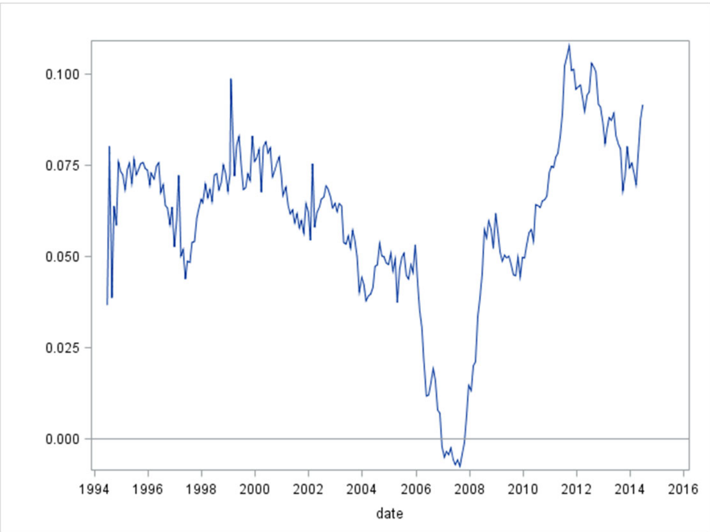
Next, we investigate the persistence of the Fβeta and LIQ factors using shock response functions. We calculate the percentage of a shock at month *t* that we expect to impact the Fβeta and LIQ at month *t* + 12. The results show that the chances of a time *t* shock to each of the four liquidity proxies persisting after 12 months are 261%, 38%, 194%, and 54%, respectively, as reported in Table 3. The ILLIQ and HL liquidity ratios have mild persistence, but the TO and LM liquidity ratios have markedly high persistence.[19] Both the common factor and the LIQ factors show substantial persistence, at 60% and 47%, respectively.

We then create time-series plots for the common factor, innovation in liquidity, Fβeta, and the LIQ factor, as shown in Figure 2. Panels A and B show that the common factor has obvious persistence over time. However, its AR(2) residuals demonstrate little sign of autocorrelation. Generally, the volatility of the shocks to liquidity decreases in magnitude over time. The market average Fβeta (Panel C), an indicator of the market-wide liquidity risk, exhibits some large decreases between 2005 and 2007, when the stock market underwent a series of reforms, and between 2008 and 2009, when the global financial crisis struck the Chinese market. The LIQ factor (Panel D) shows no obvious autocorrelation but exhibits considerable fluctuations throughout the entire sample period. This indicates its potential ability to explain the time-series variations in stock returns.

Figure 2 Time-series plots of common factor LIQ, Fβeta, and LIQ

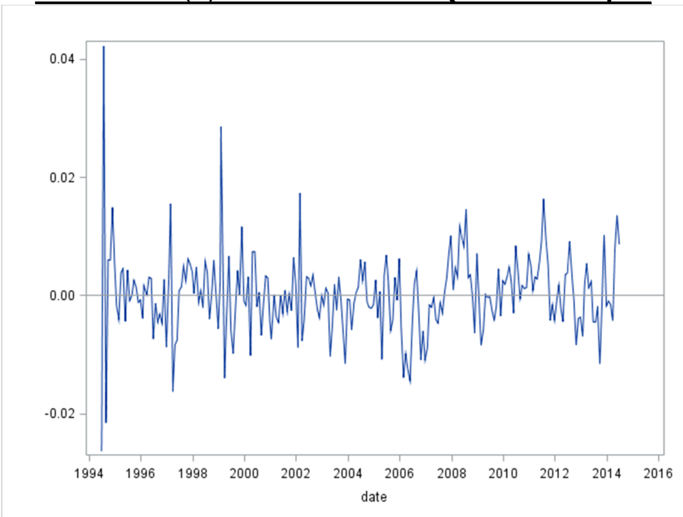
The figure plots the time-series of common factor LIQ, Fβeta, and LIQ. The common factor LIQ is the first principal component extracted from the four liquidity proxies. Fβeta is the firm-level sensitivity factor by performing a time-series regression for each stock's excess return on the AR(2) fitted extracted common factor ($\hat{F}_t$) constructed by taking the first principal component of turnover ratio (TO), trading speed (LM), price impact (ILLIQ), and trading cost (HL) extracted by the asymptotic principal components analysis approach (APC) of Connor and Korajczyk (1986). TO is the turnover ratio of Datar *et al.* (1998), LM is the trading speed ratio of Liu (2006), ILLIQ is the illiquidity ratio of Amihud (2002), and HL is the high-low trading cost ratio of Corwin *et al.* (2012). Refer to Appendix A for the exact definitions. Panels A and B plots the time-series of the common factor LIQ and the AR(2) residual of the common factor LIQ, respectively. Panel C plots the time-series of Fβeta, which is the monthly mean Fβeta over firms. Panel D plots the time-series of LIQ, where LIQ is the monthly return of a hedging portfolio formed by buying high Fβeta stocks and selling low Fβeta stocks.

Panel A: Common factor LIQ time-series plot

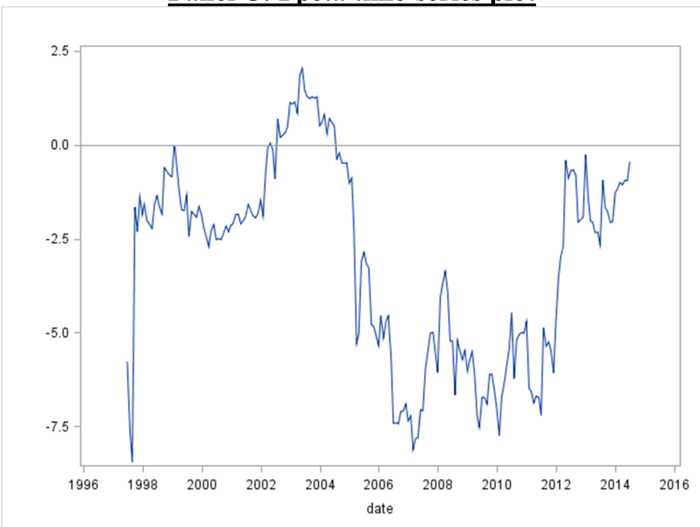


[19] This is because the TO and LM ratios are measures formed using trading information from the past 12 months, whereas the ILLIQ and HL capture liquidity components of shorter periods (3 months and 1 month, respectively).

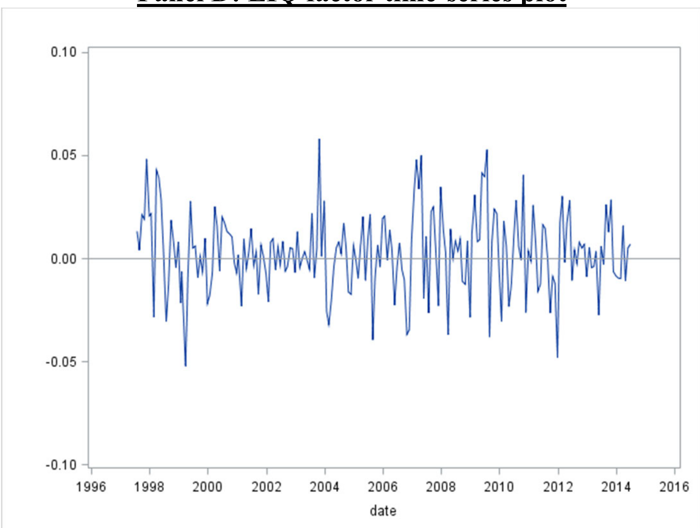
Panel B: AR(2) common factor LIQ time-series plot



Panel C: Fβeta time-series plot



Panel D: LIQ factor time-series plot



4.2 Empirical Results

4.2.1 Results on factor models

The average annual number of stocks in each of the 25 portfolios varies slightly across the different panels. In general, most portfolios consist of 50 to 60 firms. We first perform a regression on all six factor models (Eqs. (1) to (6)). We report the results in Table 4. As the intercepts are the focus in the time-series asset pricing test, we report only the numbers of significant regression intercepts and the adjusted R^2s in each of the three panels. These results show that the LIQ5F model (Eq. (6)) has the highest adjusted R^2 value. However, in terms of the number of significant intercepts, the LIQ3F and LIQ4F models outperform the other models (especially the WML4F model), with lower numbers of significant intercepts. Averaged over the three panels, the LIQ3F and LIQ4F models yield 2.00 and 2.67 significant intercepts (at the 5% significance level) out of the 25 regressions, respectively. In comparison, the FF3F and WML4F models produce 3.00 and 4.33, respectively. These results also suggest that momentum does not help improve the model performance in China.

Table 4 Number of Significant Factor Coefficients for the Tested Models (July 1994–June 2014)

$$R_{pt} - R_{ft} = \alpha_p + \Sigma\, b_{pt}F_p + \varepsilon_{pt}$$

$$\textit{(where } F = MP_t,\ SMB_t,\ HML_t,\ WML_t \textit{ or/and } LIQ_t\textit{)}$$

This table presents the number of significant factor coefficients for the six tested multifactor asset-pricing models. The 5% and 10% columns represent the number of significant factor coefficients at 5% and 10% significance levels, respectively. The six models are the CAPM (Eq. 1), FF3F (Eq. 2), LIQ3F (Eq. 3), LIQ4F (Eq. 4), WML4F (Eq. 5), and LIQ5F (Eq. 6) models. At the end of June of each year, all selected firms in China's stock market are sorted according to their market capitalisation (size), book-to-price ratio of equity (B/P), and firm-level liquidity ratio (LIQβ). Firms are then ranked into quintiles independently by size and factor beta (Fβeta), or B/P and Fβeta, or Fβeta only. Twenty-five two-way sorted portfolios are then formed by the intersection of the size-quintile and Fβeta-quintile portfolios (Panel A) or the B/P-quintile and Fβeta-quintile (Panel B) or the Fβeta-quintile only (Panel C) portfolios. Average size, B/P, and Fβeta of component firms are calculated for each of the 25 two-way sorted portfolios. R_p is the value-weighted monthly return on each of the 25 portfolios. R_f is the risk-free return. *MP* is the excess monthly return on the market portfolio, $R_m - R_f$, and R_m is the value-weighted market return. *SMB* is the simple average of the returns on the three small-stock portfolios, minus the returns on the three big-stock portfolios. *HML* is the simple average of the returns on the two high-B/P portfolios, minus the returns on the two low-B/P portfolios. *WML* is the simple average of the returns on the two winner-stock portfolios (with the highest average prior performance over the previous 11-month nominal stock return, lagged one month), minus the returns on the two loser-stock portfolios (with the lowest average prior performance over the previous 11-month nominal stock return lagged one month). Fβeta is the firm-level sensitivity factor obtained by performing a time-series regression for each stock's excess return on the AR(2) fitted extracted common factor ($\hat{F}_t$). *LIQ* is the simple average of the returns on the high-Fβeta portfolios minus the returns on the low-Fβeta portfolios. The *t-statistic* used is the Newey West adjusted *t*-statistic. The AR^2 is the adjusted R^2, and the Range presents the minimum and maximum adjusted R^2 of the regressions of the 25 portfolios.

CAPM (eq. 1)	Panel A		Panel B		Panel C	
	5%	10%	5%	10%	5%	10%
Intercept	12	14	4	4	1	2
AR2	0.83		0.85		0.88	
Range	0.71	0.93	0.74	0.91	0.80	0.91

FF3F (eq. 2)	Panel A		Panel B		Panel C	
	5%	10%	5%	10%	5%	10%
Intercept	3	9	3	5	3	4
AR2	0.92		0.88		0.89	
Range	0.85	0.96	0.78	0.92	0.82	0.92
LIQ3F (eq. 3)	Panel A		Panel B		Panel C	
	5%	10%	5%	10%	5%	10%
Intercept	3	7	1	3	2	5
AR2	0.93		0.87		0.89	
Range	0.87	0.96	0.76	0.92	0.83	0.93
LIQ4F (eq. 4)	Panel A		Panel B		Panel C	
	5%	10%	5%	10%	5%	10%
Intercept	4	5	2	3	2	5
AR2	0.93		0.89		0.90	
Range	0.88	0.96	0.81	0.93	0.83	0.93
WML4F (eq. 5)	Panel A		Panel B		Panel C	
	5%	10%	5%	10%	5%	10%
Intercept	6	9	4	6	3	5
AR2	0.92		0.89		0.89	
Range	0.85	0.96	0.78	0.92	0.82	0.92
LIQ5F (eq. 6)	Panel A		Panel B		Panel C	
	5%	10%	5%	10%	5%	10%
Intercept	6	9	4	5	4	5
AR2	0.93		0.89		0.90	
Range	0.87	0.96	0.81	0.93	0.83	0.93

4.2.2 Results on liquidity four-factor model

In this section, we further examine the detailed regression results from the LIQ4F model. In the LIQ4F model, we add the LIQ factor to the MP, SMB, and HML factors to form the model given by Eq. (4). To save space, we report only the intercepts, the coefficients of the LIQ factor, the Durbin-Watson d-statistic, and the adjusted R^2s of the LIQ4F regressions. We also include the intercepts from the FF3F regressions for a close comparison.

Panel A of Table 5 reports the regression results for the 25 Fβeta-size sorted portfolios. The magnitudes of the intercepts are small, with a high percentage of insignificant values (84% or 21/25). The average adjusted R^2 is 0.8925, which suggests that almost all of the portfolios' returns can be explained by factors in the model. For the coefficients of the newly constructed LIQ factor, 64% (72%) of the LIQ coefficients are significant at the 5%

Table 5 Time-Series Results on the Liquidity Four-Factor Model (July 1994–June 2014)

$$R_{pt} - R_{ft} = a_p + b_pMP_t + s_pSMB_t + h_pHML_t + \psi_pLIQ_t + \varepsilon_{pt}$$

At the end of June of each year, all selected firms in China's stock market are sorted according to their market capitalisation (size), book-to-price ratio of equity (B/P), or firm-level liquidity factor beta (Fβeta). Firms are then ranked into quintiles independently by size and factor beta (Fβeta) (Panel A), or B/P and Fβeta (Panel B), or Fβeta only (Panel C). Twenty-five two-way sorted portfolios are then formed by the intersection of the size-quintile and Fβeta-quintile portfolios (Panel A) or the B/P-quintile and Fβeta-quintile portfolios. Average size, B/P, and liquidity of component firms are calculated for each of the 25 two-way sorted portfolios. R_p is the value-weighted monthly return on each of the 25 portfolios. R_f is the risk-free return. *MP* is the excess monthly return on the market portfolio, $R_m - R_f$, and R_m is the value-weighted market return. *SMB* is the simple average of the returns on the three small-stock portfolios minus the returns on the three big-stock portfolios. *HML* is the simple average of the returns on the two high-B/P portfolios minus the returns on the two low-B/P portfolios. Fβeta is the firm-level sensitivity factor obtained by performing a time-series regression for each stock's excess return on the AR(2) fitted extracted common factor ($\hat{}F_t$) constructed by taking the first principal component of turnover ratio (TO), trading speed (LM), price impact (ILLIQ), and trading cost (HL) using the asymptotic principal components analysis approach (APC) of Connor and Korajczyk (1986). *LIQ* is the simple average of the returns on the low-Fβeta portfolios minus the returns on the high-Fβeta portfolios. *T-statistic* indicates the Newey West adjusted *t*-statistic. The *d*-statistic is from the Durbin-Watson test for autocorrelation.

Panel A (LIQ & Size sorted)												
			Coefficients					**t-statistics**				
			Size quintiles					Size quintiles				
			Small	→			Big	Small	→			Big
LIQ4F Intercept	LIQ quintiles	Low	0.0064	-0.0018	-0.0017	-0.0023	-0.0007	2.62	-1.17	-1.05	-1.28	-0.52
			0.0039	-0.0031	-0.0041	-0.0037	0.0005	1.63	-2.07	-2.49	-2.26	0.30
		↓	0.0031	0.0005	-0.0025	-0.0023	-0.0007	1.45	0.32	-1.56	-1.18	-0.34
			-0.0005	-0.0010	-0.0015	-0.0023	-0.0016	-0.23	-0.58	-0.85	-1.35	-0.99
		High	-0.0010	-0.0012	-0.0033	-0.0026	0.0004	-0.47	-1.07	-1.95	-1.43	0.20
			Coefficients					**t-statistics**				
			Size quintiles					Size quintiles				
			Small	→			Big	Small	→			Big
LIQ	LIQ quintiles	Low	0.47	0.25	0.39	0.39	0.51	2.76	1.98	2.62	2.67	4.96
			0.55	0.25	0.25	0.16	0.64	2.16	2.42	3.21	1.61	5.38
		↓	0.20	-0.05	-0.02	-0.04	0.07	0.88	-0.48	-0.20	-0.33	0.72
			-0.38	-0.43	-0.24	-0.35	-0.17	-1.84	-3.25	-1.77	-2.87	-1.41
		High	-0.46	-0.18	-0.32	-0.36	-0.92	-3.52	-2.10	-2.89	-3.59	-7.05
			d-statistic					**Adjusted R^2**				
			Size quintiles					Size quintiles				
			Small	→			Big	Small	→			Big
d-statistic & R^2	LIQ quintiles	Low	2.16	2.43	2.08	1.87	1.82	0.90	0.94	0.93	0.93	0.96
			1.90	2.21	2.22	1.83	2.10	0.88	0.95	0.95	0.94	0.91
		↓	2.15	2.26	2.01	2.04	2.03	0.91	0.94	0.95	0.93	0.92
			1.84	2.13	2.18	2.07	2.26	0.92	0.95	0.93	0.93	0.89
		High	1.84	2.37	2.15	1.92	2.07	0.92	0.96	0.92	0.93	0.89
			Coefficients					**t-statistics**				
			Size quintiles					Size quintiles				
			Small	→			Big	Small	→			Big
FF3F Intercept	LIQ quintiles	Low	0.0077	-0.0011	-0.0006	-0.0013	0.0007	2.94	-0.73	-0.36	-0.66	0.45
			0.0054	-0.0024	-0.0034	-0.0032	0.0023	1.84	-1.77	-2.05	-1.94	1.12
		↓	0.0036	0.0003	-0.0026	-0.0024	-0.0005	1.69	0.22	-1.60	-1.25	-0.26
			-0.0015	-0.0021	-0.0022	-0.0033	-0.0021	-0.61	-1.16	-1.28	-1.81	-1.26
		High	-0.0022	-0.0017	-0.0041	-0.0036	-0.0021	-1.01	-1.51	-2.47	-1.88	-0.91

Panel B	(LIQ & B/P sorted)											
LIQ4F Intercept			**Coefficients**					**t-statistics**				
			B/P quintiles					B/P quintiles				
			Low	→			High	Low	→			High
	LIQ quintiles	Low	0.0064	-0.0018	-0.0017	-0.0023	-0.0007	2.62	-1.17	-1.05	-1.28	-0.52
			0.0039	-0.0031	-0.0041	-0.0037	0.0005	1.63	-2.07	-2.49	-2.26	0.30
		↓	0.0031	0.0005	-0.0025	-0.0023	-0.0007	1.45	0.32	-1.56	-1.18	-0.34
			-0.0005	-0.0010	-0.0015	-0.0023	-0.0016	-0.23	-0.58	-0.85	-1.35	-0.99
		High	-0.0010	-0.0012	-0.0033	-0.0026	0.0004	-0.47	-1.07	-1.95	-1.43	0.20
LIQ			***Coefficients***					**t-statistics**				
			B/P quintiles					B/P quintiles				
			Low	→			High	Low	→			High
	LIQ quintiles	Low	0.47	0.25	0.39	0.39	0.51	2.76	1.98	2.62	2.67	4.96
			0.55	0.25	0.25	0.16	0.64	2.16	2.42	3.21	1.61	5.38
		↓	0.20	-0.05	-0.02	-0.04	0.07	0.88	-0.48	-0.20	-0.33	0.72
			-0.38	-0.43	-0.24	-0.35	-0.17	-1.84	-3.25	-1.77	-2.87	-1.41
		High	-0.46	-0.18	-0.32	-0.36	-0.92	-3.52	-2.10	-2.89	-3.59	-7.05
d-statistic & R^2			***d-statistic***					**Adjusted R^2**				
			B/P quintiles					B/P quintiles				
			Low	→			High	Low	→			High
	LIQ quintiles	Low	2.16	2.43	2.08	1.87	1.82	0.90	0.94	0.93	0.93	0.96
			1.90	2.21	2.22	1.83	2.10	0.88	0.95	0.95	0.94	0.91
		↓	2.15	2.26	2.01	2.04	2.03	0.91	0.94	0.95	0.93	0.92
			1.84	2.13	2.18	2.07	2.26	0.92	0.95	0.93	0.93	0.89
		High	1.84	2.37	2.15	1.92	2.07	0.92	0.96	0.92	0.93	0.89
FF3F Intercept			**Coefficients**					**t-statistics**				
			B/P quintiles					B/P quintiles				
			Low	→			High	Low	→			High
	LIQ quintiles	Low	0.0013	-0.0016	-0.0026	-0.0003	0.0010	0.57	-0.72	-1.27	-0.12	0.31
			-0.0004	-0.0021	0.0009	0.0011	-0.0002	-0.15	-0.93	0.46	0.52	-0.11
		↓	-0.0024	0.0009	-0.0019	-0.0045	0.0006	-1.08	0.32	-0.98	-2.85	0.34
			-0.0068	-0.0028	-0.0017	-0.0014	-0.0019	-2.63	-1.37	-0.79	-0.80	-0.93
		High	-0.0042	-0.0036	-0.0049	-0.0009	-0.0003	-1.88	-1.81	-2.02	-0.30	-0.09
Panel C (LIQ sorted only)												
LIQ4F Intercept			**Coefficients**					**t-statistics**				
			LIQ quintiles					LIQ quintiles				
			1-5	→			21-25	1-5	→			21-25
	LIQ quintiles	Low	-0.0031	-0.0023	-0.0006	-0.0035	-0.0022	-1.55	-1.15	-0.32	-1.41	-1.04
			-0.0030	-0.0031	-0.0011	-0.0046	0.0015	-1.89	-1.78	-0.53	-2.36	0.57
		↓	0.0005	-0.0020	-0.0037	-0.0024	-0.0054	0.21	-0.89	-1.81	-1.41	-2.62
			-0.0005	0.0008	0.0015	0.0012	-0.0025	-0.28	0.34	0.77	0.58	-1.00
		High	0.0018	-0.0012	0.0002	-0.0018	0.0012	0.83	-0.58	0.05	-0.95	0.50
LIQ			***Coefficients***					**t-statistics**				
			LIQ quintiles					LIQ quintiles				
			1-5	→			21-25	1-5	→			21-25
	LIQ quintiles	Low	0.70	0.68	0.28	0.05	-0.68	5.73	5.45	2.80	0.36	-4.20
			0.78	0.63	0.09	-0.25	-0.95	6.53	4.39	0.76	-1.72	-4.17
		↓	0.16	0.34	-0.08	-0.42	-0.69	1.22	2.67	-0.63	-3.04	-4.90
			0.43	0.64	-0.09	-0.35	-0.62	3.18	4.74	-0.76	-2.33	-3.21
		High	0.57	0.31	-0.28	-0.54	-0.83	4.20	2.33	-2.10	-4.77	-3.69

			d-statistic					**Adjusted R^2**				
			LIQ quintiles					LIQ quintiles				
			1-5	→			21-25	1-5	→			21-25
d-statistic & R^2	LIQ quintiles	Low	1.99	2.05	2.23	2.19	1.79	0.92	0.89	0.90	0.86	0.89
			2.23	2.11	1.99	2.04	2.09	0.93	0.92	0.92	0.89	0.86
		↓	1.87	1.86	2.28	2.49	2.19	0.92	0.91	0.91	0.90	0.90
			2.14	2.07	2.10	2.14	1.98	0.92	0.84	0.91	0.91	0.88
		High	1.91	2.30	1.90	1.90	2.09	0.90	0.91	0.83	0.90	0.86
			Coefficients					**t-statistics**				
			LIQ quintiles					LIQ quintiles				
			1-5	→			21-25	1-5	→			21-25
FF3F Intercept	LIQ quintiles	Low	-0.0012	-0.0005	0.0002	-0.0034	-0.0041	-0.52	-0.22	0.11	-1.43	-1.64
			-0.0009	-0.0013	-0.0008	-0.0052	-0.0011	-0.44	-0.70	-0.42	-2.78	-0.35
		↓	0.0009	-0.0011	-0.0039	-0.0035	-0.0073	0.43	-0.46	-2.06	-1.92	-3.59
			0.0007	0.0026	0.0012	0.0002	-0.0042	0.37	0.95	0.69	0.10	-1.56
		High	0.0034	-0.0004	-0.0006	-0.0033	-0.0011	1.59	-0.17	-0.22	-1.56	-0.40

(10%) level. The lowest Fβeta portfolios tend to have positive LIQ coefficients, whereas most of the negative LIQ coefficients occur in the high-Fβeta portfolios. The intercepts from the FF3F regressions exhibit a negative return-Fβeta relation for the size-controlled portfolios (across columns). The average return difference between the lowest and highest Fβeta portfolios decreases from 38 basis points (FF3F) to 15 basis points (LIQ4F) after the LIQ factor is added in the regression model. These results suggest that rational investors demand higher returns for smaller and less liquid firms in China.

The results shown in panels B (Fβeta-B/P sorted portfolios) and C (Fβeta sorted portfolios) are similar to those in Panel A. However, the impact of the LIQ factor is stronger in Panel C (76% significant LIQ coefficients) and slightly weaker in Panels A (64%) and B (64%). The mean-adjusted R^2s of the LIQ4F model regressions range from 0.8925 (Panel B) to 0.8953 (Panel C). In general, the adjusted R^2s of the models are all high (> 0.89), with an average value of 0.9050. The negative return-Fβeta pattern remains consistent in the intercepts of the FF3F regressions in panels B and C, but is mostly wiped out by the LIQ4F model.

4.2.3 Model performance horse-race tests

In this section, we test how well the various sets of pricing factors explain the excess returns of the portfolios formed in the previous section. We examine six of the multifactor asset-pricing models (the CAPM, FF3F, LIQ3F, WML4F, LIQ4F, and LIQ5F models) and evaluate their overall explanatory performances. The results are shown in Table 6.

Theoretically, if a particular asset-pricing model captures all of the factors that affect stock returns, then the intercepts of the time-series regressions on the returns of the 25 portfolios should be jointly equal to zero. We check whether this is so using the GRS F-test (Gibbons *et al.*, 1989), with the null hypothesis that the 25 intercepts are jointly equal to zero. We expect a better model to produce a higher p-value of the GRS F-test (less likely to reject the null hypothesis). Panel A shows that most of the models have insignificant GRS *F*-test results, except for the CAPM, which has a *p*-value less than 5%. The LIQ4F and LIQ5F models have the highest *p*-values (0.25 and 0.27, respectively) of the GRS test, indicating that they outperform the other models.

Table 6 Summary Statistics for Tests of Asset Pricing Factor Models (July 1994–June 2014)

At the end of July of each year, all selected firms in China's stock market are sorted according to their market capitalisation (size), book-to-price ratio of equity (B/P), and firm-level stock factor beta (Fβeta). Firms are then ranked into quintiles independently by size and Fβeta (Panel A), or B/P and Fβeta (Panel B), or Fβeta only (Panel C). Twenty-five two-way sorted portfolios are then formed by the intersection of the size-quintile and Fβeta-quintile portfolios (Panel A) or the BP-quintile and Fβeta-quintile portfolios. This table tests the performance of various asset pricing models with or without the LIQ factor. The GRS statistic and corresponding p-value test the null hypothesis that intercepts of the 25 portfolios are jointly zero for various factor models. $A|a_i|$ is the average absolute value of the intercepts. $A|a_i|/A|r_i|$ is the average absolute value of the intercept over the average absolute value of r_i, which is the average return on portfolio i minus the average of the portfolio returns. $A(a_i^2)/A(r_i^2)$ is the average square of the absolute value of the intercept divided by the average square of the absolute value of r_i. $A(a\^{}_i^2)/A(u\^{}_i^2)$ is the average squared intercept over the average squared value of r_i, corrected for sampling error in the numerator and denominator. The last column provides the average adjusted R^2.

	GRS	p_GRS	$A\|a_i\|$	$A\|a_i\|/A\|r_i\|$	$A(a_i^2)/A(r_i^2)$	$A(a\^{}_i^2)/A(u\^{}_i^2)$	$A(R^2)$
Panel A. 25 Size-LIQ portfolios							
CAPM	1.90	0.01	0.0058	1.21	1.57	0.95	0.8330
FF3F	1.37	0.12	0.0025	0.52	0.25	0.49	0.9221
LIQ3F	1.23	0.22	0.0021	0.45	0.20	0.43	0.9256
WML4F	1.34	0.14	0.0027	0.57	0.50	0.29	0.9241
LIQ4F	1.19	0.25	0.0021	0.44	0.19	0.41	0.9272
LIQ5F	1.17	0.27	0.0023	0.49	0.22	0.42	0.9292
Panel B. 25 B/P-LIQ portfolios							
CAPM	0.80	0.74	0.0021	0.95	0.90	0.94	0.8523
FF3F	0.91	0.59	0.0020	0.92	0.84	0.73	0.8837
LIQ3F	0.79	0.75	0.0022	1.01	0.93	0.82	0.8708
WML4F	1.06	0.39	0.0022	1.00	1.01	0.75	0.8855
LIQ4F	0.78	0.76	0.0020	0.91	0.75	0.66	0.8925
LIQ5F	0.94	0.55	0.0023	1.04	0.94	0.70	0.8944
Panel C. 25 LIQ portfolios							
CAPM	0.88	0.63	0.0018	1.00	0.99	0.99	0.8754
FF3F	1.09	0.36	0.0021	1.20	1.89	1.19	0.8851
LIQ3F	0.99	0.48	0.0019	1.09	1.36	0.97	0.8931
WML4F	1.11	0.34	0.0022	1.24	2.03	1.15	0.8868
LIQ4F	0.95	0.54	0.0021	1.17	1.45	0.99	0.8953
LIQ5F	0.99	0.48	0.0022	1.24	1.64	0.97	0.8971

We then follow Fama and French (2015, 2016) in forming four horse-race test statistics with which to further compare the relative performances of the competing models. The average absolute intercept, $A|a_i|$, should be smaller for a better fitted model. Panel A shows that the LIQ3F and LIQ4F models have the smallest values, specifically four basis points lower than the FF3F model and six basis points lower than the WML4F model. The next two ratios measure the proportion of the portfolio returns that is left unexplained by a pricing model. $A|a_i|/A|r_i|$ is the average absolute intercept divided by the average absolute portfolio return dispersion.[20] $A(a_i^2)/A(r_i^2)$ is a similar measure in the squared form. The fourth ratio, $A(a\hat{}_i^2)/A(u\hat{}_i^2)$, is a modified version of $A(a_i^2)/A(r_i^2)$ adjusted for sampling errors in both the numerator and denominator.[21] The test results in Panel A show that the LIQ4F has the lowest values for these four evaluation ratios and the LIQ3F and LIQ5F models are the first and second runners-up rated by these ratios, respectively, outperforming the FF3F and WML4F models. The CAPM produces the highest percentage of unexplained portfolio returns.

The last column reports the average adjusted R^2s. Panel A shows that the CAPM has the lowest adjusted R^2 (0.8330) and that the LIQ5F model has the highest (0.9292). The LIQ4F model has a higher adjusted R^2 (0.9272) than the FF3F model (0.9221). The test results shown in panels B and C generate similar rankings for the competing models to those reported in Panel A. In general, the GRS *F*-test results, and the model performance evaluation ratios from Table 6, provide evidence that the LIQ4F model is a better multifactor asset-pricing model than the FF3F or WML4F model for explaining average stock returns in China. Therefore, we decide to use the LIQ4F model as our main testing model in the following tests.

4.2.4 Anomaly portfolios and factor models

So far, we have tested the performance of the LIQ4F and other factor models in explaining the returns on portfolios, which are formed on the basis of (or partially on the basis of) the rankings of the stocks' liquidity betas. As Liu *et al.* (2019) point out, how well a factor model explains the anomaly returns is a key measurement of the model's usefulness. In this section, we put the competing models to the test with a series of well-documented anomalies in China's stock market, comparing their ability to explain the anomaly portfolios' returns. We use eight anomalies that are found by Liu *et al.* (2019) to yield significant abnormal positive returns in China's stock market. The anomalies include the earnings-to-price ratio (EP), book-to-price ratio (BP), cash-flow-to-price ratio (CP), profitability measure (ROE), stock return volatility (VOL), stock return reversal (REVER), and two turnover ratios with different time frames (TURN_1M and TURN_12M). Appendix D provides detailed definitions of the anomaly measures.

We construct the anomaly portfolios as follows. For each of the eight anomaly measures, we independently sort the sample stocks into five size (market capitalisation)

[20] We define R_i as portfolio *i*'s monthly excess return, R as the average of Ri across the 25 portfolios, and r_i as portfolio *i*'s return dispersion, which is calculated as $r_i = R_i – R$.

[21] $a\hat{}_i^2$ is the difference between the squared intercept and the square of its standard error. $u\hat{}_i^2$ is the difference between the squared portfolio return dispersion r_i^2 and the square of its standard error.

portfolios and five anomaly portfolios. We then form 25 double-sorted portfolios from the intersection of the size sorted quintiles and the anomaly sorted quintiles.[22] With each set of the anomaly portfolios, we obtain the value-weighted portfolio returns as the targets to be explained by the factor models. We conduct the GRS *F*-test and the alpha based horse-race tests used in Table 6 for these anomaly portfolios. A better factor model generates lower GRS test values and smaller percentages of unexplained portfolio returns indicated by the alpha-based ratios. Table 7 reports the test results for the FF3F and LIQ4F performances on the eight sets of anomaly portfolios. Although we run the tests for all six of the competing models specified by Eqs. (1) to (6), the results generally suggest that the LIQ4F (and occasionally the LIQ3F) model is a better fit than the other models. Therefore, we only report the test results of the FF3F and LIQ4F models in Table 7.

Table 7 Summary Statistics for Tests of Asset Pricing Factor Models (July 1994–June 2014)

At the end of July of each year, all selected firms in China's stock market are sorted according to their market capitalisation (size) and one of the eight anomaly measures. The definition of the anomaly measures are detailed in Appendix D. Firms are then ranked into quintiles independently by size and the anomaly measure. Twenty-five two-way sorted portfolios are then formed by the intersection of the size-quintile and anomaly-quintile portfolios. This table tests the performance of FF3F and LIQ4F. The GRS statistic and corresponding p-value test the null hypothesis that intercepts of the 25 portfolios are jointly zero for various factor models. $A|a_i|$ is the average absolute value of the intercepts. $A|a_i|/A|r_i|$ is the average absolute value of the intercept over the average absolute value of r_i, which is the average return on portfolio i minus the average of the portfolio returns. $A(a_i^2)/A(r_i^2)$ is the average square of the absolute value of the intercept divided by the average square of the absolute value of r_i. $A(\hat{a}_i^2)/A(\hat{u}_i^2)$ is the average squared intercept over the average squared value of r_i, corrected for sampling error in the numerator and denominator. The last column provides the average adjusted R^2.

Anomaly	Model	GRS	p_GRS	$A\|a_i\|$	$A\|a_i\|/A\|r_i\|$	$A(a_i^2)/A(r_i^2)$	$A(\hat{a}_i^2)/A(\hat{u}_i^2)$	$A(R^2)$
EP	**FF3F**	2.09	0.00	0.0030	0.622	0.408	0.639	0.9146
	LIQ4F	2.05	0.00	0.0030	0.618	0.398	0.633	0.9147
BP	**FF3F**	1.37	0.12	0.0021	0.434	0.188	0.414	0.9246
	LIQ4F	1.33	0.15	0.0021	0.433	0.186	0.407	0.9245
CP	**FF3F**	0.95	0.54	0.0019	0.429	0.195	0.446	0.8903
	LIQ4F	0.85	0.67	0.0019	0.427	0.188	0.434	0.8904
ROE	**FF3F**	2.56	0.00	0.0033	0.708	0.573	0.714	0.9163
	LIQ4F	2.42	0.00	0.0033	0.709	0.570	0.714	0.9164
VOL	**FF3F**	1.26	0.20	0.0025	0.574	0.413	0.595	0.9220
	LIQ4F	1.23	0.22	0.0026	0.591	0.419	0.598	0.9222
REVER	**FF3F**	1.46	0.09	0.0023	0.560	0.322	0.515	0.9171
	LIQ4F	1.37	0.13	0.0022	0.521	0.297	0.493	0.9179
TURN_1M	**FF3F**	2.09	0.00	0.0024	0.486	0.260	0.506	0.9083
	LIQ4F	1.98	0.01	0.0024	0.498	0.257	0.496	0.9087
TURN_12M	**FF3F**	1.75	0.02	0.0022	0.475	0.251	0.486	0.9134
	LIQ4F	1.58	0.05	0.0023	0.484	0.242	0.469	0.9139

[22] Following Liu *et al.* (2019), we construct decile univariate sorted anomaly portfolios. The test results for the univariate sorted portfolios are similar to those for the double-sorted portfolios.

The first three anomalies, EP, BP, and CP, are all related to the valuation of the stocks' fundamentals. In China, value stocks are found to generate higher expected returns than growth stocks. For these three sets of anomalies, the GRS test shows that the LIQ4F explains the portfolio returns better than the FF3F model as it has lower *F*-test values. Across these three anomalies, the LIQ4F model's average GRS test value is 1.41 and that of the FF3F model is 1.47. The LIQ4F also constantly exhibits lower alpha-based horse-race ratios than the FF3F model. The ROE portfolios represent the profitability anomaly, a positive return difference found between firms with robust and weak profitability. For the ROE portfolios, the LIQ4F model again has a lower GRS statistic (2.42) than the FF3F model (2.56). Its horse-race ratios are also slightly lower than or equal to those of the FF3F model. For the portfolios sorted by return reversals (REVER) and turnovers (TURN_1M and TURN_12M), the results are similar to those discussed earlier. The GRS tests suggest that LIQ4F outperforms the FF3F model in all three settings, whereas 9 out of the 12 horse-race ratios support the same rating. The results for the LIQ4F on the volatility (VOL) portfolios are the weakest. Although the GRS test results favour the LIQ4F, the horse-race ratios suggest that the FF3F model is slightly better. Across all eight sets of anomaly portfolios, the adjusted R^2s of the regressions are unanimously higher for the LIQ4F than for the FF3F model. Therefore, overall, the test results in Table 7 further support that the liquidity augmented model, the LIQ4F, outperforms the other models examined in this study.

4.3 Robustness Tests

4.3.1 Time-series robustness tests

Studies document that exogenous factors and anomalies may influence the relations between risk and return. These exogenous factors and anomalies include the potential existence of nonlinear risk-return relations, missing factors, seasonality, and conditional markets. To address these potential issues, we perform robustness tests on high moment (coskewness and cokurtosis) risks, residual risks, seasonality, and both up- and down-market conditions.

Kraus and Litzenberger (1976) and Kostakis *et al.* (2012) demonstrate that high moment factors have explanatory power over stock returns. Hence, we first investigate the effects of the coefficients of squared and cubed market premiums (i.e. coskewness and cokurtosis risks) on the LIQ4F model, calculating these effects as follows:

$$R_{pt} - R_{ft} = a_p + b_p MP_t + s_p SMB_t + h_p HML_t + \psi_p LIQ_t + \varphi_p(MP_t - \overline{MP})^2 + \phi_p(MP_t - \overline{MP})^3 + \varepsilon_{pt}, \tag{7}$$

where $\overline{MP}$ is the mean market risk premium, φ_p captures the coskewness effect, and ϕ_p

captures the cokurtosis effect.

To conserve space, we do not tabulate the detailed results of the high moment tests. The patterns of the intercepts MP, SMB, HML, and LIQ are similar to those seen in the previous factor test results. For the high moment coefficients, we find that only 12% to 28% of the coskewness coefficients and 12% to 28% of the cokurtosis coefficients are significant at the 5% level for the three sets of portfolios formed earlier. The mean adjusted R^2s of the high moment model change slightly (by -0.10% to 0.08%) compared to those of the LIQ4F model. In general, the high moment test results show that coskewness and cokurtosis have relatively minor additional influences on stock returns in the Chinese market.

We also perform robustness tests on the residual risk and up- and down-market conditions. To conserve space, the results are not reported. Adding residual risk to the model does not significantly affect its explanatory power. The results of the up- and down-market models are quite similar, with the down-market having a slightly stronger and more significant effect on the factors concerned and on the more insignificant intercepts. In general, the results of these two robustness tests are quite similar to those for the LIQ4F model (Table 5). When performing the seasonality test, we control seasonality by month and test whether the distribution of the intercepts and the coefficients of those factors in each month are identically distributed. We find that on average, only 1.44 of 25 portfolios have significant intercepts from the regressions by month across the three panels. All of the MP coefficients and more than half of the SMB coefficients are significant at the 5% level. Approximately 36% of the LIQ coefficients are significant at the 5% level, with most of these scattered across different months. The mean adjusted R^2s for the three panels range from 0.8981 to 0.9342, with a mean value of approximately 0.9113. In general, these results are similar to those from the LIQ4F model. This outcome further demonstrates that the LIQ4F model has a strong capacity to capture the variability of returns across individual months. The evidence from the monthly test shows that the results of the model are fairly consistent rather than driven by a few unusual months. Therefore, in general, we find no significant evidence of monthly seasonality in China's stock market.

4.3.2. Cross-sectional tests

To investigate the robustness of our time-series tests, we perform cross-sectional tests for the various factor models. To make these tests consistent with the time-series tests, we modify Fama and French's (1992) approach. Specifically, we construct 27 portfolios on the basis of the pre-beta (market beta) sorting and the previous three portfolio sortings of Fβeta-size, Fβeta-B/P, and Fβeta only. We first form three pre-beta portfolios and then three size (B/P) portfolios in each pre-beta portfolio. Finally, we form three Fβeta portfolios for each pre-beta-size (pre-beta-B/P) portfolio. For the Fβeta sorted-only factor, 9 portfolios are formed for each pre-beta portfolio, resulting in a total of 27 portfolios in each sorting.[23] The pre-ranking beta is estimated using a rolling window OLS regression over the previous 36 monthly returns. We then run the time-series regressions for each of the 27 portfolios to estimate the factor loadings of the LIQ4F mode or the LIQ4F with squared and cubed market premiums to capture the higher moment effects, as follows:

$$R_{pt} - R_{ft} = a_p + b_p MPt + s_p SMB_t + h_p HML_t + \psi_p LIQ_t + \varphi_p (MP_t - \overline{MP})^2 + \phi_p (MP_t - \overline{MP})^3 + e_{it} \quad (8)$$

The first sub-period (or portfolio-forming period) is from July 1997 to June 1998. At the beginning of the test period (the second sub-period, starting from July 1998), the portfolio returns (based on portfolio ranking in the first sub-period) are regressed against the factor loading ($b_{p,t\text{-}1}$, $s_{p,t\text{-}1}$, $h_{p,t\text{-}1}$, $\psi_{p,t\text{-}1}$, φ_p, and ϕ_p) as estimated in the first sub-period.

The factor loadings are updated monthly up to the month before the computation of the portfolio returns. For the LIQ4F model, only $b_{p,t\text{-}1}$, $s_{p,t\text{-}1}$, $h_{p,t\text{-}1}$, and $\psi_{p,t\text{-}1}$ are estimated. The regressions are as follows:

$$R_{pt} - r_{ft} = \gamma_{0t} + \gamma_{1t}\, b_{p,t\text{-}1} + \gamma_{2t}\, s_{p,t\text{-}1} + \gamma_{3t}\, h_{p,t\text{-}1} + \gamma_{4t}\, \psi_{p,t\text{-}1} + \gamma_{5t}\, \varphi_{p,t\text{-}1} + \gamma_{6t}\, \phi_{p,t\text{-}1} + \mu_{pt} \quad (9)$$

The regressions in Eq. (9) are performed for each of the 204 months (July 1997 to June 2014), with a total of 204 regressions run in the test period (i.e. t = 1 to 204). Hence, there are 204 estimated gamma coefficients. t-tests are conducted for the mean estimated gamma coefficients.

Table 8 reports the results of Eq. (9). As in the time-series tests, we find all of the average cross-sectional regression intercepts to be statistically insignificant. As with Fama and French's (1992) results, we find that the MP factor's premiums are insignificant in the models. The SMB factor results are better, demonstrating average coefficients significant at the 1% level in Panel A. All of the six LIQ factor coefficients are significant at the 5% level in the three panels. This suggests that the liquidity factor has a strong cross-sectional impact on the portfolio returns. In addition, the mean adjusted R^2s are much lower (between 0.1866 and 0.4006) than those reported in the time-series tests. However, the adjusted R^2s of the LIQ4F regressions remain higher than those of the FF3F model (not tabulated) in all three panels. We also check the robustness of the LIQ4F model by including high moment effects in the model. We find that the high moment coefficients are mostly insignificant. In general, the cross-sectional results also support the finding that the liquidity factor plays an important role in explaining stock returns in China.

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23 We also try a 125-portfolio formation format (5 x 5 x 5). The regression results are similar, with slightly weaker significant coefficients for the LIQ factors.

Table 8 Cross-sectional results on liquidity four-factor model (July 1997–June 2014)

We modify Fama and French's (1992) approach to construct 27 portfolios. We then run time-series regressions for each of the 27 portfolios to estimate the factor loadings of the liquidity four-factor model, LIQ4F, or LIQ4F with higher moment risks as follows: $R_{pt} - R_{ft} = a_p + b_p MP_t + s_p SMB_t + h_p HML_t + \psi_p LIQ_t + \varphi_p (MPt - \overline{MP})2 + \phi_p (MPt - \overline{MP})3 + \varepsilon_{pt}$. The first sub-period (portfolio forming period) is from July 1997 to June 1998. In the beginning of the test period (starting from July 1998), portfolio returns (based on portfolio ranking in the first sub-period) are regressed against the factor loading ($b_{p,t\text{-}1}$, $s_{p,t\text{-}1}$, $h_{p,t\text{-}1}$, $\psi_{p,t\text{-}1}$, φ_p, and ϕ_p) estimated in the first sub-period. The factor loadings are updated monthly up to the month prior to the computation of the portfolio returns. The regressions are as follows: $Rpt - r_{ft} = \gamma_{0t} + \gamma_{1t} b_{p,t\text{-}1} + \gamma_{2t} s_{p,t\text{-}1} + \gamma_{3t} h_{p,t\text{-}1} + \gamma_{4t} \psi_{p,t\text{-}1} + \gamma_{5t} \varphi_{p,t\text{-}1} + \gamma_{6t} \phi_{p,t\text{-}1} + \varepsilon_{pt}$. Regressions are performed for each of the 204 months (July 1997–June 2014) in the test period, with a total of 204 regressions run in the test period (i.e. t = 1 to 204). Hence, there are 204 estimated coefficients of γ_{0t}, γ_{1t}, γ_{2t}, γ_{3t}, γ_{4t}, γ_{5t} and γ_{6t}. The t tests are applied on the mean estimated coefficients of γ_{0t}, γ_{1t}, γ_{2t}, γ_{3t}, γ_{4t}, γ_{5t} and γ_{6t}. T-statistics are Newey-West adjusted t-statistics. The percentage of number of significant coefficients out of the 204 regressions is reported. The average and range of adjusted R^2 of the 204 regressions are also reported.

	γ_0	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	Adj R^2	Range for Adj R^2
Panel A (Fβeta & Size sorted)									
LIQ4F	0.0107	-0.0048	0.0084***	0.0020	0.0026**			0.3831	[-0.1328,0.8549]
t-statistic	1.34	-0.58	3.17	1.12	2.27				
significant number	29%	24%	69%	15%	28%				
LIQ4F + High moments	0.0116	-0.0058	0.0086***	0.0015	0.0026**	0.0005	-0.0001	0.4006	[-0.1548,0.8454]
t-statistic	1.42	-0.70	3.24	0.88	2.21	0.47	-0.38		
significant number	21%	21%	67%	10%	25%	11%	16%		
Panel B(Fβeta & B/P sorted)									
LIQ4F	0.0066	-0.0002	0.0028	0.0024	0.0024**			0.2323	[-0.1607,0.7617]
t-statistic	1.07	-0.03	1.08	1.41	1.98				
significant number	19%	22%	21%	37%	28%				
LIQ4F + High moments	0.0055	0.0008	0.0021	0.0027	0.0026**	0.0007	-0.0002	0.2509	[-0.2156,0.7938]
t-statistic	0.86	0.14	0.83	1.61	2.13	0.74	-0.59		
significant number	14%	19%	18%	34%	26%	13%	15%		
Panel C (Fβeta sorted only)									
LIQ4F	0.0038	0.0024	0.0021	0.0018	0.0026**			0.1866	[-0.1681,0.7848]
t-statistic	0.51	0.36	0.88	0.93	2.11				
significant number	22%	22%	18%	16%	30%				
LIQ4F + High moments	-0.0012	0.0069	0.0027	0.0026	0.0028**	-0.0016	0.0003	0.2119	[-0.2726,0.8018]
t-statistic	-0.15	1.01	1.08	1.29	2.26	-1.47	1.40		
significant number	17%	17%	20%	18%	25%	10%	13%		

** Significant at the 5% level; *** Significant at the 1% level.

V. Conclusions

We investigate the role of liquidity in explaining stock returns in the Chinese stock market from July 1994 to June 2014. We use the APC method to construct a new liquidity factor that captures and combines the four different dimensions of liquidity into one factor. We also compare the performance of liquidity and other multifactor asset-pricing models (i.e. the CAPM, FF3F, LIQ3F, LIQ4F, WML4F, and LIQ5F models) in China.

Our results are consistent with those of Fama and French (1992) and Carhart (1997) in that most of the well-known factors (MP, SMB, HML, and LIQ) have different levels of explanatory power regarding the variations in mean excess returns, except for the momentum factor (WML). In our model, the intercepts are generally insignificant, which is consistent with our expectation. The reasonably high values of the adjusted R^2s also provide evidence that supports the validity of the multifactor models. We use the GRS *F*-test and other horse-race ratios to compare the performance of various multifactor models in explaining returns on both liquidity sorted portfolios and anomalies. We find that the LIQ4F model outperforms other multifactor asset-pricing models in assessing China's stock returns.

We also check the robustness of the LIQ4F model by performing cross-sectional tests in relation to other models or tests on other effects, including tests on residual risk, nonlinear high moment effects, up- and down-market conditions, and the monthly seasonality effect. We find that the residual risk and the coskewness and cokurtosis factors have no explanatory power in predicting the time-series stock returns. The cross-sectional results are consistent with the time-series results.

In general, multifactor models work well for examining the Chinese stock market. We find that the LIQ4F model outperforms other multifactor asset-pricing models in explaining the average excess stock returns in the market. The findings in this study can provide new insights into liquidity and asset-pricing models in relation to China, which is an important emerging market worldwide. The liquidity factor models documented in this study can help both individual and institutional investors establish more accurate benchmarks for estimating their costs of capital, to evaluate and select their investment projects, and to form optimal investment portfolios for their investments in China.

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Appendix A

Construction of four liquidity proxies

We construct four liquidity proxies: turnover ratio (Datar, Naik, and Radcliffe, 1998; Chan and Faff, 2005), Amihud's (2002) illiquidity ratio, Liu's (2006) liquidity ratio, and Corwin and Schultz's (2012) daily high-low ratio. Measure (1) proxies for the trading-quantity component, while measure (2) represents the price-impact component. Measures (3) and (4) proxy for the trading speed and transaction cost components, respectively. Liquidity proxies are calculated for each July from 1994 to June 2012, and they are defined as follows:

A) Trading quantity component

1) Turnover ratio (TO): the average of the monthly number of shares traded scaled by the average number of shares outstanding over 12 months before July.

B) Price impact component

2) Amihud's illiquidity ratio (ILLIQ): the daily ratio of absolute stock return to its dollar volume, after eliminating the highest 0.5% upper tail observations, averaged over 3 months before July. This can be interpreted as the daily price response associated with one dollar of trading volume, thus serving as an approximate measure of price impact.

$$ILLIQ_{i,t} = (1/N_{i,t})\sum_d(|r_{i,d,t}|/vol_{i,d,t}), \quad (A.1)$$

where $|r_{i,d,t}|$ is the absolute value of return on stock i on day d in period t, $vol_{i,d,t}$ is the trading volume in monetary units in local currency of stock i on day d, and $N_{i,t}$ is the number of trading days (with non-zero volume) for stock i in period t.

C) Trading speed component

3) Liu's (2006) price speed ratio. The standardised turnover-adjusted number of zero-trading days can capture multiple dimensions of liquidity, such as trading speed, trading quantity, and trading cost, with a particular emphasis on trading speed, that is, the continuity of trading and the potential delay or difficulty in executing an order (four dimensions of liquidity – trading quantity, trading speed, trading cost, and price impact).

$$\text{Illiquidity} = [\text{No. of zero-trading days in prior 12 months} + (1/(\text{12-month turnover}))/\mathit{Deflator}]\times 21\times 12/\mathit{NoTD}, \quad (A.2)$$

where 12-month turnover is turnover during the prior 12 months, calculated as the sum of daily turnover over the prior 12 months; daily turnover is the ratio of the number of shares traded on a day to the number of shares outstanding at the end of the day; *NoTD* is the total number of trading days in the market over the prior x months; and *Deflator* is chosen such that $0 < (1/(\text{12-month turnover}))/\text{Deflator} < 1$ for all sample stocks, and it serves as a tiebreaker when two stocks have the same number of zero-trading days. For our analysis, *Deflator* is 200,000,000. The number is much larger than the one used by Liu (2006) because some of our sample stocks are traded very infrequently.

D) Trading costs component

4) Corwin and Schultz's (2012) daily high-low trading cost liquidity ratio (HL):

$$HL = 2(e^{\alpha} - 1)/(1 + e^{\alpha}), \tag{A.3}$$

where $\alpha = (\sqrt{2\beta} - \sqrt{\beta})/(3 - 2\sqrt{2}) - \sqrt{[\gamma/(3 - 2\sqrt{2})]}$ and $\beta = E\{\sum_{j=0}^{1} [\ln(H^0_{t+j}/L^0_{t+j})]^2\}$ and $\gamma = [\ln(H^0_{t,t+1}/L^0_{t,t+1})]^2\}$, with H^0_{t+j} (L^0_{t+j}) being observed high (low) stock price for day t+j and $H^0_{t,t+1}$ ($L^0_{t,t+1}$) being the observed high (low) price over the 2 days t and t+1.
$E(\cdot)$ is the expectation operator.

Appendix B

Formation of Fama-French three factors and momentum

Following previous studies, we use monthly return data on non-financial companies only with appropriate adjustments for capital changes. We employ value-weighted market returns with cash dividends reinvested as proxy for the market index. For the risk-free rate, we use the 1-month China Central Bank deposit rate from July 1994 to June 2012 in this study.

To avoid the so-called look-ahead bias, accounting data at the fiscal year-end in calendar year $t-1$ are matched to stock returns for the period between July of year t to June of year $t+1$. Firm size is measured by market capitalisation or market value of equity. It is defined as the product of stock price and the number of shares outstanding at the end of June in year t. The book-to-market ratio (B/P) is computed as the ratio between a firm's book equity per share at the fiscal year-end in calendar year $t-1$ and its market price at the end of December of year $t-1$. Thus, to be included in our sample, a firm should have both stock price and number of outstanding shares for December of year $t-1$ and June of year t, as well as book equity for fiscal year $t-1$. In addition, we only include observations with positive book equity.

For each year from July of year t to June of year t+1, stocks are assigned to one of two portfolios of size (Small (S) and Big (B)) on the basis of their firm size at the end of June in year t. The same stocks are independently sorted into three portfolios of B/P (Low (L), Medium (M), and High (H)) on the basis of their B/P. Six portfolios (S/L, S/M, S/H, B/L, B/M, and B/H) are then formed at the intersection of size and B/P and in a way such that they have approximately equal numbers of stocks. The value-weighted monthly returns on the six portfolios are calculated each month over the 12 months following portfolio formation. Repeating this procedure for every year results in 204 value-weighted monthly returns from July 1995 to June 2012 for each of the six portfolios.

SMB (small minus big) is the simple average of the returns on the small-stock portfolios minus the returns on the big-stock portfolios:

$$SMB = [(S/L - B/L) + (S/M - B/M) + (S/H - B/H)]/3 \tag{B.1}$$

Similarly, *HML* (high minus low) is the simple average of the returns on the high-B/P portfolios minus the returns on the low-B/P portfolios:

$$HML = [(S/H - S/L) + (B/H - B/L)]/2 \tag{B.2}$$

We follow L'her *et al.*'s (2004) approach to construct the momentum factor. For each month from July of year t to June of year t+1, stocks are ranked by their size and prior performance. The size is based on the ME value at the end of June in year *t*, whereas the prior performance is based on the compounded stock return from July in year *t*-1 to May in year *t*. Excluding the most recent month's return can attenuate the continuation effect caused by the bid-ask spread. Winners (*W*) are the top 30% of the total stocks with the highest average prior performance. Losers (*L*) are the bottom 30% of the total stocks with the lowest average prior performance. Neutrals are the remaining 40% of the stocks. Six portfolios (*S*/*L*, *S*/*M*, *S*/*W*, *B*/*L*, *B/M*, and *B*/*W*) are formed at the intersection of size and prior performance. The value-weighted monthly returns on the six portfolios are calculated each month over the 12 months following portfolio formation. *WML* (winner minus loser) is the simple average of the returns on the winner-stock portfolios minus the returns on the loser-stock portfolios:

$$WML = [(S/W - S/L) + (B/W - B/L)]/2 \tag{B.3}$$

Appendix C

We follow Korajczyk and Sadka (2008) in performing the following asymptotic principal components (APC) estimation. In an approximate factor-model setting for a balanced panel (complete data), Connor and Korajczyk (1986) show that n-consistent estimates (up to a linear transformation) of the latent factors, F^i, are obtained by calculating the eigenvectors corresponding to the k largest eigenvalues of

$$\Omega^{i,\mu}{}_{t,\tau} = (L^{i\prime}L^i)_{t,\tau}/n \tag{C.1}$$

In Eq. (C.1) L^i is the n x T matrix of shocks to liquidity measure *i* and $L^{i\prime}$ is the inverse of L^i, while (t,τ) and n represent months and number of observations respectively. They refer to these estimates as APC. Note that Ω is a T x T matrix so that the computational burden of the eigenvector decomposition is independent of the cross-sectional sample size, n. This implies that factor estimates can be obtained for very large cross-sectional samples. Standard approaches to principal components or factor analysis are often unimplementable on large cross-sections because they require eigenvector decompositions of n x n matrices.

The APC approach applies an alternative estimator of the factor model that accommodates missing data. From Connor and Korajczyk (1987), we estimate each element of Ω by averaging over the observed data. Let L^i be the data for liquidity measure i with missing data replaced by zeros. Define N^i to be an n x T matrix for which $N^i_{j;t}$ is equal to one if $L^i_{j;t}$ is observed and is zero if $L^i_{j;t}$ is missing. Define

$$\Omega^{i,\mu}{}_{t,\tau} = (L^{i\prime}L^i)_{t,\tau}/(N^{i\prime}N^i)_t \tag{C.2}$$

In Eq. (C.2), $\Omega^{i,\mu}{}_{t,\tau}$ is the unbalanced panel equivalent of Ω^i, in which the (t,τ) element is defined over the cross-sectional averages of the observed data only. Ω^i is guaranteed to be positive semi-definite in a balanced panel but $\Omega^{i\mu}$ is not. In large cross-sections, however, we have not encountered cases in which $\Omega^{i,\mu}$ is not positive definite. The estimates of the (within-measure) latent factors, $\bar{F}^i$, are obtained by calculating the eigenvectors for the k largest eigenvalues of $\Omega^{i,\mu}$.

We then estimate the (across measure) common factor(s) ($\hat{}F_t$) across all four measures of liquidity. This is done by stacking the liquidity measures into L' = $[L^{1}{}';L^{2}{}'; \ldots ; L^{4}{}']$, forming Ω^μ using L and extracting the eigenvectors of Ω^μ (the cross-sectional measure). As in Korajczyk and Sadka (2008), we choose the sign so that the factors represent liquidity rather than illiquidity. Due to the autocorrelation in F_t, we also follow Korajczyk and Sadka (2008) by fitting an AR(2) model for F_t to create the systematic liquidity factor ($\hat{}F_t$).

We calculate the individual firm-level stock's (liquidity) factor sensitivity (Fβeta) by performing a time-series regression for each stock's excess return on the extracted factor (the $\hat{}F_t$) as follows. The regressions are performed over 36 month rolling windows which contain at least 12 months' stock returns. We then use the factor beta ratio (Fβeta) as the firm-level liquidity proxy for individual firms.

$$R_{j,t} = \beta_{i*}\hat{}F_t + \hat{}\varepsilon_{i,t} \quad \text{(C.3)}$$

In Eq. (C.3), $R_{j,t}$ is the stock *i*'’s month *t* return and β_i is the factor sensitivity (Fβeta).

Appendix D

Definition of eight anomaly measures

We follow Liu *et al.* (2019) to compile eight anomalies which generate positive abnormal returns in China and form portfolios on the basis of these anomalies. We then perform horse-race tests on these portfolios. The anomalies are as follows:

1) Earnings-to-price ratio (EP): the most recently reported net profit divided by the product of the closing price and the number of outstanding shares at the end of previous month, where the net profit must be greater than zero.

2) Book-to-price ratio (BP): the most recently reported book equity divided by the product of the closing price and the number of outstanding shares at the end of previous month, where the book equity must be greater than zero.

3) Cash-flow-to-price ratio (CP): the net change in cash or cash equivalents between the two most recent cash statements divided by the product of the closing price and the number of outstanding shares at the end of previous month, where the net change in cash must be greater than zero.

4) Return-on-equity (ROE): the most recently reported net profit divided by the most recently reported book equity.

5) Reversal (REVER): the cumulative daily return over the past month, where there must be no less than 20 trading days in the previous month.

6) One-month turnover (TURN_1M): the average of daily ratio of trading volume over number of outstanding shares over the past previous month.

7) Twelve-month turnover (TURN_12M): the average of the monthly one-month turnover defined above over the past 12 months.

8) Volatility (VOL): the standard deviation of daily returns over the previous month, where there must be no less than 20 trading days in the previous month.