Liquidity: A hidden gem of factor investing

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Master thesis

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Erasmus School of Economics

Program in

Financial Economics

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June 2018

Abstract

We create a new liquidity framework to understand liquidity risk in asset-pricing anomalies and generate trading strategies from firm level to aggregate level. For firm level liquidity, we show that liquidity as identified by trading volume, delivers positive risk premium that can't be explained by common risk factors. For aggregate level, we show that funding liquidity measured by betting-against-beta (BAB) return difference from high margin and low margin group produces significant risk-adjusted returns, furthermore, liquidity strategy enhanced by quality is not subsumed to market wide liquidity risk anymore. We show that liquidity, as a characteristic rather than covariance, accounts for the common variation in returns.

Acknowledgements

I would first like to thank my thesis supervisor Antti Yang. He consistently allowed this paper to be my own work, but steered me in the right the direction whenever he thought I needed it. This accomplishment would not have been possible without his support.

I would also like to acknowledge Professor Laurens Swinkels as the first reader of this thesis, and I am gratefully indebted to his for his very valuable comments on this thesis.

Finally, I must express my very profound gratitude to my parents for providing me with unfailing support and continuous encouragement throughout my years of study and through the process of researching and writing this thesis. Thank you.

To my parents.

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Chapter 1

Introduction

The financial crisis of 2008 depicted a dramatic outline on the importance of liquidity in financial markets. The existence of negative liquidity spirals and the contagious nature of liquidity pervasively across asset classes, magnify and prolong the level of financial crises. Empirical evidence suggest that liquidity can predict stock returns, both at the cross section and time series level. Over the past years, liquidity is generally defined as the ability which enables investors to buy or sell a security quickly, anonymously, smoothly at a market price which is equal to its fair value and without huge price impact.

Liquidity premium can be explained through risk based theory. Investors require liquid asset and are willing to pay for it with higher price than less liquid one. In equilibrium, investors receive reward of higher returns on average from the willingness to take liquidity risk and hold illiquid asset. According to Amihud, Mendelson, and Pedersen (2006)[7], the sources of illiquidity are as follows: exogenous transaction costs such as brokerage fees, order-processing costs, or transaction taxes; demand pressure and inventory risk from market maker with risk exposure on the changes of price; private information such as order flow and fundamentals of security; easiness to search and find a counter party to trade. Furthermore, liquidity exhibits various linkage with existing common risk factors like size, value and quality and is conditional on the market wide liquidity status, such that we should note the complexity when dig deep to liquidity. Acharya and Pedersen (2005) [1] provide various channels for liquidity: (i) commonality in liquidity with the market liquidity; (ii) return sensitivity to market liquidity; (iii) liquidity sensitivity to market returns.

Our paper sheds light on a unified framework to understand the various liquidity channels and provide comprehensive perspectives to implement liquidity related investment strategy from firm level and aggregate level, from characteristic to covariance in the cross-section and time series, as illustrated in figure 7.4. At firm level, we choose 12-month rolling average trading volume to construct dollar neutral firm level liquidity factor, which achieve 2.51% monthly average return after adjusted by common risk factors including SMB, HML and MOM, indicating our liquidity factor is not the projection of existing factors, ie., our hedging strategy gain abnormal return that can't be explained by systemic risk premium.

At aggregate level, we differentiate market liquidity and funding liquidity concept, that market liquidity refers to level of easiness assets can be traded on the market, while funding liquidity refers to the availability for investors to reach funding to support the positions. Brunneimer and Pedersen (2008)[15] investigate the interaction between the two forms of liquidity, find out that capital and collateral requirements link funding and trading liquidity of financial intermediaries: a funding liquidity shock forces asset in the short position, combining with drop of price and shrinkage of market liquidity, correspondingly, market liquidity shocks followed by higher margin calls, accelerate funding liquidity risk as the increase of funding out-flows. During market wide liquidity downturns, as funding resource deteriorates, liquidity providers lose the power sustain their funding positions, induced by higher margin requirements of collateralize loans worsening the shortage of funding resource.

For funding liquidity, we follow Chen and Lu (2017) [16] to construct a funding liquidity factor, that is derived from two dollar-neutral betting against beta (BAB) portfolios return difference, from the highest margin and the lowest margin group, where the margin requirement is proxied by stocks idiosyncratic risk. Unlike their original paper, we use dollar neutral BAB factor rather than beta neutral (market neutral) BAB factor, since we intend to create zero dollar hedging investment strategy rather than keep portfolio market risk neutral.

For market wide liquidity, we use TED as a barometer of market liquidity condition to further examine our quality enhanced liquidity strategy performance. Quality enhanced liquidity strategy is derived from inter-sectional model and constructed from portfolio with the lowest liquidity and highest quality. We test whether quality enhanced liquidity strategy can be immune from 'flight to quality' and 'flight to liquidity', referring to episodes in which risky securities become especially illiquid, the fragility of liquidity trading strategy. Our consideration of such strategy stems from the high quality and liquid stocks are more desirable in volatile times. Unlike most of the previous researches on these two phenomena centering on the transition from stocks to bonds, we focus on the stock market solely. We implement quantile regression to confirm the hypothesis that the lowest 20th percentile return from quality enhanced portfolio is independent from market wide liquidity-indicated by TED spread. Comparing with the lowest 20th percentile return from simple liquidity strategy-the long only position on the lowest liquid portfolio, which has significant loading on TED spread.

The size effect in finance literature refers to the observation that smaller firms, on average have higher expected returns than larger firms overtime. The risk based theory explaining that firm size represent liquidity risk, the higher premium for smaller firms is attributed to liquidity risk embedded in them, leading to lower price on small firms to ensure higher expected return. We explore the interaction relationship between liquidity premium and size premium from factor regression and double sorting portfolio. From factor regression, it turns out that 3.99% monthly alpha is left from firm level liquidity factor after adjusted by MKT, SMB and HML. From the 5*5 independently double sorted portfolio on size and liquidity, size effect does not hold across all liquidity quartiles, especially in the highest trading volume quartile, confirming that the liquidity premium is not the simple projection of size premium.

The liquidity characteristics (level of liquidity) of assets pervasively affect their returns. Finance theory predicts a positive relation between liquidity level and required rates of return (Amihud and Mendelson (1986)[6]), because illiquid assets must offer a higher expected return than their liquid counterparts in order to attract investors. Recent research suggests that the liquidity characteristic and liquidity covariance structure are related. It is possible that the liquidity effect is subsumed by the liquidity covariance (Watanabe and Watanabe (2008)[36]), the liquidity covariance dominates the liquidity characteristics(Acharya and Pedersen (2005)), or both independently impact returns (Korajczyk and Sadka (2008)[25]). Thus, we explore our liquidity both from characteristic and covariance. Liquidity covariance, the liquidity beta, is derived from the covariace structure of its return with liquidity. We find that liquidity characteristic has greater explanatory power for returns during whole sample period than liquidity covarianc.

The rest of the paper is organized as follows. In Section 2, we review the related literature and assumption, section 3 describes our data, section 4 discuss empirical methodology, section 5 show our empirical results, and we draw our conclusion at last section.

Chapter 2

Literature review

The liquidity premium in financial markets has been extensively documented in literature. We suggest to take a step forward to view liquidity in empirical finance from two forms of liquidity: individual(firm) level liquidity, and aggregate level liquidity.

2.1 Firm-level liquidity

On the firm level, finance theory predicts a positive relation between liquidity and required rates of return. The liquidity relates to firm level is centered on the research on the trading activity. AW Lo and Wang (2000)[27] depicts comprehensive definition on trading volume as an indication of liquidity, from dollar volume to share volume, from individual to aggregate, from absolute to relative perspective.

Amihud (2002)[4] proposes a measure of illiquidity ratio calculated by the ratio between the average absolute daily return and average daily trading dollar volume over a time span. The author demonstrate that a positive cross-sectional relation between expected stock returns and illiquidity, confirm that liquidity is a priced factor in cross sectional asset.

Brennan and Subrahmanyam (1996) [14] suggest that private information play a key role for investors to create significant illiquidity costs for uninformed investors, such that the required rates of return is higher for securities that are relatively illiquid. The author propose to use price impact,ie., bid-ask spreads to capture liquidity status, which account for stock returns in cross sections of individual firms.

Datar and Naik (1998) [20] implement stock turnover to define liquidity and predict that the lower turnover means longer average holding period of the stock, implying lower liquidity, resulting in the higher expected return.

2.2 Funding liquidity

On the aggregate level, Brunnermeier and Pedersen (2008)[15]develop a model to connect firm level liquidity reflecting the stocks' ease of being traded with funding liquidity reflecting investors' ease and cost of obtaining funding. 'Liquidity spirals' can arise when liquidity dry-up circle is activated. Funding liquidity drives the fluctuation of market liquidity and volatility. Specifically, tightness in funding conditions leads investor to drop high-margin requirement securities if it is capital-intensive, which accelerates the decline of market liquidity and induces higher market volatility. Therefore, funding liquidity shocks ultimately affect valuation via the risk premium from volatility and liquidity, such shocks can be triggered when market wide economic conditions or investment opportunities are deteriorating.

Adrian, Etula, and Muir (2014) [2] find that shocks to broker-dealer leverage leverage accounts for the dispersion of stock returns sorted by size, book-to-market, and momentum. They point out that broker-dealer leverage shocks on another hand capture market wide funding liquidity shocks. due to high correlation between leverage growth and broker-dealer asset growth.

Krishnamurthy (2002) [26] suggests to measure funding liquidity premium through two assets with similar characteristics but different liquidity. A just-issued, defined as on-the-run, thirty-year treasury bond and a thirty-year bond issued three months ago, defined as off-the-run, has similar cash flows, however, the on-the-run bond is significantly more liquid than its off-the-run counterpart, thus the funding liquidity premium can be extracted from the price difference of the securities pairs.

However, we mention that each of these liquidity measures may have systematic and asset-specific components, besides, the systematic components of different liquidity measures may be correlated, which are due to the error-prone estimations of the same facet of liquidity or the different facets of liquidity are correlated by nature. There is no single agreement on the measurement of liquidity.

2.3 Market regime

The liquidity premium varies with to the market wide liquidity over time. Vayanos(2004)[35] approach the conditional market liquidity by analyzing liquid and illiquid asset pairs return. The author find that liquidity premium vary considerably over time. During extreme market, risk averse investors trigger higher market volatility so that assets become more negatively correlated with volatility, and liquidity premium widen dramatically, showing 'flight to liquidity' effect.

In an extreme case, Amihud et al (1990)[5] posit that the rising market wide illiquidity during 1987 crash lead to return decline happened in large proportion in relatively more liquid stocks, even after controlling for the market effect and the stocks beta coefficients. This suggests two effects are incurred on stock return when expected market wide illiquidity rises: (i) The commonality of decline in stock price and increase in expected return to all stocks; (ii) Substitution effect from less liquid to more liquid stocks 'flight to liquidity'. For low liquid stocks, the two effects are complementary, both affecting stock returns in the same direction. However, for liquid stocks, the two effects happen in opposite directions. Unexpected rise in market illiquidity negatively affects stock prices, thus increases the relative demand for liquid stocks and mitigates their price decline. Moreover, higher expected market wide illiquidity induces investors to demand higher expected return on stocks, that is only willing to pay lower price for illiquid stocks. Liquid stocks become relatively more attractive and weaken expected liquidity premium. Acharya and Pedersen (2005)[1] confirm that liquid stocks tend to perform well during market liquidity dry-up. What's more, the expected liquidity premium can be weaken or even reversed, denoted as liquidity discount, during such liquidity crises.

Baker and Stein (2004)[12] show that aggregate market liquidity is the sentiment indicator, specifically, aggregate measures of equity issuance and share turnover are highly correlated, which together significantly explain cross sectional stock return.

2.4 Covariance and characteristic

While extensive theoretical and empirical literatures have analyzed the relation between various firm characteristics and the cross section of expected returns. Amihud and Mendelson (1986) [6] show that stocks with high spreads have higher average returns than stocks with lower spreads. Sadka (2006)[33] measures liquidity using the components of the price impact model. Most of these authors find evidence for pricing of liquidity as a characteristic.

In contrast, Lou and Sadka(2011)[28] examine whether liquid premium still holds based on both liquidity characteristic sorted and liquidity covariance sorted portfolio during the 2007-2008 financial crisis. Liquid assets are supposed to be desirable in terms of transaction cost, it is inevitable that liquid stocks tend to suffer much greater losses than illiquid stocks. The authors conclude that, during market wide illiquidity period, portfolio managers should care about the stocks liquidity covariance structure rather than liquidity characteristic.

There are debates on the source of liquidity premium, possible explanations are stocks exposure to some not-yet-understood common risk component or simple mispricing. Stock with low liquidity means inability to be traded smoothly lead to exemption from huge price draw-down during turbulent period. Theoretically, investors would be willing to pay higher price for stocks with such buffering benefits. Alternatively, investors may prefer low liquid stocks to high liquid stocks due to cognitive biases or some other not-yet-understood reason. To determine which of the two explanations better explain the liquidity premium, we seek to separate components of mispricing and systematic risk, defined by Daniel and Titman (1998)[19] as characteristic versus covariance.

2.5 Hypotheses

In this paper, we investigate liquidity related investment strategy and posit hypotheses as follows:

Hypothesis 1: Firm level liquidity strategy by taking long position on illiquid portfolio and short position on liquid portfolio measured by 12-month rolling average trading volume, on average should earn a positive premium.

To define the individual liquidity, we define average trading volume as the quantities that are traded during past 12 month. We rely on the concept that higher trading volume indicate higher liquidity level of stocks.

Hypothesis 2: Funding liquidity strategy by taking long position of dollar neutral BAB portfolio from high margin requirement and short position of dollar neutral BAB portfolio from low margin requirement should earn a positive premium.

The return difference of a BAB portfolio isolate funding liquidity from overall liquidity. Taking the return difference between two BAB portfolios enables us to smooth out the possible time variation in margin requirement and maintain time-varying funding liquidity shocks.

Hypothesis 3: The liquidity factor is not just a different projection of existing risk factor, rather, liquidity risk premium (both funding and firm level) can't be explained by the other common systematic risk factors, like size, value and momentum.

Hypothesis 4: Liquidity premium arise from stock characteristics rather than the covariance structure of returns relate to characteristics.

We examine two explanation on liquidity risk premium. The validation of systematic risk to explain low-liquid risk premium rely on the fact that stocks with a high loading on the liquidity factor should outperform stocks with a low loading on the liquidity factor. This pattern should be observed irrespective of the absolute level of stock liquidity. If, however, after controlling for the observed level of return variability, loadings on the low-liquidity factor are unable to explain cross-sectional stock returns,ie.,portfolio with low liquidity covariance failed to generate higher return than high liquidity covariance portfolio within the liquidity characteristic percentile, then we conclude that it's liquidity characteristic that dominate liquidity premium.

Hypothesis 5: Liquidity as an investment strategy enhanced by quality, that the long only position on the intersectional portfolio with high quality and low liquidity, harvest higher return with lower volatility than simple liquidity strategy alone, that the long only position on the lowest liquid portfolio, and the return from quality enhanced strategy is independent of market wide liquidity crisis.

Quality enhanced liquidity strategy tends to perform better when traditional liquidity suffers large drawdowns, and vice verse, so strategy that trade on quality and liquidity signals generate relatively more steady returns than do strategies that trade on liquidity alone.

Chapter 3

Methodology

This paper examines whether and to what extent liquidity can be an investment strategy to yield high returns, from aggregate level (market and funding) liquidity to firm level liquidity, from liquidity characteristic to liquidity covariance. We examine U.S. equities market. With sample extended from June 1962 to December 2017, the research allows us to check for the presence and persistence of the liquidity effect over the years during markets up and down.

We test if the funding liquidity and firm level liquidity risk premium can be explained by the existing systemic risk factors. Then we consider liquidity premium is attributed to liquidity characteristic or liquidity covariance. Further, we analyze the relationship between liquidity premium with size premium. Finally, we explore liquidity trading strategy and quality enhanced liquidity strategy performance during tight or loose market wide liquidity regimes.

3.1 Portfolio construction

3.1.1 Firm level liquidity

Chordia, Subrahmanyam, and Anshuman (2000) [17] show that trading activity if measured by volume or turnover is negatively correlated with expected returns. Tkac (1996)[34] considers individual dollar volume normalized by aggregate market dollar-volume to measure liquidity and show that low volume stocks on average generate higher expected returns than high volume stocks. Conrad, Hameed, and Niden (1994)[18] posit liquidity measured by total number of trades capture the cross sectional return variation.

We note from Berk(1995)[13] observation that variables related to price can't capture actual movement under improper risk-adjustment. We adopt stock trading volume, representing the total number of shares traded for a given time frame, to measure firm level liquidity. Intuitively, higher trading volume indicate higher liquidity in the market, besides, higher transaction costs from higher volume transaction will slow trade and thus reduce liquidity of stocks, which is associated with higher bid/ask spreads.

Trading activity in financial market manifested itself in multi-perspective, even for trading volume, there are various definitions, from individual volume and aggregate volume, from share volume to dollar volume and from share-weighted volume to equal/value weighted volume. In order to capture the impact from firm level liquidity, we implement individual trading volume as liquidity proxy in this paper. Furthermore, we use rolling 12 months rolling average trading volume to reduce statistical noise and smooth effects from outliers.

It is often presumed that investing in less liquid stocks is equivalent to investing in small size stocks. The liquidity effects over time on stock excess return differ across stocks by their size within liquidity group. Akbas et al.(2010)[3] liquidity is highly correlated with size and value exposure, small value stocks have higher liquidity premium than small growth stocks, especially during market downturn, conversely, small growth stocks have higher liquidity premium than small value stocks during market booming period.

We further analyze the relationship with size premium by independently and separately sort stocks by size(market capitalization) and rolling 12 months trading volume (liquidity measure). In order to have a deep understanding of the relationship, we construct two sets of portfoliovalue weighted and equal weighted.

The construction of firm level liquidity mimicking factor is similar to the construction of SMB and HML in Fama and French (1993)[21]. Given that stocks with high trading volume usually have lower size than stocks with low trading volume, liquidity factors that result from ranking solely based on trading volume can be affected by the size premium and not represent the premium attributed to the liquidity. We mitigate this issue by constructing 5-by-5 portfolio, independently sorted on trading volume and size. We obtain value-weighted and equal-weighted monthly returns on 25(5*5) portfolios. The mimicking firm level liquidity factor return is monthly average return on the 5 value weighted lowest-liquid (quintile1) portfolios minus the monthly average return on the 5 value weighted highest-liquid (quintile5) portfolios:

$$LIQ_{firm} = \frac{1}{5}\sum_{i=1}^{5} size_i/Vol_{low} - \frac{1}{5}\sum_{i=1}^{5} size_i/Vol_{high} \tag{3.1}$$

where $size_1/Vol_{low}$ denotes the monthly value weighted average return on lowest liquid portfolio (lowest trading volume) with size rank as 1, etc.

3.1.2 Funding liquidity

Funding liquidity, the easiness or availability to obtain funding, is often recognized to be interrelated with market liquidity and firm level liquidity. If stocks that yield low returns during market wide funding liquidity crisis, such stocks pertain higher funding illiquidity, higher volatility and eventually higher premium. We consider financial up and down in the form of stocks margin requirements and restriction on the availability to reach risk free rate borrowing. We use market beta to capture the funding constrain from market and idiosyncratic risk to grasp the individual effect to funding liquidity. Following Chen and Lu (2017)[16], we propose an approach to extract unobserved funding liquidity from observed asset price dynamics.

We start with analyzing on the individual funding margin requirement. Given that there is no consensus on the definition of margin requirement, common proxies as analyst coverage, size, idiosyncratic risk and some well known liquidity factors. Theoretically, stocks with high idiosyncratic volatility indicate the security return fluctuate dramatically over a short time period. A lower idiosyncratic volatility means that a security's value retain rather stable over a period of time, denoting low margin constrain and stock return is independent of the market wide liquidity condition. We note that higher β stock normally show larger total volatility, and capture partial volatility co-movement between stocks and market, the first round sorting on idiosyncratic volatility rather than total volatility alleviate the impact from market impact . Following Ang et al.(2006)[9], we measure idiosyncratic volatility each month as the standard deviation of the residuals $\epsilon_{i,t}$ from regressing the monthly returns of individual stocks in excess of the one-month T-bill rate on the returns to the FamaFrench three-factor.

$$R_{i,t} = \alpha_i + \beta_{mkt,i} R_{mkt,t} + \beta_{smb,i} R_{smb,t} + \beta_{hml,i} R_{hml,t} + \epsilon_{i,t} \tag{3.2}$$

where R_i is monthly returns of individual stocks in excess of the one-month T-bill rate, R_{mkt} is the market premium at time t, R_{smb} and R_{hml} represent the returns on portfolios capturing the size and the book-to-market effect, respectively.

Each month, stocks are ranked in ascending order on the basis of their previous period idiosyncratic volatility and assigned into 5 groups. Group 1 includes stocks with the lowest idiosyncratic volatility, that is the lowest margin requirement group, while group 5 includes stocks with the lowest idiosyncratic volatility.

Our funding liquidity measure is based on the betting against beta (BAB) factor, we form BAB factor within each margin group. Frazzini and Pedersen(2014)[22], who develop a theoretical model in which the investors' leverage constraints can manifested on the return spread between low-beta stocks and high-beta stocks, where the time variation in a BAB factor depends on both the market wide liquidity condition and assets' sensitivity to the market wide liquidity. Margin requirements drive the availability for the ease to get funding and determine the level of sensitivity. Investors constrained by funding requirement are willing to pay higher price for high-beta stocks with embedded leverage, so that they don't face funding constrain to lever investment portfolios. The BAB premium driven from that is even higher for margin stocks.

We intent to investigate zero dollar investment strategy, rather than focusing on market neutral, that the way BAB is originally constructed. The BAB factor is constructed using value-weighted portfolios formed on size and beta to mitigate size bias.

First, we use a 2-year rolling windows and require at least 12 observations with monthly data to get the estimation of β for each stocks from the following regression:

$$R_{i,t} = \alpha_i + \beta_{mkt,i} R_{mkt,t} + \epsilon_{i,t} \tag{3.3}$$

where R_i is monthly returns of individual stocks in excess of the one-month T-bill rate, R_{mkt} is the market premium at time t, $\hat{\beta}_{mkt,i,t}$ is the ex-ante value for each stocks.

We use conditional sorting to construct funding liquidity factor. In each margin group, we additionally construct six value-weighted portfolios formed on lagged size and beta, from which size denotes market capitalization calculated by multiplying a company's shares outstanding by the market price per share. At each calendar month, in each margin group, stocks are assigned to two size-sorted portfolios based on the lagged market capitalization and three beta-sorted portfolios (low, medium, and high) based on the 30th and 70th percentile lagged beta distribution. Portfolios are re-balanced every calendar month. We get value weighted return and achieve averaged return of the small and large portfolio to form a low-beta and high-beta portfolio:

$$r_{t+1}^{H} = \frac{1}{2}(r_{t+1}^{H,small} + r_{t+1}^{H,large}) \tag{3.4}$$

$$r_{t+1}^{L} = \frac{1}{2}(r_{t+1}^{L,small} + r_{t+1}^{L,large}) \tag{3.5}$$

We form the dollar-neutral BAB, which is a self-financing portfolio taking long position on the low-beta portfolio and short position on the high-beta portfolio in each margin group:

$$r_{t+1}^{BAB} = r_{t+1}^{L} - r_{t+1}^{H} \tag{3.6}$$

where r_{t+1}^{L} is the value weighted returns on the low beta portfolio, r_{t+1}^{H} is the value weighted returns on the high beta portfolio.

The BAB factor is the return on a portfolio taking long position on low-beta portfolios and short position on high-beta portfolios. The funding liquidity factor is defined as the return difference of BAB portfolio from high-margin group and BAB portfolio from low-margin portfolio. The way to extract funding element can not only smooth out the potential time variation in margins but also capture time-varying funding liquidity shocks.

$$LIQ_{funding} = r_{t+1}^{BAB_H} - r_{t+1}^{BAB_L} \tag{3.7}$$

where $r_{t+1}^{BAB_H}$ is the BAB portfolio return within the highest margin group, $r_{t+1}^{BAB_L}$ is the BAB portfolio return within the lowest margin group.

3.2 Factor analysis

Pastor and Stambaugh (2003)[31], Acharya and Pedersen (2005) [1] and Sadka(2006) [33] each test whether liquidity risk is priced based on two-stage Fama-MacBech regressions on cross-sectional assets, instead, we analyze liquidity risk premium by constructing liquidity factor mimicking portfolio and investigating the relationship with existing systemic risk factors. A factor mimicking portfolio is a portfolio of assets constructed to capture the premium from a background factor. For our liquidity research, the firm level factor mimicking portfolio stands for the hedging strategy of taking long position on the lowest liquid portfolio and short position on the highest liquid portfolio, while funding level factor denotes the long position on the highest margin requirement group BAB portfolio (group5) and short position on the lowest margin requirement group BAB portfolio (group1).

Asness et al. (2013) [11] point out that liquidity risk can only explain a small fraction of value and momentum return premium and co-movement. We examine if our liquidity factors are just different projection of existing risk factors. We run regression with liquidity factors as independent variable and add common risk factors including the market factor, the size factor, the value factor and the momentum factor, sequentially. If the regression left with significant intercept α, it indicates that investors need to include liquidity along with the other factors to form efficient portfolios. In other words, liquidity premium is fundamentally priced rather than the projection of existing investment strategies. We analyze how our funding liquidity and firm level liquidity factor can explain size, value and momentum premium, for which liquidity factors used as the single explanatory variable in the regression. Moreover, the BAB factor is also added to funding liquidity regression analysis to investigate the extent of funding liquidity factor capturing BAB premium, vice verse. The QMJ factor is added to firm level liquidity regression to see the interaction between quality investing and liquidity investing.

3.3 Market regime

All the liquidity analyses up to the point are unconditional. We shift focus to a conditional analysis that the liquidity premium are dependent on time varying market wide liquidity regimes. Pastor and Stambaugh (2003)[31] propose that asset price should reflect premium for the sensitivity of stock returns to market-wide liquidity: stocks with greater exposure to market liquidity shocks, with greater systematic liquidity risk should earn higher returns.

In order to further explore hedging strategy in turbulent period, inspired by Asness, Frazzini, and Pedersen (2017)[10], who define quality investing strategy that goes long on high-quality stocks and shorts low-quality stocks earns significant risk-adjusted returns during market downturns. We further construct quality enhanced liquidity investment strategy and test if it could survive from market drawdown.

Quality investing can be defined in a variety of ways but is typically associated with buying profitable stocks with low leverage and stable earnings. The most commonly used quality characteristic can be grouped into three main categories: profitability, safety and earnings quality. Moreover, the extension on the definition of quality include firms' capital structure, as asset growth, equity issuance and dividend payouts. Piotroski and So (2012)[32] argue that quality investment strategy represent a joint valuation together with another accounting item based measure of financial strength, the Piotroskis (2000) F-score (include Sloans accruals and Granthams quality to combine as one quality score), have dramatically outperformed traditional value strategy.

Novy-Marx (2013)[30] finds that gross profitability performs relatively better than the other quality strategies such as Grahams quality, ROIC and earnings quality, especially among large-cap US stocks. Following his insights, we implement gross profitability, the gross profits-to-assets ratio as the proxy for quality investing strategy. The combination of quality and liquidity approach that we use is also consistent with the recent surge among academic researches on conditional investment.

We sort stocks into 5 quintile based on liquidity proxy, defined as trading volume in the previous paragraph, and independently sort stocks into 5 quintile based on quality, proxied by gross profitability, which generate 25(5*5) portfolios in total. We calculate the following month value and equal weighted return on the 25 portfolios, in addition, we investigate the combined quality-liquidity portfolios, the intersection of the highest quality and the lowest liquidity portfolio.

In order to investigate the liquidity investing strategy performance during time varying liquidity period, we start with the definition on the market wide liquidity regime. The TED spread serves as market wide liquidity measurement in our model. The TED spread is the difference in yields between three-month Eurodollar deposits (effectively LIBOR) and three-month US T-bills. Thus it represents the risk premium charged on top-rated interbank loans versus risk-free loans to the US government. Historically, market observers have focused on the TED spread. Since both T-bills and Eurodollar futures are highly liquid and liquidity effects are pronounced at longer maturities. TED spread is largely a measure of credit risk, that wider spread represents deteriorating market wide liquidity condition. Frazzini and Pedersen (2014)[22] use TED spread as a measure of funding regimes and volatility of the TED spread as an empirical proxy for funding liquidity risk. Consistent with previous research, they find that a higher TED spread indicate investors facing tightness of funding constraints, possibly resulting from decreasing availability of bank credit over time, leading to a deterioration of liquidity returns over time.

TED spread is acknowledged as market wide liquidity regime separator, that the TED spread represent the level of market sentiment. In September 2008, TED spreads dramatically reached the maximum level since the Black Monday in 1987. Jones (2002)[24] finds that average spread measure exhibits frequent sharp spikes that often coincide with market downturns. We don't take ex-ante position on the threshold value of TED spreads to define market regime, rather, liquidity crises regime are defined as days in the right tail of the distribution.

We implement quantile regression to examine whether TED is a deterministic factor on the different percentile of strategies return. Mello and Perrelli (2003)[29] posit that explanatory variables can affect the dispersion, skewness, stretch one tail, fatten the other etc. If dependent variable pertain conditional distribution, it is inappropriate to estimate dependent variable using simple regression technique. The main difference between standard and quantile regression lies in the weighting schemes and the interpretation on the effect to dependent variable from all factors. Quantile regression thus provide relationships across the lower and the upper tails of the return distribution and automatically account for outliers, or extreme events in the distribution.

$$R_{i,t} = \alpha_i + \beta_{mkt,i} R_{mkt,t} + \lambda_i TED_t + \epsilon_{i,t} \tag{3.8}$$

where R_i represent conditional monthly lowest 20th percentile return from two strategies, namely quality enhanced liquidity and long only illiquidity strategy. The reason we choose such breakpoint aims at capturing the extreme case scenario. If lowest 20th return from quality enhanced liquidity strategy loads insignificantly on TED spread, while soly liquidity strategy is opposite, then we conclude that quality enhanced strategy is relatively independent on market wide liquidity dry-up.

3.4 Covariance or characteristic

As Lou and Sadka(2011)[28] pointed, Liquidity characteristic may be considered as an average effect, the mean effect overtime, whereas liquidity covariance, represented as liquidity beta may signify a volatility or correlation effect over time. We want to explore whether it is the covariance of return pattern, to what extent the liquidity of stock is exposed to the liquidity of the market or whether it is the liquidity characteristic itself, the liquidity level that determines the expected returns. We start by highlighting the difference between liquidity characteristic and liquidity covariance. We define stock's liquidity characteristic on firm-level liquidity, which denotes the 12 months rolling average trading volume. Correspondingly, we define the coefficient on liquidity factors β_{liq}, the covariance of its returns with changes in liquidity level. We estimate equity liquidity betas from 24 months rolling window regression from the following model and use market premium as the control variable:

$$R_{i,t} = \alpha_i + \beta_{mkt,i} R_{mkt,t} + \beta_{liq,i,t} R_{liq,t} + \epsilon_{i,t} \tag{3.9}$$

where R_i denotes monthly returns in excess of t-bill rate of stock i, R_{mkt} is the market premium at time t, R_{liq} represents firm level liquidity factor return, respectively. The coefficient of liquidity factor β_{liq}, is the measure for return sensitivity of a stock to liquidity variation. We allow β_{liq} for any given stock to vary over time. Stocks with higher liquidity betas are more sensitive to liquidity shocks.

To better explore the performance of strategies based on the liquidity characteristic and liquidity covariance, following Daniel and Titman (1998) [19] methodology, conditional sorting and diagonal analysis, we construct portfolios by sequentially sorting stocks equally into 5 portfolios according to the magnitude of the liquidity characteristic of prior month. Secondly, within each liquidity characteristic quintile, we conditionally sort stocks based on their ex-ante liquidity covariance β_{liq}.

We then calculate the following months average return from 25(5*5) portfolios. We separate low liquid stocks with high and low loadings on the liquidity factor-different in liquidity covariance, ie., different β_{liq}. If the covariance-based explanation for the higher observed returns of low liquid stocks is correct, a low-liquid stock with a high-liquidity factor loading should have a low average return. In contrast, if characteristic rather than covariance determine prices, a low-liquid stock should have a high return regardless of its loading. Moreover, it will guide the portfolio construction on liquidity investment.

Chapter 4

Data

In this research project, we use the Center for Research in Security Prices (CRSP) database and Wharton Research Data Services (WRDS) for from January 1st, 1962 until December 31st, 2017. The long time span covering several liquidity crisis periods eliminate data snooping doubt on our analysis.

There are huge debates and divergence on the use of NASDAQ data to analyze liquidity premium. Based on Anderson and Dyl(2007)[8], NASDAQ trading volume is over-counted due to increased level of trading on ECNs and changes to the order-handling rulesis not comparabe with NYSE. They examine the NYSE and NASDAQ trading volume relationship by a matched sample from two markets on shares outstanding and find that discrepancy has widened, such that many researchers use an adjustment factor to make NASDAQ volumes comparable to NYSE. However, Harris (2011) using data from 1993-2010, find that volumes between NYSE and NASDAQ stocks have gradually tend to similar, resulting in the homogenization of US equity markets. We don't separate or exclude NASDAQ market from the NYSE and AMEX, so that we could keep the whole data set and have more comprehensive view on the liquidity premium. which is consistent with our goal to maintain a simple unified approach and minimize the pernicious effects of data snooping.

We use monthly trading volume (Compustat data item VOL) as the main measurement of firm level liquidity. We also examine trading volume data by 'winsorizing' using 1st and 99th percentile, and the results are not been affected.

Given that the trading characteristic of ordinary equities might differ from those of others, stocks with sharecode of 10 and 11 are retained i.e., we discard certificates, American Depositary Receipts (ADRs), shares of beneficial interest, units, companies incorporated outside the United States, American Trust components, closed-end funds, preferred stocks, and Real Estate Investment Trusts (REITs). Moreover, to be included in the sample for a given month, the stock had to satisfy the following criteria: (1) Its returns in the current month and the previous 24 months are available from CRSP, and sufficient data be available to calculate the size; (2) Sufficient data be available on the COMPUSTAT tapes to calculate quality; (3) Each stock is required to have 150 days of observations over the previous year;

We define the variables used in the research as following:

We define gross profitability as firms revenues minus costs of goods sold and divided by total assets (Compustat data items REV, COGS and AT, respectively).

We define market capitalization as share price multiplied by the number of shares outstanding to determine the size of the stocks.

We use the difference between the three-month T-bill and LIBOR rates (TED spread) to identify market wide liquidity regime. The TED spread is computed using daily T-bill and LIBOR data from the Federal Reserve of St-Louis FRED database. We convert TED spread into monthly to be consistent with other factors. Our TED data run from December 1984 to December 2017.

We download SMB, HML and MOM factors from Ken-French website. All other factors including BAB, QMJ, Sadka liquidity factor, Amihud liquidity factor and Pastor and Stambaugh liquidity factor are from authors' website.

Table 4.1: This table shows the summery of the data. Eligible stocks are defined as ordinary common shares traded on the NYSE, AMEX, or NASDAQ with share code 10 and 11 from January 1963 through December 2017. Quality define as gross profitability ((REV- COCG)/AT following Novy-marx (2013). Winsorized trading volume using 1th percentile and 99th percentile. The mean, medium and standard deviation of Size and Volume is in 10^5.

	Mean	Medium	Std. Dev.	Skewness	Kurtosis
Size	18.63	1.34	117.00	20	661
Volume	0.87	0.06	6.63	97	19176
Winsorized volume	0.73	0.06	2.69	8.37	96.1
Quality	0.30	0.28	0.52	-153	39497
Price	27.65	14.63	954.00	189	40761
Share outstanding	0.54	0.12	2.75	26	1372
TED	0.55%	0.44%	0.40%	1.96	9.19

Chapter 5

Results

5.1 Liquidity factor correlation

Panel A of Table 5.1 reports the pairwise correlations among two liquidity factors that we construct ie., Liq_{firm} and $Liq_{funding}$, and other liquidity factors, including the return of a long-short portfolio sorted by the Amihud illiquidity measure, the Pastor and Stambaugh (2003)[31] traded factor is the value-weighted return on the 10-1 portfolio sorted on historical liquidity betas, the variable component of Sadka (2006)[33] market liquidity factor, TED spread and betting against beta (BAB) of Frazzini and Pedersen (2014). The Liq_{firm} significantly and positively correlated with BAB, TED and Amihud illiquidity measure, indicating that our liquidity factor is not isolated from current literature. We consistently find a negative relationship between BAB returns and the TED spread, confirming the hypothesis that TED act as market wide liquidity indication, accompanied by negative impact on the BAB premium. The negative correlation between Liq_{firm} and $Liq_{funding}$ show that firm liquidity premium is low when funding liquidity risk is high, or when stocks have high funding liquidity premium. PS_trade is derived from trading activity, while we don't find any significant correlation with our liquidity factors, one possible explanation could be PS_trade is constructed on the liquidity beta sorting, which is consistent with our finding on covariance and characteristic analysis,that liquidity beta and liquidity characteristics capture different perspective of liquidity.

Panel B and Panel C report the correlation when market premium is negative and positive, respectively. The correlation of $Liq_{funding}$ with all other liquidity measurement is higher when market premium is negative, suggesting that our funding liquidity premium denotes the ample availability of funding resource and steady funding condition during market downturn.

Table 5.1: This table presents pairwise correlations among the $Liq_{funding}$, Liq_{firm} and other liquidity measures from January 1963 through December 2017. Other liquidity factors include Amihud factor, which is the long-short equity portfolio sorted by individual stocks measure. PStrade is the Pastor and Stambaugh (2003) traded factor. Sadka is the variable component of Sadka (2006) market liquidity factor. BAB is the Frazzini and Pedersen (2014) 'betting against beta' factor. Panels A, B, and C report pairwise correlations calculated over the full sample, the months with positive market returns, and the months with negative market returns, respectively

Panel A: Pairwise correlations - unconditional

	Liq_{firm}	$Liq_{funding}$	BAB	TED	Sadka	PS_trade	Amihud
Liq_{firm}	1.00						
$Liq_{funding}$	**-0.11**	1.00					
BAB	**0.47**	**0.56**	1.00				
TED	**0.09**	**0.13**	**-0.31**	1.00			
Sadka	0.01	**0.15**	0.18	-0.28	1.00		
PS_trade	0.04	0.08	0.04	0.05	0.05	1.00	
Amihud	**0.11**	**0.23**	0.06	-0.09	-0.06	-0.01	1.00

Panel B: Pairwise correlations - negative market premium

	Liq_{firm}	$liq_{funding}$	BAB	TED	Sadka	PS_trade	Amihud
Liq_{firm}	1.00						
$Liq_{funding}$	**-0.35**	1.00					
BAB	**0.34**	**0.62**	1.00				
TED	0.04	**0.23**	**-0.46**	1.00			
Sadka	-0.05	**0.21**	**0.21**	**-0.42**	1.00		
PS_trade	0.14	0.09	0.01	0.04	**0.20**	1.00	
Amihud	0.11	**0.31**	-0.04	-0.05	-0.01	-0.01	1.00

Panel C: Pairwise correlations-positive market premium

	Liq_{firm}	$liq_{funding}$	BAB	TED	Sadka	PS_trade	Amihud
Liq_{firm}	1.00						
$Liq_{funding}$	-0.09	1.00					
BAB	**0.56**	**0.47**	1.00				
TED	0.07	0.13	**-0.21**	1.00			
Sadka	0.13	0.13	**0.18**	-0.13	1.00		
PS_trade	-0.07	0.70	-0.07	0.01	-0.07	1.00	
Amihud	0.08	**0.21**	0.12	-0.13	-0.10	-0.05	1.00

5.2 Liquidity sorted portfolio

Table 5.2 presents excess returns over T-bills and alphas with respect to, respectively, the CAPM model, the Fama and French (1993) 3-factor model (including the size factor SMB and the value factor HML in addition to the market factor MKT) , of portfolios sorted into quintiles based on their 12 month rolling average trading volume over the full sample period.

We see that excess returns and alphas decrease monotonically in trading volume quintile, with significant t statistics for both equal weighted and value weighted portfolios, confirming that illiquid stocks outperform liquid stocks on average.

Consistent with Amihud and Mendelson (1986)[6], who suggest investors demand a premium for less liquid stocks, so that expected returns should be negatively related to the level of liquidity, we document negative and significant cross-sectional relationship between average stock returns and the level of trading volume. The right-most column reports the return difference between the highest and lowest quintile and the associated t-statistic, showing that illiquid stocks earn higher average excess returns than liquid stocks (between 96 and 73 basis points per month depending on the value weighted and equal weighted portfolios), therefore, we can reject the null hypothesis of no difference in average excess returns in different trading volume portfolios (t-statistics ranging between 6.32 and 5.96).

Table 5.2 also reports time-series average post-formation period characteristics of each trading volume quintile portfolios. Not surprisingly, monthly trading volume (the ranking variable) increases from the lowest to the highest quintile. As for return volatility consideration, low liquidity portfolios are not volatile than high liquidity portfolios if volatility is evaluated by standard deviation of return. The standard deviation range from illiquid quintile1 0.12 to liquid quintile5 0.13, indicating that the higher return from illiquid portfolio doesn't accompanied by higher volatility, casting doubt on the risk-return theory if we evaluate risk in the standard deviation perspective. Quality defined as gross profitability doesn't show any monotonic trend, motivating the further analysis on the quality enhanced liquidity strategy. The size increase monotonically from the least liquid to the most liquid quintile. Liu (2006)[31] tests on a sample of US stocks by double-sorting them by both liquidity (as measured by trading volume) and size, and argues that stocks of smaller firms have higher returns because they are less liquid and suggest investors in smaller firms require higher returns for accepting liquidity risk. We dive deeper on whether liquidity investing as an separate strategy or only the projection on size, that the illiquid risk premium can be captured by size premium in the next chapter.

Table 5.3 reports the BAB portfolio return in different margin group. The higher level of idiosyncratic risk accompanied with higher margin requirement, delivers considerably lower returns. The BAB premium increases as the margin requirement decreases, however, the increasing trend is disrupted by the middle margin group to be monotonic. The difference of average excess return from two BAB portfolios return of the lowest margin group to the highest margin group is 177 basis point and significant in 95% level.

Table 5.2: This table shows the average monthly returns and the post-ranking characteristic of the trading volume-sorted portfolios from January 1963 through December 2017. Eligible stocks are defined as ordinary common shares traded on the NYSE, AMEX, or NASDAQ with sharecode 10 and 11. At each month, eligible stocks are sorted into 5 portfolios according to trading volume, where 1 indicates the low-liquidity group and 5 indicates the high-liquidity group. Reported for each quintile value and equal weighted portfolio average monthly return. The alphas are estimated as intercepts from the regressions of excess portfolio post-ranking returns on excess market returns (CAPM alpha) and on the Fama-French factor returns (Fama-French alpha). Returns and alphas are in monthly percent. Size and Volume is in 10^5. The t-statistics are in parentheses and 5% statistical significance is indicated in bold.

		Liquidity quintile					
		Low	2	3	4	High	Diff
	Excess return	**1.42**	**1.04**	**0.83**	**0.58**	0.50	**0.96**
		(6.68)	(4.32)	(3.28)	(2.21)	(1.99)	(6.32)
EW	CAPM-alpha	**0.94**	**0.45**	0.13	-0.12	**-0.25**	
		(6.48)	(3.20)	(0.93)	(-0.96)	(-2.53)	
	3-factor-alpha	**0.65**	**0.19**	-0.07	**-0.22**	**-0.29**	
		(6.59)	(2.39)	(-0.97)	(-3.24)	(-3.99)	
	Excess return	**1.74**	**1.74**	**1.65**	**1.41**	**1.05**	**0.73**
		(10.06)	(9.43)	(8.75)	(7.36)	(6.16)	(5.96)
VW	CAPM-alpha	**1.32**	**1.25**	**1.09**	**0.87**	**0.51**	
		(12.52)	(13.78)	(13.39)	(13.10)	(19.06)	
	3-factor-alpha	**1.09**	**1.05**	**0.94**	**0.81**	**0.54**	
		(12.92)	(19.32)	(16.78)	(14.40)	(21.93)	
	Volume	0.02	0.08	0.22	0.54	3.70	
	Size	1.15	1.95	4.14	10.15	80.19	
	Quality	0.28	0.31	0.32	0.31	0.31	
	Std. Dev.	0.12	0.14	0.15	0.15	0.13	

Table 5.3: This table shows the average monthly returns of BAB portfolios in each margin group from January 1963 through December 2017. Idiosyncratic volatility is calculated following Ang et al. (2006). Eligible stocks are defined as ordinary common shares traded on the NYSE, AMEX, or NASDAQ with sharecode 10 and 11. At each month, eligible stocks are sorted into 5 portfolios according to idiosyncratic volatility, where 1 indicates the low-margin group and 5 indicates the high-margin group (large idiosyncratic volatility). The BAB factor is constructed using six value-weighted portfolios formed on size and beta. At the end of each calendar month, stocks are assigned to two size-sorted portfolios based on their market capitalization and to three beta-sorted portfolios (low, medium and high) based on the 30th and 70th percentile. Portfolios are value-weighted, refreshed every calendar month. Reported for each quintile portfolio average monthly excess returns. The alphas are estimated as intercepts from the regressions of excess portfolio post-ranking returns on excess market returns (CAPM alpha) and on the Fama-French factor returns (Fama-French alpha). Returns and alphas are in monthly percent. The t-statistics are in parentheses and 5% statistical significance is indicated in bold.

	Margin quintile					
	Low	2	3	4	High	Diff
Excess return	0.13	**0.39**	**0.31**	**0.82**	**1.89**	**1.77**
	(1.82)	(2.45)	(4.42)	(5.32)	(6.75)	(3.89)
CAPM-alpha	0.07	**0.31**	0.28	**0.57**	**1.32**	
	(0.58)	(2.03)	(1.93)	(2.96)	(3.53)	
3-factor-alpha	0.01	**0.24**	0.17	0.45	**1.16**	
	(1.72)	(2.24)	(1.15)	(1.24)	(2.99)	

5.3 Liquidity and size

Practitioners and academics have long held consensus that liquidity premium is highly correlated with size premium. We also find size increase along with the increase of liquid characteristic portfolio. Amihud and Mendelson (1986)[6] find that the size effect is closely linked to liquidity risk, measured as bid-ask spread. Overall, these sorts of studies confirm that small firms contribute to the risk embedded in illiquid firms. These researchers, following classical theory, essentially claim that smaller firms are riskier than larger firms on average and identify there are commonalities and co-movement for underlying sources of risk from liquidity and size. In a recent study, Ibbotson et al. (2013)[23] empirically studied the effect on returns from different levels of liquidity proxied by turnover across all size quintile portfolios of publicly traded stocks, and find that within each size quintile portfolio, low liquidity portfolios generally earned higher returns than the high liquidity portfolios, however, the size impact is quite inconsistent across various levels of liquidity portfolios.

In order to analyze the interacted relationship between size and liquidity premium, We independently sort 5-by-5 portfolios based on size and liquidity from value weighted and equal weighted. Table 5.4 reports the results of the 25 size-liquidity portfolios average raw return (along with their standard deviation below). Moving across the columns, there is a significant liquidity trend, as the stocks with lowest liquidity on average outperform the ones with highest liquidity, and that the outperformance is almost monotonically decrease across the size quintiles. The same holds in equally weighted portfolios. What's more, this presents another way to control for size in looking at the liquidity effect.

Conversely, the size effect does not hold strictly along with the liquidity quintiles, especially the middle size portfolio disrupt size premium in both equal weighted and value weighted portfolios. Small size portfolio at liquid quintile2 with average return of 0.21% even under-perform large stock within the same liquidity quintiles with average return 2.11%, thus we can't conclude liquidity strategy as equal to size strategy. Therefore, size does not capture liquidity, i.e. the liquidity premium holds regardless of size group. Conversely, the size effect does not hold across all liquidity quintiles, especially in the highest trading volume quintile. Specifically, among low liquidity stocks, small-sized stock portfolio doesn't earn higher returns than the large stock portfolio, the opposite is true for high liquid stocks. It's worth to noting that the liquidity premium is higher in small portfolios than it in the large portfolios, as the dispersion between high liquidity and low liquidity is wider in small group.

Table 5.4: This table shows the value weighted and equal weighted average monthly returns of double independently sorted portfolios on size and liquidity (trading volume) from January 1963 through December 2017. Eligible stocks are defined as ordinary common shares traded on the NYSE, AMEX, or NASDAQ with share code 10 and 11. At each month, eligible stocks are independently and separately sorted into quintiles according to each stocks size and rolling 12 months rolling trading volume (liquidity measure). Reported for each intersection portfolio value and equal weighted portfolio average monthly returns and return standard deviation. Returns are in monthly percent.

	Value Weighted portfolio					Equal weighted portfolio				
Quintiles	Low LIQ	2	3	4	High LIQ	Low LIQ	2	3	4	High LIQ
Small	1.81	0.21	-1.47	-3.51	-6.79	1.22	-0.61	-2.47	-4.42	-7.76
Std. Dev.	6.18%	8.07%	4.73%	12.52%	16.78%	6.67%	8.51%	10.10%	12.88%	17.22%
2	2.40	2.09	1.00	-0.62	-2.73	2.40	2.00	0.83	-0.78	-2.83
Std. Dev.	4.92%	6.72%	8.28%	10.06%	13.04%	4.97%	6.82%	8.36%	10.17%	13.22%
3	2.43	2.41	2.10	1.22	-0.60	2.46	2.41	2.03	1.09	-0.74
Std. Dev.	4.58%	5.42%	6.75%	8.22%	10.63%	4.60%	5.52%	6.87%	8.36%	10.77%
4	2.18	2.25	2.16	2.00	1.08	2.24	2.25	2.17	1.99	0.97
Std. Dev.	4.53%	4.40%	4.95%	6.16%	8.40%	4.41%	4.44%	5.09%	6.39%	8.64%
Large	1.97	2.11	2.13	1.96	1.45	1.95	2.21	2.15	1.93	1.50
Std. Dev.	5.73%	4.73%	4.13%	4.34%	4.32%	5.33%	4.81%	4.22%	4.50%	5.13%

5.4 Liquidity as a factor

We probe more deeply into the potential underpinnings of liquidity premium by constructing liquidity factor both on firm level and funding liquidity level. We examine whether our liquidity factor can be absorbed by other common risk factors. Table 5.5

reports the results of time series regressions in which both liquidity factors are the dependent variable and various common risk factors are the explanatory variables. We find that when Liq_{firm} is regressed on the market premium over the July 1962 to December 2017, the intercept is 4.09% per month with a t-statistic of 16.43, which is significantly different from zero, suggesting that the CAPM can't explains the returns to firm level liquidity pretty well. The next columns add the factors of SMB, HML, MOM and QMJ. We see that the Liq_{firm} has a significantly negative market and size exposures. As would be expected, the Liq_{firm} has the negative market exposure, firm level liquidity premium is lower during market drawdown, the 'flight to liquidity' and 'flight to quality' effect contribute to such negative loading. The value exposure of Liq_{firm} is positive, one possible explanation is that illiquid stocks have lower prices and the value factor HML is taking long position on relatively low price stocks, we would expect a positive HML loading.

Table 5.5 also reports time series regression results of $Liq_{funding}$ on a variety of factors. It shows in columns 2 that although the funding liquidity factor is based on the BAB portfolios, the latter cannot fully explain the return spread of $Liq_{funding}$: the alpha is still significant with magnitudes of 0.9% per month. Columns 3 to 6 present the results when several common risk factors are added sequentially, including the market factor, the size factor, the value factor and the momentum factor. $Liq_{funding}$ has a significant positive loading on the market premium, suggesting the fact that funding liquidity co-movement with market premium, which is opposite to the Liq_{firm}. Comparing with the Liq_{firm}, $Liq_{funding}$ loading on other common risk factors are less obvious. $Liq_{funding}$ loads negatively on the Liq_{firm}. This observation could possibly due to stocks with high funding liquidity premium also pertain high trading volume. Overall, there are significant rooms left unexplained for liquidity factors using common risk factors.

Table 5.5: This table reports time series alphas, beta loadings, and adjusted R^2 when Liq_{firm} and $Liq_{funding}$ are regressed on common risk factors from January 1963 through December 2017. Common factors include the BAB factor, the size factor, the value factor, the Carhart momentum factor and QMJ factor. Returns and alphas are in monthly percent. The t-statistics are in parentheses and 5% statistical significance is indicated in bold.

	Firm level liquidity factor as dependent variable				
	(1)	(2)	(3)	(4)	(5)
Alpha(%)	**4.09**	**3.99**	**3.44**	**2.48**	**2.51**
	(16.43)	(16.81)	(15.97)	(11.79)	(10.44)
MKT	**-0.84**	**-0.68**	**-0.56**	**-0.15**	**-0.20**
	(-14.80)	(-11.93)	(-10.74)	(-2.77)	(-3.26)
SMB		**-0.59**	**-0.62**	0.02	-0.10
		(-7.22)	(-8.62)	(0.24)	(-1.10)
HML		**0.25**	**0.47**	**0.73**	**0.78**
		(2.91)	(5.93)	(9.73)	(9.45)
MOM			**0.64**	**0.49**	**0.54**
			(12.61)	(10.73)	(10.39)
QMJ				**1.58**	**1.56**
				(13.72)	(11.43)
$Liq_{funding}$					**-0.07**
					(-2.61)
adj.R^2	27%	35%	49%	63%	68%

	Funding liquidity factor as dependent variable					
	(1)	(2)	(3)	(4)	(5)	(6)
Alpha(%)	**1.80**	**0.90**	**0.80**	**0.60**	**0.63**	0.74
	(2.16)	(3.08)	(2.92)	(2.78)	(2.62)	(1.49)
MKT	**0.18**		**0.21**	**0.74**	**0.68**	**0.66**
	(4.98)		(3.11)	(2.80)	(2.73)	(2.59)
BAB		**0.93**			**0.81**	**0.73**
		(3.77)			(2.88)	(2.50)
SML			**0.72**	**0.69**	0.69	0.71
			(5.55)	(5.40)	(1.42)	(0.74)
HML			0.21	0.11	0.061	0.20
			(0.49)	(0.75)	(1.03)	(1.20)
MOM				0.34	0.11	0.32
				(1.74)	(1.26)	(0.80)
Liq_{firm}						-0.62
						(-1.69)
adj. R^2	8%	17%	9%	10%	18%	18%

Acharya and Pedersen (2005) [1] explicitly provide a simple equilibrium model of liquidity adjusted CAPM and suggest that including liquidity as common risk factor improves pricing accuracy. We test liquidity to act as common risk factor by examine how Liq_{firm} can help to explain common risk factors and capture the risk premium from them. As showed in the table 5.6, the alphas of the value factor and the momentum factor are not statistically significant, with significant loading on the Liq_{firm}, indicating that Liq_{firm} capture the factor premium of these two systematic factors. Liq_{firm} continuously fail to capture factor premium from size (SMB) and quality (QMJ) factor, with 0.24% monthly alpha unexplained, leading us to further explore the interaction between quality and size with liquidity investment strategy.

$Liq_{funding}$ works well to explain the size and momentum premium but fail to explain value premium. Although our $Liq_{funding}$ is derived from BAB factor, which indeed has significant loading on liquidity factor, however, with 0.31% unexplained monthly alpha left. Although $Liq_{funding}$ can't fully capture all value premium statistically, the alpha is economically insignificant.

Both liquidity factors are able to capture momentum premium, with insignificant alpha from both liquidity factor regression, showed in table 5.6, which is consistent with the findings of Sadka (2006)[33], who posit that if trading volume used to project demand of the stocks, there is a contemporaneous and structural connection between overreaction and high trading volume. The variations in liquidity help to explain a component of the excess profits from both price and earnings momentum strategies, besides, momentum portfolio generate higher return under positive liquidity shocks than negative shocks. Moreover, Pastor and Stambaugh (2003)[31] find that liquidity spread explains half of the excess returns earned from momentum portfolios.

We also mention that the cross sectional liquidity premium is economically substantial and not driven merely by the extreme portfolios since we construct liquidity factor mimicking portfolio with adjustment of size. Finally, we show cumulative return from our liquidity factors and other common risk factors in figure1, Liq_{firm} outperform all the other factors.

Table 5.6: This table reports the time series alphas, beta loadings, and adjusted R^2 when common risk factors are regressed on theLiq_{firm} (Panel A) and $Liq_{funding}$ (Panel B) and the market factor. Common factors include the BAB factor, the size factor, the value factor, the Carhart momentum factor and QMJ factor. Returns and alphas are in monthly percent. The t-statistics are in parentheses and 5% statistical significance is indicated in bold.

Panel A				
	SMB	HML	MOM	QMJ
Liq_{firm}	**-0.17**	**0.11**	**0.23**	**0.24**
	(-10.52)	(7.05)	(10.15)	(21.65)
Alpha(%)	**0.72**	-1.41	-0.18	**-0.44**
	(5.61)	(-1.13)	(-0.97)	(-4.91)
adj. R^2	15.81%	7.70%	14.89%	47.16%
Panel B				
	SMB	HML	MOM	BAB
$Liq_{funding}$	**0.25**	0.06	0.15	**0.57**
	(2.35)	(0.19)	(0.93)	(2.35)
Alpha(%)	0.16	**0.15**	0.92	**0.31**
	(0.04)	(2.94)	(2.13)	(4.25)
adj. R^2	7.5%	0.1%	0.5%	9.0%

5.5 Liquidity as a strategy

As shown above that liquidity premium is not the projection of existing risk factor, we start to demonstrate that liquidity as an investment strategy. Besides the hedging strategies represented by two liquidity factors, we further explore long only and quality enhanced liquidity strategies.

Liquidity strategy is often criticized by its vulnerable performance during crisis due to 'flight to quality' and 'flight to liquidity'. In order to construct liquidity based strategy that continuously outperform, we combine with quality investing. Table 5.7

show average raw return from 25 portfolio, formed from independent sorting of stocks into five quintiles on liquidity and quality, with liquidity proxied by 12 months rolling average trading volume and quality by gross profitability. Admittedly, junk is more correlated with illiquid stocks and quality is more linked to liquid stocks, while there are plenty of liquid and junk stocks, illiquid and quality stocks so that we can examine the interactions between liquidity and quality. Besides, quality characteristic seems to be flat among liquidity quintile portfolios, as showed in table 5.2.

When we look into table 5.7, among the high-quality stocks, the value weighted illiquid portfolio has monthly average return of 2.69% while the most liquid portfolio has a return of 1.56%. For junk stocks, the illiquid stock portfolio has monthly average return of 1.63% while the most liquid stock portfolio has a monthly return of 1.25%. The best return comes from combining quality with illiquid stocks, while the worst return comes from junk stocks with high-liquid stocks. Given that high quality stocks tend to outperform junk stocks in general, comparing stocks of same liquidity level, the liquidity effect is fighting a headwind due to the low quality of liquid stocks. In other words, illiquid quality stocks outperform liquid quality stocks, and illiquid junk stocks outperform liquid junk stocks, although the middle liquid level portfolios suffer from a liquid-quality composition effect. The corner portfolio with the highest quality and the lowest liquidity portfolio continuously outperform the others.

The relation between liquid and quality/junk present another challenge for asset pricing models. For example, the returns to illiquid portfolios are not less stable than liquid portfolios, the same goes to quality quintiles. The return standard deviation of quality portfolio is 4.61% or 5.96% depends on value weighted and equal weighted, while the junk portfolio return standard deviation is 5.61% or 7.11%, respectively within the high liquid group. This makes risk-based explanations for the liquidity effect more challenging not only because of its very high Sharpe ratio, but also because of the riskiest illiquid stocks the illiquid junk stocks are not the securities that drive a significant positive liquidity premium, as a risk story implies, with only 1.63% monthly return on average. Rather, it is the illiquid and quality stocks that seem to drive the high expected returns. These results are difficult to reconcile in a risk based framework and suggest that high quality illiquid stocks may be under-priced. There remains the possibility of new risk-based explanations we have not yet considered. However, admittedly, since liquidity is measured with noise and there are a lot of debates on how to measure it, we interpret these results with caution.

Table 5.7: This table shows the value weighted and equal weighted average monthly returns of double independently sorted portfolios on gross profitability ((REV-COCG)/AT, as defined by Novy-marx (2013) and liquidity (trading volume) from January 1963 through December 2017. Eligible stocks are defined as ordinary common shares traded on the NYSE, AMEX, or NASDAQ with stock code 10 and 11. At each month, eligible stocks are independently and separately sorted into quintiles according to each stocks size and rolling 12 months rolling trading volume (liquidity measure). The highest gross profitability portfolios are called quality. Reported for each intersection portfolio value and equal weighted portfolio average monthly returns and return standard deviation. Returns are in monthly percent.

	Value Weighted portfolio					Equal weighted portfolio				
Quintiles	Low LIQ	2	3	4	High LIQ	Low LIQ	2	3	4	High LIQ
Quality	2.69	2.77	2.38	2.09	1.56	2.28	2.28	1.76	1.58	1.37
Std. Dev.	5.02%	5.58%	5.41%	5.25%	4.61%	6.16%	6.73%	6.53%	6.46%	5.95%
2	2.36	2.12	2.14	1.90	1.34	2.05	1.63	1.46	1.37	1.20
Std. Dev.	5.16%	5.91%	5.69%	5.38%	5.04%	5.71%	6.66%	6.79%	6.77%	6.51%
3	2.41	2.14	2.09	1.87	1.38	1.85	1.53	1.42	1.19	1.08
Std. Dev.	5.72%	5.67%	5.63%	5.64%	4.93%	6.03%	6.35%	6.59%	6.77%	6.43%
4	2.13	1.85	1.77	0.02	1.36	1.86	1.30	1.11	1.13	0.94
Std. Dev.	5.10%	5.35%	5.08%	4.91%	4.92%	5.49%	6.21%	6.22%	6.41%	6.19%
Junk	1.63	1.76	1.81	1.79	1.26	1.44	1.33	1.16	0.88	0.64
Std. Dev.	4.39%	4.92%	5.55%	6.09%	5.61%	4.87%	5.53%	6.73%	7.53%	7.11%

To analyze the quality enhanced liquidity strategy, we regress the corner portfolio on common risk factors, that the intersection portfolio from the highest quality quintile and the lowest liquidity quintile. We assume that long-only investors take long position on the illiquid portfolio, ie., the lowest trading volume of quintile1 at table 5.2. We analyze the strategy performance by employing the standard CAPM, the Fama and French 3-factors model and the 4-factors model augmented of momentum factor on average monthly return. The results are presented at table 5.8, the monthly alphas are all significant at 95% level, from 0.87% to 0.59% depends on the adjusting factors. Besides, long only illiquid portfolio show positive and statistically significant monthly alphas (1.34%, 1.11% and 1.11%). One possible explanation is the 'flight to quality' and 'flight to liquidity' trend during market drawdown, where the quality stocks are relatively more attractive, thus weakening the effect of illiquidity premium. At the same time, the prices of liquid stocks drop more than the prices of illiquid stocks thus increasing the relative demand for quality stocks and mitigates price decline from illiquid stocks. Figure 2 shows the cumulative return from these two strategies, quality enhanced illiquidity strategy outperform long only illiquidity strategy, we interpret as quality enhanced strategy pertain lower downside risk during market drawdown, which protect it from losing accrued return over time.

Table 5.9 reports the results on the quantile regression on the TED spread and market premium as control variable, TED has significant negative impact on the lowest 20th return for long only illiquid strategy with t statistic -2.18. While for quality enhanced strategy, TED doesn't significantly explain return, even in the lowest 20th percentile, that is the lowest return from quality enhanced portfolio is not attribute to the market wide liquidity condition.

We assume that liquidity investment strategy return during market wide liquidity crisis are strongly related to the TED spread, such co-movement lead to 'flight to quality' and 'flight to liquidity', while TED spread has no explanatory power on quality enhanced portfolio return. The deep dive from quantile regression ascertain our conjecture that the lowest 20th of strategy return without enhanced by quality has significant loading on TED spread, indicating that strategy return might suffer from shocks of market downturn, especially liquidity dry-up.

Table 5.8: This table shows time series regressions of two liquidity based long only strategies on common risk factors from January 1963 through December 2017. Panel A reports time series alphas, beta loadings, and adjusted R2 when the lowest liquidity portfolio (lowest 12 months rolling trading volume) return in excess of risk free rate on the common risk factors. Panel B reports the time series alphas, beta loadings, and adjusted R2 when quality based liquidity portfolio return in excess of risk free rate on the common risk factors. Quality based liquidity portfolio is intersection portfolio of the highest quality quinitle and the lowest liquidity quintile. Common factors include The explanatory variables are Fama and French (1993) size factor and value factor and Carhart (1997) momentum factor. Returns and alphas are in monthly percent. The t-statistics are in parentheses and 5% statistical significance is indicated in bold.

	Long low liquid strategy			Quality enhanced strategy		
	(1)	(2)	(3)	(1)	(2)	(3)
Alpha(%)	**1.34**	**1.11**	**1.13**	**0.88**	**0.59**	**0.59**
	(12.99)	(13.65)	(13.64)	(6.92)	(5.50)	(5.42)
MKT	**0.79**	**0.77**	**0.76**	**0.67**	**0.68**	**0.67**
	(34.06)	(39.70)	(38.72)	(23.51)	(26.49)	(25.94)
SMB		**0.47**	**0.47**		**0.41**	**0.41**
		(17.27)	(17.29)		(11.31)	(11.30)
HML		**0.42**	**0.41**		**0.55**	**0.55**
		(14.34)	(13.66)		(14.02)	(13.60)
MOM			-0.03			-0.01
			(-1.37)			(-0.20)
adj. R^2	64%	78%	78%	45%	62%	62%

Table 5.9: This table shows time series regressions of liquidity strategy returns on TED spread and market premium from December 1984 (first available date for the TED spread) through December 2017. It reports the time series alphas, factor loadings from quantile regression of long only illiquid strategy return and quality enhanced liquidity portfolio return on TED spread and market premium as control variable, respectively, we use 20th, and 80th as break-point. Returns and alphas are in monthly percent. The t-statistics are in parentheses and 5% statistical significance is indicated in bold.

Quantile regression						
	Long low liquidity strategy			Quality enhanced strategy		
	(1)	(2)	(3)	(1)	(2)	(3)
	q20	q50	q80	q20	q50	q80
MKT	**0.67**	**0.63**	**0.59**	**0.65**	**0.55**	**0.48**
	(12.68)	(14.13)	(15.77)	(15.39)	(8.91)	(6.53)
TED	**-1.55**	**-0.92**	-0.30	-1.52	-0.86	-0.07
	(-2.18)	(-2.51)	(-0.51)	(-1.69)	(-1.21)	(-0.13)
Alpha(%)	0.35	**1.56**	**3.29**	-6.37	**1.27**	**3.28**
	(0.86)	(8.64)	(9.11)	(-0,27)	(3.75)	(8.82)

5.6 Liquidity as covariance or characteristic

Liquidity literature are using liquidity covariance pattern instead of measuring the liquidity characteristic itself to explain cross sectional return. Daniel and Titman (1998)[19] pose an diagonal methodology to examine whether characteristic or the sensitivity to the liquidity factor has a larger impact on a stocks performance.

Table 5.10 shows the raw return from conditional sorting of liquidity characteristic and liquidity covariance. The raw return across liquidity characteristic vary strongly than the return across β_{liq}; that is, the portfolios in each rows are similar in terms of the return β_{liq} but differ according to liquidity characteristic (proxied by trading volume), thus supporting the hypothesis that liquidity premium is highly dependent on characteristic rather than covariance structure.

Contrary to the conclusion from Lou and Sadka (2011)[28], liquidity covariance dominate on the return structure to the portfolios' expected return during 2007-2008 financial crisis, the high liquidity beta portfolios, both liquid and illiquid in their characteristic, exhibited more significant drop than low liquidity beta portfolios. We don't find covariance dominance structure in our analysis, one possible explanation is that investors indeed prefer more liquid portfolios over the turbulent period, and high β_{liq} stocks are more vulnerable to the market drawdown, that the longer span covered in the paper mitigate dominance effect during crisis. Under illiquid market wide conditions, many investors sell more liquid stocks with smaller bid/ask spread to lower transaction cost compared with illiquid assets with increasingly higher transaction cost. As a result, the price reaction to aggregate liquidity changes could actually be stronger for stocks that are more sensitive to market liquidity change. Also, prices of liquid stocks react strongly to aggregate liquidity shocks if such stocks are held mostly by the more liquidity-sensitive investors, from which the sensitivity is captured by β_{liq}. Our long sample analysis from 1962 to 2017 provide comprehensive liquidity investing structure rather than merely crisis focused insights. In conclusion, liquidity covariance is not directly linked to expected return, however, it is useful for portfolio selection to consider covariance structure during market drawdown.

Table 5.10: This table shows the value weighted average monthly returns of conditional sorted portfolios liquidity beta and liquidity (trading volume) from January 1963 through December 2017. Eligible stocks are defined as ordinary common shares traded on the NYSE, AMEX, or NASDAQ with sharecode 10 and 11. At each month, eligible stocks are sequentially and conditionally sorted into 5 portfolios according to the magnitude of rolling 12 months rolling average trading volume (liquidity measure) of previous period. Second, within each liquidity characteristic quintile, stocks are further sorted based on their ex-ante liquidity covariance (liquidity beta).Reported for each intersection portfolio value average monthly returns and return standard deviation. Returns and alphas are in monthly percent. Size and Volume is in 10^5.

		Liquidity quintiles					Portfolio characteristics (Size)				
		Low LIQ	**2**	**3**	**4**	**High LIQ**	**Low LIQ**	**2**	**3**	**4**	**High LIQ**
	High β_{liq}	2.32	2.15	1.99	1.81	**1.37**	1.35	2.09	4.38	10.42	93.88
	Std. Dev.	4.69%	4.67%	4.56%	4.35%	**4.07%**					
	4	1.84	1.77	1.73	1.57	1.33	2.35	3.65	7.63	19.02	152.00
β_{liq}	Std. Dev.	4.01%	4.21%	4.26%	4.22%	4.07%					
quintiles	**3**	1.95	2.00	1.96	1.84	1.40	1.37	2.53	5.83	14.65	115.00
	Std. Dev.	3.91%	4.38%	4.76%	4.85%	4.78%					
	2	2.38	2.72	2.54	2.26	1.71	0.73	1.44	3.00	7.76	57.03
	Std. Dev.	4.34%	5.82%	6.13%	6.42%	5.99%					
	Low β_{liq}	**3.69**	3.55	3.22	3.15	2.39	0.37	0.69	1.35	2.91	18.98
	Std. Dev.	**6.57%**	7.93%	8.26%	8.99%	8.30%					
		Portfolio characteristics (vol)					Portfolio characteristics (ex-post β_{liq})				
		Low LIQ	**2**	**3**	**4**	**High LIQ**	**Low LIQ**	**2**	**3**	**4**	**High LIQ**
	High β_{liq}	0.02	0.09	0.22	0.52	2.93	0.95	0.98	0.96	0.91	0.68
β_{liq}	**4**	0.02	0.1	0.27	0.69	4.2	0.15	0.14	0.14	0.13	0.12
quintiles	**3**	0.02	0.09	0.26	0.69	4.9	-0,09	-0.14	-0.16	-0.15	-0.13
	2	0.02	0.09	0.22	0.6	4.67	-0.41	-0.54	0.57	-0.57	-0.49
	Lowβ_{liq}	0.02	0.08	0.2	0.46	3.65	-1.53	-1.83	-1.91	-1.98	-1.75

Chapter 6

Conclusion

6.1 Summary

Liquidity plays a crucial role in financial markets. Academic researchers, practitioners, and policy makers are interested in how to correctly measure liquidity. In this paper, we analyze liquidity risk premium from firm level to aggregate level, from time series and cross section of stock returns, and provide following implication for liquidity investment.

Our firm level liquidity factor and funding liquidity factor cannot be explained by other stock market risk premium, and significant account for existing common risk factors, indicating our liquidity factors capture the risk premium that existing model fail to include and liquidity factors potentially act as common risk factor. Further, we specifically examine the relationship between size and liquidity, confirming that liquidity investment strategy is hardly the other projection of size. We show that quality enhanced liquidity portfolio performance is independent of market wide liquidity crisis. We also conduct analysis on the liquidity premium as covariance or characteristics using conditional sorting method of Daniel and Titman(1998)[19]. We find that liquidity characteristic rather than the covariance structure has stronger explanation power on liquidity premium during the whole sample period, results that do not lend support to Lou and Sadka (2011)[28] who suggest that liquidity covariance is more important than liquidity characteristic, especially during extreme crisis. Lastly, we implement quantile regression to test our quality enhanced liquidity strategy performance during market wide liquidity condition, showing our strategy is immune from 'flight to quality' during market wide liquidity crisis.

6.2 Future work

In our empirical work we use trading volume as the proxy for firm level liquidity and idiosyncratic risk as proxy for margin requirement, of course, there is always the possibility that these measures are not able to fully represent the liquidity condition of the stocks, and associate some unknown and as yet undiscovered risk factors, or the anomalies in behavioral analysis. However, we mitigate by the noise through analyzing risk adjusted returns, adjusted by Fama and French factors and market exposure to control well-known return determinants, and our results is robust after adjustment.

In addition, our using of TED spread to split market wide liquidity regime is limited and arbitrary, which we think further investigation on the indicators and implementation of Markov-chain model to detect market regime would appear to be a reasonable topic. Besides, adding macroeconomic indicators is another perspective to fully reflect market risk consideration when identifying stock market regimes.

Furthermore, it is interesting to examine the persistence feature of liquidity as an investment strategy, for which could reach optimal re-balancing frequency and reduce transaction costs. It would also be useful to explore whether some form of systematic liquidity risk is priced in other financial markets, such as fixed income markets or international equity markets.

Chapter 7

Figures

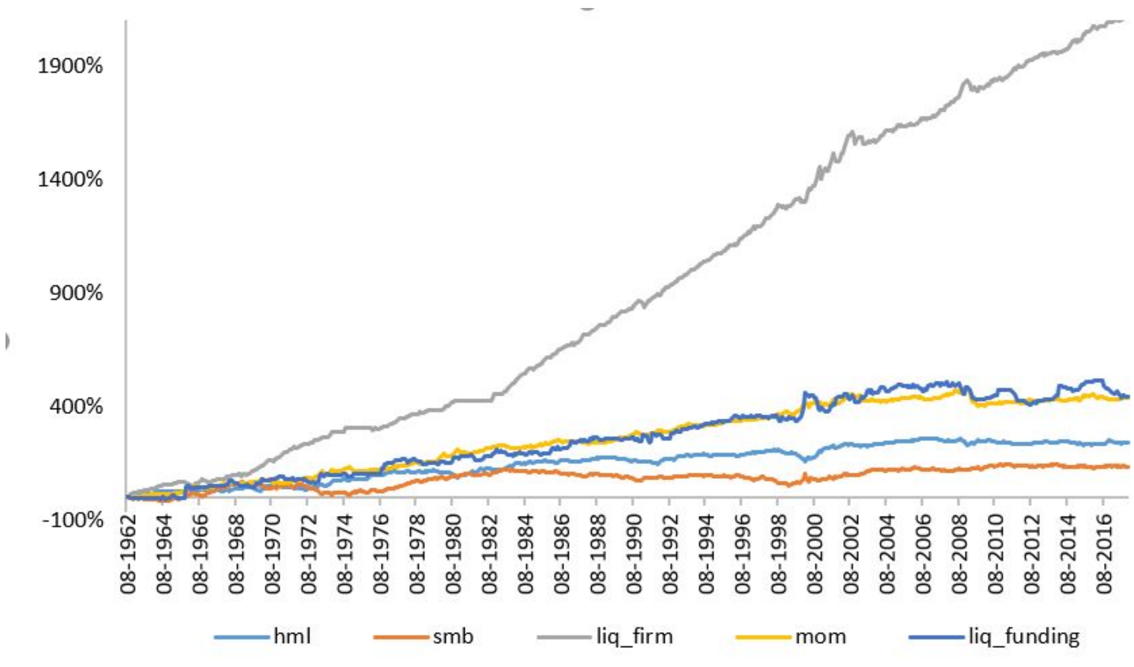

Figure 7.1: This figure shows cumulative returns of $Liq_{funding}$, Liq_{firm} and other systemic risk factors from January 1963 through December 2017. Other liquidity factors include size (small-minus-big, SMB), book-to-market (high-minus-low, HML), and momentum (up-minus-down, MOM).

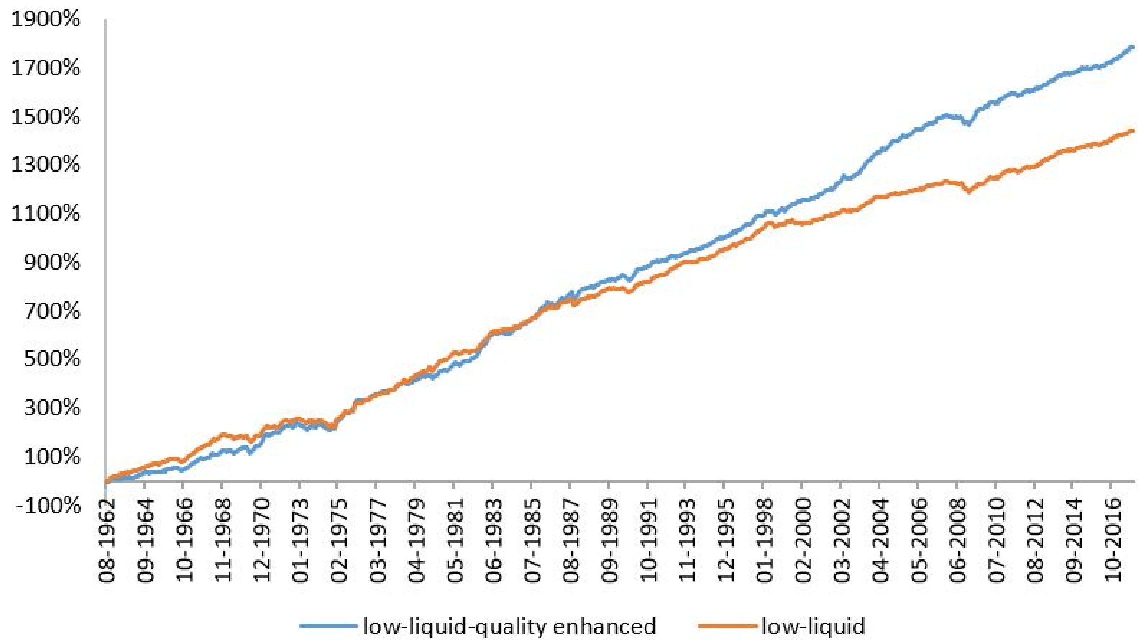

Figure 7.2: This figure shows cumulative returns from January 1963 through December 2017.Quality enhanced liquidity strategy is taking long position on the intersection portfolio of the highest quality quintile and the lowest liquidity quintile. Low-liquid strategy is taking long position on the illiquid portfolio, ie., lowest trading volume of quintile1 at Table2.

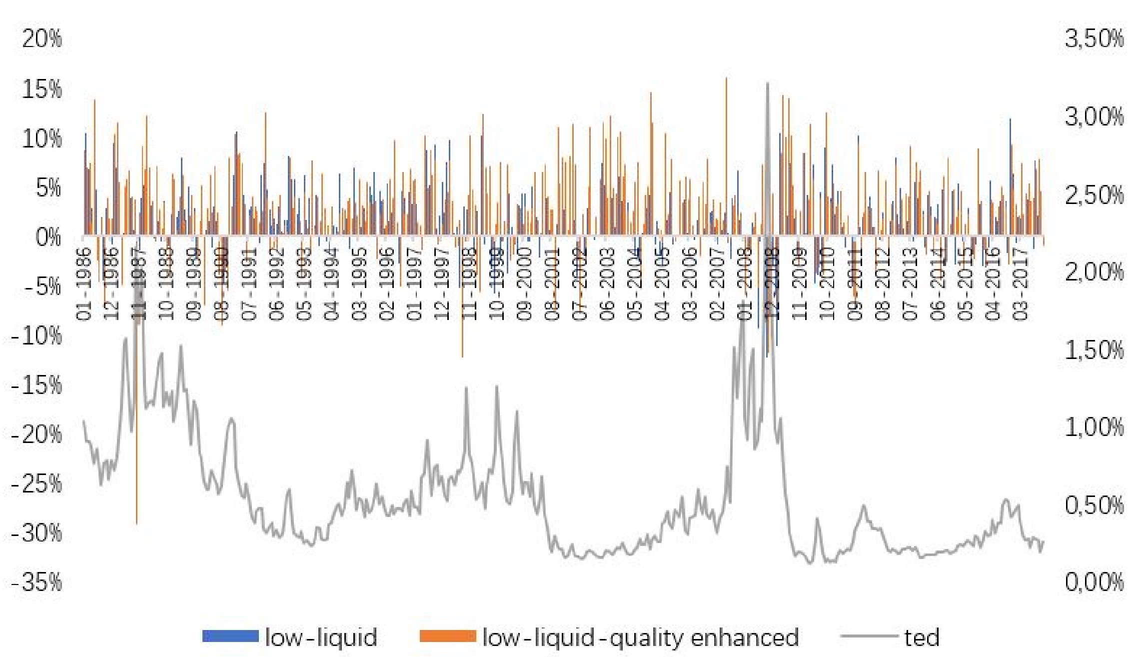

Figure 7.3: This figure shows monthly time series two strategies return (left scale) and TED spread (right scale) from January 1986 through December 2017. Quality enhanced liquidity strategy is taking long position on the intersection portfolio of the highest quality quintile and the lowest liquidity quintile. Low-liquid strategy is taking long position on the illiquid portfolio, ie., lowest trading volume of quintile1 at Table2.

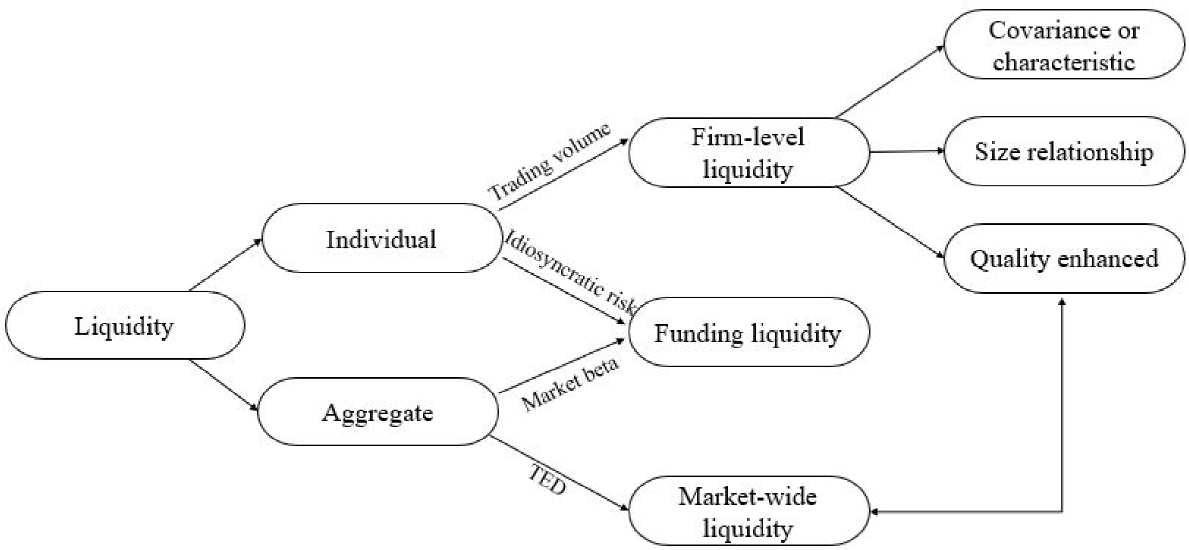

Figure 7.4: This figure shows the liquidity framework presented in the paper. For individual, firm-level liquidity is proxied by trading volume, for aggregate, market-wide liquidity is proxied by Ted. The individual part of funding liquidity is captured by idiosyncratic risk; the aggregate part of funding liquidity is captured by market beta. Firm level liquidity premium interacts with size but not the projection of size. Liquidity characteristic accounts for the return variance rather than liquidity covariance. The quality enhanced portfolio performance is independent of the market-wide liquidity condition.

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