Understanding the Controversy of Liquidity Beta

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Abstract

This paper provides a new perspective on liquidity beta. Within the framework of a liquidity-as-sentiment model, we point out that liquidity beta can be treated as a sentiment measure rather than a liquidity risk gauge. Consistent with the sentiment-based view on liquidity beta but in contradiction to the risk-based interpretation, we document a negative relation between liquidity beta and stock returns on the Chinese stock market. In contrast to US evidence, the strategy of going long in high and short in low liquidity beta stocks leads to a significantly negative risk-adjusted return of -1.17% per month in China. This *reverse liquidity beta effect* persists over different subperiods and is more pronounced during the financial crisis. The empirical result is robust to different weighting schemes, alternative asset pricing models, alternative liquidity measures, and other well-known determinants of cross sectional returns. Further analysis shows that liquidity beta well predicts future stock returns and the reverse liquidity beta premium is mainly driven by the underperformance of high liquidity beta stocks following high market liquidity episodes.

EFM classification: 310; 320; 330; 620

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

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Abstract

This paper provides a new perspective on liquidity beta. Within the framework of a liquidity-as-sentiment model, we point out that liquidity beta can be treated as a sentiment measure rather than a liquidity risk gauge. Consistent with the sentiment-based view on liquidity beta but in contradiction to the risk-based interpretation, we document a negative relation between liquidity beta and stock returns on the Chinese stock market. In contrast to US evidence, the strategy of going long in high and short in low liquidity beta stocks leads to a significantly negative risk-adjusted return of -1.17% per month in China. This *reverse liquidity beta effect* persists over different subperiods and is more pronounced during the financial crisis. The empirical result is robust to different weighting schemes, alternative asset pricing models, alternative liquidity measures, and other well-known determinants of cross sectional returns. Further analysis shows that liquidity beta well predicts future stock returns and the reverse liquidity beta premium is mainly driven by the underperformance of high liquidity beta stocks following high market liquidity episodes.

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1. Introduction

The central theme of this study is to examine the impact of liquidity beta (measured as the covariation of a stock's return with unexpected changes in aggregated liquidity) on stock returns in China's equity market, an order-driven market characterized by a great number of young and inexperienced individual investors.[1] As the largest and most liquid emerging market, the Chinese stock market is known for its unprecedented trading volume in the world and exceptionally strong "commonality in turnover" and "commonality in liquidity" during economic peaks and valleys (Karolyi *et al.* 2012). The market is also known for its strict institutional restrictions such as short-sale constraints. All of these features, which are quite different from the US market, provide us an "out-of-sample" test on the relation between liquidity beta and stock returns (Lo & MacKinlay 1990). Moreover, it also enables us to differentiate the contradictory pricing implications of liquidity beta as a generally perceived liquidity-risk metric (Pástor & Stambaugh 2003) from that as our proposed sentiment-related measure.

Alongside of the main theme, there are several closely-related aims in this study:

Firstly, we extend prior Chinese research by employing a much comprehensive dataset, which spans a period of 16 years (1998-2013) and covers more than 2000 stocks. Obviously, the much longer sample period and richer dataset will result in more statistical power for asset pricing tests as portfolios become more diversified (Fama & French 2012).

Secondly, we extend the theoretical liquidity-as-sentiment model (Baker & Stein 2004) to a multiple-risky-asset setting and derive its testable asset pricing implications in the cross section, thus providing a new theoretical perspective on the relation between liquidity beta and stock returns. Instead of treating liquidity beta as a (liquidity) risk gauge, our proposed sentiment-based hypothesis perceives liquidity beta as a sentiment measure and predicts a ***reverse liquidity beta effect***, which helps to reconcile the mixed findings in prior international studies. Moreover, the sentiment-based hypothesis is in vast contrast with the predictions from any risk-based asset pricing models.

Thirdly, we provide compelling empirical evidence that high liquidity beta stocks have lower average returns in China, which is consistent with the proposed liquidity-as-sentiment hypothesis but not with the risk-based view. The documented reverse liquidity beta effect persists over the

[1] By the end of 2013, the number of A-share accounts held by individual investors exceeds 0.18 billion in China. Moreover, around 44% percent of the individual investors are less than 40 years old. These market statistics are retrieved from the 2013 China Securities Depository and Clearing Statistical Yearbook (in Chinese).

entire sample period and different subsample periods as well. The empirical result is also 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, the documented pricing impact of liquidity beta effect renders 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 to CAPM and Fama-French three-factor models. There is, however, only some weak evidence that the augmented model offers a marginal increase in explaining the common variation in stock returns.

Fifthly, we investigate the return predictability of liquidity beta in the context of Fama-MacBeth framework, controlling the effect of other known variables that affect the cross sectional 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.

Last but not least, we provide further evidence on the question of when the market does require such a large reverse liquidity premium by looking at the long-and-short portfolio over different liquidity states. The return spread between the high and the low liquidity beta portfolio is strikingly negative (e.g. -1.76% per month on a risk-adjusted basis) following the high market-wide liquidity level (high sentiment) in the previous month. In contrast, the return spread is much less pronounced (e.g. -0.59% per month on a risk-adjusted basis) when preceded by a month characterized by low liquidity (low sentiment).

Summing up, our work contributes to the evolving literature on the liquidity beta-return relation both theoretically and empirically. From a theoretical perspective, we provide an alternative, behavioral view on the ambiguous asset pricing implications of liquidity beta. The seemingly striking reverse liquidity beta effect predicted by our extended liquidity-as-sentiment model uncovers the connection between sentiment-driven liquidity fluctuation and subsequent stock returns. More importantly, we point out the controversy of liquidity beta, which could well be a sentiment measure rather than a commonly perceived (liquidity) risk metric. In that sense, our work provides supportive evidence on how sentiment plays a role in financial markets (Ho & Hung 2009; Baker *et al.* 2012). From an empirical perspective, we provide "out-of-sample" evidence on liquidity beta and asset pricing beyond the US market, which is important for avoiding the data-snooping problem (Lo & MacKinlay 1990). Moreover, the paper uses a few methodological improvements in its estimation of portfolio returns. For example, we decompose the monthly returns of the long-only and the zero-cost portfolios following the methodology provided by Liu and Strong (2008), which reflects the actual gains earned by investors following a buy-and-hold strategy or a long-and-short strategy. Therefore, the return series we obtained alleviates the upward bias associated with size or illiquidity effect due to the rebalancing method commonly adopted in the previous literature (Asparouhova *et al.* 2010).

The structure of the paper is as follows. Section 2 reviews the literature and gives a brief introduction to the Chinese stock market. 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 discusses the implications of our results and concludes.

2. Literature Review

2.1. Liquidity Beta as a Priced Factor

The liquidity-return relation has long been a recurrent topic in finance. A growing body of empirical evidence appears to suggest that both the liquidity level and the exposure to aggregate liquidity (the 'liquidity beta') are important determinants of cross-sectional differences in stock returns.

Regarding the liquidity level as a pricing factor, it seems straightforward to argue that investors demand a positive premium for holding illiquid securities (see, among others, Amihud and Mendelson (1986) for the theoretical setup). This notion is confirmed by numerous empirical studies, which show that a large bid-ask spread, enlarged price impact, and low turnover ratio uniformly predict lower expected returns in the cross section of individual securities (Amihud & Mendelson 1986; Brennan & Subrahmanyam 1996; Brennan *et al.* 1998). More recent international evidence further demonstrates that the illiquidity premium also prevails in international markets (Florackis *et al.* 2011; Lam & Tam 2011; Amihud *et al.* 2013; Chai *et al.* 2013).

With respect to systematic liquidity exposure as a priced risk factor, the literature builds on the key finding in 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). Risk-averse investors are concerned about this systematic and time-varying component of liquidity, as transaction costs can substantially increase in case of adverse market liquidity shocks.[2] Pástor and Stambaugh (2003) study the implication of "commonality in liquidity" in the cross-section of US stocks and show that stocks with *high* return sensitivity to market liquidity shocks (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 (il-)liquidity shocks. In an integrated analysis Korajczyk and Sadka (2008) provide further evidence that liquidity risk is priced in the cross section of US stocks return even after controlling for the firm-specific liquidity level. Summing up, US evidence suggests 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 affect asset prices.

Recent international evidence, however, is not in line with the *high liquidity beta effect* found in the US market. In a comprehensive international study Lee (2011) concludes that the return covariation with market liquidity 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 Pástor and Stambaugh market-wide liquidity factor: stocks with *high* liquidity beta earn *low* raw and risk-adjusted returns instead.[3] 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 significantly negative liquidity beta premia for a number of developed markets (see table 3 and 4 of Liang and Wei (2012)).[4] Apparently, the counterevidence in international markets challenges the risk-based view that high liquidity beta stocks are riskier and should earn higher returns in equilibrium.

The mixed and somewhat ambiguous evidence on the return-liquidity risk relation motivates our study as we shed new light on the dynamic relation between (stock-by-stock) liquidity betas and expected stock returns by analyzing the Chinese stock market, a deep liquid emerging market with strong presence of retail investors, which is perfect for testing hypotheses on the sentiment-based view on liquidity risk.

[2] 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.
[3] Although Martínez *et al.* (2005) adopt three market-wide liquidity measures in the article, only the Pástor and Stambaugh liqudity measure (they adopt) has been detrended and thus can be used to calculate the sensitivity to innovations of market liquidity across stocks. The other two market liquidity measures contain both expected market liquidity and the unexpected liquidity shocks (but they interpreter both as innovations of market liquidity). Therefore, readers should be cautious on the inferences they drawn from the evidence using the other two liquidity measures.
[4] Within the framework of a rational asset pricing model, it is undesirable to take on more systematic liquidity risk, thereby a positive liquidity risk premium is expected in equilibrium.

We take a new perspective by looking at one of the driving forces of market liquidity, investor sentiment, and examining its testable implications. We base our analysis on a theoretical (behavioral) model similar as in Baker and Stein (2004), which posits that in a market with short-sales constraints and sentiment investors, market liquidity is a valid gauge of investor sentiments.[5,6] The presence of sentiment investors implies the market price is a weighted average of the valuations from sentiment investors as well as rational investors. The short-sales constraints imply that sentiment investors will (mostly) compete with rational investors in setting the price whenever their "bullish" valuation is higher than the market, boosting up liquidity. During periods of extremely high liquidity, sentiment investors dominate the market. This causes substantial overpricing of the asset and leads to lower subsequent returns. Consistent with these theoretical justifications, we provide supportive time-series evidence that investor sentiment, proxied by the number of newly opened individual investor accounts, well predicts near-term market liquidity. 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 that the "commonality in liquidity" in international markets is mainly driven by demand side factors such as investor sentiment and correlated trading (Karolyi *et al.* 2012).[7]

The above liquidity-as-sentiment model is abstracted from a single-risky-asset market. To test its cross sectional impact, it is natural for us to extend the model to a multiple-risky-asset market and derive its testable pricing implications. Our extension of the cross sectional effect is based solely on the fact that during a broad wave of extreme optimism or pessimism among sentiment investors, not all stocks are influenced to the same extent. By treating aggregated liquidity as a sentiment index (the 'liquidity-as-sentiment assumption'), we argue that *high* liquidity beta stocks, i.e. stocks that react strongly to liquidity (sentiment) shocks, tend to be sentiment-prone, while *low* or even negative liquidity beta stocks are sentiment-immune.

It is well known in the sentiment literature that sentiment-prone stocks tend to be speculative and difficult-to-value, possibly small and growth firms with unstable future cash flows and large return volatility (Baker & Wurgler 2006). By definition, sentiment-prone stocks gain more attention from sentiment investors as they offer more room for speculation than sentiment-

[5] The assumptions of short sales constraints and the existence of irrational investors are common in the behavioral finance literature to guarantee the sentiment induced mispricing (De Long *et al.* 1990).

[6] Somewhat more subtle, Baker and Stein (2004) argue that the sentiment-driven liquidity fluctuation well explains the large swings of market liquidity over time and is more consistent with the predictive power of shocks in aggregated liquidity for subsequent market returns as is documented in Jones (2002). When sentiments are high (low), manifested by beneficial (adverse) liquidity shocks, subsequent returns are expected to be lower (higher).

[7] In fact, investor sentiment and correlated trading are highly related. Kumar and Lee (2006) demonstrate that retail investors tend to trade the same assets simultaneously, inducing correlated trading and return comovement. Similar findings of correlated trading by retail investors are also well-documented in the Chinese stock market (see eg. Feng & Seasholes 2004, among others).

immune stocks (which typically have stable cash flows). More crucially, sentiment-prone stocks are more likely to be overvalued due to the influence of sentiment investors in a market with strong short-sales constraints. This is also consistent with the theoretical predictions from the static asset pricing model in Miller (1977) that the market price reflects the most optimistic investors, while the pessimist investors can simply choose not to trade or close out existing positions, given the short-sales constraints. In dynamic asset pricing models, however, the market price can even be higher than the valuation of the most optimistic investors as it contains the option to resell (Harrison & Kreps 1978). Therefore, the most overvalued stocks are also the ones that are most affected by sentiment investors. As long as sentiment wanes and fundamentals are revealed in the long run, sentiment-prone stocks are expected to have lower expected returns in subsequent periods. Empirically, consistent evidence is documented in Baker and Wurgler (2007) that sentiment-prone stocks, ceteris paribus, earn lower average returns than sentiment-immune stocks. They also find that sentiment-prone stocks perform relatively well during liquid episodes but plunges during liquidity downturns, while sentiment-immune stocks are relatively stable throughout the different liquidity episodes.[8] Based on the above theoretical justifications and empirical evidence, we will test the hypothesis that stocks with *high* liquidity beta earn lower expected (subsequent) returns than *low* liquidity beta stocks.

2.2. The Institutional Background of the Chinese Stock Market

China has two major exchanges, one in Shanghai and the other in Shenzhen. The two exchanges have no functional differences and grow rapidly since they were launched in the early 1990s.[9] By 2001, the Chinese stock market has become Asia's second largest and world's eighth largest market with a total market capitalization of USD 524 billion (Gannon & Zhou 2008); the number of listed companies grew to 1187 during the same period (Tian 2011). At the end of 2013, the total number of listed companies exceeds 2400.

Several distinctive features of the Chinese stock market are worth mentioning. First, the market is dominated by young and inexperienced retail investors.[10] Second, unlike other emerging markets, the Chinese stock market is extremely liquid, comparable to many developed markets (Amihud *et al.* 2013). In fact, 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)). Thirdly, there are stringent regulations in short selling for investors, which makes it very difficult to arbitrage away the mispricing of a certain stock (Mei *et al.* 2009). The unique setup makes it a natural experiment to test our alternative, sentiment-based view on the relation between liquidity

[8] This is also consistent with the "flight to quality" effect within the stock market.
[9] In total, there were only 14 stocks listed on the two exchanges at the end of 1991.
[10] Refer to footnote 1.

risk and stock returns. Finally, for historical reasons, common shares in the two exchanges are classified as A-shares and B-shares, which are denominated in local currency (RMB) and foreign currency (USD or Hong Kong dollar), respectively.[11] As A-shares comprise the lion's share of the market, we exclusively focus on these.[12]

3. Data and Variable Construction

3.1. Data

We first carefully construct a reliable data set of 2521 Chinese A-shares from Thomson Datastream (TDS), which is free of survival bias.[13] 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 additionally retrieve from Datastream a variety of daily variables, including the total return index, trading volume, unadjusted closing price, and number of floating shares. Daily stock returns are calculated from the total return index, which adjusts for stock splits and dividend payments. We apply a return filtering procedure by setting the daily return to be missing if any daily return is above 10% (or 5% for ST stocks).[14] For the construction of risk factors for our time-series asset pricing tests, we also download monthly market capitalization (MV) and book-to-market ratio (B/M) for the same period.[15] Appendix A illustrates in detail the procedure to calculate the risk factors (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

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[11] Historically, the A-shares and B-shares were perfectly segmented as domestic (foreign) investors only had access to A-shares (B-shares). However, such restrictions are now removed as domestic investors can also invest in B-shares from February 2001 onwards and qualified foreign institutional investors (QFII) can invest in A-shares from 2003 onwards.

[12] Currently only 86 firms list B-shares in addition to A-shares.

[13] We construct the list of the Chinese A-shares from the Datastream lists of FCHINA, WSCOPECH, DEADCH. To avoid duplicates or "spurious" stocks, we retain only common stocks with local exchange ticker symbols. Following conventions, we exclude PT stocks from our analysis.

[14] This return filtering procedure is motivated by the fact that Chinese stocks have been imposed of a daily price limit of 10% (5%) for normal stocks (ST stocks) by The China Securities Regulatory Commission (CSRC). Exceptions for the 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, thereby excluded from our sample when calculating daily return, liquidity measures and etc.

[15] 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.

To make our estimation result comparable to findings in other markets, we adopt the price reversal measure of market-wide liquidity as proposed in Pástor 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.

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

where $r_{i,d,t}$ is the (percentage) return on stock *i* on day *d* during month *t*, $r^e_{i,d,t}$ the return for stock *i* in excess of the value-weighted market return on day *d* during month *t*, $v_{i,d,t}$ the trading volume (measured in millions of the local currency) for stock *i* on day *d* during month *t*, and $\varepsilon_{i,d+1,t}$ the error term. The coefficient $\gamma_{i,t}$ 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 $\gamma_{i,t}$ is, the lower is the liquidity of the stock *i* in month *t*. Following the convention in the literature (Pástor & 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 previous month.[16]

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 ($\hat{\gamma}_{i,t}$) during month *t*.

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

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 the all the three market liquidity

[16] 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).

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 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).[17]

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 risk and the equity premium (defined as the excess return of the market portfolio over risk-free rate) over the entire sample periods. Both series are standardized with zero means and unit variance.

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 stock excess returns (over risk-free rate) on the non-traded market liquidity risk factor (L_t) and the value-weighted excess return of the market portfolio (MKT_t).

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{Liq} L_t + \varepsilon_{i,t} \qquad [3.5]$$

The coefficient of the liquidity risk factor, β_i^{Liq}, measures the return sensitivity of a 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. 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,

[17] Pástor 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.

however, can be a formidable task, given that there is no universal or uncontroversial measure of sentiment. Our back-of-envelope calculation, however, provides strong supporting evidence for the notion that the time-variation of market liquidity is driven by sentiment. We use the monthly number of newly opened individual investor accounts, NA_t, as a direct proxy of the number of sentiment investors and test the following hypothesis:

Hypothesis 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).*

We perform a simple predictive regression, in which the monthly market-wide liquidity is regressed on the lagged number of new individual investor accounts with intercept. We also include the lagged market-wide liquidity in the model to account for the persistence in liquidity.

$$\widehat{MWL}_t = \alpha + \theta \widehat{MWL}_{t-1} + \phi NA_{t-1} + \xi_t \tag{4.1}$$

The impact of sentiment investors on the time-series variation of market liquidity is evident. 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 investor sentiment.

We are aware that some economists might argue that the increased number of new investors could also be driven by extremely high liquidity and optimism in prior period, the bandwagon effect (sentiment investors hop onto the bandwagon). In that sense, the number of new individual investor accounts and market liquidity may act as a system. To account for this, we also estimate a VAR(1) model with market liquidity and the number of new individual investor accounts. Our aim is to see how sentiment investors and our market liquidity interact and identify the Granger causality between sentiment investors and the market. (For the sake of brevity, results are unreported.) The impact of sentiment investors on market liquidity remains evident. The number of new individual accounts Granger cause liquidity at 5% level and the causality flow is stronger from the number of new individual investor accounts to market liquidity than the reverse channel. Overall, the time-series evidence advocates that when sentiment becomes excessive, bullish investors enter the market and push up subsequent market liquidity.

[Insert Table 1 here]

4.2. Portfolio Formation and Descriptive Statistics

Our ultimate goal is to test whether stocks with different sensitivities to the innovations of market-wide liquidity, thus liquidity beta, have different average returns (on a risk-adjusted basis). To this end, 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 5 years (the pre-formation/selection years). The quintile portfolios are then held passively throughout the holding period of one year. Monthly returns are then linked across years to form the return series over the entire sample period. It should be noted that all the value-weighted (equal-weighted) portfolio returns are calculated according to the method proposed in Liu and Strong (2008), which eliminates, or at least alleviates, any upward bias associated with size or illiquidity effect due to the rebalanced method commonly adopted in the prior literature.

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 average price of the composite stocks, using market-to-book ratio as a proxy, 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 low liquidity beta quintile portfolio are large and value stocks, which are more likely to be sentiment-immune. In contrast, stocks in the high liquidity beta quintile portfolios are small and growth stocks, which are most likely to be influenced by sentiment-driven liquidity shifts (sentiment-prone).

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.[18] 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.

[18] 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.

[Insert Table 2 here]

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

Our ultimate goal 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 test the following hypothesis:

Hypothesis II: *Stocks with high liquidity beta earn lower expected (subsequent) returns than low liquidity beta stocks.*

For the sake of brevity we only report the regression results for the value-weighted portfolios using the Fama-French three-factor model.[19]

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \varepsilon_{i,t} \qquad [4.2]$$

*w*here $(R_{i,t} - R_{f,t})$ is the return in excess of the risk-free rate for portfolio *i* at period *t*. MKT_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.

[Insert Table 3 here]

[19] 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 the CAPM and Carhart's four factor model. Results are available upon request.

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 sample period into two subsamples with an equal length of eight years (1998-2005 and 2006-2013). In the first subperiod (**Panel B of Table 3**), the value-weighted long-short return spread is -0.70% on a risk-adjusted basis with respect to Fama-French three-factor model. During the second subsample period (**Panel C of Table 3**), which is characterized by dramatic market volatility and includes the 2008-2009 global financial crisis, 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.

In an unreported analysis we also check the risk-adjusted return patterns of the equal-weighted quintile portfolios for the entire sample period and subsample periods. The pattern of average returns across quintile portfolios remains virtually intact, except that the equal-weighted long-and-short return spread is 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 even a number of large cap stocks, generally considered as safe assets, suffered huge losses (even bankruptcy) during the liquidity crisis. Overall, the reverse liquidity beta effect we documented above is well in line with our predictions from the sentiment-driven liquidity fluctuation and its impact in the cross section. Again, 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.

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. In Appendix C, we provide additional out-of-sample evidence that the reverse liquidity effect is also present on major developed markets, as it also exists for the aggregated EU market.

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:

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

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

*w*here $(R_{i,t} - R_{f,t})$ is the return in excess of the risk-free rate for portfolio *i* at period *t*. MKT_t is the excess return of the value-weighted market portfolio for period *t*, $(MKT_t - \overline{MKT})^2$ is the coskewness factor at period *t*, $\overline{MKT}$ 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 three-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 Pástor 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.[20]

[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 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 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

[20] 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 (Floracki *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.

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 twelve 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. 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.[21] 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

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

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 to 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 individual stock's return volatility.

[Insert Table 6 here]

6. Further Analysis

6.1. Augmented Fama-French Four Factor Model

Given the compelling evidence of the reverse liquidity beta effect documented in the prior two sections, 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 size (MV), book-to-market ratio (B/M), and liquidity beta (β_i^{Liq}) to obtain the $2\times3\times3$ 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 B/M and β_i^{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 B/M 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.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \beta_i^{LMH} LMH_t + \varepsilon_{i,t} \qquad [6.1]$$

*w*here $(R_{i,t} - R_{f,t})$ 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 B/M double-sorted portfolios as the set of the test portfolios. We also use the 4×5 MV and B/M sorted portfolios excluding the microcap stocks as an alternative set of the test portfolios. MKT_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 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 7**. 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 model 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 the 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 has smaller intercepts than the CAPM model. Finally, the average adjusted R^2 is the highest for the augmented four-factor model.

For robustness purpose, we replace the MV and B/M sorted portfolios with the MV and Liquidity beta 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 7 here]

6.2. 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 additionally apply the cross-section regression approach by Fama and MacBeth (1973) for estimating the marginal ability of liquidity beta in predicting returns. We also explicitly control for a number of well-known firm characteristics (such as size, value), which are linked with cross sectional returns. 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 year *t*-1 to forecast the monthly return from January to December in year *t*. 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 FM regressions estimated on all stocks (Fama & French 2008).[22]

The results (**Table 8**) are completely in line with our findings in portfolio sorts. We find consistent evidence for a significantly negative relation between estimated liquidity beta and future stock returns, which also controls for market capitalization, book-to-market ratio, and even momentum (See specification 1 and 2 in **Table 8**). That is, liquidity beta is a separate channel to impact stock returns, in addition to size, value and momentum factors. Higher liquidity beta of a stock implies lower future returns. In its most general form, we also include the natural log of the Amihud ratio to control for the illiquidity of the stock. The factor loading on liquidity beta remains negative, though the negative return-liquidity beta relation becomes much less significant. This, however, is expected given the mounting empirical evidence documented in the prior literature that illiquid stocks tend to have high liquidity risk (beta), while liquid stocks with low liquidity risk (Acharya & Pedersen 2005), the so called "flight to liquidity" effect.

[Insert Table 8 here]

[22] However, an unreported analysis including micro stocks shows that the FM regression results are qualitatively similar. They are available from the authors upon request.

6.3. When Is the Reverse Liquidity Beta Premium Required?

Given the strikingly large reverse liquidity beta effect, an important empirical question remains: Is the reverse liquidity beta premium time-varying? Or in other words, when does the market command such a premium? As we argued in Section 2, the reverse liquidity beta effect is mainly due to the sentiment-induced mispricing in the cross section. As long as sentiment wanes and prices revert to the fundamental values, the returns of high liquidity beta stocks tend to plunge. Therefore, we explicitly validate such a hypothesis by focusing mainly on the conditional average return patterns instead of the unconditional average returns. We split the return series into high- and low-liquidity periods using the previous month's measure of liquidity level. High (low) liquidity periods are defined as the month in which the market liquidity level is above (below) the entire sample median. Then, we compute both the average raw returns and risk-adjusted returns for the long-and-short portfolio for the two separate periods and overall.

[Insert Table 9. here]

The results shown in **table 9** are well in line with our expectation. When the previous month' liquidity is high, the average conditional return of the high-minus-low portfolio is strikingly large at -1.76% per month on a risk-adjusted basis. On the contrary, the risk-adjusted return of the high-minus-low portfolio is at -0.59% per month following a low market liquidity level in the previous month, which is only about one third of the return spread immediately after high liquidity level periods. **Figure 3** also plots the conditional returns patterns for the long-only quintile portfolios at both extremes (Q1 and Q5 portfolios). As is expected, the Q1 portfolio is sentiment immune with little return variation after the high (or low) liquidity level in prior month. However, the Q5 portfolio is highly prone to the shifts in sentiment with great return variation after the high (or low) liquidity level in prior month. The average future (raw) returns of high liquidity beta stocks are strongly negative when prior-month's market liquidity level is high.

Overall, we find strong evidence that the **reverse liquidity beta premium** is time-varying and when the sentiment-driven liquidity level is high in the previous month, subsequent returns of the value-weighted high-minus-low portfolio are particularly low.

7. Discussion and Concluding Remarks

In this article we provide a new perspective on the relation between liquidity beta and cross-sectional stock returns. We focus on the Chinese stock market, a deep liquid emerging market known for its strong presence of sentiment investors and the stringent short-sales constraints. The somewhat different investment environment (from the US market) provides a natural experiment to evaluate the distinct theoretical predictions from the traditional risk-based view and our proposed sentiment-related view on the dynamic relation between liquidity betas and the cross section of stock returns.

Our extended liquidity-as-sentiment model treats liquidity beta as a sentiment measure rather than commonly perceived (liquidity) risk gauge. It also posits that *high* liquidity beta stocks are sentiment-prone, while *low* liquidity beta stocks sentiment-immune. The joint effect of investor sentiment and restricted short-sales facilitates the predictions of a **reverse liquidity beta effect**: *high* liquidity beta stocks tend to have *lower* average returns than *low* liquidity beta stocks.

Consistent with the predictions from the sentiment-related view but in contradiction with the risk-based view, we document a strikingly large reverse liquidity beta premium: Stock returns decrease monotonically from *low* liquidity beta stocks to *high* liquidity beta stocks on a risk-adjusted basis. The zero-cost portfolio, which goes long in high liquidity beta stocks and short in low liquidity beta stocks, produces a significantly negative abnormal return of -1.17% per month. The reverse liquidity beta effect persists over the entire sample period and various subsample periods as well. In particular, the zero-cost strategy incurs a huge loss of -1.35% per month in the second subsample period which includes the 2008-2009 financial crisis.

The documented reverse liquidity beta premium is also robust to different weighting schemes, alternative asset pricing models, other liquidity risk measures, and commonly known firm characteristics and risk factors.

In a further analysis, we first augment the Fama-French three-factor model with a reverse liquidity beta mimicking factor. Given that Fama-French three-factor model already explains common return variation quite well, the augmented model adds little incremental explanatory power for stock returns.

In the next step, we run the Fama-Macbeth cross-sectional regression and show that liquidity beta offers a separate channel in predicting returns after controlling for a stock's market capitalization, book-to-market ratio, return momentum, and even liquidity level.

Finally, we check the conditional return patterns and conclude that the strikingly large return spread (between low liquidity beta stocks and high liquidity beta stocks) is mainly driven by the fact that high liquidity beta stocks are strongly underperforming low liquidity beta stocks following high liquidity periods.

We hope the results of this paper will provide concrete empirical evidence and new insights on the puzzling liquidity beta effect in financial markets. The strongly negative liquidity beta premium in China (and even the aggregated EU market in Appendix C) should not be interpreted as overly striking. Rather, it is consistent with the demand side explanation (eg. investor sentiment) on the time-variation of market liquidity and how the pricing implication of "commonality in liquidity" could differ under such market conditions as the strong presence of sentiment investors and short-sales constraints. It also suggests that popular liquidity beta measures used in Pástor and Stambaugh (2003) and Liang and Wei (2012) may not necessary capture a stock's liquidity risk exposure, but rather its return sensitivity to sudden sentiment shifts. Finally, our results also raise the need for more research in this field to the development of more reprehensive liquidity risk measures in China and other non-US markets, which is left for future research.

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

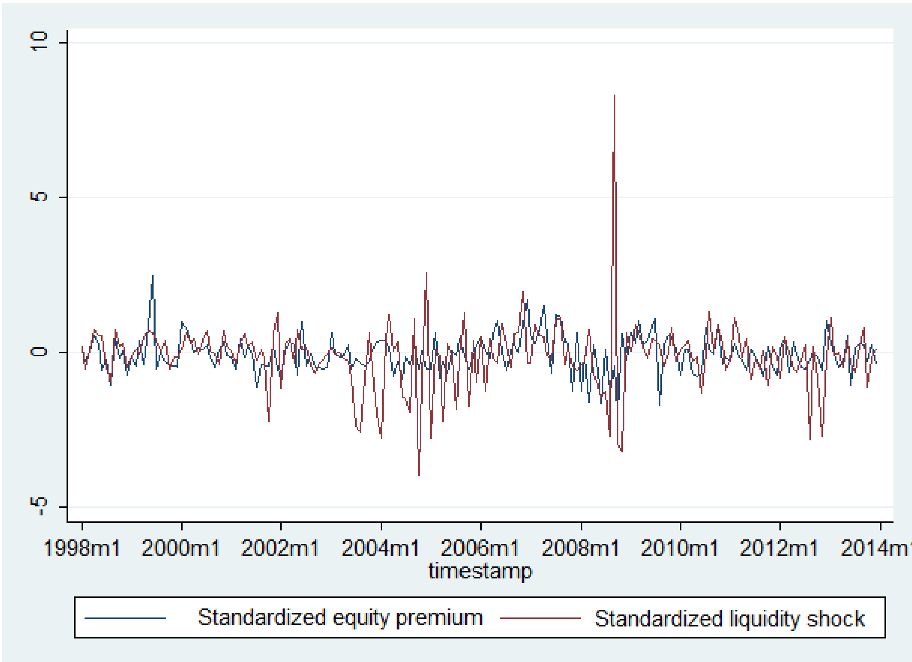

Figure 2. Cumulative Returns for Value-weighted Low Liquidity Beta Quintile Portfolio, High Liquidity Beta Quintile Portfolio, and Market Portfolio, Jan 1998-Dec 2013

31-Dec-1997 = 1.00 Chinese yuan

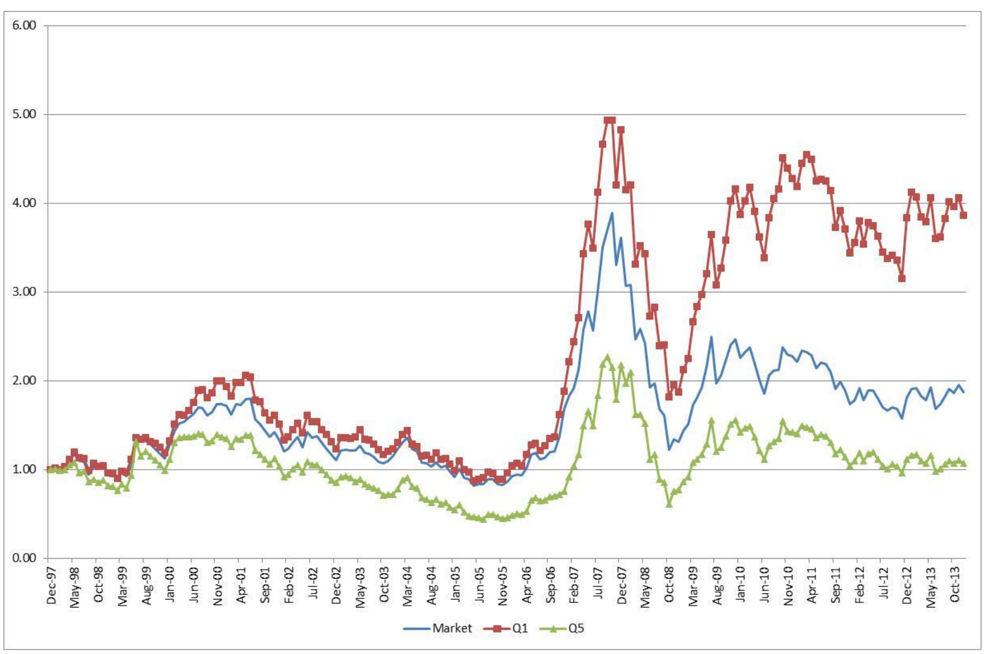

Figure 3. Conditional Cross-Sectional Return Patterns for Low (Q1) and High (Q5) Liquidity Beta Quintile Portfolios, Jan 1998-Dec 2013

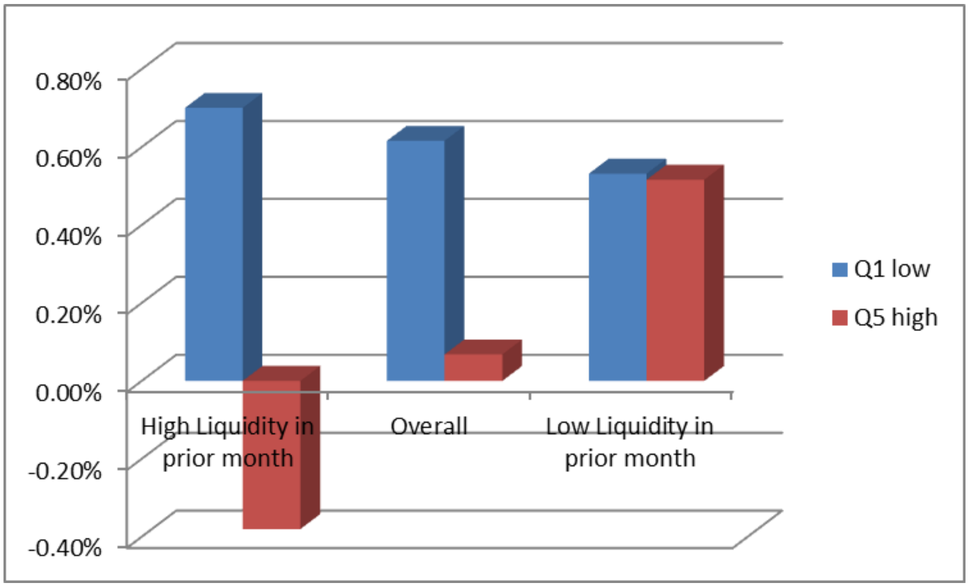

Table 1. Predictive Regression

The table presents the estimation results of the predictive regression, in which the monthly market-wide liquidity is regressed on the lagged number of new individual investor accounts and the lagged market-wide liquidity with intercept. Both the market liquidity and the number of new individual investor accounts are normalized to have zero mean and unit variance. *Newey–West adjusted t*-statistics are also reported in italic. *,**, and *** stand for significance at 10%, 5% and 1% level.

	Const.	*MWL*	*NA*	*Adj.* R^2
Average	-0.21**	0.097	0.177**	3.62
t-statistics	*-2.38*	*0.54*	*2.22*	

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	11.62	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, value-weighted, decomposed method

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 Jan. 1998 to Dec. 2013. Panel B and C report the subsample results for Jan. 1998 to Dec. 2006 and Jan. 2007 to Dec. 2013, respectively. *Newey–West adjusted t*-statistics are reported in italic. *,**, and *** stand for significance at 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*
Market	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	0.93	0.95	0.94	0.94	0.92	0.29
Panel B:Value-weighted quintile portfolios, Jan 1998 – Dec 2006						
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*
Market	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	0.9	0.97	0.97	0.96	0.92	0.12
Panel C:Value-weighted quintile portfolios, Jan 2007 – 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*
Market	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	0.95	0.94	0.94	0.95	0.93	0.44

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 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*
Market	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	0.94	0.91	0.89	0.87	0.87	0.08
			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*
Market	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	0.94	0.95	0.94	0.94	0.92	0.29

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 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*
Market	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	0.96	0.93	0.95	0.93	0.96	0.68

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 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. Regression Statistics from the Asset Pricing Models, Jan 1998 - Dec 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 B/M 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 10%, 5% and 1% level for the GRS statistics.

	GRS	$SR(\alpha)$	$\lvert\alpha\rvert$	$adj.R^2$
5-by-5 portfolios sorted on size and B/M				
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 B/M, 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 8: Average slopes and t-statistics from Monthly Cross-Sectional Regressions, Jan 1998 - Dec 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; lnBM, 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 10%, 5% and 1% level.

	Const.	**lnMV**	**lnBM**	**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 9. Conditional Average Return of the Zero-Cost Portfolio

The first column reports the average monthly raw returns of the zero-cost portfolio which go long the high liquidity beta stocks and short low liquidity beta stocks following a month with high liquidity level and a month with low liquidity level, as well as the overall average. The second column performs the same analysis on the risk-adjusted returns, which accounts for the Fama-French three-factors.

	Q5-Q1 Raw Return	Q5-Q1 Risk-adjusted Return
High Liquidity Level in prior month	-1.18%	-1.76%
Overall	-0.43%	-1.17%
Low Liquidity Level in prior month	0.32%	-0.59%

Appendix A: Construction of Market, SMB, HML, and WML factors

The return of the market portfolio in month *t* is a value-weighted average constructed from all the individual stock returns from month *t*. The market factor (the excess market return) in month *t* 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 size (MV) and the ratio of book equity to market equity (B/M) 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 B/M 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 B/M portfolios minus the average return on the two low B/M portfolios (the middle B/M groups are not considered). The WML factor is constructed in a similar way, except that the B/M 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:

$$ILLIQ_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} |R_{i,d,t}| / VO_{i,dt} \qquad [A.1]$$

where $R_{i,d,t}$ is the daily return for stock *i* at day *d* of month *t*. $VO_{i,dt}$ is the daily trading volume associated with $R_{i,d,t}$. $D_{i,t}$ is the total number of trading days within that month for stock *i*. 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.

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

where N_t is the total number of stocks available in month *t*. Following Korajczyk and Sadka (2008), the cross-section data of $ILLIQ_{i,t}$ 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 understand that there is an adverse shock to aggregate liquidity.

Appendix C: Out-of-Sample Evidence of the European market

In the subsection, we replicate the univariate portfolio sorts on liquidity betas (estimated using Pástor and Stambaugh (2003) price reversal measure) to the aggregated EU markets for the sample period from January 1994 to June 2013. All the stock data are retrieved from Thomson Datastream (TDS). As is discussed in the introduction section, the reverse liquidity beta effect is not unique. In fact, a number of developed markets have significantly negative liquidity beta premium (Liang & Wei 2012). It should be noted, however, the number of individual stocks in many developed markets is usually not large enough to estimate the market liquidity precisely. To remedy this, we group all the individual stocks in the developed EU markets together to derive the EU market-wide liquidity risk factor. In a second step, we sort stocks into decile portfolios according to their estimated liquidity betas (estimated over the prior 5 years).[23] The decile portfolios are then held for the next 12 months. The procedure repeats each year, so that the monthly returns are linked across different years to obtain the time series of portfolio returns over the entire sample periods. Again, we find the same reverse liquidity beta pattern in the aggregated EU market, after adjusting for the Carhart's four factors (See **Table A.1**). The out-of-sample evidence in the EU markets confirms the **reverse liquidity beta effect** in international markets and is again in vast contrast to the high liquidity beta effect in the US stock market.

[23] The EU countries included are Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom, which are exactly the same used by Fama and French to construct the EU risk factors. Following Fama and French, all the returns are measured in US Dollars. The risk-free rates and Fama-French four factors for the EU markets are obtained from Kenneth R. French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Table. A.1. The risk-adjusted returns of the liquidity-beta sorted decile portfolios in EU market, January 1994 – June 2013

The table reports the risk-adjusted returns of the value-weighted decile portfolios sorted on liquidity betas of the stocks from January 1994 to June 2013 associated with the Carhart's four factor regression. *Newey–West* adjusted *t*-statistics in italic are also reported. *,**, and *** stand for significance at 10%, 5% and 1% level.

Liquidity Beta	Alpha	*t*-statistics
D1 = low	0.28	*1.16*
D2	0.37**	*2.53*
D3	0.16	*1.02*
D4	0.06	*0.48*
D5	0.14	*1.10*
D6	0.04	*0.34*
D7	-0.12	*-1.39*
D8	-0.13	*-1.03*
D9	-0.13	*-0.95*
D10 = high	-0.28	*-1.03*
D10-Q1	-0.63*	*-1.80*

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