The Price of Liquidity Beta in China:
A Sentiment-based Explanation

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Abstract

The conventional, risk-based view on liquidity beta is a dismal story for China: High liquidity beta stocks underperform low liquidity beta stocks by 1.17% per month in China. This striking pattern is robust to different weighting schemes, competing factor models, alternative liquidity measures, and other well-known determinants of cross-sectional returns. We propose a competing, sentiment-based explanation on the *reversed* pricing pattern. Consistent with our new perspective, liquidity beta is a negative return predictor at the firm level. Moreover, the return differential between high and low liquidity beta stocks is more dramatic following high market liquidity periods.

JEL classification: G12; G15

Keywords: Liquidity; Liquidity Beta; Sentiment; Asset Pricing; China

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Abstract

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1. Introduction

A prevailing view in the asset pricing literature postulates that the return sensitivity of a stock to the shifts in market-wide liquidity, so called *liquidity beta*, should be a priced factor (Pastor & Stambaugh 2003; Korajczyk & Sadka 2008): Risk-averse investors fear (and are unable to diversify away) the sudden, unanticipated liquidity plunges due to the phenomenal "commonality in liquidity" (Chordia *et al.* 2000; Huberman & Halka 2001; Amihud 2002). Therefore, high liquidity beta stocks should earn high risk-adjusted returns than low liquidity beta stocks.

The above risk-based view on liquidity beta is further rationalized in the theoretical work of Brunnermeier and Pedersen (2009), who posit that the key determinant of the time-variation in "commonality in liquidity" is the uncertain funding constraints faced by traders. As the margin trading mechanism used by traders is subjected to the funding status of the overall economy, swings in funding supply impact on market liquidity in the same direction. Moreover, constraints in market liquidity also feedback on funding liquidity, causing (occasional) liquidity spirals (Brunnermeier & Pedersen 2009). Overall, the time-varying funding constraints fit well with the risk-based pricing channel of liquidity beta, and can be easily incorporated into the traditional rational asset pricing framework. Empirically, Fontaine *et al.* (2015) find consistent evidence in support of the *supply-side* story (*i.e.* funding liquidity) in the US stock market.

Despite its plausibility, there can be other alternative pricing channels of liquidity beta. A recent article by Karolyi *et al.* (2012) offers new insights on this issue, as they investigate the determinants of "commonality-in-liquidity" across the world: There are two different sets of factors which could independently or jointly induce the sudden change in market-wide liquidity. The first set is the *supply* side variables represented by funding liquidity, while the second set, which is more "behavioral", is the *demand* side variables best represented by investor sentiment (Karolyi *et al.* 2012). If sentiment, manifested by irrational investors' excessive trading volume, is the main source of liquidity shifts as evidenced in Baker and Stein (2004), then we have to accommodate ourselves to a new, sentiment-based perspective: Stocks with high liquidity beta are also the stocks whose prices are highly "sentimental". Within such a behavioral (asset pricing) framework, the relation between liquidity beta and stock returns is reversed, as there is ample evidence both theoretically and empirically to suggest that sentiment prone stocks have *lower* (unconditional) expected returns than sentiment immune stocks (Baker & Wurgler 2006, 2007).[1] In an unfortunate note, risk-averse investors who (mistakenly) hold a large portion of these "seemingly risky" stocks are not compensated with the "extra" risk premium. On the contrary, they are worse off on a risk-adjusted basis.

[1] We have more to say on this new perspective in the literature review section.

The overarching theme of this study is to shed light on the seemingly *controversial* relation between liquidity beta and stock returns in China. As the largest emerging stock market known for its unprecedented number of retail investors, its market-wide liquidity measure surpasses many developed markets and is comparable to the US stock market (Amihud *et al.* 2013). China also tops in the ranking of "commonality in turnover" and "commonality in liquidity" in a cross-country comparison (see figure 1 in Karolyi *et al.* 2012). Intuitively, liquidity shocks should be a major concern for all market participants in China due to its exceptionally strong "commonality in liquidity". Nevertheless, Karolyi *et al.* (2012) choose to exclude China in their cross-country regression as they coin China an "outlier" in their dataset. This make our study particularly interesting and highly relevant, as we provide further evidence on the "outlier", which could avoid the data snoop issue in the sense of Lo and MacKinlay (1990).

It should also be noted that funding constraints are not likely to be a major factor, as Chinese retail investors, who subject to investor sentiment, use their own excess capital (eg. deposit) for trading (Burdekin & Redfern 2009). In addition, margin trading is not introduced prior to 2010, which challenges the *supply-side*, risk-based pricing channel of liquidity beta. Therefore, our study provides the complementary evidence on the possible, alternative (sentiment-based) pricing channels of liquidity beta in the international markets.

Alongside of its main focus on liquidity beta and its asset pricing implications, this paper contributes to the evolving literature on market liquidity in a number of ways.

Firstly, we extend prior research on China (Narayan & Zheng 2010) by employing a much more comprehensive dataset, which covers the entire Chinese A-share markets (more than 2521 stocks). Moreover, our sample spans 16 years (1998–2013) and includes the most recent 2008 financial crisis period, which yields more insights on the impact of market-wide liquidity risk. Obviously, the much longer sample period and richer dataset (compared with prior studies) will result in more statistical power for asset pricing tests as portfolios become more diversified (Fama & French 2012).

Secondly, we perform a portfolio analysis to provide compelling empirical evidence that the conventional, risk-based view on liquidity beta is of the wrong sign when encountering the empirical data in the Chinese stock market, where high liquidity beta stocks underperform low liquidity beta stocks by a magnitude of 1.17% per month on a risk-adjusted basis. This striking return differential, however, is consistent with our proposed sentiment-based view. Moreover, the documented reversed liquidity beta effect persists over the entire sample period and different subsample periods as well.

Thirdly, we carry out a batch of robustness analyses to show that the striking reversed liquidity beta effect is robust to different weighting schemes, alternative asset pricing models, alternative liquidity measures, and other well-known determinants of cross-sectional returns such as size, value, momentum, and volatility.

Fourthly, we investigate the return predictability of liquidity beta at the stock level by the conventional Fama-MacBeth cross-sectional regression, while controlling for the effect of other known variables that may affect the stock returns. The results suggest that liquidity beta is a separate channel in predicting future returns in addition to market capitalization, book-to-market ratio and other firm characteristics.

Fifthly, the documented pricing impact of the liquidity beta effect allows us to augment the Fama-French three factor model with a (reverse) liquidity beta mimicking portfolio. We then test whether the augmented Fama-French four-factor model offers increased power in explaining the cross sectional stock returns compared with CAPM and Fama-French three-factor models. There is, however, some weak evidence that the augmented model offers a marginal increase in explaining the common variation in stock returns.

Sixthly, we provide further evidence on the time variation of the reverse liquidity beta effect. We find that market liquidity reliably forecasts the return spread between high liquidity beta portfolio and low liquidity beta portfolio after controlling the effects of market volatility and other risk factors. A one-standard-deviation increase of market liquidity is linked with an "extra" return dispersion of 63 basis points in subsequent periods. Our documented conditional pattern is very similar to the contrarian predictability found in prior sentiment-based literature (Baker & Wurgler 2006). At a more broad level, the further evidence provides supportive evidence on how sentiment plays a role in financial markets (Ho & Hung 2009; Baker *et al.* 2012).

Last, but not least, though the major contribution of the paper is empirical, we do provide a simplified theoretical framework to generate the economic insights on the sentiment impact on liquidity and stock returns in the cross section. Our model shares the same key assumption as in the behavioral framework of Baker and Stein (2004), which features a class of irrational investors, who are overconfident about their own private signals. Their sentimental behavior lowers the price impact of trades, thus boosts up market liquidity in general (the liquidity-as-sentiment prediction). However, we differ from Baker and Stein (2004)'s one-risky-asset setting, but adopt a (static) multiple-risky-asset setting as in Easley and O'hara (2004), which utilizes the partial revealing rational expectation equilibrium (REE) condition. The key prediction of our version of the liquidity-as-sentiment model is that in equilibrium, higher sentiment/liquidity beta stocks tend to have lower expected returns, which highlights the sentiment-based pricing channel of liquidity beta throughout our paper.

The structure of the paper is as follows. Section 2 gives a brief introduction to the Chinese stock market and reviews the relevant literature. Section 3 describes the data and the construction of the variables. Section 4 presents the empirical methodology and the estimation results. Section 5 provides a series of robustness checks. Section 6 performs a batch of further findings. Section 7 builds the theoretical model and explains its economic intuition. Section 8 discusses the implications of our results and concludes.

2. Literature Review

2.1. The Introduction of the Chinese Stock Market

There are two major security exchanges in mainland China: the Shanghai Stock Exchange (SHSZ) and the Shenzhen Stock Exchange (SZSE). The two exchanges have no functional difference, except that SHSZ is larger than SZSE in terms of market capitalization. At the end of 2013, both exchanges were ranked among the top 12 stock exchanges in the world based on the total value of market capitalization (see **Table 1**). The combined market capitalization of SHSZ and SZSE was equivalent to 42% of China's GDP in 2013.[2] For historical reasons, common shares in the two exchanges are classified as A-shares and B-shares, which are denominated in local currency and foreign currency (USD or Hong Kong dollar), respectively. As A-shares comprise the lion's share of the market, we focus exclusively on the A-share market for our empirical analyses.[3]

[Insert Table 1 here]

Several distinctive features regarding the Chinese A-share market are worth mentioning:

First and foremost, the Chinese market is well known for its dominance of a huge number of young and inexperienced retail investors, who generates massive speculative trading volume in the local stock market. According to the 2013 annual report of China Securities Depository and Clearing Corporation, there are more than 53 million valid individual investor accounts in SHSE and SZSE, among which 44% of the account holders are less than 40 years old. Less than 20% of the retail investors have an education background of bachelor degree or above. As is shown in the last column of Panel A of **Table 1**, on average, stocks in SHSE and SZSE turned over at least

[2] The GDP data are from the National Bureau of Statistics of China.
[3] The value of B-shares accounts for less than 4% of the total market capitalization in China.

1.49 and 2.65 times in 2013, which is much higher than the average turnover ratio for most of the developed markets. A further breakdown on the stock holdings and trading activities in SHSE (Panel B of **Table 1**) provides more insights: Individual investors hold directly more than 21% of the total market capitalization of the stocks in SHSZ. In comparison, stock holdings by professional institutions—including investment funds, pension funds, security companies, insurance companies, asset under management (AUM) and qualified foreign institutional investors (QFII)—was less than 15% as of 2013. More strikingly, trading activities by individual investors accounted for 82.24% of the total trading volume in 2013.[4] It is well known in the financial literature that retail investors are highly influenced by sentiment. They hold less diversified portfolio, have more incentives to trade speculative stocks, and engage in unsophisticated trading strategies such as trend following or correlated trading (Feng & Seasholes 2004; Kumar & Lee 2006).

Secondly, unlike most other emerging markets, the Chinese stock market is extremely liquid. The aggregated liquidity level, measured by the Amihud ratio, is comparable to, or even better than many developed markets (Amihud *et al.* 2013).

Thirdly, the phenomena of "commonality in liquidity" and "commonality in trading" are more pronounced in China than any other markets (see Figure 1 in Karolyi *et al.* (2012)). The exceptionally strong "commonality in liquidity" (and its induced market liquidity shocks) well establishes itself as a major concern for all market participants.

Fourthly, the Chinese stock market is characterized by heavy regulation, and short-sales of stocks are prohibited by law. The stringent constraints on short selling make it very difficult to arbitrage away the mispricing at the market level as well as the stock level (Mei *et al.* 2009).

Finally, margin trading, a key mechanism which will destabilize market liquidity and can cause occasional liquidity spirals as described in Brunnermeier and Pedersen (2009), has not been introduced in China until March 2010. As retail investors in China use mainly their own capital for trading, the effect of supply side determinants of "commonality in liquidity" (eg. funding liquidity) seems secondary in our sample period.

Overall, the strong presence of retail investors, who uses their own excess capital for trading, challenges the supply-side pricing channel of liquidity beta (*i.e.* funding risk). Rather, it seems to

[4] Unfortunately, we do not have the breakdown data for SZSE. However, there are no reasons to believe that individual investors play a lessor role in SZSE as compared with SHSE. In fact, the percentage of stocking holding and the composition of trading volume by individual investors is more likely to be higher for SZSE than SHSE, as individual investors tend to hold small and speculative stocks, which are mostly listed in SZSE. This is also supported by the much higher turnover ratio in SZSE than in SHSE (see the last column of Panel A of Table 1).

weigh more on the demand-side pricing channel of liquidity beta (*i.e.* sentiment demand). This makes our dataset an interesting case to explore the implications of our alternative, sentiment-based explanation on the relation between liquidity risk and stock returns.

2.2. Literature

The liquidity-return relation has long been a recurrent topic in finance. There is mounting evidence that liquidity influences stock returns both in the time series and in the cross section.[5] In the time-series dimension high market liquidity is associated with lower returns in the subsequent periods (Jones 2002; Baker & Stein 2004) In the cross section, there exists a strong illiquidity premium both in the US and in the international markets (Amihud & Mendelson 1986; Brennan & Subrahmanyam 1996; Brennan *et al.* 1998; Florackis *et al.* 2011; Lam & Tam 2011; Amihud *et al.* 2013; Chai *et al.* 2013). Moreover, the difference in a firm's systematic liquidity exposure (*i.e.* liquidity beta) is also a viable channel through which liquidity impacts stock returns (Lee 2011; Liang & Wei 2012). However, the empirical results are a bit mixed across markets as we briefly review the dominant risk-based view and our own proposed sentiment-based view on the pricing of liquidity beta in the next two subsections.

2.2.1 The Risk-based View

Liquidity beta, defined as the covariation of a stock's return with the innovations of the market-wide liquidity, has long been thought as a viable channel through which liquidity systematically influences the expected stock returns in the cross section.

This strand of literature builds on some of the key findings from the market microstructure research that liquidity is time-varying and the fluctuations in firm-specific liquidity co-move with that of the market-wide liquidity, known as "commonality in liquidity" (Chordia *et al.* 2000; Huberman & Halka 2001; Amihud 2002). Given the phenomenal "commonality in liquidity", Pastor and Stambaugh (2003) postulate that in a standard asset pricing framework, market-wide liquidity is a state variable and thereby should be priced in the cross section. In their logic, a stock with higher return sensitivity to market liquidity shifts (the state variable) is less desirable to investors and must offer a higher (risk-adjusted) return in compensation. In an important theoretical work, Brunnermeier and Pedersen (2009) further rationalize the phenomenal "commonality in liquidity" by assuming that the time variation of market liquidity is triggered by the (uncertain) funding shortages inherent in margin trading, which provides a valid reason for market liquidity to be treated as an indicator of the investment environment or macroeconomy (a

[5] While the focus of the paper is on the equity market, the liquidity-return relation has also been studied extensively in other asset markets, such as the bond and FX markets (Chen *et al.* 2007; Mancini *et al.* 2013).

state variable). Similarly, using an overlapping generation model, Acharya and Pedersen (2005) argue that risk-averse investors are concerned about this systematic and time-varying component of liquidity ("commonality in liquidity"), as transaction costs can substantially increase in case of adverse market liquidity shocks.[6] To sum up, within the traditional asset pricing framework, liquidity beta (return sensitivity to market liquidity shifts) is treated as a valid risk gauge. Higher liquidity beta stocks are inherently riskier and must be associated with higher expected returns in equilibrium, everything else being equal.

Empirically, Pastor and Stambaugh (2003) study the cross-sectional pattern between liquidity beta (return sensitivities to aggregate liquidity shocks) and expected stock returns in the US. They find that stocks with *high* liquidity beta earn *high* risk-adjusted returns, confirming that systematic liquidity (risk) is a priced state variable. Similar *high liquidity beta effects* are confirmed in Acharya and Pedersen (2005) and Liu (2006), who use alternative (il-)liquidity proxies to derive the innovations in market-wide liquidity. In an integrated analysis Korajczyk and Sadka (2008) provide further evidence that liquidity beta is priced in the cross section of US stocks, even after controlling for the firm-specific liquidity level. Summing up, US evidence seems to suggest that the covariation of a stock's returns with market-wide liquidity shocks is a viable channel, independent of market risk, through which liquidity systematically affects asset prices.

Evidence from the interntional markets, however, is not completely in line with the *high liquidity beta effect*. In a comprehensive international study, Lee (2011) concludes that the return covariation with market liquidity (liquidity beta) is never priced in developed or emerging markets outside the US (see table 3 of Lee (2011)). Similarly, Martínez *et al.* (2005) find a *reverse liquidity beta effect* for the Spanish stock market using the Pastor and Stambaugh (2003) market-wide liquidity factor: Stocks with *high* liquidity beta earn *low* raw and risk-adjusted returns instead. Nguyen and Lo (2013) find no liquidity beta premium at all in New Zealand. In a cross country analysis, Liang and Wei (2012) again document a number of negative liquidity beta premia for several developed markets (see table 3 and 4 of Liang and Wei (2012)). Apparently, the mixed evidence in international markets poses questions for the risk-based view that high liquidity beta stocks are riskier and should earn higher returns in equilibrium.

2.2.2 The Sentiment-based View

We sidestep the risk-based pricing channel, and propose an alternative, behavioral explanation for the possible *reversed* liquidity beta effect. Our behavioral explanation is motivated by the

[6] This line of reasoning assumes that investors face some solvency constraints and maybe forced to liquidate their positions at an unknown period time in the future. Therefore, they are subject to the uncertainty of transaction costs.

novel liquidity-as-sentiment perspective in Baker and Stein (2004). In their model, the financial market is featured with a group of irrational sentiment investors who are overconfident about their own private information. The presence of sentiment investors implies that they will "push away" rational investors in setting the market price whenever their "bullish" valuation is higher than the market, boosting up liquidity. With some maintained conditions, Baker and Stein (2004) conclude that market liquidity is a direct measure of investor sentiment.[7] They also predict that during periods of extremely high liquidity, sentiment investors dominate the market, causing substantial mispricing of the risky asset and lead to lower subsequent returns.

Note that Baker and Stein (2004)'s liquidity-as-sentiment model focused solely on the time series dimension in a one-risky-asset market. It is natural for us to extend their logic to the cross section. The extension of the cross sectional effect is based on the economic intuition (and empirical fact) that during a broad wave of sentiment induced liquidity shock, not all stocks are influenced to the same extent. We thus build a theoretical multiple-risky-asset model, which follows Easley and O'hara (2004), utilizing the partial revealing rational expectation equilibrium (REE) condition. As liquidity is endogenously driven by investor sentiment, our model underscores the mapping from liquidity beta to a stock's sentiment proneness (or sentiment-induced mispricing): That is, *high* liquidity beta stocks (*i.e.* stocks reacting strongly to liquidity shocks) tend to be sentiment-prone, while *low* liquidity beta stocks are sentiment-immune. Therefore, the key prediction of our version of the liquidity-as-sentiment model is that in equilibrium, higher sentiment/liquidity beta stocks tend to have lower expected returns (see the consolidated model in Section 7).

Our model prediction is consistent with the stylized fact in the behavioral literature that sentiment-prone stocks deliver lower expected returns on a risk-adjusted basis (Baker & Wurgler 2006). These stocks are more speculative and more difficult to arbitrage. They tend to be small, opaque companies with unstable cash flows and excessive return volatility. Their valuation has the most disagreement among investors and is thus linked with a higher degree of mispricing according to the well-known Miller (1977)'s conjecture. That is, when short selling is not allowed, the transaction price of the sentiment prone stocks reflects the most optimistic investors, while the opinions of the pessimists are simply neglected as they choose not to trade (or hold a position). In a more formal dynamic asset pricing framework, it is predicted that the market price

[7] It should be noted that the liquidity-as-sentiment argument has strong empirical supports. For example, Karolyi *et al.* (2012) conclude that the "commonality in liquidity" in international markets is mainly driven by demand side factors such as investor sentiment and correlated trading. Consistent with these theoretical and empirical justifications, we provide supportive time-series evidence that both individual investor sentiment (as proxied by the number of newly opened individual investor accounts) and institutional investor sentiment (as proxied by the equity fund flows) well predict the near-term market liquidity (see Appendix C for more detail). The strong predictability lends strong support to the notion that market liquidity can be treated as a sentiment index, which is also consistent with the recent findings.

can even be higher than the valuation of the most optimistic investors as it contains the option to resell (Harrison & Kreps 1978). In other words, the most mispriced stocks are also the ones that are most affected by sentiment investors due to various market frictions in practice. The key point here is that on average, *high* liquidity beta stocks (sentiment-prone stocks) are more susceptible to overvaluation as they are systematically preferred by sentiment investors due to the speculative nature. In an unfortunate tone, *high* liquidity beta stocks earn lower (risk-adjusted) returns in subsequent periods (as sentiment investors systematically bet wrongly on their valuation). Moreover, as sentiment wanes and fundamentals are revealed over time, sentiment-prone stocks are subject to the most dramatic price reversion, indicating even lower average returns in the cross section. Empirically, consistent evidence is documented in Baker and Wurgler (2007) that sentiment-prone stocks, *ceteris paribus*, earn lower average returns than sentiment-immune stocks (the unconditional pattern). They also find that sentiment-prone stocks, *ceteris paribus*, perform relatively well during high sentiment (liquidity) episodes, but plunges in low sentiment (liquidity) periods (the conditional pattern).

Based on the above theoretical justifications and empirical evidence, we postulate that the sentiment-based pricing channel of liquidity beta implies a reversed liquidity beta premium: Stocks with high liquidity beta earn lower expected (subsequent) returns than low liquidity beta stock, everything else equal.

3. Data and Variable Construction

3.1. Data Sources

We carefully construct a reliable dataset of 2521 Chinese A-shares from Thomson Datastream (TDS), which is free of survival bias.[8] This comprehensive list of stocks covers virtually all the A-shares listed on both the Shanghai and Shenzhen stock exchanges from January 1998 to December 2013. We then retrieve from Datastream a variety of daily variables, including the total return index, price index, trading volume, (unadjusted) closing price, and number of shares outstanding. We first filter out all the non-trading days due to national holidays or exchange closure. We then apply a specific daily return filtering procedure by setting the daily return to be missing if any daily return is above 10% (or 5% for ST stocks).[9] For the construction of Fama-

[8] We construct an initial list of the Chinese A-shares from the Datastream lists of FCHINA, WSCOPECH, DEADCH. We then leave out duplicates or "spurious" stocks, and retain only common stocks with local exchange ticker symbols. Following conventions, we exclude PT stocks from our analysis.

[9] The return filtering procedure is motivated by the fact that Chinese A-shares are restricted to a daily price limit of 10% (5%) for normal stocks (ST stocks) by the China Securities Regulatory Commission (CSRC). Exceptions for the

French risk factors, we also download monthly market capitalization (*MV*) and book-to-market ratio (*BTM*) data for the sample stocks.[10] **Appendix A** illustrates in detail the procedure to calculate the Fama-French risk factors (e.g. market, size, value, and momentum factors). Following the convention, we use the monthly rate of the one-year bank time-deposit in China as the risk-free rate.

3.2. Construction of the Market-wide Liquidity Risk Measure

To make our estimation result comparable to findings in other markets, we adopt the price reversal measure of market-wide liquidity as proposed in Pastor and Stambaugh (2003), which is widely used as in Martínez *et al.* (2005) and Liang and Wei (2012). Using daily data within each month, we first estimate the monthly price-reversal measure of liquidity for each stock using the following regression.

$$r^e_{j,d+1,t} = \theta_{j,t} + \phi_{j,t} r_{j,d,t} + \gamma_{j,t} sign\left(r^e_{j,d,t}\right) v_{j,d,t} + \epsilon_{j,d+1,t} \qquad [3.1]$$

where $r_{j,d,t}$ is the return on stock *j* on day *d* during month *t*, $r^e_{j,d,t}$ the return for stock *j* in excess of the value-weighted market return on day *d* during month *t*, $v_{j,d,t}$ the trading volume (measured in millions of the local currency) for stock *j* on day *d* within month *t*, and $\epsilon_{j,d+1,t}$ the error term. The coefficient $\gamma_{j,t}$ well captures the dimension of firm-level liquidity associated with the volume-related return reversal. Such a price reversal effect is typically negative. That is, the more negative $\gamma_{j,t}$ is, the lower is the liquidity of the stock *j* in month *t*. Following the convention in the literature (Pastor & Stambaugh 2003; Acharya & Pedersen 2005), we impose two constraints for a stock to be included in our sample to calculate the market-wide liquidity. First, we require at least 15 observations for each stock within the month to estimate the firm-specific liquidity measure. Second, we filter out stocks with share prices less than 1 Chinese yuan or exceeding 500 Chinese yuan at the end of the previous month.[11]

The estimated monthly market-wide liquidity, $\widehat{MWL}_t$, is then calculated as the cross-sectional average of the estimated return-reversal effect per firm ($\hat{\gamma}_{j,t}$) during month *t*. The cross-section

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price limit only occur on special trading days, such as stock split, first trading day after IPO, M&A, or stock suspension. In any cases, these days are rare events, and thereby excluded from our sample when calculating daily return, liquidity measures, and etc.

[10] Before 1999, however, Datastream has a very small coverage of *BTM* data for the Chinese stocks (less than 10%). Therefore, we use the *BTM* data compiled by the research department of China International Capital Corporation Limited (CICC) for the sample period before 1999. We merge the two datasets by the unique local exchange ticker symbols for each individual stock.

[11] The inclusion of penny stocks (low price stocks) will bias upward the illiquidity premium, leading to spurious detection of the liquidity effect (Asparouhova *et al.* 2010).

data of $\hat{\gamma}_{j,t}$ are "winsorized'' at the 1st and 99th percentiles in each month to avoid the impact of outliers due to data error.

$$\widehat{MWL}_t = \frac{1}{N_t}\sum_{i=1}^{N_t} \hat{\gamma}_{j,t} \qquad [3.2]$$

3.3. Construction of the Market-wide Liquidity Shocks

To obtain the innovations in market liquidity, we follow the conventional adjustment procedures in the prior literature by fitting the following AR(2) model to account for a potential long-term trend and autocorrelations in the liquidity series (Acharya & Pedersen 2005; Lou & Sadka 2011).

$$\left(\frac{m_{t-1}}{m_0}\right)\widehat{MWL}_t = a + b_1\left(\frac{m_{t-1}}{m_0}\right)\widehat{MWL}_{t-1} + b_2\left(\frac{m_{t-1}}{m_0}\right)\widehat{MWL}_{t-2} + u_t \qquad [3.3]$$

where m_{t-1} is the total market value at the end of month t-1 of all the stocks included in the month t sample, m_0 corresponds to the total market value in the base period (December 1992), and the ratio $\frac{m_{t-1}}{m_0}$ serves as a common detrending factor for all three market liquidity terms in the equation. We do not employ the lags of $\frac{m_{t-1}}{m_0}$ in the equation simply to avoid the shocks that are mechanically induced by price changes in the market over time. Such detrending procedures are commonly used in the literature (Acharya & Pedersen 2005; Watanabe & Watanabe 2008).[12]

The systematic liquidity risk factor is taken as the fitted residual of Eq. [3.3] scaled by 100 to obtain more convenient magnitudes of the non-traded liquidity risk factor, L_t.

$$L_t = \frac{1}{100}\hat{u}_t \qquad [3.4]$$

Figure 1 plots the systematic liquidity shocks and the return of the market portfolio in excess of the risk-free rate (the equity premium) over the entire sample period. Both series are standardized with zero means and unit variance. As is portrayed in **Figure 1**, the standardized liquidity shock series varies much more dramatically than the standardized equity premium, indicating that market liquidity may often have overreacted to upturns and downturns of the market. Such a pattern is as expected given that market liquidity is a valid proxy for investor sentiment.

Perhaps the most salient features of our constructed liquidity series are its occasional downward spikes, indicating months with especially low estimated liquidity. A further check on the downward spikes reveals that it is consistent with the timing of major financial episodes both locally and globally: The 9-11 terrorist attack in 2001, 2004 tightening monetary policy by

[12] Pastor and Stambaugh (2003) adopt a very similar procedure to estimate the innovations in market liquidity by fitting a modified AR(1) model on the detrended first differences in market liquidity.

China's central bank, 2008 global financial crisis, and 2010 European sovereign debt crisis in 2010. Moreover, the apparent upward trending of the liquidity series between 2006 and 2007 also coincides with the dramatic market boom in China, which reaches its historical high on 16 Oct 2007.

3.4. Estimation of the Stock-by-stock Liquidity Betas

To obtain the stock-by-stock measure of liquidity risk exposure (liquidity beta) we follow the standard estimation procedure as in Lou and Sadka (2011) by regressing monthly excess returns (over the risk-free rate) of the *j*-th stock on the non-traded market liquidity risk factor (L_t) and the value-weighted excess return of the market portfolio ($RMRF_t$).

$$R_{j,t} = \alpha_j + \beta_j^{RMRF} RMRF_t + \beta_j^{Liq} L_t + \varepsilon_{j,t} \qquad [3.5]$$

The coefficient of the liquidity risk factor, β_j^{Liq}, measures the return sensitivity of the *j*-th stock to unanticipated shocks in market-wide liquidity and is commonly referred to as the liquidity beta. We are aware that there are other cross-sectional factors that have explanatory power for cross-sectional returns, such as size and value. We do not model these effects directly in equation [3.5], but we are careful to ensure that we control for the Fama-French factors and other cross-sectional factors in assessing how liquidity beta is priced in our asset pricing tests in the following sections.

4. Methodology and Results

4.1. Portfolio Formation and Descriptive Statistics

To test whether there is a systematic relation between liquidity beta and expected returns, we follow the typical portfolio formation strategy in the investment literature: At the beginning of each year (formation year), all eligible stocks are sorted into five quintile portfolios based on their historical liquidity betas estimated by equation [3.5] using monthly data over the prior five years (the pre-formation/selection years). The quintile portfolios are held passively throughout the holding period of one year. To alleviate the upward bias associated with size or illiquidity effect due to the rebalanced method commonly adopted in the prior literature (Asparouhova *et al.* 2010), value-weighted (or equal-weighted) monthly returns over the holding period are calculated according to Liu and Strong (2008), which reflects the actual gains or losses earned by the investors. Monthly returns are then linked across years to form the return series over the entire sample period.

Table 2 first presents summary statistics for composite stocks in the liquidity beta sorted quintile portfolios. On average, we have around 211 stocks in each quintile portfolio during the 18-year sample period. At the end of the portfolio selection period, the average market capitalization (in millions of Chinese yuan) of the composite stocks decreases monotonically from low liquidity beta stocks to high liquidity beta stocks. The fact that high liquidity beta stocks tend to be small sized local firms reinforces our argument that these stocks are "sentimental", as retail investors in China tend to concentrate on small cap stocks.[13] This, however, is in vast contrast to the evidence in the US (Pastor & Stambaugh 2003), as high liquidity beta stocks in the US tend to be large cap stocks, which are mainly held by institutional investors. The average market-to-book ratio does not have a very clear pattern. However, low liquidity beta stocks tend to have lower valuation than high liquidity beta stocks at the end of the portfolio selection period. Overall, the average firm characteristics in the quintile portfolios are consistent with our expectations: Stocks in the high liquidity beta quintile portfolios are small and glamour stocks which are more likely to be sentiment-prone, while stocks in the low liquidity beta quintile portfolio are large and value stocks which are more likely to be sentiment-immune.

The middle and bottom panel of **Table 2** report the geometric mean, arithmetic mean, and standard deviation of monthly returns for the value-weighted and equal-weighted quintile portfolios and their associated zero-cost hedge portfolios, respectively.[14] Two remarkable features emerge from the table. First, the average monthly return decreases monotonically from the low liquidity beta quintile portfolio (Q1) to the high liquidity beta quintile portfolio (Q5). On average, the value-weighted zero-cost high-minus-low portfolio (Q5-Q1) yields an average monthly loss of -0.64% throughout the whole sample period. **Figure 2** plots the long-term cumulative returns for the long-only Q1 and Q5 portfolios throughout the sample period (using the market portfolio as a benchmark). Secondly, the return volatility (roughly measured by the standard deviation of monthly returns) increases monotonically with the liquidity beta, thus from Q1 to Q5. At first sight, it seems counterintuitive that lower liquidity beta portfolios have higher returns in equilibrium, although they are less risky.

[Insert Table 2 here]

[13] To address the concern that liquidity beta is an imperfect proxy for size, we would like to point out that it is unlikely to be the case, because the Chinese stock market has a very strong size premium. If liquidity beta is a proxy for size, then a pure sorting on liquidity beta should produce a monotonic increasing pattern of returns from low liquidity beta portfolio to high liquidity beta portfolio, which is apparently in contrast to the empirical pattern we observe in panel B and C of table 2.

[14] The geometric mean is the compound monthly return realized by the portfolios over the sample periods, which, unlike the arithmetic mean, is not diminished by the variability of the returns.

4.2. Patterns in Risk-adjusted Returns for Liquidity Beta-sorted Portfolios

Our goal here is to verify whether stocks with different sensitivities to the innovations of market-wide liquidity, thus liquidity beta, have different average returns (on a risk-adjusted basis). Therefore, we state our major testable hypothesis below:

Testable Hypothesis: *Stocks with high liquidity beta earn lower expected (subsequent) returns than low liquidity beta stock, everything else being equal.*

For the sake of brevity we only report the regression results for the value-weighted portfolios using the Fama-French three-factor model.[15]

$$R_{i,t} = \alpha_i + \beta_i^{RMRF} RMRF_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \varepsilon_{i,t} \qquad [4.1]$$

*w*here $R_{i,t}$ is the excess return over the risk-free rate for portfolio i at period *t*. $RMRF_t$ is the excess return of the value-weighted market portfolio for period *t*. SMB_t is the size factor during period *t*. HML_t is the value factor at period *t*.

Panel A of **Table 3** reports the risk-adjusted returns and the factor loadings of the quintile portfolios. As it stands, the low liquidity beta quintile portfolio (Q1) earns a significantly positive Fama-French alpha of 0.34% per month, while the high liquidity beta quintile portfolio (Q5) significantly underperforms by a significantly negative alpha of -0.55% per month. Moreover, it seems that the low liquidity beta quintile portfolio Q1 is less exposed to systematic risk (as measured by market beta) and the size factor (SMB) than the high liquidity beta quintile portfolio, but loads more heavily on the value factor than the high liquidity beta quintile portfolio Q5.

All these pieces of evidence are consistent with the average firm characteristics documented in the previous section. That is, low liquidity beta stocks are less exposed to sentiment, while they are characterized by large capitalization and relatively low valuation compared to high liquidity beta stocks. The value-weighted long-short portfolio (Q5-Q1), constructed also by the method of Liu and Strong (2008), confirms the underperformance of the high-minus-low strategy with a strikingly negative risk-adjusted return of -1.17% per month with regard to the Fama-French three-factor model.

In unreported analyses, we also check the risk-adjusted return patterns of the equal-weighted quintile portfolios sorted on liquidity beta. The pattern of average returns across quintile portfolios remains virtually intact, except that the equal-weighted long-and-short return spread is

[15] We do not use Carhart's four-factor model mainly because momentum is not significantly priced in China. Momentum does not seem to be a global phenomenon as it is not priced in a number of Asian markets such as Japan and Hong Kong (Lam & Tam 2011; Fama & French 2012). However, all of our results are robust when using Carhart's four-factor model and therefore are omitted for brevity.

a bit less pronounced than the value-weighted one. The fact that the negative return spread (between high liquidity beta stocks and low liquidity beta stocks) is more pronounced for the value-weighted portfolio is a telling story. It is consistent with the anecdotal evidence that some stocks are highly preferred by irrational investors, having unjustifiable high valuation (and thus large market capitalization). These large-sized stocks have strong sentiment proneness and suffer huge sentiment-induced mispricing. Overall, the reverse liquidity beta effect we documented above is well in line with our predictions from the liquidity-as-sentiment model and its impact in the cross section. Obviously, it contradicts the US evidence that high liquidity beta stocks earn higher risk-adjusted returns than low liquidity beta stocks, but agrees with the recent empirical evidence in international markets.

[Insert Table 3 here]

4.3. Subsample Analysis

Given the relatively long time-span of the dataset, it is fair to examine whether the return spread pattern of the long-and-short portfolio varies over different time periods. To this end, we divide our entire sample into two subsamples with an equal length of eight years (1998-2005 and 2006-2013). It is worth noting that a number of extreme market events concentrated in the latter subsample period. First, it starts with the 2006-2007 bubble period, which is characterized with excessive sentiment and massive overvaluation as the Shanghai A-share index more than doubled in 2006 and rising by a further 96% in 2007 (Burdekin & Redfern 2009). Subsequent to the bubble period is the well-known 2008-2009 financial crises (during which the stock market drawdown exceeded more than 65%), followed by the European sovereignty debt crisis in 2010. Therefore, we refer to the former subsample period as “the tranquil period” and the latter subsample period as “the volatile period”.

Comparing the return differentials of the high and low liquidity beta portfolios between “the tranquil period” and “the volatile period” yields additional insights on the pricing implications of liquidity beta. If the global crisis represents a funding liquidity shortage (the supply side determinant of the commonality-in-liquidity) more than a sentiment plunge (the demand side determinant of the commonality-in-liquidity), then the liquidity beta of “the volatile period” should behave more as a risk gauge than as a sentiment indicator. In that case, we would expect the Q5-Q1 return dispersion to be bigger (i.e., less negative) than that in “the tranquil period”. However, if the local stock market is less constrained by funding liquidity, but rather subjects to the long-run correction to its prior massive overvaluation (during 2006-2007). We would then expect the liquidity beta of “the volatile period” to behave more like a sentiment indicator and the Q5-Q1 return differential to be more negative than that in “the tranquil period”.

Interestingly, we find the effect of the funding liquidity shortage to be, at most, secondary. In "the tranquil period" (Panel B of **Table 3**) the value-weighted long-short return spread is -0.70% on a risk-adjusted basis with respect to the Fama-French three-factor model. During "the volatile period" (Panel C of **Table 3**), however, the value-weighted return spread becomes much more pronounced: That is, the risk-adjusted return for the long-short portfolio is -1.35% per month estimated by the Fama-French three-factor model. The increased magnitude of the (negative) return spread in the long-and-short portfolio lends further support to our sentiment-based explanations on the pricing of liquidity beta.

5. Robustness

In this section, we perform a series of robustness tests in which we adopt alternative asset pricing models for potential sources of the risk-adjusted return, we also use alternative market liquidity measures to derive stock-by-stock liquidity betas, and finally we control for various firm-characteristics (such as size, value, momentum, liquidity level, price level, idiosyncratic risk, and return volatility), which are known to have cross-sectional effects in stock returns.

5.1. Comparison of the Alternative Asset Pricing Models

In this part, we evaluate the robustness of the reverse liquidity beta effect under alternative asset pricing models, such as the higher-moment CAPM and the liquidity-augmented four-factor models. Kraus and Litzenberger (1976) argue that risk-averse investors have a preference for stocks with positive skewness if the market is also positively skewed. Later empirical studies document that higher-order moments help explain the cross-sectional variation in stock returns (Lambert & Hübner 2013). These findings render the evaluation of whether comovement risk captures the liquidity beta pattern we observe. Similarly, we also test whether the liquidity beta effect is subsumed by the liquidity level effect (illiquidity premium) using the liquidity-augmented four-factor model. Those alternative asset pricing models are specified as follows:

$$R_{i,t} = \alpha_i + \beta_i^{RMRF} RMRF_t + \psi_i (RMRF_t - \overline{RMRF})^2 + \varepsilon_{i,t} \qquad [5.1]$$

$$R_{i,t} = \alpha_i + \beta_i^{RMRF} RMRF_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \beta_i^{IML} IML_t + \varepsilon_{i,t} \qquad [5.2]$$

*w*here $R_{i,t}$ is the excess return over risk-free rate for portfolio *i* at period *t*. $RMRF_t$ is the excess return of the value-weighted market portfolio for period t, $(RMRF_t - \overline{RMRF})^2$ is the comovement factor at period t, $\overline{RMRF}$ is the time-series average of the market excess returns, SMB_t is the size factor during period t, HML_t is the value factor at period t, IML_t is the liquidity level factor (or called illiquidity factor) for period *t*, constructed exactly in the way suggested in Lam and Tam (2011).

Table 4 reports the estimation results under alternative asset pricing models. The inclusion of the comovement factor does not change the pattern of the risk-adjusted returns across the quintile portfolios, though the significance level become less pronounced for the high liquidity beta quintile portfolio. Moreover, the alpha of the long-and-short portfolio remains significantly negative at -1.10% per month under the higher-moment CAPM model. In the same vein, the pattern of risk-adjusted returns for the liquidity-beta sorted quintile portfolio is robust to the inclusion of a liquidity level factor.

[Insert Table 4 here]

5.2. Adoption of Alternative Market-wide Liquidity Measures

In this subsection, we investigate the robustness of our results to the liquidity risk measure used to estimate the historical liquidity beta. The Pastor and Stambaugh (2003) market-wide liquidity risk measure captures the price-reversal dimension of liquidity. Another commonly used liquidity risk measure is constructed from the firm-specific Amihud ratio (Amihud 2002), which captures the price impact dimension of liquidity (Liang & Wei 2012). The detailed estimation procedure is presented in **Appendix B**. **Table 5** presents the estimation results using the alternative market liquidity risk measure. As it stands, the reverse liquidity beta effect is robust to the liquidity risk measure adopted, although it becomes a bit less pronounced using the alternative liquidity risk measure. The inverse relation between liquidity beta and risk-adjusted return remains over the entire sample period. Moreover, it remains costly to pursue the long-and-short strategy as the Fama-French alpha is significantly negative at -0.55% per month. Thus, the similar return pattern we observe using the Amihud measure lends support to the existing findings that the pricing of the liquidity beta is mainly due to the across-measure of systematic liquidity shocks rather than the idiosyncratic within-measure of the individual liquidity shocks.[16]

[Insert Table 5 here]

5.3. Controlling for Cross-sectional Pricing Effects

To account explicitly for other well-know factors or priced characteristics in the cross section of stocks, we perform a series of two-way sort control tests. That is, we first form quintile portfolios

[16] Recent studies, however, point out that Amihud ratio impose a strong small-firm bias, making it difficult to disentangle the liquidity level effect from size effect (Florackis *et al.* 2011). Therefore, in unreported analysis, we also adopt the turnover version of the Amihud ratio and use it to estimate the market-wide liquidity shocks and stock-by-stock liquidity beta. Results are very similar and therefore are omitted for brevity.

based on a particular firm characteristic (eg. size, book-to-market ratio). Then, within each characteristic quintile, we further sort stocks into quintile portfolios based on their ranking in liquidity beta. Finally, we merge across the firm-characteristic portfolios to form quintile portfolios that have dispersion only in liquidity beta but contain all aspects of the characteristics. The estimation results for the liquidity beta sorted quintile portfolios, which accounts for other well-known pricing factors are reported in **Table 6**.

Controlling for Size

Small firms are known to have abnormally high average returns (Banz 1981). Moreover, small firms are generally more difficult to value, which makes them riskier and demands a higher return in equilibrium. Could the portfolio of low liquidity beta stocks contain a disproportionately large number of small stocks? The characteristic-control procedure suggests that size characteristics do not drive the result. After we control for the market capitalization of the stocks, the long-and-short portfolio retains a significantly negative Fama-French alpha of -0.65% per month over the entire sample period.

Controlling for the Book-to-Market Ratio

Stocks with high book-to-market ratios tend to have high average returns, everything else being equal (Fama & French 1992). Thus, if the value effect was responsible for the return spread, we would expect that the low (high) liquidity beta portfolio contains a disproportionately larger number of value stocks (growth stocks) than growth stocks (value stocks). This, however, is not the case in our sample. When we control for the book-to-market ratios, the long-short portfolio retains a large Fama-French alpha of -1.03% per month over the entire sample period.

Controlling for Momentum

We next control for return momentum, measured as the cumulative returns over the past 12 months. The results in the line labeled "Controlling for Momentum" indicate that the pattern of the risk-adjusted returns is robust to controlling for the momentum effect. The Fama-French alpha of the long-and-short portfolio remains significant with -1.07% per month. Examinations of alternative measures of momentum such as the cumulative returns over the past three or six months reveal very similar results, which we do not report here for the sake of brevity.

Controlling for the Liquidity Level

Mounting evidence suggests that firm-specific liquidity level is a priced characteristic (Amihud & Mendelson 1986). If liquidity level is to explain the reverse liquidity beta effect we observe, illiquid stocks must also have low liquidity beta at the same time, giving them higher returns in equilibrium.[17] We check this explanation by adopting the Amihud ratio as a valid proxy for firm-specific liquidity level. Controlling for the liquidity level does not affect the return patterns we observe. The long-short portfolio retains a negative Fama-French alpha of -0.62% per month, with a *t*-statistic of -2.11. In an unreported analysis, we also employ quoted spread and the turnover ratio respectively as proxies for the firm-specific liquidity level. These estimations yield very similar result and are omitted for brevity.

Controlling for the Price Level

Bhardwaj and Brooks (1992b, a) find that low-share-price stocks earn abnormal return (before transaction cost), especially in January. Moreover, they posit that the share price level seems to capture certain factors such as transaction costs (bid-ask spread), the degree of neglected and mispriced risk. We explicitly control for the price level and find that the Fama-French alpha is still large at -0.83% per month, with a *t*-statistic of -2.51. Therefore, the return patterns are not distorted by the share price level.

Controlling for Idiosyncratic Risk

Ang *et al.* (2006, 2009) provide ample evidence that idiosyncratic volatility (relative to the Fama-French three-factor model) is priced in the cross section of stock markets. That is stocks with higher idiosyncratic risk earn lower average returns than stocks with low idiosyncratic risk. Computing firm-specific idiosyncratic volatility following Ang *et al.* (2006, 2009), we show that exposure to ideosyncratic risk is not an explanation in our findings. The Fama-French alpha remains statistically large at -1.23% per month after controlling for the idiosyncratic volatility.

Controlling for Return Volatility

Stocks with large return volatility are generally considered to be more difficult to value and riskier than stocks with low return volatility. The line labeled "Controlling for volatility" indicates that the average return pattern is not driven by the volatility effect. The Fama-French alpha remains statistically large at -1.05% per month after controlling for the return volatility of the individual stock.

[Insert Table 6 here]

[17] However, existing literature would suggest that illiquid stocks tend to have high liquidity beta, consistent with the "flight to liquidity" effect.

6. Further Analysis

6.1. Return Predictability of Liquidity Beta

While portfolio analyses are easy to interpret, a large amount of cross-sectional information is lost in the process of portfolio formation. Therefore, we apply the Fama and MacBeth (1973) cross-section regression approach to estimate the marginal return predictability of liquidity beta, while controlling for other firm characteristics (such as size, value) that are known for predicting returns at the firm level. For each month we regress the cross section of excess stock returns on K explanatory variables including a stock's liquidity beta. Similar to the setup in portfolio sorts, the explanatory variables are updated only once a year. Thus, we use explanatory variables estimated using information up till the end of the prior year to forecast the monthly return from January to December in current year. The model specification is as follows.

$$r_j = b_0 + \sum_{k=1}^{K} b_k X_{j,k} + \xi_j \qquad [6.1]$$

where r_j is the excess return of the j-th stock, $X_{j,k}$ is the k-th explanatory variable (eg. *lnMV*, *lnBTM*, and etc), and ξ_j is the error term. Note that we have omitted the time-dimension subscript for notation ease. Following Fama and French (2008) we impose that the market beta of individual stocks is one (as a constant in the regression), which is motivated by the empirical fact that market beta has little empirical power in explaining the cross-sectional stock returns once size and value factors are included. Moreover, we also exclude microcap stocks in the regression as these stocks are likely to dominate the FM regressions estimated on all stocks (Fama & French 2008).[18]

Table 7 reports the FM regression results. When controlling for the market capitalization and the book-to-market ratio, we find a strong negative relation between estimated liquidity beta and future stock returns, significant at the 5% level (specification 1). When we also control for the return momentum in the prior year, the coefficient on the liquidity beta decreases slightly, but remains marginally significant at around the 10% level (specification 2). It is worth mentioning that the coefficients on the size, value, and momentum proxies are all significant and have the expected signs, consistent with the literature that they are priced firm characteristics in the cross section. When we further augment the model with the natural log of the Amihud ratio, all the factor loadings still have the expected signs (specification 3). That is, illiquid stocks command a higher return, while high liquidity beta indicated lower returns in subsequent periods. Unfortunately, neither coefficient is significant at the conventional level.

[18] However, an unreported analysis including micro stocks shows that the FM regression results are qualitatively similar and therefore are omitted for brevity.

Overall, the result of the FM regression lends further support to our interpretation of liquidity beta as a measure of sentiment proneness, rather than a gauge of risk. The negative return predictability of liquidity beta at the stock level reinforces the sentiment story that the valuation of high liquidity beta stocks is pushed up by sentiment investors, which leads to lower expected returns in subsequent periods. Apparently, the negative pricing channel via which liquidity beta passes through to future stock returns can only be incorporated in a behavioral asset pricing framework, rather than a rational risk-based one.

[Insert Table 7 here]

6.2. Augmented Fama-French Four-Factor Model

Given the compelling evidence of the reverse liquidity beta effect we document at the portfolio level and the stock level as well, it is reasonable to augment the Fama-French three-factor model by a traded factor, *LMH* (low liquidity beta minus high liquidity beta), which mimics the reverse liquidity beta premium. Empirically, sentiment-prone stocks (high liquidity beta) tend to be small and growth firms, indicating possible correlations between liquidity beta and firm size or book-to-market ratio. Therefore, we propose a triple-way sequential sorting method to form the reverse liquidity beta factor, which alleviates the correlation with the size or value factors within the Fama-French framework. The sequential sorting method proceeds as follows:

At the end of each year, all available stocks are sorted in the order of market capitalization (*MV*), book-to-market ratio (*BTM*), and liquidity beta (β_j^{Liq}) to obtain the 2×3×3 value-weighted portfolios. The 18 value-weighted portfolios are then held for a year, and monthly returns of the portfolios are linked across the years. The *MV* breakpoints are the 90% of the aggregated market capitalization in the main boards. The *BTM* and β_j^{Liq} breakpoints are the 30th and 70th percentiles. The reverse liquidity beta mimicking factor is then calculated as the simple mean of the return differentials between the low liquidity beta portfolio and the high liquidity beta portfolio (within each *MV* and *BTM* double sorted group).

Our primary goal is to test whether the following augmented four-factor model with the reverse liquidity beta factor is better than the CAPM model and the Fama-French three-factor model in explaining the cross sectional returns.

$$R_{i,t} = \alpha_i + \beta_i^{RMRF} RMRF_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \beta_i^{LMH} LMH_t + \varepsilon_{i,t} \qquad [6.2]$$

*w*here $R_{i,t}$ is the return in excess of the risk-free rate for the test portfolio *i* at period *t*. Following the convention (Fama & French 1993, 2012), we use the 5×5 *MV* and *BTM* double-sorted portfolios as the set of the test portfolios. We also use the 4×5 *MV* and *BTM* sorted portfolios excluding the microcap stocks as an alternative set of the test portfolios. $RMRF_t$ is the excess return of the value-weighted market portfolio for period *t*. SMB_t is the size factor during period *t*. HML_t is the value factor at period *t*. LMH_t is the reverse liquidity beta factor for period *t*.

To compare the explanatory power of the augmented model with the CAPM and Fama-French three-factor model, we follow Fama and French (2012) by assessing their adjusted R^2s and the statistical significance of the regression intercepts using the Gibbons, Ross and Shanken (GRS) *F*-test (Gibbons *et al.* 1989). The intuition behind the test is that a sufficient asset pricing model should be able to explain the returns of portfolios that are created from the variables used to construct the risk factors. The results are displayed in **Table 8**. For the set of 5×5 test portfolios, the null hypothesis of joint zeros for the regression intercepts are rejected for all the competing models, indicating none of the models is fully able to explain the return variation. The Fama-French three-factor model and the augmented four-factor model have much lower average of the absolute (regression) intercepts and much higher average adjusted R^2 than the CAPM model, suggesting both models have a better model fitting than the CAPM model. However, there is no evidence that the augmented four-factor model is more efficient than the Fama-French three-factor model.

When excluding the microcap stocks (the 4×5 testing portfolios), the GRS test results suggest that all three competing models perform relatively well as the null hypothesis of the GRS test is not rejected in each case. Comparing the average of the absolute (regression) intercepts, both the Fama-French three-factor model and the augmented four-factor model have smaller intercepts than the CAPM model. Finally, the average adjusted R^2 is the highest for the augmented four-factor model.

For robustness purposes, we replace the *MV* and *BTM* sorted portfolios with the *MV* and β_i^{Liq} sorted portfolios as the testing portfolios and rerun the regressions. In these cases, the augmented four-factor model is slightly better than the Fama-French three-factor model in terms of the GRS test and the adjusted R^2. Overall, our results suggest that the reverse liquidity beta factor adds marginal explanatory power within the Fama-French asset pricing framework.

[Insert Table 8 here]

6.3. The Time-variation of The Return Differential

The strikingly large return differential between high and low liquidity beta stocks indicates that high liquidity beta stocks underperform low liquidity beta stocks by 1.17% per month on average (the unconditional pattern). Moreover, the return spread between the two groups of stocks varies dramatically over the entire sample period as shown in **Figure 3** (the conditional pattern). The fluctuation of the return spread leads to an important remaining question: Does the return differential vary in a predictable way as indicated by the sentiment-driven liquidity shifts? The evaluation of this problem corroborates to the testable hypothesis: The return spread between high and low liquidity beta stocks becomes more dramatic after the high liquidity (sentiment) period.

Our empirical strategy is based on the following predictive regression:

$$R_{high-low,t} = \alpha_0 + \beta_1 LIQ_{t-1} + \beta_2 VOL_{t-1} + c' F_t + \varepsilon_{i,t} \quad [6.2]$$

*w*here $R_{high-low,t}$ is the monthly value-weighted return differential between the high liquidity beta portfolio and the low liquidity beta portfolio (in section 4.3). LIQ_{t-1} is the lagged market-wide liquidity level. For consistency, we use the detrended Pastor and Stambaugh (2003)'s return-reversal measure of liquidity as our proxy for the monthly market liquidity (see Eq. [3.2] and Eq. [3.3]).[19] VOL_{t-1} is the lagged market volatility, calculated as the standard deviation of the daily value-weighted returns of the market portfolio within the month. For ease of comparison, both predictive variables (LIQ_{t-1} and VOL_{t-1}) are standardized to have zero mean and unit variance based on their sample moments. F_t is the vector of the (contemporaneous) Fama-French three factors, which are used to control for the cross-sectional risk dispersion.

The return spread between high and low liquidity beta stocks, represents a strategy to go long sentiment prone stocks while simultaneously going short sentiment immune ones. Given that market liquidity is a direct measure of investor sentiment (the liquidity-as-sentiment argument in Baker and Stein (2004)), we should expect a negative relation between market liquidity (sentiment) and subsequent return differential, the so-called contrarian predictability as shown in Baker and Wurgler (2006). It should also be noted that our inclusion of market volatility serves two purposes. First, volatility might be another viable return predictor as it leads the investment environment. Second, market volatility is highly correlated with the funding risk channel in "commonality-in-liquidity" (Brunnermeier & Pedersen 2009), which we use as an additional check for the (possible) impact of the funding risk channel in the specific market.

The results of the predictive regressions are shown in **table 9**. Specifically, we consider all combinations of the predictive regression, starting from the unconditional model with no predictive variables, moving to the single-predictor model, and ending with the all-inclusive model with both predictors. As it stands, the first column reproduces the unconditional risk-

[19] Our result also holds when we use other conventional measures of market liquidity such as the cross-sectional average of the Amihud ratio. Results are omitted for brevity.

adjusted return dispersion between high and low liquidity beta stocks, which is -1.17% per month. The second column shows the net effect of the market liquidity on subsequent return differentials after controlling for the Fama-French factors. It suggests that a one-standard-deviation increase of market liquidity in the prior month is linked with an "extra" return dispersion of 63 basis points per month, which is significant at the 10% level. The third column seems to suggest that the net effect of the market volatility ("funding risk channel") on subsequent return differentials is negligible, as the coefficient on the volatility term is indistinguishable from zero. The last column provides the results for the all-inclusive model. Again, we find that market liquidity is a reliable contrarian predictor for the subsequent return dispersion between high and low liquidity beta stocks as the coefficient is marginally significant at the 10% level. If market liquidity is one standard deviation higher than its normal level, the subsequent return differential is expected to be -1.81%, after controlling for the effects of market volatility and the Fama-French risk factors.

Overall, the empirical result of contrarian predictability is well in line with our sentiment-based hypothesis (the second testable hypothesis). Since market liquidity is a valid gauge of investor sentiment (Baker & Stein 2004), it predicts negatively the future return dispersion between sentiment-prone stocks and sentiment-immune stocks. It is also highly consistent with the findings in Baker and Wurgler (2006), who use a more or less similar predictive model to capture the contrarian predictability of investor sentiment in the cross section. Overall, we find strong evidence that the *reverse liquidity beta effect* is time-varying, and when the liquidity-as-sentiment level is high in the previous month, subsequent returns of the high-minus-low liquidity beta portfolio are particularly low.[20]

[Insert Table 9. here]

7. Economic Intuition

Though the contribution of the paper is mainly empirical, we do provide a simplified theoretical framework to depict the relation among investor sentiment, market liquidity, and stock returns in the cross section.

7.1. Model Setup

Following Easley and O'hara (2004), we consider a one-period model: At time 0 investors choose their portfolios, and at time 1 all terminal cash flows (*i.e.* dividends) are realized. There are I+1

[20] The contrarian predictability of market liquidity also holds when we exclude the 2007–2008 financial crisis period, during which the return differential is particularly volatile. Results are omitted for brevity.

assets traded in the financial market: one risk-less asset (i.e., bond) and $I > 1$ risky assets (i.e., stocks). The bond is in unlimited supply; its payoff is one, and its price is normalized to one. The stock *i* has a total supply of one unit; it has a price of $\tilde{p}_i$, endogenously determined in the financial market, and its payoff $\tilde{v}_i \sim N(\bar{v}_i, 1/\rho_{v_i})$ with the mean $\bar{v}_i > 0$ and the precision $\rho_{v_i} > 0$.

There is one type of optimizing traders, which is a [0,1] continuum of the sentiment investors. These sentiment investors are assumed to have the constant absolute risk aversion (CARA) utility function with the risk aversion parameter $\gamma > 0$. Each sentiment investor *n* observes the stock price $\tilde{p}_i$ and is overconfident about his ability so that he overestimates the future payoff of stock *i* as $\tilde{s}_{n,i} = \tilde{v}_i + k_i \tilde{\varepsilon}_{n,i}$, where the estimation error $\tilde{\varepsilon}_{n,i} \sim N(0, 1/\rho_{\varepsilon_i})$ with $\rho_{\varepsilon_i} > 0$ and $0 < k_i < 1$ which reflects how overconfident they are (Kyle & Wang 1997). Apparently, higher k_i^{-1} indicates higher overconfidence (sentiment). Here we assume all sentiment traders have the same overconfidence k_i and estimation error $\tilde{\varepsilon}_{n,i}$ for stock *i*. We denote $\theta_i = \frac{1}{k_i^2} > 1$ as the measure of the level of sentiment (overconfidence), and then the private signal received by the sentiment investor *n* can be rewritten as

$$\tilde{s}_{n,i} = \tilde{v}_i + \tilde{\eta}_{n,i}, \qquad \tilde{\eta}_{n,i} \sim N(0, 1/\theta_i \rho_{\varepsilon_i}) \tag{7.1}$$

In other words, θ_i can be regarded as the sentiment impact on stock *i*. Here it should be noted that we follow the same economic mechanism as in Baker and Stein (2004) to motivate how sentiment influences the investment behavior.

In addition, there are also liquidity traders in the market who trade $\tilde{x}_i$ unit of the risky asset of stock *i*. We assume $\tilde{x}_i$ is normally distributed with mean $0 \leq \bar{x}_i < 1$ and its precision $\rho_{x_i} > 0$. Finally, we assume all random variables independent of each other.

Following Grossman and Stiglitz (1980) and Easley and O'hara (2004), we consider a linear equilibrium, where the market price $\tilde{p}_i$ depends linearly on the signals and the liquidity trading.

$$\tilde{p}_i = \alpha_i + \beta_i \tilde{v}_i + \lambda_i \tilde{x}_i \tag{7.2}$$

where α_i, β_i, and λ_i can be determined in the equilibrium.

Given the CARA-normal setup, the demand function of the sentiment investor *n* is

$$D_n(\tilde{p}_i, \tilde{s}_{n,i}) = \frac{E(v_i | \tilde{p}_i, \tilde{s}_{n,i}) - \tilde{p}_i}{\gamma Var(v_i | \tilde{p}_i, \tilde{s}_{n,i})} \tag{7.3}$$

Then, the equilibrium price is determined by the market-clearing condition for stock *i*:

$$\int_0^1 D_n(\tilde{p}_i, \tilde{s}_{n,i})dn + \tilde{x} = 1 \quad [7.4]$$

Lemma 1. *There exists a unique, linear, partial revealing REE with the price function,*

$$\tilde{p}_i = \alpha_i + \beta_i \tilde{v}_i + \lambda_i \tilde{x}_i \quad [7.5]$$

where

$$\frac{\beta_i}{\lambda_i} = \frac{\theta_i \rho_{\varepsilon_i}}{\gamma}, \qquad \psi_i = \left(\frac{\beta_i}{\lambda_i}\right)^2 \rho_{x_i} = \frac{\theta_i^2 \rho_{\varepsilon_i}^2 \rho_{x_i}}{\gamma^2},$$

$$\alpha_i = \frac{\bar{v}\rho_{v_i} - \psi_i \left(\frac{\beta_i}{\lambda_i}\right)^{-1} \bar{x}_i - \gamma}{\rho_{v_i} + \psi_i + \theta_i \rho_{\varepsilon_i}}, \qquad \beta_i = \frac{\psi_i + \theta_i \rho_{\varepsilon_i}}{\rho_{v_i} + \psi_i + \theta_i \rho_{\varepsilon_i}}, \quad [7.6]$$

$$\lambda_i = \frac{\psi_i \left(\frac{\beta_i}{\lambda_i}\right)^{-1} \bar{x}_i + \gamma}{\rho_{v_i} + \psi_i + \theta_i \rho_{\varepsilon_i}}$$

Proof see Appendix D.

7.2. Sentiment, Liquidity, and Expected Returns

According to Kyle (1985), we define the liquidity of stock *i* as the inverse of price impact.

$$LIQUIDITY_i = \frac{1}{\lambda_i} = \frac{\rho_{v_i} + \frac{\rho_{\varepsilon_i}^2 \rho_{x_i}}{\gamma} \theta_i^2 + \theta_i \rho_{\varepsilon_i}}{\frac{\rho_{\varepsilon_i} \rho_{x_i}}{\gamma} \theta_i + \gamma} \quad [7.7]$$

Apparently, $\frac{\partial LIQUIDITY_i}{\partial \theta_i} = \frac{\rho_{\varepsilon_i}\left(\left(\rho_{\varepsilon_i}\rho_{x_i}\theta_i + \gamma^2\right)^2 - \rho_{v_i}\rho_{x_i}\gamma^2\right)}{\gamma\left(\rho_{\varepsilon_i}\rho_{x_i}\theta_i + \gamma^2\right)^2} > 0$, if $\theta_i > \frac{\gamma\sqrt{\rho_{v_i}\rho_{x_i}} - \gamma^2}{\rho_{\varepsilon_i}\rho_{x_i}}$. It indicates that higher investor sentiment, higher liquidity of the stock, which is consistent with Baker and Stein (2004)'s key finding that market liquidity can be regarded as a measure of investor sentiment.[21]

Proposition 1. *Higher investor sentiment, higher liquidity.*

The intuition of the proportion resembles the logic in Baker and Stein (2004) that the increase of market liquidity is a pure manifestation of investor sentiment. As sentiment investors get more optimistic about the prospects of the stocks, this leads to the increase of liquidity (eg. a lower price impact of trades). In other words, market liquidity is a sentiment indicator.

[21] For example, following Tang (2014), we set ρ_{v_i} at 25, which means the annual volatility is around 20%. We standardize $\bar{v}_i = 1$, $\rho_{\varepsilon_i} = 25$ and $\bar{x} = 0$. We set ρ_{x_i} at 10, which means the annual volatility of liquidity supply is 30% of total supply, and $\gamma = 10$. Then $\frac{\gamma\sqrt{\rho_{v_i}\rho_{x_i}} - \gamma^2}{\rho_{\varepsilon_i}\rho_{x_i}} = 0.23 < 1 < \theta_i$. In this setting, $\frac{\partial LIQUIDITY}{\partial \theta} > 0$ always holds.

We then model the relation between (cross sectional) stock returns and sentiment/liquidity beta. According to Easley and O'hara (2004), the return of stock *i* is defined as

$$RETURN_i = E[\tilde{v}_i - \tilde{p}_i] = \frac{\gamma(1-\bar{x}_i)}{\rho_{v_i} + \frac{\rho_{\varepsilon_i}^2 \rho_{x_i}}{\gamma}\theta_i^2 + \theta_i \rho_{\varepsilon_i}}. \qquad [7.8]$$

In addition, we define the return sensitivity of stock *i* to investor sentiment θ_i as the sentiment beta,

$$\begin{aligned} BETA_i &= \frac{\partial RETURN_i}{\partial \theta_i} \\ &= -\frac{\gamma(1-\bar{x}_i)}{\left(\rho_{v_i} + \frac{\rho_{\varepsilon_i}^2 \rho_{x_i}}{\gamma}\theta_i^2 + \theta_i \rho_{\varepsilon_i}\right)^2} \left(2\frac{\rho_{\varepsilon_i}^2 \rho_{x_i}}{\gamma}\theta_i + \rho_{\varepsilon_i}\right) < 0 \end{aligned} \qquad [7.9]$$

Plugging Equation [7.8] into [7.9] leads to the following

$$RETURN_i = -\frac{\rho_{v_i} + \frac{\rho_{\varepsilon_i}^2 \rho_{x_i}}{\gamma}\theta_i^2 + \theta_i \rho_{\varepsilon_i}}{2\frac{\rho_{\varepsilon_i}^2 \rho_{x_i}}{\gamma}\theta_i + \rho_{\varepsilon_i}} BETA_i \qquad [7.10]$$

By using the fact that $\frac{\partial RETURN_i}{\partial BETA_i} = -\frac{\rho_{v_i} + \frac{\rho_{\varepsilon_i}^2 \rho_{x_i}}{\gamma}\theta_i^2 + \theta_i \rho_{\varepsilon_i}}{2\frac{\rho_{\varepsilon_i}^2 \rho_{x_i}}{\gamma}\theta_i + \rho_{\varepsilon_i}} < 0$, we have thus established the relation between stock return and sentiment beta.

Proposition 2. *Higher investor sentiment/liquidity beta*, *lower stock return*.

The proposition builds on the economic intuition that during a broad wave of sentiment induced liquidity shock, not all stocks are influenced to the same extent. It is also consistent with the empirical fact in Baker and Wurgler (2006, 2007) that sentiment prone stocks have lower equilibrium returns than sentiment immune stocks.

It is also worth noting we do not model explicitly the relation between liquidity beta and stock return for the consideration of mathematical rigor, as market liquidity is endogenously driven by investor sentiment in our model setting. Given that liquidity is an indicator of market sentiment (proposition 1), it follows directly that higher liquidity beta stocks would also have lower expected returns. In other words, expected stock returns are decreasing in liquidity beta.

8. Discussion and Concluding Remarks

This article complements our understanding on the pricing implications of liquidity beta in the financial markets. Empirically, it suggests that the conventional, risk-based view on liquidity beta is a dismal story in China: High liquidity beta stocks underperform low liquidity beta stocks by 1.17% per month.

The strong negative liquidity beta premium in China, however, should not be interpreted as overly striking, as the key message of the article suggests that there exist competing asset pricing channels of liquidity beta (*i.e.* funding risk *vis-à-vis* investor sentiment). In a deep liquid emerging market, where retail investors rely on their own excess capital for trading, funding risk is less of a concern. Therefore, the liquidity beta is no more a risk gauge. Rather it reflects the sentiment proneness of the individual stock. Accordingly, the sentiment-based pricing channel implies that *high* liquidity beta stocks, which are sentiment prone, tend to have *lower* average returns than *low* liquidity beta stocks, which are sentiment immune.

Consistent with our proposed sentiment-based pricing channel, but in contradiction with the risk-based pricing channel, we find that the zero-cost strategy, which goes long in high liquidity beta stocks and short in low liquidity beta stocks, incurs more dramatic loss (-1.35% per month) in the recent subsample period ("the volatile period") than in the earlier subsample period ("the tranquil period"). Moreover, the conditional patterns for the return spread between high liquidity beta stocks and low liquidity beta stocks reinforced our sentiment-based conjecture: High market liquidity is associated with enlarged return dispersion between the two groups of stocks over subsequent periods. The documented pattern is highly consistent with the well-known contrarian predictability of investor sentiment proposed in the recent behavioral literature. Overall, the documented empirical patterns set an unfortunate tune for investors who (mistakenly) concentrate on high liquidity beta stocks as an investment style, without considering the economic sources of the market-wide liquidity fluctuations in the financial market.

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Figure 1. The Standardized Liquidity Shocks and the Standardized Equity Premium, January 1998–December 2013

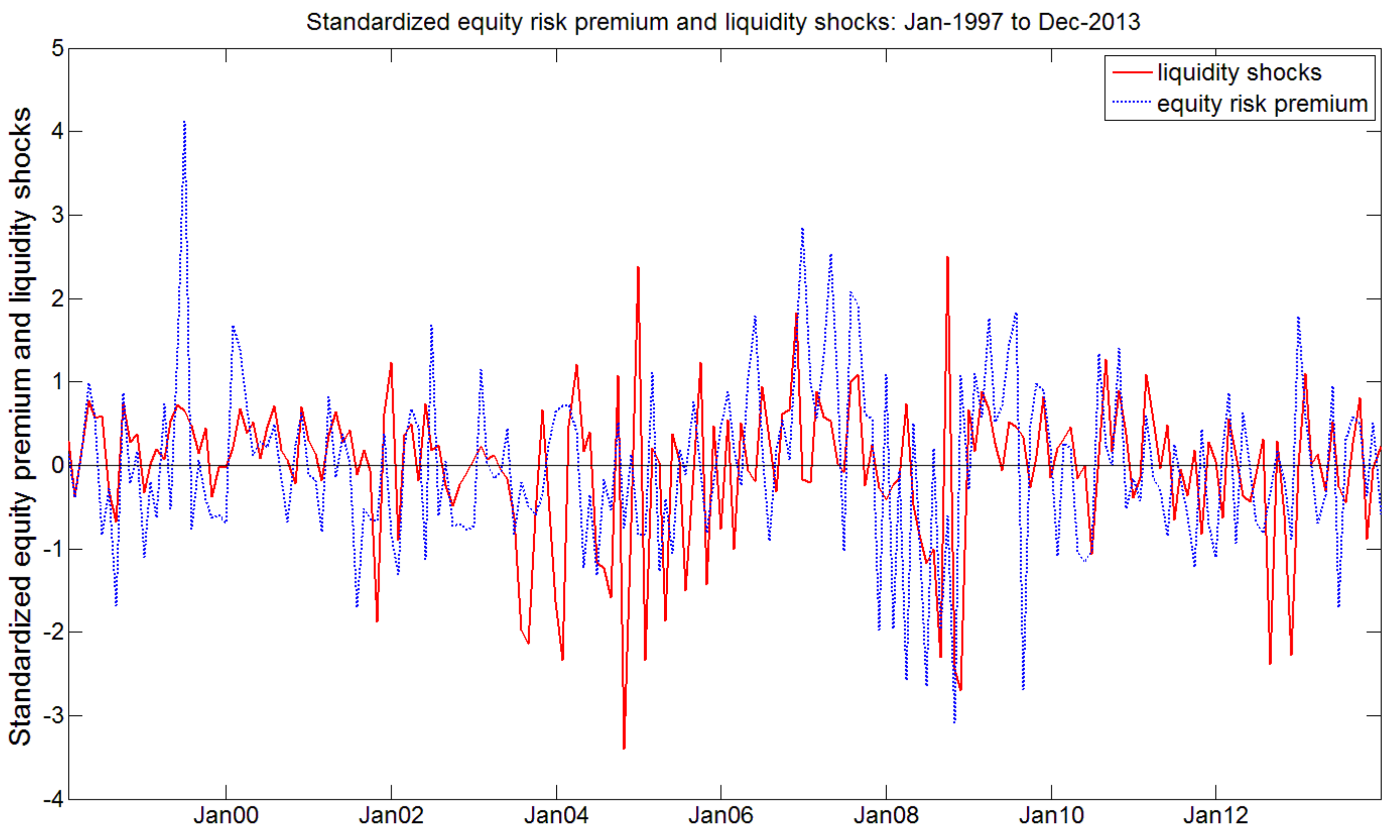

Figure 2. Cumulative Returns for Value-weighted Low Liquidity Beta Quintile Portfolio, High Liquidity Beta Quintile Portfolio, and Market Portfolio, January 1998–December 2013

31-Dec-1997 = 1.00 Chinese yuan

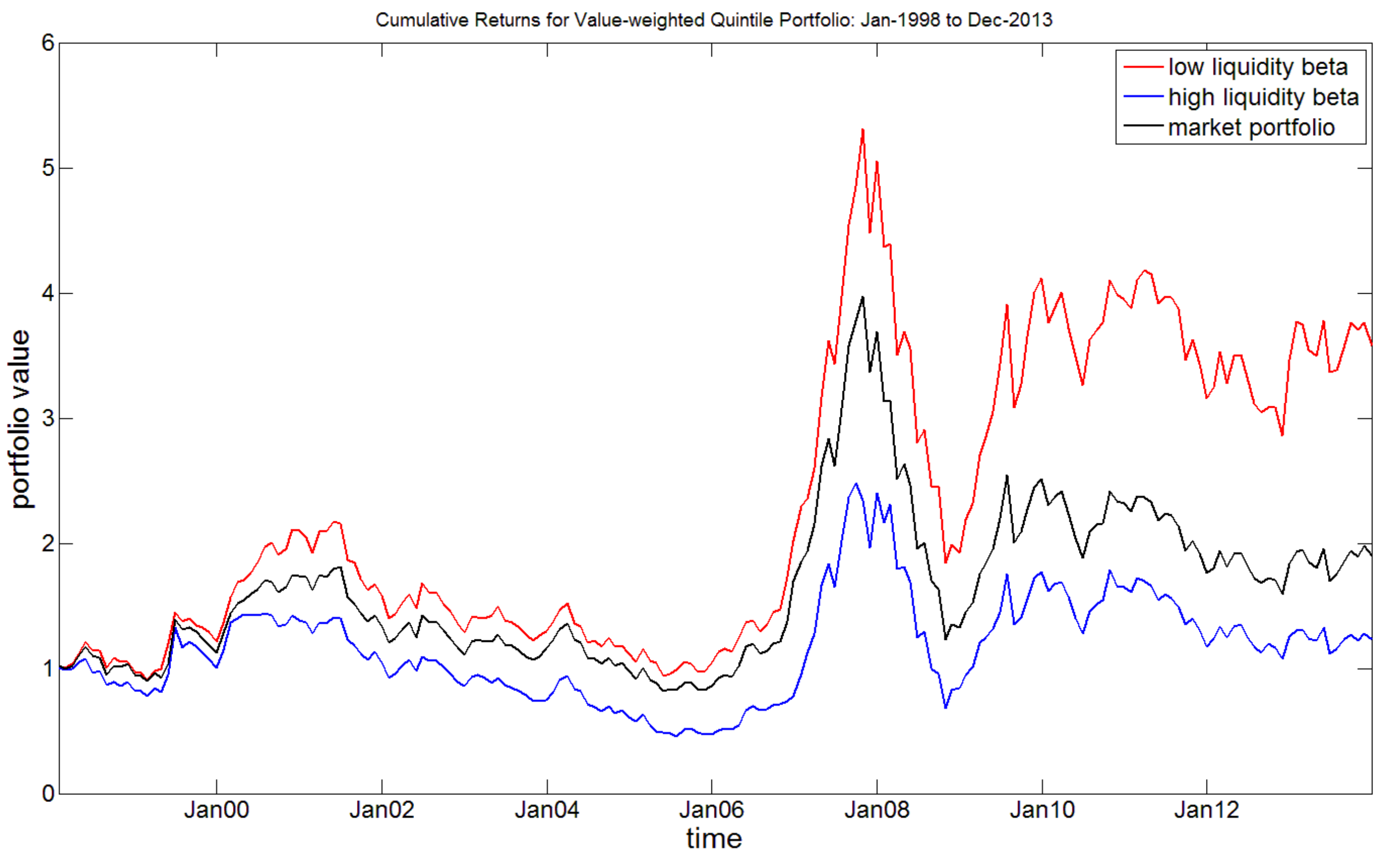

Figure 3. Time-series Plot of the Value-weighted High-minus-low Liquidity Beta Portfolio, January 1998–December 2013

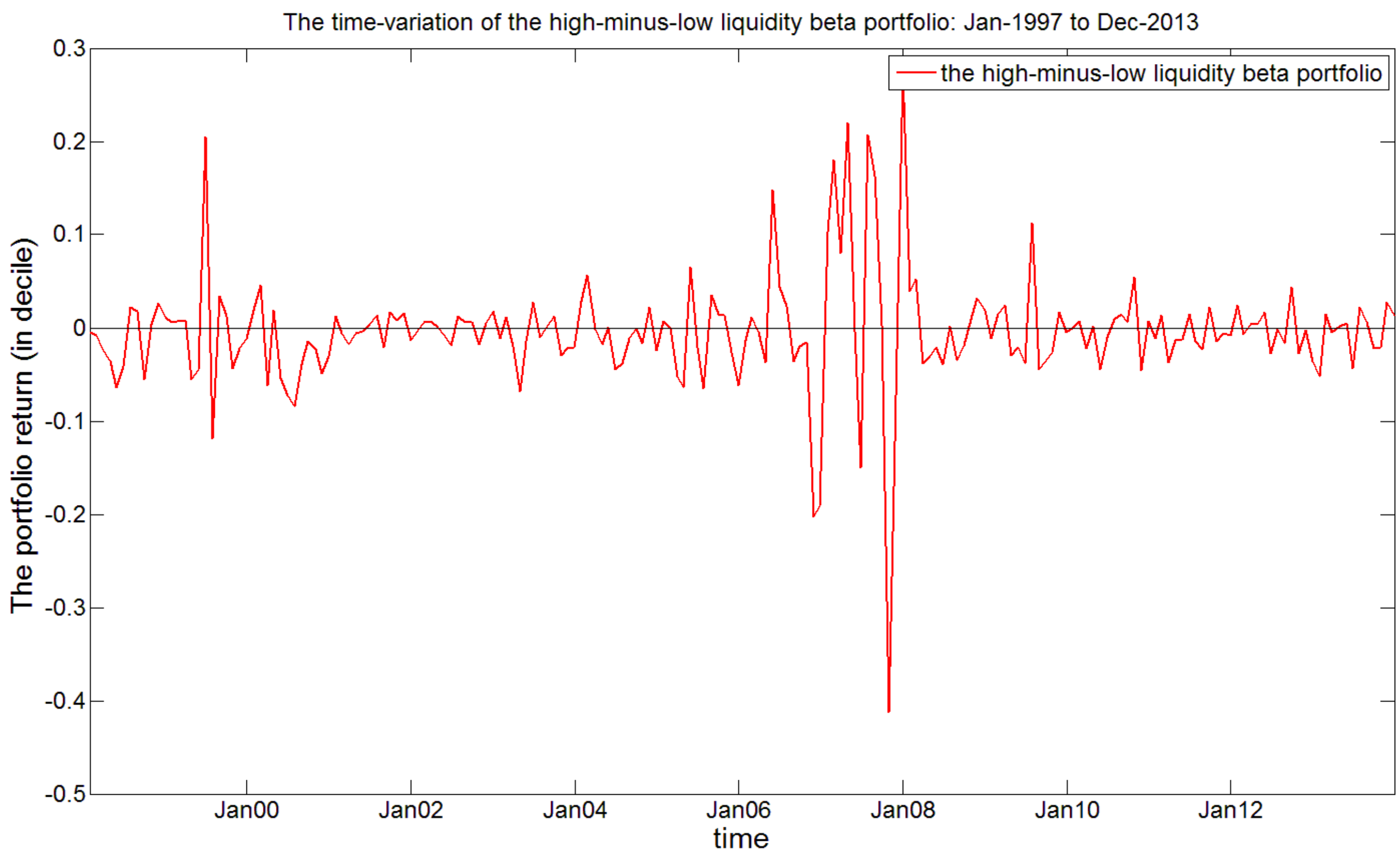

Table 1. Statistics of Stock Exchanges

Panel A: Ranking of the major stock exchanges by the total value of market capitalization as of 31/12/2013

	Exchange Name	# of Stocks Local	Foreign	(1). Market Capitalization (in USD million)	(2). Trading Volume (in USD million)	(2)/(1)
1	NYSE	1852	519	17,949,883.80	13,700,450.50	76.33%
2	NASDAQ	2328	309	6,084,969.70	9,584,742.20	157.52%
3	Japan Exchange Group	3408	11	4,543,169.10	6,304,927.50	138.78%
4	London Stock Exchange	2164	572	4,428,975.30	3,050,891.50	68.88%
5	Euronext (Amsterdam, Brussel, Lisbon, Paris)	935	127	3,583,899.70	1,661,878.30	46.37%
6	HongKong Stock Exchange	1553	90	3,100,777.20	1,323,373.30	42.68%
7	Shanghai Stock Exchange	953	0	2,496,989.90	3,731,128.90	149.43%
8	TMX Group–Canada	3810	76	2,113,821.80	1,371,477.70	64.88%
9	Deutsche Börse	639	81	1,936,106.30	1,334,544.90	68.93%
10	SIX Swiss Exchange	236	36	1,540,699.80	676,957.70	43.94%
11	Shenzhen Stock Exchange	1536	0	1,452,153.60	3,858,509.00	265.71%
12	Australian Securities Exchange	1951	104	1,365,958.10	881,555.60	64.54%

Panel B: Breakdown of the ownership structure and total trading volume for the Shanghai Stock Exchange as of 31/12/2013

	Market Capitalization	Trading Volume
Individual Investors	21.78%	82.24%
Legal Person	63.64%	2.46%
Financial Institutions:	14.58%	15.3%
- Investment Funds	4.54%	6.18%

Source: Statistics of the major exchanges are from the yearly reports of the World Federation of Exchanges (http://www.world-exchanges.org); Statistics of the breakdown data of Shanghai Stock Exchange are from Annual Fact Book issued by Shanghai Stock Exchange. Note: Trading volume is measured as the dollar trading volume of the entire year. Financial Institutions include brokerage and security firms, investment funds (mutual funds), pension funds, asset under management, and QFII (qualified foreign institutional investor). Legal Person includes all other companies, corporations, enterprises, departments, juridical association and agents.

Table 2. Descriptive Statistics

Panel A of the table presents the summary statistics of the composite stocks in the liquidity beta sorted quintile portfolios. N_obs, the average number of the composite stocks at the end of the portfolio selection year; MV, the average market capitalization (measured in millions of Chinese yuan) of the composite stocks at the end of the portfolio selection year; MTBV, the average ratio of the market equity to book equity of the composite stocks at the end of the portfolio selection year; LIQ Beta, the average liquidity beta of the composite stocks estimated using Equation 3.5 with the 5-years data prior to the portfolio formation year. Panel B and C report the geometric means, arithmetic means and standard deviations of the monthly returns of the value-weighted and equal-weighted liquidity beta-sorted quintile portfolios from January 1998 to December 2013, respectively.

Liquidity Beta	**Q1 = low**	**Q2**	**Q3**	**Q4**	**Q5 = high**	**Q5-Q1**
Panel A:Firm characteristics prior to the portfolio formation period						
MV	7,811.42	5,692.13	5,539.35	5,378.67	5,193.73	
MTBV	5.49	6.43	5.81	6.99	6.76	
LIQ Beta	-0.37	-0.12	0.03	0.17	0.44	
N_obs	211	211	211	211	211	
Panel B:Value-weighted quintile portfolios, Jan 1998–Dec 2013						
Geometric mean (%)	0.67	0.55	0.34	0.29	0.11	-0.64
Arithmetic mean (%)	1.00	0.91	0.72	0.72	0.56	-0.43
Standard deviation (%)	8.13	8.57	8.82	9.28	9.65	6.26
Panel C:Equal-weighted quintile portfolios, Jan 1998–Dec 2013						
Geometric mean (%)	1.00	0.96	0.81	0.83	0.67	-0.39
Arithmetic mean (%)	1.41	1.39	1.26	1.27	1.11	-0.34
Standard deviation (%)	9.17	9.41	9.62	9.59	9.50	3.03

Table 3. Cross-Sectional Patterns of the Value-weighted Portfolios, January 1998–December 2013

Panel A reports the Fama-French three-factor model regression results of the value-weighted liquidity beta-sorted quintile portfolios and the long-and-short portfolio (Q5-Q1) for the entire sample period from January 1998 to December 2013. Panels B and C report the subsample results for January 1998–December 2005 and January 2006–December 2013, respectively. RMRF, SMB, and HML are the market, size, and value factors, respectively. Newey–West adjusted *t*-statistics are reported in italic. *, **, and *** stand for significance at the 10%, 5% and 1% level.

Liquidity Beta	**Q1 = low**	**Q2**	**Q3**	**Q4**	**Q5 = high**	**Q5-Q1**
Panel A:Value-weighted quintile portfolios, Jan 1998 – Dec 2013						
Alpha	0.34***	-0.12	-0.37**	-0.48***	-0.55**	-1.17***
	2.61	*-0.93*	*-2.32*	*-2.63*	*-2.53*	*-2.93*
RMRF	0.97***	0.98***	0.99***	1.03***	1.07***	0.12
	28.7	*34.5*	*30.31*	*27.62*	*21.69*	*1.27*
SMB	-0.02	0.29***	0.33***	0.45***	0.44***	0.57***
	-0.51	*5.76*	*4.78*	*6.08*	*4.14*	*3.76*
HML	0.04	0.23***	0.25***	0.23***	0.08	0.33*
	0.94	*3.2*	*4.65*	*2.74*	*0.98*	*1.68*
Adj. R^2	93%	95%	94%	94%	92%	29%
Panel B:Value-weighted quintile portfolios, Jan 1998 – Dec 2005						
Alpha	0.13	0.07	-0.28***	-0.28	-0.48**	-0.70**
	0.65	*0.63*	*-2.62*	*-1.54*	*-2.1*	*-2.02*
RMRF	0.94***	1.04***	0.99***	1.03***	1.07***	0.13
	14.01	*41.4*	*54.2*	*37.81*	*21.69*	*1.08*
SMB	0.02	0.16***	0.11**	0.17**	0.21*	0.14
	0.27	*3.79*	*2.12*	*2.43*	*1.83*	*0.97*
HML	0.08	0.09*	0.06	-0.06	-0.21**	-0.34***
	1.05	*1.72*	*1.18*	*-0.77*	*-2.51*	*-2.67*
Adj. R^2	90%	97%	97%	96%	92%	12%
Panel C:Value-weighted quintile portfolios, Jan 2006 – Dec 2013						
Alpha	0.52***	-0.23	-0.38	-0.55**	-0.49	-1.35**
	2.94	*-1.05*	*-1.32*	*-2.11*	*-1.5*	*-2.15*
RMRF	0.99***	0.95***	0.99***	1.02***	1.06***	0.1
	34.24	*31.94*	*21.41*	*22.09*	*17.7*	*0.97*
SMB	-0.04	0.33***	0.41***	0.53***	0.50***	0.68***
	-0.75	*6*	*5.12*	*7.77*	*4.06*	*4.19*
HML	0.02	0.30***	0.31***	0.35***	0.20***	0.62***
	0.53	*3.71*	*4.92*	*4.71*	*2.65*	*3.15*
Adj. R^2	95%	94%	94%	95%	93%	44%

Table 4. Cross-Sectional Patterns under Alternative Asset Pricing Models

The table reports the regression results for the value-weighted liquidity beta sorted quintile portfolios and the long-and-short portfolio (Q5-Q1) under the higher-moment CAPM and Liquidity-augmented four factor models proposed in Lam and Tam (2011). We use the Amihud ratio to construct the liquidity-level factor, IML. Newey–West adjusted *t*-statistics in italic are also reported. The sampling period is from January 1998 to December 2013. *, **, and *** stand for significance at the 10%, 5% and 1% level.

Liquidity Beta	Q1 = Low	Q2	Q3	Q4	Q5 = High	Q5-Q1
			Higher-moment CAPM			
Alpha	0.76***	0.17	0.19	0.13	-0.10	-1.10***
	3.75	*0.84*	*0.95*	*0.48*	*-0.35*	*-2.64*
RMRF	0.98***	1.01***	1.04***	1.08***	1.11***	0.17**
	49.48	*31.74*	*28.40*	*22.86*	*24.15*	*2.08*
Higher moment	-0.64***	0.13	-0.22	-0.15	-0.07	0.92
	-2.82	*0.59*	*-0.81*	*-0.48*	*-0.19*	*1.64*
Adj. R^2	94%	91%	89%	87%	87%	8%
			Liquidity-augmented four-factor model			
Alpha	0.30**	-0.18	-0.40***	-0.53***	-0.57***	-1.18***
	2.22	*-1.31*	*-2.62*	*-2.98*	*-2.66*	*-2.72*
RMRF	0.99***	0.99***	0.97***	1.02***	1.05***	0.11
	36.83	*36.37*	*32.15*	*28.44*	*22.10*	*1.23*
SMB	-0.11	0.26***	0.48***	0.49***	0.56***	0.67***
	-1.48	*4.98*	*6.51*	*7.61*	*5.09*	*3.47*
HML	0.09	0.30***	0.31***	0.32***	0.12	0.36
	1.36	*3.54*	*4.61*	*3.11*	*1.30*	*1.33*
IML	0.08	0.15**	0.16	0.18***	0.12	0.08
	1.10	*2.14*	*1.59*	*2.61*	*1.33*	*0.37*
Adj. R^2	94%	95%	94%	94%	92%	29%

Table 5. Cross-Sectional Patterns Using Alternative Market Liquidity Measures

The table reports the Fama-French three-factor regression results for the liquidity beta sorted quintile portfolios and long-short portfolios using alternative market wide liquidity measure as documented in Appendix B. Newey–West adjusted *t*-statistics in italic are also reported. The sampling period is from January 1998 to December 2013. *, **, and *** stand for significance at the 10%, 5% and 1% level.

Liquidity Beta	**Q1 = Low**	**Q2**	**Q3**	**Q4**	**Q5 = High**	**Q5-Q1**
Alpha	0.04	-0.32*	-0.08	-0.24	-0.29**	-0.55*
	0.35	*-1.82*	*-0.55*	*-1.32*	*-2.10*	*-1.77*
RMRF	1.01***	0.98***	1.01***	1.00***	0.99***	-0.01
	51.10	*32.44*	*35.65*	*29.19*	*39.77*	*-0.26*
SMB	-0.16***	0.39***	0.57***	0.62***	0.79***	1.16***
	-3.90	*4.84*	*8.38*	*9.06*	*13.31*	*9.18*
HML	0.18***	0.07	0.10*	0.05	-0.07	0.00
	4.51	*0.79*	*1.72*	*0.55*	*-1.28*	*0.01*
Adj. R^2	96%	93%	95%	93%	96%	68%

Table 6. Portfolios Sorted on Liquidity Beta Controlling for Other Effects

In panel A, we first form 5 portfolios based on a particular characteristic (eg. size). Then, within each characteristic portfolio, we further sort stocks into quintile portfolios ranked by their estimated liquidity betas. Finally, we merge across the characteristic portfolios to form quintile portfolios that have dispersion only in liquidity beta but contain all aspects of the characteristic. We report the alphas associated with the Fama-French three-factor model for those value-weighted liquidity beta sorted portfolios and the long and short portfolio (Q5-Q1), which have already controlled other cross-sectional stock characteristic. Newey–West adjusted *t*-statistics in italic are also reported. *, **, and *** stand for significance at the 10%, 5% and 1% level.

Liquidity Beta	**Q1 = Low**	**Q2**	**Q3**	**Q4**	**Q5 = High**	**Q5-Q1**
Alpha Controlling for	0.10	0.16	-0.28*	-0.38**	-0.39**	-0.65*
Size	*0.72*	*1.11*	*-1.83*	*-2.56*	*-2.08*	*-1.95*
Alpha Controlling for	0.25*	-0.26*	-0.33**	-0.45**	-0.49**	-1.03***
Value	*1.75*	*-1.72*	*-1.98*	*-2.48*	*-2.34*	*-2.64*
Alpha Controlling for	0.29**	-0.17	-0.19	-0.50***	-0.48**	-1.07**
Momentum	*2.15*	*-1.22*	*-1.26*	*-2.87*	*-2.18*	*-2.55*
Alpha Controlling for	0.08	0.19	-0.38**	-0.35**	-0.38**	-0.62**
Liquidity	*0.55*	*1.32*	*-2.41*	*-2.44*	*-2.19*	*-2.11*
Alpha Controlling for	0.16	0.09	-0.31**	-0.40**	-0.47**	-0.83**
Price Level	*1.48*	*0.56*	*-2.45*	*-2.08*	*-2.29*	*-2.51*
Alpha Controlling for	0.33**	-0.26**	-0.30**	-0.44***	-0.56***	-1.23***
Idiosyncratic Risk	*2.54*	*-1.91*	*-1.97*	*-2.81*	*-2.61*	*-3.05*
Alpha Controlling for	0.28**	-0.07	-0.39***	-0.49***	-0.48**	-1.05***
Volatility	*2.13*	*-0.44*	*-3.08*	*-2.72*	*-2.52*	*-2.74*

Table 7: Average Slopes and *t*-Statistics from Monthly Cross-sectional Regressions, January 1998–December 2013

The table shows the slope coefficients and their t-statistics from monthly Fama-MacBeth cross-section regressions to predict stock returns. The predicting variables used to predict returns from January till December in year t are: lnMV, the natural log of market capitalization at the end of year t-1; lnBTM, the natural log of the ratio of book equity to market equity estimated using information at the end of year t-1; MOM, the cummulative return in prior year excluding the month December in year t-1; lnAmihud, the natural log of the amihud ratio of the stock estimated in year t-1; LIQ beta, the liquidity beta estimated using Eq. [3.5] over the prior 5 year. Fama-MacBeth slope coefficients and Newey-West adjusted *t*-statistics (in Italic) are reported. *, **, and *** stand for significance at the 10%, 5% and 1% level.

	Const.	**lnMV**	**lnBTM**	**MOM**	**lnAmihud**	**LIQ beta**
Average	3.22***	-0.23***	0.49***			-0.77**
t-statistics	*4.44*	*-3.00*	*4.75*			*-2.38*
Average	3.12***	-0.21***	0.65***	0.73***		-0.53
t-statistics	*4.27*	*-2.68*	*5.80*	*4.46*		*-1.63*
Average	4.23***	-0.19*	0.64***	0.91***	0.09	-0.35
t-statistics	*4.03*	*-1.94*	*5.66*	*5.52*	*1.10*	*-1.06*

Table 8. Regression Statistics from the Asset Pricing Models, January 1998–December 2013

The table reports the regressions using the CAPM, Fama-French three factor, and liquidity beta augmented four factor models to explain monthly excess returns on a set of testing portfolios double sorted on size and book-to-market ratio or on size and liquidity beta, with (5×5) or without (4×5) microcap stocks. The *GRS* statistics tests the null hypothesis that all the intercepts of the 25 (20) testing portfolios are jointly zero; $|\alpha|$ is the mean of the absolute intercepts of the set of testing portfolios; $adj. R^2$ is the average adjusted ; $SR(\alpha)$ is the Sharpe ratio for the intercepts. *,**, and *** stand for significance at the 10%, 5% and 1% level for the GRS statistics.

	GRS	$SR(\alpha)$	$\|\alpha\|$	$adj. R^2$
5-by-5 portfolios sorted on size and BTM				
CAPM	1.98***	0.30	0.61	76.1%
Fama-French three-factor	1.70**	0.27	0.24	92.8%
Augmented four-factor	1.79**	0.28	0.24	92.8%
4-by-5 portfolios sorted on size and BTM, excluding microcap stocks				
CAPM	1.36	0.16	0.45	78.8%
Fama-French three-factor	1.44	0.18	0.21	93.5%
Augmented four-factor	1.45	0.18	0.21	93.6%
5-by-5 portfolios sorted on size and liquidity beta				
CAPM	1.40*	0.21	0.61	76.3%
Fama-French three-factor	1.29	0.20	0.30	91.5%
Augmented four-factor	1.28	0.20	0.31	91.8%
4-by-5 portfolios sorted on size and liquidity beta, excluding microcap stocks				
CAPM	1.20	0.14	0.42	79.5%
Fama-French three-factor	1.21	0.15	0.28	92.4%
Augmented four-factor	1.20	0.15	0.29	92.7%

Table 9. Predictive Regression of the High-minus-low Liquidity Beta Portfolio

The table shows the slope coefficients and their Newey-West adjusted *t*-statistics from the predictive regression of the high-minus-low liquidity beta portfolio. The predicting variables are: The lagged market liquidity, LIQ, calculated as the detrended Pastor and Stambaugh (2003)'s return-reversal measure of liquidity (see Eq. [3.2] and Eq. [3.3]). The lagged market volatility, VOL, calculated as the standard deviation of the daily value-weighted returns of the market portfolio within the month. For ease of comparison, both predictive variables are standardized to have zero mean and unit variance based on their sample moments. The control variables are the Fama-French risk factors: RMRF, the market factor; SMB, the size factor; HML, the value factor. *, **, and *** stand for significance at 10%, 5% and 1% level.

Liquidity Beta	**1**	**2**	**3**	**4**
Alpha	-1.17***	-1.20***	-1.17***	-1.20***
	-2.93	*-3.01*	*-2.91*	*-2.99*
LIQ		-0.63*		-0.62*
		-1.69		*-1.68*
VOL			0.05	0.02
			0.12	*0.05*
RMRF	0.12	0.13	0.13	0.13
	1.27	*1.36*	*1.27*	*1.36*
SMB	0.57***	0.57***	0.57***	0.57***
	3.76	*3.82*	*3.73*	*3.81*
HML	0.33*	0.32	0.33*	0.32
	1.68	*1.64*	*1.67*	*1.64*
adj. R^2	29%	29%	29%	29%

Appendix A: Construction of Fama-French Risk Factors

The return of the market portfolio in month *t* is a value-weighted average constructed from all the available stock returns from month *t*. The excess return of the market in month *t*, denoted as *RMRF*, is then the difference between the rate of return of the market portfolio and the risk-free rate. Following the convention, we use the rate of the one-year time-deposit as the risk-free rate in China. The size and value factors, denoted as *SMB* and *HML* respectively, are constructed in a similar manner as in Fama and French (1993). That is, at the end of each year, all available stocks are sorted on market capitalization (*MV*) and the ratio of book equity to market equity (*BTM*) to form the 2×3 value-weighted portfolios. The 6 value-weighted portfolios are then held for a year and monthly returns of the portfolios are linked across the years. The (empirical) size breakpoints are constructed from stocks listed in the main boards of both Shanghai and Shenzhen stock exchanges only. The aim is to avoid sorts that are dominated by the plentiful but less important tiny stocks listed on the two alternative boards, SME and ChiNext, in the Shenzhen Stock Exchange. Big stocks are those in the top 90% of the aggregated market capitalization in the main boards. The *BTM* breakpoints are the 30th and 70th percentiles. The *SMB* factor is then the difference between the average return on the three low *MV* portfolios and the average return on the three high *MV* portfolios. The *HML* factor is the average return on the two high *BTM* portfolios minus the average return on the two low *BTM* portfolios (the middle *BTM* groups are not considered). The *WML* factor is constructed in a similar way, except that the *BTM* sorts are replaced by the momentum sorts. Following the convention in the literature, momentum is defined as the cumulative return in the prior year excluding the last month of that year (Fama & French 2012; Annaert *et al.* 2013). The *WML* factor is then the difference between the average return on the two high momentum portfolios and the average return on the two low momentum portfolios.

Appendix B: The Amihud Version of the Liquidity Risk Measure

The widely used Amihud (2002) return-to-volume ratio, Amihud ratio, offers a convenient way to measure the illiquidity of individual stocks. Following Liang and Wei (2012), we also use it to estimate the market-wide liquidity shocks. The alternative measure of the market liquidity shocks is simple to implement for certain historical datasets with only daily volume data available. The estimation procedure is documented below.

We first define the return-to-volume ratio for an individual stock as follows:

$$ILLIQ_{j,t} = \frac{1}{D_{j,t}} \sum_{d=1}^{D_{j,t}} |r_{j,d,t}| / v_{j,d,t} \qquad [A.1]$$

where $r_{j,d,t}$ is the daily return for stock *j* at day *d* of month *t*. $v_{j,d,t}$ is the daily trading volume (measured in millions of the local currency) associated with $r_{j,d,t}$. $D_{j,t}$ is the total number of trading days within that month for stock *j*. This measure captures the average price impact for a stock. A stock is illiquid if its return has moved up or down more dramatically by one unit of the trading volume.

The monthly market-wide illiquidity ratio, *MILLIQ*, is then measured as the arithmetic mean of the individual return-to-volume ratio across stocks.

$$MILLIQ_t = \sum_{j=1}^{N_t} ILLIQ_{j,t} \qquad [A.2]$$

where N_t is the total number of stocks available in month *t*. Following Korajczyk and Sadka (2008), the cross-section data of $ILLIQ_{j,t}$ are "winsorized'' at the 1st and 99th percentiles each month to avoid the impact of outliers due to data error.

To account for the persistence in the monthly market illiquidity series, we follow Korajczyk and Sadka (2008) by applying an AR(2) process to obtain the unexpected component of the market illiquidity.

$$\left(\frac{m_{t-1}}{m_0}\right) \widehat{MILLIQ}_t = a + b_1 \left(\frac{m_{t-1}}{m_0}\right) \widehat{MILLIQ}_{t-1} + b_2 \left(\frac{m_{t-1}}{m_0}\right) \widehat{MILLIQ}_{t-2} + u_t \qquad [A.3]$$

where m_{t-1} is the total market value at the end of month *t*-1 of all the stocks included in the month *t* sample, m_0 corresponds to the total market value in the base period (December 1992), and the ratio $\frac{m_{t-1}}{m_0}$ serves as a common detrending factor for the all the three market liquidity terms in the equation. We do not employ the lags of $\frac{m_{t-1}}{m_0}$ in the equation simply to avoid the shocks induced mechanically by price changes in the market over time.

Since *MILLIQ* is an illiquidity measure, we take the negative of the series of the fitted residual of Equation [A.3], scaled by 100, to obtain the market-wide liquidity shocks.

$$L_t = -\frac{1}{100}\hat{u}_t \qquad \text{[A.4]}$$

When the value of L_t decrease, we may interpreter that there is an adverse shock to aggregate liquidity.

Appendix C: Is the Fluctuation of Market Liquidity Driven by Sentiment?

Our analysis hinges upon the theoretical argument that market liquidity can be treated as a sentiment index (Baker & Stein 2004). Justifying such a theoretical argument empirically, however, can be a formidable task, given that there is no universal or uncontroversial measure of sentiment. Our back-of-the-envelope calculation, however, provides strong supporting evidence for the notion that the time-variation of market liquidity is strongly influenced by market sentiment in China. Given that individual investors dominate the trading activities in China (see **Table 1**), we use the monthly number of newly opened individual investor accounts in Shanghai Stock Exchange as a valid proxy for the retail investor sentiment and explicitly test the following hypothesis:

Hypothesis A.I: *When the market becomes overly optimistic (pessimistic), revealed by increased (decreased) number of new individual investors queuing to open investment accounts, the near-term market liquidity is expected to rise (fall), everything else equal.*

Empirically, we rely on the conventional predictive regression, in which the monthly market liquidity in month *t* is regressed on a constant, its own lagged value, the lagged value of the newly opened individual investor account ($SHIIA_{t-1}$), and the lagged value of the equity fund flows ($FLOW_{t-1}$). For consistency, we use the detrended Pastor and Stambaugh (2003)'s return-reversal measure of liquidity (see Eq. [3.2] and Eq. [3.3]) as the proxy of market liquidity (denoted as LIQ). The inclusion of the lagged market liquidity in the model is to account for the persistence in liquidity. The *SHIIA* series is scaled by its prior six month moving average to ensure the stationarity. The inclusion of the equity mutual flows is to control for the effect of institutional sentiment. All the series are checked for stationarity before included in the regression. For ease of comparison, all the series are then normalized to have zero mean and unit.

$$LIQ_t = \alpha + \rho LIQ_{t-1} + \theta SHIIA_{t-1} + \phi FLOW_{t-1} + \xi_t \qquad \text{[A.5]}$$

Table A.1 presents the estimation results of the predictive regression. The first column represents the case that only the individual investor sentiment is included in the predictive model. The near-term market liquidity loads significantly on lagged number of new individual investor accounts, indicating that market liquidity are (partly) driven by shifts in individual investor sentiment. The second column represents the case that only institutional investor sentiment is included in the predictive model. The near-term market liquidity loads significantly on the equity fund flow, indicating that market liquidity are also (partly) driven by shifts in institutional investor sentiment. The last column represents the all-inclusive model with both individual and institutional sentiment included. Again, we find very compelling evidence that both sentiment measures have a significantly positive impact on future market liquidity, after controlling the autocorrelation in market liquidity. Moreover, the impact of individual investor seems higher that of institutional investor as the magnitude of the coefficient on $SHIIA_{t-1}$ is slightly higher than that on $FLOW_{t-1}$. Overall, our results are evident that market liquidity is strongly influenced by shifts in investor sentiment, which lends strong support to the theoretical argument by Baker and Stein (2004) that market liquidity is a valid sentiment index.

[Insert Table A.1 here]

Table A.1. Predictive Regression

The table presents the estimation results of the predictive regression, in which the monthly market liquidity is regressed on a constant, its own lagged value, the lagged value of the newly opened individual investor account, and the lagged value of the equity fund flows. LIQ_{t-1} denotes the lagged monthly market liquidity. $SHIIA_{t-1}$ denotes the lagged number of newly opened individual investor accounts, scaled by its prior six-month moving average. $FLOW_{t-1}$ denotes the lagged monthly equity fund flow. For ease of comparison, all the series are normalized to have zero mean and unit variance. Newey–West adjusted *t*-statistics are also reported in italic. *, **, and *** stand for significance at the 10%, 5% and 1% level.

	Const.	LIQ_{t-1}	$SHIIA_{t-1}$	$FLOW_{t-1}$	*Adj. R^2*
Average	0.00	0.25*	0.11**		7.44%
t-statistics	*0.00*	*1.80*	*2.25*		
Average	0.00	0.27**		0.10*	7.36%
t-statistics	*0.00*	*2.13*		*1.83*	
Average	0.00	0.25*	0.10**	0.09*	7.83%
t-statistics	*0.00*	*1.87*	*2.16*	*1.80*	

Appendix D: Proof of Lemma 1

Observing the price is equivalent to observing the following signal about the stock payoff $\tilde{v}_i$:

$$\tilde{s}_{p,i} = \frac{\tilde{p}_i - \alpha_i - \lambda_i \bar{x}_i}{\beta_i} = \tilde{v}_i + \left(\frac{\beta_i}{\lambda_i}\right)^{-1} (\tilde{x}_i - \bar{x}_i), \qquad \text{[A.6]}$$

which conditional on $\tilde{v}_i$ is mean $\tilde{v}_i$ and precision $\psi_i = \left(\frac{\beta_i}{\lambda_i}\right)^2 \rho_{x_i}$. By Bayes's rule, we can compute the conditional moments as follows:

$$E(\tilde{v}_i \mid \tilde{s}_{n,i}, \tilde{p}_i) = \frac{\bar{v}\rho_{v_i} + \psi_i \tilde{s}_{p,i} + \theta_i \tilde{s}_{n,i}}{\rho_{v_i} + \psi_i + \theta_i \rho_{\varepsilon_i}}, \qquad \text{[A.7]}$$

$$Var(\tilde{v}_i \mid \tilde{s}_{n,i}, \tilde{p}_i) = \frac{1}{\rho_{v_i} + \psi_i + \theta_i \rho_{\varepsilon_i}}. \qquad \text{[A.8]}$$

Plugging the conditional moments into Equation [7.3] in section 7, we get

$$D_i(\tilde{p}_i, \tilde{s}_{n,i}) = \frac{(\bar{v}\rho_{v_i} + \psi_i \tilde{s}_{p,i} + \theta_i \rho_{\varepsilon_i} \tilde{s}_{n,i}) - (\rho_{v_i} + \psi_i + \theta_i \rho_{\varepsilon_i})\tilde{p}_i}{\gamma}. \qquad \text{[A.9]}$$

Using the market-clearing condition of Equation [7.4] in section 7, we get

$$\tilde{p}_i = \frac{\bar{v}\rho_{v_i} - \psi_i \left(\frac{\beta_i}{\lambda_i}\right)^{-1} \bar{x}_i - \gamma}{\rho_{v_i} + \psi_i + \theta_i \rho_{\varepsilon_i}} + \frac{\psi_i + \theta_i \rho_{\varepsilon_i}}{\rho_{v_i} + \psi_i + \theta_i \rho_{\varepsilon_i}} \tilde{v}_i + \frac{\psi_i \left(\frac{\beta_i}{\lambda_i}\right)^{-1} + \gamma}{\rho_{v_i} + \psi_i + \theta_i \rho_{\varepsilon_i}} \tilde{x}_i, \qquad \text{[A.10]}$$

and then we solve

$$\frac{\beta_i}{\lambda_i} = \frac{\psi_i + \theta_i \rho_{\varepsilon_i}}{\psi_i \left(\frac{\beta_i}{\lambda_i}\right)^{-1} + \gamma} \Rightarrow \frac{\beta_i}{\lambda_i} = \frac{\theta_i \rho_{\varepsilon_i}}{\gamma}, \qquad \text{[A.11]}$$

and other parameters. □

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