Low Liquidity Beta Anomaly in China

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Abstract

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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. Karolyi et al. (2012) offer new insights on this debate, 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). Interestingly, Karolyi et al. (2012) coin China an "outlier" in their dataset (due to its extremely high "commonality in liquidity"), and rerun their cross-country regressions by excluding China for robustness of their findings. Intuitively, liquidity shocks should be a major concern for all market participants due to its exceptionally strong "commonality in liquidity" within the local market of China. The above features 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 are subject to investor sentiment, use their own excess capital for trading (Burdekin & Redfern 2009). In addition, margin trading was not introduced prior to 2010 in China, a fact "challenging" the *supply-side*, risk-based pricing channel of liquidity beta. Therefore, our study provides complementary evidence on the possible, alternative (sentiment-based) pricing channels of liquidity beta in international markets.

Alongside 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, from the theoretical perspective, we aim to shed light on why the conventional risk-based view on liquidity beta is often of the wrong sign when encountering empirical data in some international markets. We provide an alternative sentiment-based explanation on the price of liquidity beta, which could reconcile the *reversed* liquidity beta effect in China. Our sentiment-based view builds on the "liquidity-as-sentiment" argument of Baker and Stein (2004), and the economic intuition that the sentiment impact on asset prices varies in the cross section (Baker & Wurgler 2006, 2007). The behavioral view predicts that higher liquidity beta stocks tend to be more sentiment prone stocks, and thus have lower expected returns in equilibrium. More importantly, the time variation of the return differential between low and high liquidity beta stocks is led by shifts in investor sentiment in a predictable manner. Overall, the behavioral perspective highlights the sentiment-based pricing channel of liquidity beta throughout our paper.

Secondly, we provide compelling empirical evidence on the pricing of liquidity beta in China, the largest emerging market. We document that the conventional risk-based view on liquidity beta is of the wrong sign when encountering the empirical data in the Chinese stock market. At the portfolio level, high liquidity beta stocks underperform low liquidity beta stocks by a magnitude of 0.92% per month (see **Table 2**). This striking return differential, however, is consistent with our proposed sentiment-based view, because high liquidity beta stocks tend to be sentiment prone while low liquidity beta stocks tend to be sentiment immune. The striking reversed liquidity beta effect is robust to different weighting schemes and alternative asset pricing models.

Thirdly, we investigate the return predictability of liquidity beta at the firm level based on the Fama and MacBeth (1973) cross-sectional regression. We find consistent evidence that liquidity beta is a strong negative return predictor at the firm level. The inverse relation between liquidity beta and (subsequent) stock returns is robust when we include other well-known determinants of cross-sectional returns. These 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.

Fourthly, we investigate the time-series determinant(s) of the low liquidity beta anomaly in China. Using market-wide turnover as our proxy of investor sentiment, we find that investor sentiment reliably forecasts the return spread between low liquidity beta portfolio and high liquidity beta portfolio after controlling for other possible economic mechanisms.[2] A one-standard-deviation increase in investor sentiment is linked with an "extra" return of 41 basis points (bps) for the low-minus-high hedge portfolio in subsequent periods (see **Table 5**). The documented conditional pattern lends strong support that the reverse liquidity beta effect in China is indeed triggered by sentiment-based mispricing. It is also consistent with the so-called contrarian predictability found in prior sentiment-based literature (Baker & Wurgler 2006). At a more broad level, the documented time-series evidence provides supportive evidence on how sentiment plays a role in financial markets (Ho & Hung 2009; Baker et al. 2012).

The structure of the paper is as follows. Section 2 provides a brief introduction to the Chinese stock market, reviews the relevant literature, and develops the testable hypotheses. Section 3 describes the data and the construction of the key variables. Section 4 presents the empirical methodology and the main estimation results. Section 5 provides further analyses on the time-series determinant(s) of the low liquidity beta anomaly. Section 6 performs a battery of robustness checks and extensions. Section 7 discusses the implications of our results and concludes.

[2] We are aware that the time variations of market turnover could be driven by investor sentiment as well as other factors, such as market volatility, liquidity, and economic uncertainty. Therefore, in our time-series tests we carefully control for other possible economic mechanism(s) to ensure that the observed net effect of market turnover reflects shifts in investor sentiment.

2. Literature Review

2.1. Features of the Chinese Stock Market

Carpenter et al. (2020) highlight that it is crucial to understand the "real value" of China's stock market in fueling the growth of the world's second-largest economy. 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 A2** in Han and Li (2017)). The combined market capitalization of SHSZ and SZSE was equivalent to 42% of China's GDP in 2013.[3] 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.[4]

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. According to Han and Li (2017), stocks in SHSE and SZSE, on average, turned over at least 1.49 and 2.65 times in 2013, which is much higher than the average turnover ratio for most of the developed markets. Individual investors hold directly more than 21% of the total market capitalization of the stocks in SHSE. 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 (see **Table A2** in Han and Li (2017)). It is well known in the financial literature that retail investors are highly influenced by sentiment. They hold less diversified portfolios, have more incentives to trade

[3] The GDP data are from the National Bureau of Statistics of China.

[4] The value of B-shares accounts for less than 4% of the total market capitalization in China.

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), was not 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 use their own excess capital for trading, challenges the supply-side pricing channel of liquidity beta (*i.e.* funding risk). Rather, it seems to 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. Relevant Literature and Hypotheses Development

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 international markets (Amihud & Mendelson 1986; Brennan &

[5] While the focus of the paper is on the equity market, the liquidity-return relation has also been studied extensively in other markets. See Chen et al. (2014) and Mancini et al. (2013) for evidence from the bond and FX markets.

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 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

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

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 tables 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 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

[7] It should be noted that the liquidity-as-sentiment argument has strong empirical support. 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 D 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.

periods of extremely high liquidity, sentiment investors dominate the market, causing substantial mispricing of the risky asset and lead to lower subsequent returns.

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 to the cross-sectional effect is based on the economic intuition (and empirical facts) that during a broad wave of sentiment induced liquidity shock, not all stocks are influenced to the same extent. By treating market liquidity as a valid gauge of investor sentiment, we are able to map from the liquidity beta to the sentiment proneness of a stock. We argue that high liquidity beta stocks (*i.e.*, stock reacts more strongly to liquidity shocks) tend to be sentiment-prone, while low (or even negative) liquidity beta stocks tend to be sentiment-immune. Given that liquidity is endogenously driven by investor sentiment (the liquidity-as-sentiment argument), one of the key predictions of the multi-asset liquidity-as-sentiment model is that *higher* sentiment/liquidity beta stocks tend to have *lower* expected returns in equilibrium (*i.e.*, the unconditional pattern).

Note this 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 dynamic asset pricing framework, it is predicted that 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). 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 addition to the unconditional pattern (*i.e.*, high liquidity beta stocks earn lower expected risk-adjusted returns than low liquidity beta stocks), a more critical issue is to understand the time-series behavior of the *relative* return of low liquidity beta stocks over the high liquidity beta stocks. If the return differential between low and high liquidity beta stocks are indeed driven by sentiment-induced mispricing, we should expect that as sentiment wanes and fundamentals are revealed over time, sentiment-prone stocks are subject to the most dramatic price reversion. This implies that following high sentiment periods, the *relative* return of low liquidity beta stocks (over high liquidity beta stocks) should become more pronounced due to mispricing correction (*i.e.*, the conditional pattern). Therefore, another key prediction of the multi-asset liquidity-as-sentiment model is that we should expect the time variation of the return differential (between low liquidity beta stocks and high liquidity beta stocks) to be "lead" by investor sentiment in a predictable manner. Empirically, consistent evidence is documented in Baker and Wurgler (2007) that sentiment immune stocks performs relatively well over sentiment prone stocks subsequent to high sentiment (liquidity) periods.

Based on the above theoretical justifications and empirical evidence, we postulate that the relation between liquidity beta and stock returns is reversed within the behavioral (asset pricing) framework. We make the following two predictions regarding the pricing impact of liquidity beta in China.

Hypothesis I: *Stocks with low liquidity beta earn higher expected returns than high liquidity beta stocks, everything else equal.*

Hypothesis II: *The return spread between low and high liquidity beta stocks becomes more pronounced following high sentiment periods.*

3. Data and Variable Construction

3.1. Data Sources

Our sample data are retrieved from Thomson Reuters Datastream. We start by construct a reliable stock list of 3100 Chinese A-shares from July 1996 to December 2016. The initial list covers virtually all A-shares listed on both the Shanghai and Shenzhen stock exchanges, and is free of survivorship bias. Based on the stock list, we then retrieve a variety of market and financial data items, including the total return index, price index, trading volume, (unadjusted) closing price, and number of shares outstanding. For the daily datafile, we apply several filtering rules to clean the data: First, we remove all the non-trading days due to national holidays or exchange closure. Second, we set the daily return to be missing if any daily return is above 10% (or 5% for ST stocks).[8] For the monthly datafile, we exclude stocks that have (just) become public within the past six months. In each month, we also exclude the stocks which have consecutive zero (daily) returns over the past 90 days. This filtering rule is designed to prevent our results from being influenced

[8] 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 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.

by stocks that are suspended. Our final sample include 2977 (unique) stocks after applying all these filtering rules.[9]

The risk factors in China are constructed similarly as in Fama and French (2015) by using the 2×3 double-sorted portfolios, which are formed in July each year and holds for 12 months. The size factor (SMB) is the arithmetic average of the three size factors generated in the 2×3 bivariate sorts for the value (HML), profitability (RMW), and investment (CMA) factors. The breakpoints for the size, value, profitability, and investment portfolios are determined solely by A-shares listed in Shanghai Stock Exchange and Shenzhen Main Board, which is similar to the NYSE criteria in the US. Following the convention, the monthly rate of the one-year bank time-deposit is used as the proxy for the risk-free rate in China (Han & Li 2017; Liu *et al.* 2019; Han *et al.* 2020).

3.2. Construction of the Market-wide Liquidity Risk Measure

To make our estimation results 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.

[9] Our final sample covers a prolonged sample period. As a general feature of the emerging markets, the number of valid stocks grows over time. It starts from around 300 stocks in 1996 to more than 2700 stocks in 2006. The time-series average is approximately 1190 stocks during the full sample period.

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.[10]

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 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).[11]

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.

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

In unreported analysis, we double check 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. We find that the standardized liquidity

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

[11] 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.

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 feature 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 they are consistent with the timing of major financial episodes both locally and globally: The 9-11 terrorist attack in 2001, 2004 tightening monetary policy by 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 October 16th, 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.[12] **Figure 1** plots the full-sample distribution of liquidity beta. By construction, liquidity betas centers around zero (*i.e.*, zero mean). This means that high (low) liquidity beta stocks tend to have a positive (negative) exposure to the market-wide liquidity shocks.

4. Main Results

[12] We would like to acknowledge an anonymous referee for pointing out the "error-in-variable" problem as the liquidity beta is estimated. To partially address the "error-in-variable" problem, we rely on weighted least square method in our parametric analysis in section 4.3.

4.1. Portfolio Formation and Descriptive Statistics

To test whether there is a systematic relation between liquidity beta and expected returns in the cross section, we follow the typical portfolio strategy in the investment literature: At the beginning of each month, all eligible stocks are sorted (in ascending orders) into five quintile portfolios based on their historical liquidity betas estimated by equation [4.5] using monthly data over the prior five years (*i.e.*, the formation period). The quintile portfolios are then held passively throughout the holding period. The number of composite stocks in each quintile portfolio grows from 19 at the beginning of our sample period (July 1996) to 476 at the end of our sample period (December 2016). This is consistent with the fast-growing feature of the Chinese A-share market, as the number of listed firms increases exponentially during the past decades. On average, we have approximately 238 composite stocks in each quintile portfolio over the 20-year sample period.

Table 1 first presents the time-series average of the (ex ante) firm characteristics for the liquidity beta sorted quintile portfolios (in **Panel A**). The ex ante liquidity beta increases monotonically from quintile 1 (Q1) to quintile 5 (Q5), as we sort stocks on liquidity beta in ascending orders. There is no noticeable difference in market beta. Similarly, there are also no clear monotonic patterns in other well-known firm characteristics such as the log of market equity (lnME), the log of book-to-market ratio (lnBTM), operational profitability (OP), asset growth (INV). However, there seems to be some systematic difference across the quintile portfolios in terms of intermediate-term returns (RET^{MOM}) and short-term returns (RET^{STREV}). On average, low (high) liquidity beta stocks tend to be stocks with relatively high (low) past intermediate-term and short-term returns in the past. To account for the possible influence by these two trend-based return indicators, we include both the momentum and short-term reversal factors in our evaluation of the risk-adjusted performances of these quintile portfolios in later sections.

Panels B (**C**) of the table report the arithmetic mean and standard deviation of the excess returns of the equal-weighted (value-weighted) quintile portfolio and the low-minus-high hedge portfolios over the full sample period. In general, the low liquidity beta quintile portfolio (Q1) delivers higher returns (over the risk-free rate) than the high liquidity beta quintile portfolio (Q5). The equal-weighted zero-cost low-minus-high portfolio (Q1-Q5) yields an average monthly return spread of 0.92% throughout the whole sample period. Similar pattern can also be found for the value-weighted counterpart: The equal-weighted low-minus-high portfolio (Q1-Q5) yields a return differential of 0.87% per month. It should be noted that while there exists relatively large return differential between Q1 and Q5 portfolios, their return volatility (measured by standard deviation) shows little difference between the two value-weighted portfolios.

[Insert Table 1 here]

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 re-state our first testable hypothesis below:

Hypothesis I: *Stocks with low liquidity beta earn higher expected returns than high liquidity beta stocks, everything else equal.*

To evaluate the portfolio performance, we adopt various benchmark models, which include the CAPM model, Fama and French three-factor model, Fama and French five-factor model, Fama and French six-factor model, and the augmented seven-factor model with the short-term reversal factor.[13]

$$R_{i,t} = \alpha_i + \beta_i^{RMRF} RMRF_t + \varepsilon_{i,t} \tag{4.1}$$

$$R_{i,t} = \alpha_i + \beta_i^{RMRF} RMRF_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \varepsilon_{i,t} \tag{4.2}$$

$$R_{i,t} = \alpha_i + \beta_i^{RMRF} RMRF_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \beta_i^{RMW} RMW_t + \beta_i^{CMA} CMA_t + \varepsilon_{i,t} \tag{4.3}$$

$$R_{i,t} = \alpha_i + \beta_i^{RMRF} RMRF_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \beta_i^{RMW} RMW_t + \beta_i^{CMA} CMA_t + \beta_i^{MOM} MOM_t + \varepsilon_{i,t} \tag{4.4}$$

$$R_{i,t} = \alpha_i + \beta_i^{RMRF} RMRF_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \beta_i^{RMW} RMW_t + \beta_i^{CMA} CMA_t + \beta_i^{MOM} MOM_t + \beta_i^{STREV} STREV_t + \varepsilon_{i,t} \tag{4.5}$$

where $R_{i,t}$ 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, HML_t, RMW_t, CMA_t, MOM_t, and $STREV_t$ are the size factor, value factor, profitability factor, investment factor, momentum factor, and short-term reversal factor, respectively.

Panel A of Table 2 reports the (risk-adjusted) performance for the equal-weighted quintile portfolio and the zero-cost low-minus-high hedge portfolio. Similar to the raw returns, the risk-adjusted returns also exhibit a monotonic decreasing pattern from low liquidity beta stocks (Q1) to high liquidity beta stocks (Q5). For example, the CAPM alpha drops from 1.09% per month for the Q1 portfolio to 0.19% per month for the Q5 portfolio. As it stands, the low liquidity beta stocks outperform their high liquidity beta counterparts on a risk-adjusted basis, which is robust under all

[13] We do not use Carhart's four-factor model mainly because the momentum factor is included in the Fama-French six-factor model and the augmented seven-factor model. However, all of our results are robust when using Carhart's four-factor model and therefore are omitted for brevity.

the alternative model specifications. Under the seven-factor model specification, the return spread of the zero-cost low-minus-high portfolio (Q1–Q5) amounts to 59 bps per month, which is statistically significant at the 5% level ($t = 2.33$).

Panel B of the table presents the alpha and the factor loadings of the quintile portfolios and the zero-cost hedge portfolio under the augmented seven-factor model. As it stands, the low-minus-high hedge portfolio only loads heavily on the size and momentum factors, but not on the other factors.

Overall, the large magnitude of the return spread of the zero-cost hedge portfolio, coupled with its statistical significance, lends strong support to our hypothesis that low liquidity beta stocks earn higher expected returns than their high liquidity beta counterparts in subsequent periods.

[Insert Table 2 here]

In **Table 3**, we double check the risk-adjusted performance for the value-weighted quintile portfolios and the low-minus-high hedge portfolio. The pattern of average returns across quintile portfolios remains virtually intact, except that the lowest liquidity beta quintile portfolio (Q1) has slightly lower returns than the second lowest liquidity beta quintile portfolio (Q2). More importantly, the value-weighted hedge portfolio is also strong in its risk-adjusted performance, as its seven-factor alpha amounts to 70 bps per month (*i.e.*, 8% per annum). The fact that the low liquidity beta anomaly remains strong for the value-weighted portfolio is a telling story. It is consistent with the anecdotal evidence that some speculative 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 reversed 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.[14]

[Insert Table 3 here]

4.3. Firm-level Evidence

[14] We would like to acknowledge one anonymous referee for pointing out the Split-Share-Structure reform back in 2005, which could potentially impact on the low liquidity beta anomaly. However, this is mainly a one-off event, which is unlikely to be the main driving force(s) of the anomaly. Our focus is to identify the key economic mechanism that would leads to the anomaly over the prolonged sample period.

While portfolio performance is 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 that are known for predicting returns at the firm level. That is, each month we regress the cross section of excess returns on K explanatory variables including the (ex ante) liquidity beta. To ensure that our main results are not driven by small-cap stocks, we perform the period-by-period cross-sectional regression using the weighted least square (WLS) method, in which the observations are weighted by the lagged market capitalization.[15] The slope coefficients are then averaged over the entire sample periods. The model specification is as follows:

$$r_j = b_0 + \sum_{k=1}^{K} b_k X_{j,k} + \xi_j \qquad [4.6]$$

where r_j is the excess return of the j-th stock, $X_{j,k}$ is the k-th explanatory variable, and ξ_j is the error term. The explanatory variables include the liquidity beta, the log of market equity (lnME), the log of book-to-market ratio (lnBTM), operating profitability (OP), asset growth (INV), intermediate-term return (RET^{MOM}) and short-term return (RET^{STREV}). 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 proxies are included.

Table 4 presents the Fama-MacBeth regression outputs using the WLS method. In the univariate regression, we find a strong negative relation between estimated liquidity beta and subsequent stock returns, as the slope coefficient amounts to –0.26 and is highly negative at the 1% level. That is, low liquidity beta stocks have relatively higher expected returns than high liquidity beta stocks in the cross section. When controlling for firm size (lnME) and the valuation ratio (lnBTM), the slope coefficient on liquidity beta shrinks to –0.16 (as compared to its value in the univariate case), but remains highly significant at the 5% (with a Newey-West t-statistic of –2.88). It is worth mentioning that the slope coefficients on lnME and lnBTM are all significant and have the expected signs, which is consistent with the literature that size and value are prominent return determinants in China. Finally, when we include all the control variables into the regression model, the slope

[15] In unreported analysis we also follow Fama and French (2008) by excluding microcap stocks in the Fama-MacBeth regression. However, our key regression results (*i.e.*, strong negative coefficient on liquidity beta) remain virtually intact whether we exclude the microcap stocks or not.

coefficient on liquidity beta remains statistically significant at the 5% level (with a Newey-West t-statistic of –2.43), though its magnitude further shrinks to –0.13.

Overall, the result of the Fama-MacBeth regression lends strong 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 firm 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 4 here]

5. Further Analysis

5.1. The Time-series Determinant of the Low Liquidity Beta Anomaly

The relatively large return differential between low and high liquidity beta stocks presents a striking unconditional pattern: On average, low liquidity beta stocks outperform high liquidity beta stocks by 92 bps per month (see **Table 2**). Moreover, the return spread between the two groups of stocks varies dramatically over time. The time variation of the return spread leads to an important remaining question: Does the low liquidity anomaly vary in a predictable way as indicated by the sentiment-driven liquidity shifts? The evaluation of this problem corroborates to our second testable hypothesis, which is restated below:

Hypothesis II: *The return spread between low and high liquidity beta stocks becomes more pronounced following high sentiment periods.*

To validate the time-series prediction on the low-minus-high liquidity beta strategy, we follow the liquidity-as-sentiment argument in Baker and Stein (2004) by using the lagged market-wide turnover as our proxy for investor sentiment, and estimate the following predictive regression on the time series of the return spread of the hedge portfolio which goes long sentiment immune stocks (*i.e.*, low liquidity beta ones) and short sentiment prone stocks (*i.e.*, high liquidity beta ones).

$$R_{low-high,t} = a + bTURN_{t-1} + \boldsymbol{c}'\boldsymbol{Z}_t + \varepsilon_{i,t} \quad [5.1]$$

*w*here $R_{low-high,t}$ is the monthly return differential between the low liquidity beta stocks and the high liquidity beta stocks (Q1-Q5 in **Section 4.2**), $TURN_{t-1}$ is the lagged market-wide turnover ratio, defined as the cross-sectional average of stock turnover over the month, and $\boldsymbol{Z}_t$ is the vector of control variables included in the predictive regression. Our key variable of interest lies on the slope coefficient on the lagged market turnover. Given that market turnover is a direct measure of investor sentiment (the liquidity-as-sentiment argument in Baker and Stein (2004)), we should expect a positive relation between market liquidity (sentiment) and subsequent return differential.

We are aware that the shifts in market turnover could also be driven by mechanisms other than sentiment. To ensure that the observed net effect of market turnover reflects mainly the impact due to investor sentiment, we control for other possible economic mechanisms that could lead to the intertemporal changes in trading volume such as lagged market volatility, liquidity, and economic uncertainty. The lagged market volatility ($Sigma$) is defined as the standard deviation of the daily market returns within the prior month. Market volatility is highly correlated with the funding risk channel in "commonality-in-liquidity" (Brunnermeier & Pedersen 2009). Therefore, we include it to purge the (possible) impact of the funding risk channel. The lagged market liquidity ($ILLIQ$) is proxied by the value-weighted average of the Corwin and Schultz (2012) implied spread measure. The lagged economic policy uncertainty index (EPU) for China, obtained from Baker et al. (2016), is included to purge the rational response of trading volume to the shifts in market conditions. We also include lagged return dispersion ($DISP$), defined as the monthly cross-sectional standard deviation of returns, as an additional control to account for possible trading activities associated with portfolio rebalancing. Finally, we also include the contemporaneous risk factors: the Fama-French five factors, the momentum factor, and the short-term reversal factor. To facilitate comparison, we have standardized the lagged predicting variables (*i.e.*, the market turnover ratio, the market volatility, the market liquidity, the EPU measure, and the return dispersion measure) before putting them into the regression model. The standardization process facilitates the comparison of the economic magnitude of these predictive variables on the return spreads.

The results of the predictive regressions are shown in **Table 5**. A number of salient features emerge from the regression output:

First, the most striking feature of the table is that investor sentiment, proxied by the market turnover, does have a strong impact on the time variation of the return spread of the low-minus-high hedge portfolio. **Panel A** reports the results for the equal-weighted return spread of the hedge portfolio: When controlling only the contemporaneous risk factors, the slope coefficient on the lagged turnover amounts to 67 bps for the equal-weighted hedge portfolio, which is statistically significant at the 1% level for the one-sided test (see specification 1). When we account for other possible mechanism one at a time (*i.e.*, market volatility, liquidity, economic uncertainty, and return dispersion), the sentiment impact on the return differential of the hedge portfolio remains strong (see specifications 2 to 5): The loadings on market turnover range from 46 bps to 68 bps, and are all statistically significant at the 10% or finer levels for the one-sided test. In the most rigid case, when we account for all possible mechanisms simultaneously, the sentiment impact continues to hold as the loadings on market turnover amounts to 41 bps with a one-sided t-statistic of 1.53 (see specification 6). The fact that investor sentiment drives the time variation of the return spread of the low-minus-high liquidity beta strategy continues to hold when we use the value-weighted hedge portfolio instead (see **Panel B**).

Second, the economic significance of investor sentiment, proxied by lagged market turnover is also impressive. A one-standard-deviation shock in turnover ratio would lead to an upward adjustment of 41 (54) bps for the equal-weighted (value-weighted) zero-cost hedge portfolio in **Panel A** (**B**). In comparison, factor loadings on other predicting variables (except for return spread) are either not significant or their magnitude cannot match that of investor sentiment. Therefore, from the economic perspective, it seems that investor sentiment is indeed a prominent time-series determinant of the low liquidity beta anomaly in China.

Overall, the empirical results of the predictive regression are well in line with our sentiment-based hypothesis. After accounting for other possible economic mechanisms, an increase in the degree of investor sentiment (*i.e.*, market turnover) would lead to strong correction in sentiment-induced mispricing, the so-called contrarian predictability as shown in Baker and Wurgler (2006). That is, the return spread between low liquidity beta stocks (*i.e.*, sentiment immune stocks) and high liquidity beta stocks (*i.e.*, sentiment prone stocks) gets more pronounced subsequent to the increase in investor sentiment.

[Insert Table 5. here]

5.2. Portfolio Turnover and Transaction Costs.

This subsection addresses the legitimate concern that whether the low liquidity beta strategy, which goes long low liquidity beta stocks and short high liquidity beta stocks, could be implemented in practice after taking transaction costs into account.

Panel A of Table 6 presents the annualized portfolio turnover of the equal-weighted liquidity beta sorted quintile portfolios and the low-minus-high hedge portfolio. According to the classification of Novy-Marx and Velikov (2015), the zero-cost liquidity beta strategy is a mid-turnover strategy, as the annualized portfolio turnover for the zero-cost hedge portfolio is approximately 150% per year.

Panel B of the table provides a back-of-the-envelope calculation of the transaction costs involved in these portfolio strategies. We report the breakeven transaction costs that would eliminate the average excess returns and the risk-adjusted returns of the testing portfolios. In general, the low liquidity beta portfolio (Q1) could withstand large transaction costs before its excess return or risk-adjusted return being wiped out. The low-minus-high liquidity-beta strategy (Q1–Q5) is also highly cost-effective with breakeven transaction costs ranges from 451 to 714 bps per month. In other words, the profits of the zero-cost low-minus-high liquidity beta strategy could well survive reasonable transaction costs in practice.

6. Robustness and Extensions

6.1. Double Sorted Portfolios

In this subsection, we examine the price of liquidity beta using double sorted portfolios, which account explicitly for other well-known priced firm characteristics in the cross section. We construct return series of the characteristic-controlled liquidity beta quintile portfolios as follows: First, we sort all stocks based on their rankings on a particular firm characteristic. Second, within each of the five characteristic-sorted portfolios, we sort sequentially stocks into quintile portfolios based on their liquidity beta. In the next step, we calculate the monthly equal-weighted portfolio returns for the 5×5 double sorted portfolios. Finally, for each month and each liquidity beta quintile, we average the returns of the five firm-characteristic portfolios to get the time series of the characteristic-controlled liquidity-beta quintile portfolios.

Table 7 presents the excess returns and the risk-adjusted returns evaluated by alternative factor models for the characteristic-controlled liquidity beta sorted quintile portfolios and the low-minus-high hedge portfolio.

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. **Panel A** of the table indicates that the low liquidity beta anomaly is not subsumed by idiosyncratic risk. After controlling for the idiosyncratic volatility, the return differential between low and high liquidity beta stocks ranges from 50 bps to 87 bps under alternative model specifications.

Bali *et al.* (2011) postulate that irrational investors have a strong preference for lottery-type stocks. Stocks with extremely high daily return in the most recent month grab the attention of these lottery investors. However, these (overvalued) lottery stocks tend to deliver low return in subsequent month. **Panel B** of the table indicates that the low liquidity beta anomaly is also robust to lottery preference. After accounting for the lottery demand, the relative return of low liquidity beta stocks (over high liquidity beta stocks) ranges from 49 bps to 84 bps under alternative model specifications, which are all significiant at the 5% or finer levels.

[Insert Table 7 here]

6.2. Other Extensions and Robustness Checks

In this section, we provide a summary of extensions and robustness checks, and their main outcomes.

Alternative factor models. Our key portfolio result that the low liquidity beta stocks outperform high liquidity beta stocks on a risk-adjusted basis is robust to alternative factor models, such as the recently proposed CH3 factor model in Liu et al. (2019). We do not rely on the Liu et al. (2019) three factors in our main analysis, because their factors are restricted from 2000 onwards, which would limit the sample period of our dataset. In fact, in the shortened sample using their market, size, and value factors (coupled with the profitability, investment, momentum, and short-term reversal factors), the zero-cost low-minus-high hedge portfolio still generates a risk-adjusted return of 0.48% per month, which is significant at the 5% level.

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). However, our documented low liquidity beta anomaly is also robust to the higher-moment CAPM model.

Similarly, we find the documented low liquidity beta effect is not subsumed by the liquidity level effect (illiquidity premium), because the alpha of the low-minus-high liquidity beta strategy remain highly positive when evaluated by the liquidity augmented four-factor model in Lam and Tam (2011).

Alternative weighting scheme. Our key portfolio result that the low liquidity beta stocks outperform high liquidity beta stocks on a risk-adjusted basis is robust to alternative weighting scheme. In unreported analysis, we find very similar patterns for the gross-return weighted quintile portfolios. The gross-return weighting scheme alleviates the upward bias associated with size or illiquidity effect when computing the (equal-weighted) portfolio return (Asparouhova et al. 2010).

Addressing the size concern. A legitimate concern is whether the documented low liquidity beta anomaly in China is a manifestation of the size effect. To address the size concern, we rely on the cutoff point of micro-cap stocks in Liu et al. (2019) by excluding the bottom 30% smallest firms in our sample. Our key portfolio result that the low liquidity beta stocks outperform high liquidity beta stocks on a risk-adjusted basis is robust to the restricted sample. The equal-weighted (value-weighted) return differential between the low liquidity beta stocks and high liquidity beta stocks amounts to 69 (66) bps per month, and is statistically significant at the 5% level.

Orthogonalized liquidity beta measure. A legitimate concern is that whether our documented low liquidity beta effect is just another manifestation of the betting against beta effect as in Frazzini and Pedersen (2014). In other words, whether the high (low) liquidity beta stocks also have high (low) market beta, which tends to show, more or less, the same "low risk premium". We believe the above concern is unfounded for at least two reasons.

First, when estimating liquidity beta of a firm, we have already controlled for the market impact (see Equation 4.5). By construction, the loadings on liquidity risk are solely determined by the fraction of variation of liquidity risk unrelated to the market risk. Therefore, the correlation between liquidity beta and market beta is moderate.

Second, to ensure the low liquidity beta effect is not driven by the betting against beta effect in China, we run a period-by-period cross-sectional regression by regressing the liquidity betas on the market betas to obtain the residual liquidity betas (defined as the intercept plus the regression residual). The residual liquidity beta can be interpreted as the component which is not explained by the market beta. We then use the residual liquidity beta to re-do the entire portfolio analysis (unreported for brevity purpose). Again, we find virtually equivalent (if not even stronger) pricing patterns in our dataset. In other words, the "betting against beta" effect (Frazzini & Pedersen 2014) cannot be the explanation for our documented low liquidity beta effect in China.

7. Discussion and Concluding Remarks

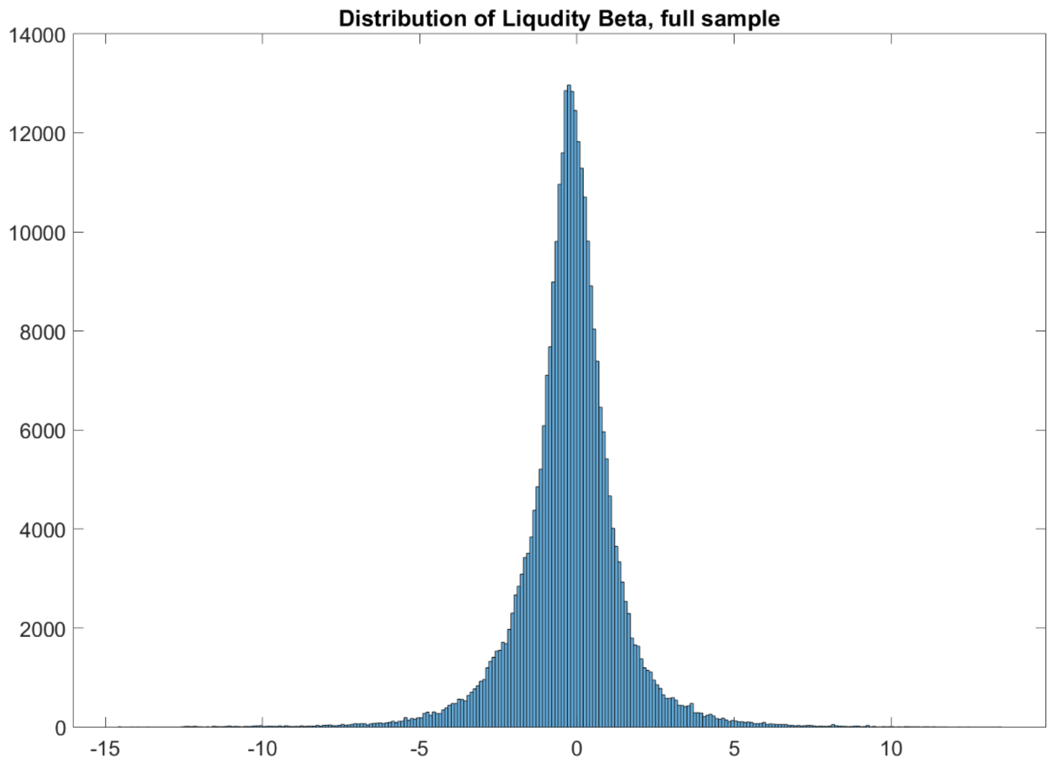
This article provides a comprehensive analysis on the relation between liquidity beta and stock returns in China, which complements our understanding on the possible pricing implications of liquidity beta in financial markets. Empirically, it documents that the conventional risk-based view on liquidity beta is a dismal story in China: High liquidity beta stocks underperform low liquidity beta stocks over the 1997– 2016 sample period.

The low liquidity beta anomaly 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 does not serve as a (valid) risk gauge. Rather it reflects the sentiment proneness of the individual stock. The sentiment-based pricing channel implies that *high* liquidity beta stocks, which are sentiment prone, tend to offer *lower* average returns than *low* liquidity beta stocks, which are sentiment immune.

Consistent with our proposed sentiment-based pricing channel, but in contrast to the risk-based pricing channel, we find that the zero-cost strategy, which goes long low liquidity beta stocks and short high liquidity beta stocks, delivers an average return spread of 59 bps per months after properly adjusted for risk exposures. More importantly, the conditional patterns for the return spread between low liquidity beta stocks and high liquidity beta stocks reinforced our sentiment-based conjecture: An increase in the degree of investor sentiment leads to an upward adjustment of the return spread in subsequent month, which is consistent with the (anticipated) correction in sentiment-induced mispricing over time. The documented conditional pattern is highly consistent with the well-known contrarian predictability of investor sentiment proposed in the behavioral literature.

Overall, our 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.

Figure 1. Histogram of liquidity beta over the full sample period



Description: The histogram plots the sample distribution of the liquidity betas over the full sample period between July 1996 and December 2016.

Table 1. Descriptive Statistics

Description: Panel A of the table presents the summary statistics of the composite stocks in the liquidity beta sorted quintile portfolios. LIQ Beta is the liquidity beta estimated using Eq. [3.5] over the prior 5 years. lnME is the natural logarithm of firm's market capitalization measured at the end of June in year t. lnBTM is the natural logarithm of firm's book-to-market equity measured at the fiscal year end in $t-1$. OP is the ratio of operational profits and book equity measured at the fiscal year ending in $t-1$. INV is the growth of total assets for the fiscal year ending in $t-1$. $\mathrm{RET}^{\mathrm{MOM}}$ is the intermediate-term return momentum, defined as the past 12-month cumulative return, skipping the most recent month. $\mathrm{RET}^{\mathrm{MOM}}$ is scaled by 12 to convert to its monthly average. $\mathrm{RET}^{\mathrm{STREV}}$ is the short-term return reversal, defined as the past one-month return. All explanatory variables are winsorized at the 0.5 and 99.5% level. Panels B and C report arithmetic means and standard deviations of the monthly excess returns of the equal-weighted and value-weighted liquidity beta-sorted quintile portfolios from July 1996 to December 2016, respectively.

	Q1 = Low	**Q2**	**Q3**	**Q4**	**Q5 = High**	**Q1 − Q5**
Panel A: Firm characteristics prior to the portfolio formation period						
LIQ Beta	-2.53	-0.93	-0.04	0.85	2.35	-4.87
Beta	1.05	1.05	1.05	1.03	1.03	0.02
lnME	9.09	9.15	8.99	9.26	9.28	-0.19
lnBTM	3.37	3.44	3.46	3.48	3.41	-0.04
OP	11.38	11.05	10.21	11.31	11.85	-0.47
INV	25.09	19.67	19.40	20.25	25.12	-0.03
$\mathrm{RET}^{\mathrm{MOM}}$	1.68	1.54	1.36	1.25	1.07	0.60
$\mathrm{RET}^{\mathrm{STREV}}$	2.41	2.69	2.19	2.00	2.16	0.25
Panel B: Equal-weighted quintile portfolios, July 1996–Dec 2016						
Arithmetic mean (%)	2.04	1.92	1.84	1.44	1.12	0.92
Standard deviation (%)	10.52	10.30	10.18	9.94	10.05	4.30
Panel C: Value-weighted quintile portfolios, July 1996–Dec 2016						
Arithmetic mean (%)	1.27	1.35	1.23	0.62	0.40	0.87
Standard deviation (%)	9.43	8.88	9.23	8.91	9.39	5.22

Table 2. Portfolio Performance of the Equal-weighted Quintile Portfolios, July 1996 - December 2016

Description: Panel A reports the monthly excess returns and the risk-adjusted returns under the CAPM, Fama-French three-factor (FF3), Fama-French five-factor (FF5), augmented Fama-French six-factor (FF6), and augmented seven-factor (FF7) models for the equal-weighted liquidity beta sorted quintile portfolios and the low-minus-high liquidity beta portfolio (Q1-Q5). Panel B reports the regression outputs of the augmented seven-factor (FF7) model. RMRF, SMB, HML, RMW, CMA, MOM, STREV are the market, size, value, profitability, investment, momentum, and short-term reversal factors, respectively. Newey–West adjusted *t*-statistics are reported in brackets. The sample period spans from July 1996 to December 2016.

	Q1 = Low	**Q2**	**Q3**	**Q4**	**Q5 = High**	**Q1 − Q5**
	Panel A: Excess Returns and Risk-Adjusted Returns					
Excess return	2.04	1.92	1.84	1.44	1.12	0.92
[t-stat]	[2.47]	[2.36]	[2.26]	[1.84]	[1.45]	[2.91]
CAPM alpha	1.09	0.98	0.90	0.53	0.19	0.91
[t-stat]	[3.72]	[3.66]	[3.85]	[2.34]	[0.88]	[3.24]
FF3 alpha	0.20	0.11	0.14	-0.17	-0.34	0.54
[t-stat]	[1.39]	[1.02]	[1.27]	[-1.58]	[-2.59]	[2.53]
FF5 alpha	0.39	0.33	0.37	0.11	-0.03	0.43
[t-stat]	[2.87]	[2.91]	[3.04]	[0.97]	[-0.22]	[1.79]
FF6 alpha	0.46	0.34	0.33	0.04	-0.14	0.59
[t-stat]	[3.20]	[3.09]	[3.03]	[0.37]	[-0.90]	[2.35]
FF7 alpha	0.44	0.30	0.32	0.01	-0.16	0.59
[t-stat]	[3.03]	[2.83]	[2.71]	[0.07]	[-0.90]	[2.33]

	Q1 = Low	Q2	Q3	Q4	Q5 = High	Q1 − Q5
	Panel B: The Augmented Seven-Factor Model					
FF7 alpha	0.44	0.30	0.32	0.01	-0.16	0.59
[t-stat]	[3.03]	[2.83]	[2.71]	[0.07]	[-0.90]	[2.33]
RMRF	1.00	1.00	1.02	1.00	1.04	-0.04
[t-stat]	[42.77]	[63.49]	[71.36]	[54.34]	[39.99]	[-0.86]
SMB	0.69	0.67	0.61	0.54	0.39	0.30
[t-stat]	[9.19]	[15.68]	[10.30]	[7.10]	[3.95]	[2.04]
HML	0.06	0.03	-0.07	-0.12	-0.17	0.22
[t-stat]	[0.63]	[0.56]	[-1.62]	[-1.06]	[-1.33]	[1.06]
RMW	-0.35	-0.25	-0.16	-0.19	-0.23	-0.13
[t-stat]	[-2.77]	[-4.45]	[-2.86]	[-3.24]	[-2.87]	[-0.76]
CMA	-0.23	-0.07	0.05	0.04	-0.04	-0.19
[t-stat]	[-1.55]	[-0.80]	[0.86]	[0.53]	[-0.27]	[-0.82]
MOM	0.13	0.04	-0.07	-0.13	-0.19	0.32
[t-stat]	[2.07]	[1.24]	[-1.92]	[-2.07]	[-2.37]	[2.72]
STREV	0.02	0.05	0.01	0.03	0.02	-0.00
[t-stat]	[0.35]	[1.18]	[0.22]	[0.92]	[0.33]	[-0.03]
Adj. R^2	0.95	0.97	0.97	0.96	0.94	0.20
Obs.	246	246	246	246	246	246

Table 3. Portfolio Performance of the Value-weighted Quintile Portfolios, July 1996 - December 2016

Description: Panel A reports the monthly excess returns and the risk-adjusted returns under the CAPM, Fama-French three-factor (FF3), Fama-French five-factor (FF5), augmented Fama-French six-factor (FF6), and augmented seven-factor (FF7) models for the value-weighted liquidity beta sorted quintile portfolios and the low-minus-high liquidity beta portfolio (Q1-Q5). Panel B reports the regression outputs of the augmented seven-factor (FF7) model. RMRF, SMB, HML, RMW, CMA, MOM, STREV are the market, size, value, profitability, investment, momentum, and short-term reversal factors, respectively. Newey–West adjusted *t*-statistics are reported in brackets. The sample period spans from July 1996 to December 2016.

	Q1 = Low	**Q2**	**Q3**	**Q4**	**Q5 = High**	**Q1 − Q5**
	Panel A: Excess Returns and Risk-Adjusted Returns					
Excess return	1.27	1.35	1.23	0.62	0.40	0.87
[t-stat]	[1.66]	[1.93]	[1.67]	[0.82]	[0.56]	[2.86]
CAPM alpha	0.38	0.50	0.33	-0.24	-0.49	0.87
[t-stat]	[2.10]	[2.95]	[3.40]	[-1.81]	[-2.99]	[3.22]
FF3 alpha	0.07	0.33	0.18	-0.41	-0.50	0.57
[t-stat]	[0.35]	[2.01]	[1.25]	[-2.36]	[-2.78]	[1.74]
FF5 alpha	0.26	0.44	0.28	-0.23	-0.35	0.61
[t-stat]	[1.47]	[2.47]	[1.79]	[-1.42]	[-1.77]	[1.77]
FF6 alpha	0.32	0.43	0.25	-0.29	-0.41	0.73
[t-stat]	[1.68]	[2.59]	[1.63]	[-1.72]	[-2.11]	[2.04]
FF7 alpha	0.31	0.45	0.33	-0.26	-0.40	0.70
[t-stat]	[1.66]	[2.41]	[2.01]	[-1.44]	[-1.66]	[1.81]

	Q1 = Low	Q2	Q3	Q4	Q5 = High	Q1 − Q5
	Panel B: The Augmented Seven-Factor Model					
FF7 alpha	0.31	0.45	0.33	-0.26	-0.40	0.70
[t-stat]	[1.66]	[2.41]	[2.01]	[-1.44]	[-1.66]	[1.81]
RMRF	1.00	0.99	1.05	0.99	1.05	-0.05
[t-stat]	[32.12]	[37.89]	[62.67]	[35.27]	[25.35]	[-0.76]
SMB	0.15	0.11	0.12	0.04	-0.06	0.21
[t-stat]	[1.49]	[1.57]	[1.82]	[0.59]	[-0.50]	[1.04]
HML	-0.00	-0.04	-0.09	0.05	-0.06	0.05
[t-stat]	[-0.04]	[-0.46]	[-1.75]	[0.53]	[-0.39]	[0.21]
RMW	-0.41	-0.13	-0.06	-0.26	-0.08	-0.33
[t-stat]	[-2.17]	[-1.36]	[-0.63]	[-2.62]	[-0.45]	[-0.96]
CMA	-0.34	-0.05	0.06	-0.25	0.03	-0.37
[t-stat]	[-1.61]	[-0.44]	[0.58]	[-2.65]	[0.14]	[-0.97]
MOM	0.12	-0.02	-0.09	-0.11	-0.13	0.25
[t-stat]	[1.71]	[-0.38]	[-1.69]	[-1.70]	[-1.53]	[1.92]
STREV	0.01	-0.02	-0.08	-0.03	-0.02	0.03
[t-stat]	[0.21]	[-0.51]	[-2.67]	[-0.67]	[-0.20]	[0.25]
Adj. R^2	0.91	0.93	0.95	0.93	0.89	0.08
Obs.	246	246	246	246	246	246

Table 4. Fama-MacBeth Cross-sectional Regressions with Weighted Least Squares, July 1996 - December 2016

Description: The table reports the results of the Fama-MacBeth cross-sectional regressions with weighted least squares (WLS). LIQ Beta, the liquidity beta estimated using Eq. [4.5] over the prior 5 years. lnME is the natural logarithm of firm's market capitalization measured at the end of June in year t. lnBTM is the natural logarithm of firm's book-to-market equity measured at the fiscal year end in $t-1$. OP is the ratio of operational profits and book equity measured at the fiscal year ending in $t-1$. INV is the growth of total assets for the fiscal year ending in $t-1$. RET^{MOM} is the intermediate-term return momentum, defined as the past 12-month cumulative return, skipping the most recent month. $\text{RET}^{\text{STREV}}$ is the short-term return reversal, defined as the past one-month return. All explanatory variables are winsorized at the 0.5 and 99.5% level. Coefficients, the WLS coefficients, are reported in the first row. Fama-MacBeth t-statistics (in parentheses) and Newey–West adjusted t-statistics (in brackets) are reported in the second and third rows below the corresponding coefficients, respectively. $Adj.R^2$ is the adjusted R-square, Firms the average number of firms in the cross-sectional regression, and Periods the number of months for the period-by-period cross-sectional regressions. The sample period is between July 1996 and December 2016.

	Const.	**LIQ Beta**	**lnME**	**lnBTM**	**OP**	**INV**	**MOM**	**STREV**	**Adj. R^2**	**Firms**	**Periods**
WLS Coef.	0.89	-0.26							0.0085	1190	246
(FM t-stat)	(1.60)	(-3.27)									
[NW t-stats.]	[1.24]	[-3.73]									
WLS Coef.	2.15	-0.16	-0.34	0.53					0.0472	1172	246
(FM t-stat)	(1.25)	(-2.60)	(-2.34)	(2.76)							
[NW t-stats.]	[1.14]	[-2.88]	[-2.25]	[2.25]							
WLS Coef.	2.35	-0.16	-0.37	0.52	0.01	-0.00			0.0575	1167	246
(FM t-stat)	(1.39)	(-2.59)	(-2.65)	(2.69)	(1.10)	(-0.47)					
[NW t-stats.]	[1.29]	[-2.99]	[-2.56]	[2.23]	[1.29]	[-0.61]					
WLS Coef.	2.71	-0.13	-0.40	0.49	0.01	-0.00	-0.02	-3.74	0.0893	1167	246
(FM t-stat)	(1.62)	(-2.33)	(-2.93)	(2.31)	(1.00)	(-0.58)	(-0.05)	(-3.73)			
[NW t-stats.]	[1.41]	[-2.43]	[-2.74]	[1.88]	[1.21]	[-0.72]	[-0.03]	[-4.25]			

Table 5. Time-Variation of the Low-minus-High Liquidity Beta Portfolio, July 1996 to December 2016

Description: The table reports the predictive regression of the zero-cost low-minus-high liquidity beta portfolio (*i.e.*, hedge portfolio). The dependent variable in Panel A (B) is the return differential of the equal-weighted (value-weighted) hedge portfolio. The predicting variables include the lagged market-wide turnover ratio (denoted as TURN(-1)), the lagged market volatility (denoted as Sigma(-1)), the lagged economic uncertainty index (denoted as EPU(-1)), the lagged market illiquidity measured by the value-weighted implied spread (denoted as ILLIQ(-1)), the lagged value-weighted cross-sectional return standard deviation (denoted as DISP(-1)). The control variables are the contemporaneous market, size, value, profitability, investment, momentum, and short-term reversal factors, respectively. Newey–West adjusted t-statistics with a lag length of 12 are reported in brackets. $Adj.R^2$ is the adjusted R-square, and Obs. is the number of observations. The sample period is between July 1996 and December 2016.

	Panel A: y = Equal-weighted Hedge Portfolio						**Panel B: y = Value-weighted Hedge Portfolio**					
	1	**2**	**3**	**4**	**5**	**6**	**1**	**2**	**3**	**4**	**5**	**6**
Const.	0.74	0.74	0.74	0.75	0.76	0.75	0.85	0.84	0.85	0.87	0.87	0.86
	[3.36]	[3.34]	[3.35]	[3.46]	[3.61]	[3.47]	[2.40]	[2.31]	[2.39]	[2.51]	[2.53]	[2.46]
TURN(-1)	0.67	0.67	0.68	0.68	0.46	0.41	0.71	0.74	0.72	0.72	0.51	0.51
	[2.65]	[2.76]	[2.75]	[2.69]	[1.54]	[1.53]	[2.89]	[2.88]	[2.84]	[2.95]	[1.76]	[1.85]
Sigma(-1)		-0.00				-0.09		-0.09				-0.21
		[-0.01]				[-0.25]		[-0.27]				[-0.47]
EPU(-1)			-0.03			0.08			-0.03			0.09
			[-0.13]			[0.28]			[-0.09]			[0.29]
ILLIQ(-1)				0.05		-0.06				0.11		0.06
				[0.22]		[-0.26]				[0.44]		[0.19]
DISP(-1)					0.37	0.46					0.34	0.42
					[1.55]	[1.71]					[0.87]	[0.88]
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
$Adj.R^2$	0.14	0.14	0.14	0.14	0.14	0.14	0.07	0.07	0.07	0.07	0.07	0.07
Obs.	245	245	245	245	245	245	245	245	245	245	245	245

Table 6. Portfolio Turnover and Transaction Cost Analysis

Description: Panel A reports the annualized portfolio turnover of the long-only liquidity-beta sorted quintile portfolios, and the zero-cost low-minus-high liquidity-beta portfolio. Panel B reports the breakeven transaction costs that would zero out the average excess returns and the risk-adjusted returns (*i.e.*, alphas) under the CAPM model, the Fama-French three-factor model (FF3), the Fama-French five-factor model (FF5), the Fama-French six-factor model (FF6), and the augmented seven-factor model (FF7). - indicates that the breakeven transaction cost is either below the threshold of 10 basis points (bps), or undefined as the pre-cost average (risk-adjusted) return is negative. The sample period is from July 1997 to December 2016.

	Q1=Low	Q2	Q3	Q4	Q5=High	Q1-Q5
	Panel A: Annualized Portfolio Turnover					
Turnover	149%	258%	290%	259%	151%	150%
	Panel B: Break-even Transaction Costs (in bps)					
Excess return	1,082	506	438	295	303	714
CAPM alpha	581	248	201	23	-	707
FF3 alpha	222	71	75	-	-	530
FF5 alpha	352	153	152	36	-	451
FF6 alpha	377	157	142	-	-	543
FF7 alpha	364	142	140	-	-	544

Table 7. Portfolios Sorted on Liquidity Beta Controlling for Other Effects

Description: Stocks are first sorted into 5 groups based on a particular characteristic: Idiosyncratic volatility (denoted as IVOL in Panel A) and lottery demand (denoted as MAX5 in Panel B). Within each characteristic group, stocks are sorted into 5 groups based on their rankings of liquidity betas. The returns of the liquidity-beta sorted quintile portfolios are then formed by averaging across the 5 characteristic groups. The table reports the monthly excess returns and the risk-adjusted returns under the CAPM, Fama-French three-factor (FF3), Fama-French five-factor (FF5), augmented Fama-French six-factor (FF6), and augmented Fama-French seven-factor (FF7) models for the equal-weighted liquidity beta sorted quintile portfolios and the low-minus-high liquidity beta portfolio (Q1-Q5). Newey–West adjusted *t*-statistics are reported in brackets. The sample period spans from July 1996 to December 2016.

	Q1 = Low	**Q2**	**Q3**	**Q4**	**Q5 = High**	**Q1 − Q5**
	Panel A: Controlling for IVOL					
Excess return	2.03	1.87	1.83	1.44	1.18	0.85
[t-stat]	[2.52]	[2.32]	[2.23]	[1.86]	[1.50]	[3.34]
CAPM alpha	1.11	0.94	0.88	0.52	0.24	0.87
[t-stat]	[4.01]	[3.54]	[3.78]	[2.34]	[1.22]	[3.77]
FF3 alpha	0.33	0.12	0.07	-0.28	-0.31	0.64
[t-stat]	[2.39]	[1.03]	[0.76]	[-2.59]	[-2.24]	[2.99]
FF5 alpha	0.47	0.32	0.26	0.09	-0.02	0.50
[t-stat]	[3.57]	[2.86]	[2.96]	[0.70]	[-0.16]	[2.25]
FF6 alpha	0.49	0.33	0.27	0.08	-0.01	0.50
[t-stat]	[3.71]	[2.94]	[3.06]	[0.62]	[-0.10]	[2.23]
FF7 alpha	0.51	0.33	0.23	0.04	-0.08	0.59
[t-stat]	[4.01]	[3.03]	[2.99]	[0.35]	[-0.59]	[2.67]

	Q1 = Low	Q2	Q3	Q4	Q5 = High	Q1 − Q5
	Panel B: Controlling for MAX5					
Excess return	1.98	1.91	1.77	1.46	1.14	0.84
[t-stat]	[2.46]	[2.34]	[2.17]	[1.87]	[1.47]	[3.26]
CAPM alpha	1.05	0.98	0.83	0.55	0.20	0.84
[t-stat]	[3.80]	[3.75]	[3.55]	[2.46]	[1.01]	[3.65]
FF3 alpha	0.23	0.15	0.08	-0.21	-0.38	0.61
[t-stat]	[1.66]	[1.18]	[0.85]	[-2.33]	[-2.93]	[2.95]
FF5 alpha	0.42	0.32	0.29	0.12	-0.07	0.49
[t-stat]	[3.29]	[3.01]	[2.72]	[0.93]	[-0.48]	[2.17]
FF6 alpha	0.43	0.33	0.29	0.11	-0.07	0.50
[t-stat]	[3.44]	[3.20]	[2.67]	[0.93]	[-0.45]	[2.16]
FF7 alpha	0.49	0.33	0.24	0.05	-0.15	0.64
[t-stat]	[3.71]	[3.38]	[2.62]	[0.48]	[-0.99]	[2.66]

Appendix

Appendix A: Variable Definition

Notation	Definition
ME and lnME	The market capitalization and the natural logarithm of the market capitalization of a stock, defined as the (natural logarithm of) firm's total market capitalization measured at the end of June in year t.
BTM and lnBTM	The book-to-market ratio and the natural logarithm of the book-to-market ratio, defined as the (natural logarithm of) firm's book-to-market equity measured at the fiscal year ending in $t-1$.
OP	Operating profitability, defined as the ratio of operational profits and book equity measured at the fiscal year ending in $t-1$, which follows from Fama and French (2017).
INV	Asset investments, defined as the growth rate of total assets for the fiscal year ending in $t-1$, which follows from Fama and French (2017).
$\mathrm{RET}^{\mathrm{MOM}}$	Intermediate-term return momentum, defined as the cumulative returns over the past 12-month rolling window, skipping the most recent month according to Fama and French (2012).
$\mathrm{RET}^{\mathrm{STREV}}$	Short-term return reversal, defined as the one-month stock returns in the prior month (Jegadeesh & Titman 1993).
IVOL	The idiosyncratic volatility, defined similarly as in Ang et al. (2006), which is the standard deviation of the residuals from the following regression. $$R_i - RF = \alpha_i + \beta_i^{RMRF} RMRF + \beta_i^{SMB} SMB + \beta_i^{HML} HML + \varepsilon_i$$ The *ex ante* IVOL measure is constructed using the above Fama-French three-factor model using daily observations over the prior month, which requires at least ten observations to run the regression.
MAX5	The lottery demand measure, defined as the average of the largest five daily returns in the prior month (Bali et al. 2011; Bali et al. 2017).

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