Pervasive Liquidity Risk And Asset Pricing

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Abstract

This paper constructs a measure of pervasive liquidity risk and its associated risk premium. I examine seven market-wide liquidity proxies and use Principal Component analysis to extract the first principal component, which captures 62% of the standardized liquidity variance. The first common factor is rewarded with a significant premium in cross-sectional asset pricing tests. Moreover, from 1971 through 2002, a difference in liquidity risk contributes 3.70% to the difference in annualized expected return between high liquidity beta and low liquidity beta stocks. Liquidity risk is different from volatility effects, and provides a partial explanation for momentum. Stock market liquidity risk is priced in the bond markets as well. Finally, there is a significant negative relation between liquidity and the conditional variance of monthly stock returns, and the liquidity measure subsumes traditional GARCH coefficients in the conditional variance.

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1 Introduction

The importance of liquidity to asset pricing has received substantial attention recently. Using a wide variety of liquidity measures, a number of empirical studies have investigated the relation between the level of liquidity and expected returns.[1] An important motive for considering a market-wide liquidity measure as an important priced factor is evidence of the existence of commonality across stocks in liquidity fluctuations.[2] If liquidity shocks are non-diversifiable and have a varying impact across individual securities, the more sensitive an asset's return is to such shocks, the greater must be its expected return. Whether and to what extent liquidity has an important bearing on asset pricing is still in debate. The first contribution of this paper is to try to resolve this debate.

The underlying difficulty for examining whether liquidity is important in asset pricing is due to the fact that liquidity is unobservable. Liquidity generally denotes the ability of investors to trade large quantities quickly, at low cost, and without substantially moving prices.[3] Different liquidity proxies have been employed in the literature. Eckbo and Norli (2005) use stock turnover, Pastor and Stambaugh (2003) develop a return reversal measure, and Acharya and Pederson (2003) investigate a price impact measure. These liquidity measures capture only noisy information of liquidity. Hence, I use Principal Component analysis to extract a common source of liquidity variation from seven different liquidity proxies constructed from daily data. I find that the first principal component captures 62% of the standardized liquidity variance, and the first three components represent 87% of the data variation. Moreover, the first component, with uniform positive loadings on the seven liquidity measures, has a correlation coefficient of -52.8% with market volatility. This is consistent with Pastor and Stambaugh's (2003) finding that periods experiencing adverse liquidity shocks generally coincide with high market volatility. The other principal components are harder to interpret. This evidence clearly shows that the first principal component captures the common source of time variation of the seven liquidity proxies.

I then use the first principal component in cross sectional asset pricing tests. Using 5×5 size and liquidity beta sorted portfolios, I find that the common liquidity factor is rewarded with a significant risk premium. Except for the first principal component,

[1]For example, Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), Brennan, Chordia, and Subrahmanyam (1998), and Datar, Naik, and Radcliffe (1998) find that less liquid stocks have higher average stock returns.

[2]Chordia, Roll, and Subrahmanyam (2000) find significant market-wide liquidity comovement even after controlling for individual liquidity determinants. Huberman and Halka (2001) document the existence of systematic liquidity by finding positive correlations in liquidity innovations across portfolios. Hasbrouck and Seppi (2001) identify only weak evidence of commonality in intraday liquidity fluctuations.

[3]Hodrick and Moulton (2005) is the only theoretical paper so far that tries to capture these three dimensions of liquidity.

the rest principal components are not priced in the cross-section of stock returns. These results indicate that although there are different liquidity proxies, which are dramatically different in theory, they share a common source of variation. I can thus extract this common source of liquidity to be a unique liquidity risk measure. This paper makes a contribution to attacking a related important question of what is the best way to represent pervasive liquidity risk.

Only a few recent studies investigate whether liquidity risk is a pervasive priced risk factor (for example, Eckbo and Norli (2005), Pastor and Stambaugh (2003), Acharya and Pederson (2003)). These studies use different liquidity proxies. This paper is most closely related to Eckbo and Norli (2002). Eckbo and Norli (2002) collect six liquidity proxies and find that all liquidity factors, except for the return reversal measure, significantly affect the cross section of portfolio returns. Instead of testing each liquidity proxy one by one, which may be inconclusive due to inconsistency of the results, the principal component analysis extracts a common source of liquidity variation. Armed with this unique liquidity risk measure, I give a conclusive answer that liquidity does matter in asset pricing. Moreover, from 1971 through 2002, a difference in liquidity risk contributes 3.70% to the difference in annualized expected return between high liquidity beta and low liquidity beta stocks. Although the seven liquidity proxies are priced individually, they lose their significance in the presence of the common liquidity factor. This evidence indicates that apart from the common liquidity part, the remaining parts of the individual liquidity measures are not priced in the cross-section of stock returns.

Liquidity risk provides a partial explanation for momentum. With the exception of the two most winner portfolios (deciles 9-10), loadings on the liquidity factor increase monotonically from the loser portfolios (decile 1) to decile 8. Adding liquidity spread to Fama-French three factors reduces momentum spread's alpha from 14.46% to 12.13% for 6/0/6 momentum portfolios, and from 16.68% to 14.12% for 12/0/3 momentum portfolios. Models with the common liquidity factor are superior to models with momentum factor in pricing the momentum portfolios. The common liquidity factor drives out the momentum factor in the pricing of 6/0/6 momentum portfolios.

There are measures of aggregate uncertainty which decrease liquidity, increase risk aversion, and cause stock prices to fall as risk premia rise. Since liquidity has a high correlation coefficient of -52.8% with market volatility, one concern here is whether the extracted liquidity factor captures only a volatility effect. I thus examine the role of liquidity in cross-sectional pricing while controlling for volatility. Using the Ang, Hodrick, Xing, and Zhang (2004) aggregate volatility measure, I find that the liquidity effect is robust to controlling for a volatility effect. This evidence implies that although liquidity and volatility are intimately related to each other, they have different cross-sectional pricing effects.

Stock liquidity risk is also priced in the bond markets. I interpret this result as evidence for a "flight to quality" effect, which is consistent with Pastor and Stambaugh's (2003) findings. By classifying samples according to their market-wide return reversal liquidity measure, Pastor and Stambaugh find that months in which liquidity drops severely tend to be months in which stocks and fixed-income assets move in opposite directions. Due to this "flight to quality" effect, it is natural to expect that stock market liquidity risk exerts an effect on the bond markets, as well.

Finally, there is a significant negative relation between market liquidity and the conditional variance of monthly stock returns, and the liquidity measure subsumes traditional GARCH coefficients in the conditional variance. By incorporating the market liquidity in the dynamics of the conditional variance of the stock return, I reexamine the risk-return tradeoff and document insignificantly positive relation.

The rest of this paper is organized as follows. Section 2 describes the construction of seven market-wide liquidity proxies. Section 3 conducts principal component analysis and extracts the common liquidity factor. Section 4 presents the cross-sectional asset pricing test results. In this section, I examine whether liquidity risk is priced in the cross-section of stock market and bond market respectively. Furthermore, I investigate the relation between liquidity and momentum effect, and relation between liquidity and volatility effect. Section 5 is devoted to examination of the relation between liquidity and the conditional variance of the stock returns. Section 6 concludes.

2 Market Liquidity Proxies

The power of the asset-pricing tests is enhanced by using large samples. Hence, I concentrate in this paper on those liquidity proxies constructed from daily data, instead of from high-frequency data which has a relatively short time period. Normally, the construction of aggregate market-wide liquidity proxies starts with a definition of firm-specific liquidity, and then aggregates to a market-wide liquidity proxy by taking the cross-sectional average after excluding the two most extreme observations at both ends of the cross-section. Following Eckbo and Norli (2002), I construct six market liquidity proxies from daily data from Jan 1963 to Dec 2002. I add one more liquidity proxy which is the illiquidity ratio of Amihud (2002). In the construction of the proxies, only the NYSE and AMEX ordinary common shares (CRSP share code 10 or 11) are included in the sample.

2.1 Bid-Ask Spread

The proportional bid-ask spread, typically calculated as the difference between the bid or offer price divided by the bid-ask midpoint, is a widely used measure of market liquidity. It directly measures the cost of executing a small trade. The spread contains two components.

The first component compensates market-makers for inventory costs, order processing fees, and/or monopoly profits. This component is transitory since its effect on stock price is unrelated to the underlying value of the securities. The second component, an adverse-selection component, arises because market-makers may trade with unidentified informed traders. In order to recover from loses to the informed traders who may have superior information, rational market-makers in a competitive environment widen the spread to recover profits from uninformed traders. As a common measure of liquidity, the bid-ask spread has certain shortcomings. Hasbrouck (1991) points out that a tick size of 1/8 limits the number of values the spread can take, thus price discreteness tends to obscure the effect of liquidity shocks in the cross section of firms.[4] Moreover, Brennan and Subrahmanyam (1996) argue that the bid-ask spread is a noisy measure of liquidity because large trades tend to occur outside the spread while small trades tend to occur inside, which means that bid-ask quotes are only good for limited quantities.

People often use intraday data to compute bid-ask spreads. In order to get longer time-series of bid-ask spreads data, I follow Eckbo and Norli (2002) to turn to a subset of stocks. As pointed out by Eckbo and Norli (2002), for those stocks that are not traded on a particular day, CRSP records bid and ask prices accordingly. Thus, in any given month there exists a cross-section of stocks that have not been traded for one or more days during the month. To avoid stale prices, only those stocks with at least 10 trading days during the month and with stock prices exceeding \$1 while below \$1000 are included in the sample. The proportional spread for stock i in month t is then given by

$$pspr_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} (p^A_{i,d,t} - p^B_{i,d,t})/(0.5p^A_{i,d,t} + 0.5p^B_{i,d,t}), \tag{1}$$

where $p^A_{i,d,t}$ and $p^B_{i,d,t}$ are the ask and the bid prices for stock i on non-trading day d in month t, and $D_{i,t}$ is the number of non-trading days for stock i in month t. The market-wide proportional spread is taken to be the cross sectional average of these stocks' monthly proportional spreads.

Eckbo and Norli (2002) identify a positive trend in the monthly market-wide proportional spread. To detrend the series, the original market-wide proportional spread series is scaled by ω_1/ω_t, where ω_t is the 24-month moving average of the spread over months $t-24$ to $t-1$, and ω_1 is the market spread value for August 1962. This adjusted market-wide proportional spread is denoted as

$$PSPR_t = (\omega_1/\omega_t) \cdot (1/N_t) \sum_{i=1}^{N_t} pspr_{i,t}, \tag{2}$$

[4]This price discreteness problem is present only in historical data. Prices are now decimal.

where N_t is the number of stocks included in the cross sectional average in month t.

Since in the original $PSPR$ measure, higher numbers represent less liquidity, I flip the sign of $PSPR$ so that a higher value represents higher liquidity.

2.2 Stock Turnover

Stock turnover is given by the ratio of trading volume to the number of shares outstanding. It is a trading activity measure that is often used as a proxy for liquidity. Amihud and Mendelson (1986) show that assets with higher spreads are allocated in equilibrium to portfolios with (the same or) longer expected holding periods. They argue that in equilibrium, the observed market (gross) return must be an increasing function of the relative spread, implying that the observed asset returns must be an increasing function of the expected holding periods. Given the fact that the turnover is the reciprocal of a representative investor's holding period and is negatively related to other liquidity costs such as bid-ask spreads, one can use it as a proxy for liquidity and the observed asset return must be a decreasing function of the turnover rate of that asset. Intuitively, in an intertemporal setting with zero transaction costs, investors will continuously rebalance their portfolios in response to changes in the investment opportunity set. In the presence of transaction costs, such rebalancing will be performed more infrequently, resulting in reduced liquidity. However, Lee and Swaminathan (2000) question the interpretation of turnover as a proxy for liquidity because the relationship between turnover and expected returns depends on how stocks have performed in the past. More specifically, they find that high volume stocks are generally glamour stocks and low volume stocks are generally value or neglected stocks. Also high volume firms and low volume firms differ significantly in terms of their past operating and price performance.

Similar to the construction of the market-wide proportional spread above, at the firm-specific level, the monthly turnover measure is the average of daily share turnover:

$$stov_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} stov_{i,d,t}, \tag{3}$$

where $stov_{i,d,t}$ is the share turnover for stock i on day d in month t, and $D_{i,t}$ is the number of observations for stock i in month t. I then aggregate by taking the cross-sectional average of the monthly firm-specific turnover to get the market-wide turnover measure. Again, to create a stationary series, the market-wide turnover is scaled by a factor v_1/v_t, where v_t is the 24-month moving average of the market-wide turnover through months t-24 to t-1, and v_1 is the value of the turnover for August 1962. This adjusted market-wide turnover is denoted as

$$STOV_t = (v_1/v_t) \cdot (1/N_t) \sum_{i=1}^{N_t} stov_{i,t}, \tag{4}$$

where N_t is the number of stocks included in the cross-sectional average in month t.

2.3 Price Impact of Trade

2.3.1 Illiquidity Ratio

A natural measure of liquidity is a stock price's sensitivity to trades. Kyle (1985) postulates that because market makers cannot distinguish between order flow generated by informed traders and by liquidity (noise) traders, they set prices as an increasing function of the order flow imbalance which may indicate informed trading. This positive relation between price change and net order flow is commonly called the price impact or Kyle's λ. The illiquidity ratio of Amihud (2002), which is defined to be absolute return divided by the dollar trading volume, reflects the absolute (percentage) price change per dollar of trading volume, and is a low frequency analog to microstructure high frequency liquidity measures. While the bid-ask spread captures the cost of executing a small trade, the illiquidity ratio, as a price impact proxy, captures the cost associated with larger trades. Furthermore, Hasbrouck (2003) shows that the Amihud (2002) illiquidity ratio is the best available price-impact proxy constructed from daily data. He uses microstructure data to estimate a measure of Kyle's (1985) λ and finds that its correlation with Amihud's illiquidity ratio is 0.47 for individual stocks and 0.9 for portfolios.

The monthly firm-specific illiquidity ratio is given by

$$illiq_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} |r_{i,d,t}|/v_{i,d,t}, \tag{5}$$

where $r_{i,d,t}$ and $v_{i,d,t}$ are the return and the dollar volume (measured in millions of dollars) for stock i on day d in month t, and $D_{i,t}$ is the number of observations for stock i in month t. Then the market-wide illiquidity ratio is the cross-sectional average of individual stocks' illiquidity ratios in each month. Since there is a declining trend in the market-wide illiquidity ratio series, the original series is adjusted by multiplying a scaling factor, m_t/m_1, where m_t is the total dollar value at the end of month $t-1$ of the stocks included in the cross-sectional average in month t, and m_1 is the corresponding value for August 1962. The scaled market-wide illiquidity ratio is denoted as:

$$ILLIQ_t = (m_t/m_1) \cdot (1/N_t) \sum_{i=1}^{N_t} iliq_{i,t}, \tag{6}$$

where N_t is the number of available stocks in month t.

Again for $ILLIQ$, higher numbers represent less liquidity. For consistency, I flip the sign of $ILLIQ$ to represent a liquidity measure.

2.3.2 Return Reversal

Pastor and Stambaugh (2003) develop a return-reversal measure as another form of price impact which reflects order-flow induced temporary price fluctuations. This measure is motivated by the Campbell, Grossman, and Wang (1993) (CGW) model and its empirical findings. In the CGW symmetric information setting, risk-averse market makers accomodate trades from liquidity or noninformational traders. In providing liquidity, market makers demand compensation in the form of a lower (higher) stock price and a higher expected stock return, when facing selling (buying) order from liquidity traders. The larger liquidity-induced trades, the greater compensation for the market makers, causing higher volume-return reversals when current volume is high. This return reversal measure reflects only temporary price fluctuations arising from the inventory control effect of price impact. It does not capture the permanent effect on price arising from asymmetric information like Amihud's illiquidity ratio in equation (5). Llorente, Michaely, Saar, and Wang (2002) and Wang (1994) show that information-motivated trading can weaken the volume-related return reversal and even produce volume-related continuations. Cooper (1999), and Lee and Swaminathan (2000) provide empirical evidence for volume-induced return continuations.

The monthly firm-specific return reversal measure (henceforth referred to as PS) is computed by running a regression using daily data within a month:

$$r^{AR}_{it+1} = \gamma_0 + \gamma_1 r_{it} + ps_{\$i}[sign(r^{AR}_{it}) \times vol_{it}] + \epsilon_{it}, \tag{7}$$

where r^{AR}_{it+1} is the excess return with respect to the CRSP value weighted market return for firm i on day $t+1$, r_{it} is the return for firm i on day t, and vol_{it} is volume in millions of dollars. Firm months with less than 15 daily return observations are excluded. $ps_{\$}$ measures the expected return reversal for a given dollar volume. The greater the expected reversal is, the lower the stock's liquidity. Therefore $ps_{\$}$ should be generally negative and larger in absolute value when liquidity is lower. The cross-sectional average of monthly individual stocks' return reversal measures is the market-wide return reversal measure. Since there is a declining trend in the absolute value of average return reversal, I follow Pastor and Stambaugh and scale the series by n_t/n_1, where n_t is the total dollar value at the end of month $t-1$ of the stocks included in the cross sectional average in month t, and n_1 is the corresponding value for August 1962. The scaled market-wide return reversal is then given by:

$$PS_{\$t} = (n_t/n_1) \cdot (1/N_t) \sum_{i=1}^{N_t} ps_{\$i,t}, \tag{8}$$

where N_t is the number of available stocks in month t.

2.3.3 Breen, Hodrick,and Korajczyk Measure

Instead of using order flow induced return reversal to measure liquidity, we can capture the same liquidity effect by examining order flow on the the concurrent return. Based on this idea, Breen, Hodrick, and Korajczyk (2000) (BHK) use high frequency data to construct a measure of liquidity by regressing return on net turnover. As in Breen, Hodrick, and Korajczyk (2000), I estimate firm-specific liquidity measure $bhk_{\$i}$ by running the following regression using daily data within a given month:

$$r_{it}^{AR} = \psi_0 + \psi_1 r_{it-1} + bhk_{\$i}[sign(r_{it}^{AR}) \times vol_{it}] + \epsilon_{it}, \tag{9}$$

$bhk_{\$}$ captures the extent to which a trade is executed without influencing the stock price. If a stock is perfectly liquid, then it trades without any concurrent price movement, while trades in illiquid stocks will lead to large concurrent price changes. Thus, the higher the $bhk_{\$}$ is, the less liquid is the stock. Taking the cross-sectional average of all individual stocks' $bhk_{\$}$ measures and using the same scaling factor as in the PS measure, I denote the adjusted market-wide BHK measure as $BHK_{\$t}$.

The above specifications in models (7) and (9) are somewhat arbitrary. Following Eckbo and Norli (2002), I add two alternative measures ps_{toi} and bhk_{toi} by estimating models (7) and (9) using turnover, instead of dollar volume vol_{it}, as an alternative order flow measure. Aggregating individual stocks' ps_{toi} and bhk_{toi} gives corresponding market-wide liquidity measures. Again for stationarity concern, I scale them by o_t/o_1, where o_t is the 24-month moving average, computed over months $t-24$ through $t-1$, of the average monthly turnover. The two scaled market-wide measures are denoted as PS_{to} and BHK_{to}. Same as $PSPR$ and $ILLIQ$, I flip the signs of $BHK_{\$}$ and BHK_{to} to represent liquidity.

One potential problem using the scaling factors for $ILLIQ$, $PS_{\$}$ and $BHK_{\$}$ is that they involve market values, which may contaminate the liquidity measures with a valuation measure that may predict returns. To address this concern, I use an alternative scaling factor o_1/o_t for these three liquidity proxies, where o_t is the 24-month moving average of the corresponding liquidity measure over months t-24 to t-1, and o_1 is the corresponding value for August 1962. It turns out that the results are very robust. To conserve space, I do not present the results using this alternative scaling factor.

2.4 Descriptive Statistics

Table 1 provides autocorrelations and contemporaneous cross-correlations for the seven scaled market-wide liquidity proxies. The scaled proxies are generally highly persistent with one-month autocorrelations ranging from 67% to 93%. The Pastor-Stambaugh return reversal proxies are comparably less persistent with one-month autocorrelations of 19% and 26% for $PS_{\$}$ and PS_{to} respectively. Because I have transformed all the seven measures to be liquidity measures, their pair-wise contemporaneous cross-correlations are all positive.

Figure 1 plots the time-series of the seven scaled market-wide liquidity proxies. Note that these different liquidity proxies consistently indicate adverse liquidity shocks during the 1970 political unrest, the 1973 oil crises, the stock market crash of October 1987, and the Russian debt crisis of 1998. All these large fluctuations are coincident among the different proxies although they are based on different theoretical arguments.

3 Principal Component Analysis

All seven individual liquidity measures capture some aspects of liquidity. Using principal Component analysis, I can extract a common source of liquidity variation. Before principal component analysis, I normalize the seven series of liquidity proxies to have mean zero and unit variance. To avoid forward-looking bias, I implement a dynamic version of principal component analysis. First, I do principal component analysis with the initial 36 months to get the first observation of the principal components in Dec 1965. Then add one more observation to the sample, redo the principal component analysis using the first 37 months data, and append the last observation to the time series of the principal components. Keep repeating this process until the end of the sample. By this way, the extracted principal components at each time t incorporate only past information.

Table 2 shows the average loadings of the principal components and the corresponding average weighting percentage for each principal component to explain the total liquidity variation. The first principal component accounts for 62% of total liquidity variation, and the first three principal components represent 87% of variation in the proxies. Moreover, all seven liquidity proxies load positively on the first principal component, which clearly shows that it tracks the common source of liquidity; while the loadings on the other principal components do not have clear patterns.

Figure 2 plots the time series of the first principal component (noted as $PC1$ hereafter) and market volatility, which is computed as the the within-month daily standard deviation of the CRSP value-weighted return. From the figure, the first principal component clearly tracks the common adverse liquidity shocks as presented by the seven liquidity proxies in Figure 1. More specifically, the first principal component drops dramatically indicating low liquidity during the 1970 political unrest time, the 1973 oil crises, the stock market crash of October 1987, and the Russian debt crisis of 1998. These are also times of high market volatility, I will take care in disentangling the two effects. Besides these common liquidity shocks, the first principal component drops sharply over the recession of 1972-1974, the Asian financial crisis in October 1997, and the burst of the hi-tech bubble in early 2000. The first principal component increases sharply, indicating liquidity improvement, after the decimalization of January 2001.

To obtain some intuition about the first principal component, the right panel of Table 2 lists the correlation between the first principal component and the seven individual liquidity proxies, together with some market variables such as the market return, market volatility and market trading volume. The market return (*mktret*) is the monthly value-weighted return of NYSE-AMEX indices constructed by CRSP. For market volatility, I use two measures. One is computed as the within-month daily standard deviation of the market return, noted as *mktvol*. The other one is the VIX index from the Chicago Board Options Exchange. Market trading volume (*volume*) is defined as the equally-weighted average of NYSE-AMEX listed stocks' trading volume. Since trading volume shows an increasing trend, I detrend the series by multiplying a scaling factor $\frac{w_1}{w_t}$, where w_t is its 24-month moving average over month $t-24$ to $t-1$, and w_1 is the corresponding trading volume for August 1962. The correlation of the first principal component with *mktvol* is -52.8%, and is -66.7% with VIX. It is also positively correlated with *volume* with a correlation coefficient of 44.5%, and *mktret* with a correlation coefficient of 32.2%. Thus, market liquidity is up when the market is up, when trading volume increases, and when market volatility decreases. The correlations imply that we can interpret the first principal component as measuring the variation in liquidity that is highly correlated with market volatility.[5]

Table 3 examines how my stock market liquidity measure $PC1$, is related to prevailing stock market and macroeconomic conditions. More specifically, I define market states by aggregate market return (*mktret*), market volatility (*mktvol*) and market trading volume (*volume*). I classify months with negative *mktret* as down markets and the remaining months as up markets. Months with greater than average *mktvol* over the sample period are classified as high volatility states and the rest as being in low volatility states. For market trading volume, I define months with higher than average *volume* over the sample to be in high trading activity states and the remainder as being in low trading activity states. Following Fujimoto (2004), I define macroeconomic states by three economic indicators. First, sample months are classified as being in expansionary or contractionary economic

[5]Note that my findings from stock market here are quite consistent with what Fleming (2003) finds from Treasury market. Using principal component analysis from seven liquidity measures for the on-the-run two-year note in Treasury market constructed from high-frequency data, Fleming finds that the first principal component measures variation in liquidity that is correlated with price volatility.

regimes according to the NBER business-cycle classification. Second, months with falling (rising) Federal Reserve discount rates are defined as expansionary (restrictive) monetary regimes. Third, months are classified into high probabilities of future recession (greater than 20%) and low probabilities of future recession (equal to or less than 20%) based on Stock and Watson's (1989) Experimental Recession Index.

By comparing the stock market liquidity measure, $PC1$, across these different market and macroeconomic states, Table 3 clearly shows that market liquidity is indeed lower under declining stock market conditions as well as declining macroeconomic environment. $PC1$ is significantly lower (indicating lower market liquidity) in down markets, high volatility state as well as low trading activity state. Besides this, $PC1$ is also significantly lower in declining macroeconomic environment, indicated by recession periods, restrictive monetary regimes, and high probability of future recession periods. Moreover, the difference is both statistically and economically significant. These results using the extracted common liquidity measure $PC1$ is consistent with Fujimoto (2004) results by using three different market liquidity proxies ($PSPR$, $ILLIQ$, $PS_{\$}$) respectively.

4 Asset Pricing Tests

4.1 Construction of Common Liquidity Factor

The first principal component is highly persistent, having a first-order auto-correlation coefficient of 77%. To remove the information which is tracked by lagged observations and thus construct a time series of innovations, I model the first principal component by an AR model. The autoregressive order of 3 is chosen by the Bayesian Information Criterion. Using the $AR(3)$ model, I construct the innovation series $L1_t$, which I define as the pervasive liquidity factor:

$$PC1_t = a + bPC1_{t-1} + cPC1_{t-2} + dPC1_{t-3} + L1_t \tag{10}$$

Figure 3 plots the time series of the innovations in the first principal component. It shows that the innovations exhibit peaks indicating larger than normal shocks in periods where there likely were shocks to liquidity, such as during the the 1973 oil crises, the recession of 1972-1974, the stock market crash of October 1987, the Asian financial crisis in October 1997, the Russian debt crisis of 1998, and the burst of the hi-tech bubble in early 2000. There are also many large (positive or negative) innovations which do not correspond to macro events.

4.2 Is common liquidity risk priced in stocks?

This section is devoted to testing whether the common liquidity factor as constructed from principal component analysis is priced in the cross section of stock returns.

4.2.1 Construction of Testing Portfolios

To isolate the size effect which maybe closely related to stock liquidity, I construct 5×5 size and liquidity beta sorted portfolios.

In each month, stocks are first sorted into 5 groups according to their previous month size. Within each size quintile, I sort stocks into quintile portfolios based on their historical liquidity betas. The portfolios are equally-weighted and rebalanced monthly.[6] A series of monthly returns on each of the 25 portfolios is obtained by linking post-formation returns across time. Stocks' historical liquidity betas are estimated by running the regression using the most recent five years of monthly data:

$$r_{i,t} = \beta_i^0 + \beta_i^M MKT_t + \beta_i^S SMB_t + \beta_i^H HML_t + \beta_i^L L1_t + \epsilon_{i,t}, \tag{11}$$

where $r_{i,t}$ denotes asset i's excess return, MKT denotes the excess return on a broad market index, and the the other two factors, SMB and HML, are payoffs on long-short spreads constructed by sorting stocks according to market capitalization and book-to-market ratio.[7] To ensure that the portfolio formation procedure uses data available only as of the formation date, in each formation month, the series of innovations $L1_t$ is recomputed from equation (10) with past data.

Panel A of Table 4 reports the risk diagnostics of our constructed 5×5 size and liquidity beta sorted portfolios. From the top panel of the table, half of the portfolios have significant FF-3 alphas, indicating the poor performance of the Fama-French three factor model in pricing the sorted portfolios. Except for the smallest and biggest size portfolios, the FF3 alphas of the High-Low β^L spread are significantly positive across size quintiles ($3.97(t = 2.59), 3.90(t = 2.57), 3.39(t = 2.26)$). Examination of the post-ranking liquidity betas shown in the bottom panel of the table demonstrates that the constructed portfolios provide sufficient dispersion in liquidity loadings. The liquidity loadings of the High-Low spread are significantly positive across all the size quintile portfolios (ranging from 0.47 to 0.60). The average $L1$ loading of the High-Low spread (noted as LIQ) across the five size quintiles is 0.55 with a t-statistic of 3.84. This evidence supports the hypothesis that the extracted common liquidity risk factor is a priced risk factor. Furthermore, the associated premium is positive, in that stocks with higher sensitivity to the extracted liquidity factor offer higher

[6] The results are robust to value-weighted portfolios.

[7] I thank Eugene F. Fama and Kenneth R. French for making these variables available online.

expected returns. It is consistent with the notion that a pervasive drop in liquidity is undesirable for investors, so that investors demand compensation for holding stocks with greater exposure to this liquidity risk.

4.2.2 Estimating the Liquidity Risk Premium

I test asset-pricing models of the form

$$E[r_t] = B\lambda_F + \beta^L \lambda_L, \tag{12}$$

where $E[r_t]$ denotes the vector of the expected excess return of the testing portfolios, B is a factor loading matrix corresponding to the traded factors, and β^L is a vector of factor loadings corresponding to the constructed common liquidity factor $L1$. λ's are corresponding risk premiums. The underlying data generating process is assumed to be:

$$r_t = \beta_0 + BF_t + \beta^L L1_t + \epsilon_t, \tag{13}$$

where F_t is a vector containing the realizations of the "traded" factors, while $L1_t$ is the constructed common liquidity factor, which is not a traded factor. For the traded factors F_t, in addition to the standard Fama and French (1993) factors MKT, SMB and HML, I include the momentum factor UMD.[8]

I use the stochastic discount factor approach and estimate λ_L by GMM method. Table 5 reports the results. I estimate the risk premium for $L1$ together with the Fama-French three factors in Model I. Model II includes the additional factor UMD. The significantly positive premium on HML indicates the presence of value effect in the testing assets. The premiums on MKT and SMB are insignificant, indicating poor performance of these two factors in explaining the cross section of returns on the testing assets. The price of the common liquidity factor $L1$ is significantly positive at the 1% level. When I include the additional UMD factor, $L1$ remains significant, while UMD is not priced. This confirms what we observe from the examination of testing portfolios in previous subsection: a pervasive drop in liquidity, as indicated by decreasing value of $L1$, is undesirable for the representative investor, so that the investor requires compensation for holding stocks with higher exposure to the liquidity factor. The results suggest that the common liquidity factor seems to be important in explaining the cross section of expected stock returns.

Since the extracted common liquidity factor is not a traded factor, the estimated risk premium is subject to the scaling problem. However, combined with the factor loading β^L,

[8] UMD is the momentum factor constructed by Kenneth French. In construction of the UMD, they use six value-weighted portfolios formed on size and prior (2-12) returns. UMD is the average return on the two high prior return portfolios minus the average return on the the two low prior return portfolios.

we can say a little more about the contribution of liquidity risk to asset i's expected return, $\beta_i^L \lambda_L$. From the risk diagnosis of the constructed testing portfolios reported in Table 4, the High-Low liquidity-beta spread has a significantly positive loading of 0.55 on $L1$ after controlling for size. Given the estimated risk premium of 0.56% in Table 5, the difference in annualized expected return between high β^L and low β^L portfolios that can be attributed to a difference in liquidity risk is $0.0056 \times 0.55 \times 12 = 3.70(\%)$.

4.2.3 Liquidity Level vs. Liquidity Risk

The above evidence suggests that liquidity risk is an important risk factor in the cross-section of stock returns. A natural question is whether the associated risk premium is due to the liquidity level, rather than liquidity risk per se. To address this question, I conduct simple examination to see whether the stocks with high liquidity risk tend to be illiquid.

Panel B of Table 4 reports the size, turnover, and illiquidity ratio of the constructed 5×5 size and liquidity beta sorted portfolios. Within each size quintile, there is an inverted U-shape pattern in size across the five β^L portfolios. The two extreme (lowest and highest) β^L portfolios have smaller size than the middle portfolios. And the highest β^L portfolios have almost the same size as the lowest β^L portfolios. The turnover from the lowest β^L to the highest β^L portfolios exhibits U-shape within each size quintile. The two extreme β^L portfolios tend to have higher turnover, and the turnover difference between these two portfolios is mixed. For the two smallest size groups, highest β^L portfolios have higher turnover, indicating better liquidity than the lowest β^L portfolios. While for the rest three size groups, the situation goes the opposite way. There is no clear pattern in the illiquidity ratio across the five liquidity beta portfolios. In general, the lowest β^L portfolios have highest illiquidity ratio, indicating lower liquidity than higher β^L portfolios. This means that the stocks with low liquidity risk actually tend to be illiquid.

The evidence from the above examination clearly shows that it is really liquidity risk to contribute to the risk premium, not the liquidity levels.

4.2.4 Are the Rest Principal Components Priced?

So far, I have only examined the importance of the first principal component in the cross-section of stock returns. An immediate question is to ask whether the other principal components are priced in the stock returns.

Following the same procedure in the examination of the first principal component, I first construct the innovation series (noted as L2 to L7) from AR model for each of the principal components. The testing assets for each of the principal component are constructed by forming the 5×5 size and corresponding liquidity beta portfolios. Table 6 reports the examination results. The model specification is $FF3 +$ Liquidity Factor, and the risk premiums are estimated by GMM.[9] From the second principal component onwards, none of them are rewarded with significant risk premiums. It clearly shows that except for the first principal component, the rest principal components are not priced in the cross-section of stock returns.

This evidence indicates that the first principal component does a good job to capture the common source of liquidity variation, thus representing a valid pervasive liquidity measure.

4.2.5 Liquidity and Momentum

Pastor and Stambaugh (2003) document that the momentum factor's importance in an investment context is reduced significantly by the inclusion of their liquidity risk spread. Moreover, they find that momentum's alpha is cut nearly in half by their liquidity risk spread. Korajczyk and Sadka (2003) find that momentum profits are greatly reduced after considering trading costs. Given this evidence, I investigate the extent to which liquidity can explain the cross-sectional momentum effect. More specifically, I want to test whether the common liquidity factor can drive out the momentum factor in the pricing of momentum portfolios.

The construction of equally-weighted $J/0/K$ momentum decile portfolios follows the methodology of Jegadeesh and Titman (1993). Specifically, at the beginning of each month t, stocks are ranked in ascending order based on their cumulative returns in the past J months. Port 1 is the worst loser portfolio, and Port 10 is the best winner portfolio. Based on these rankings, ten equally-weighted decile portfolios are formed and held for K months. In each month t, the weights on $\frac{1}{K}$ of the stocks in the entire portfolio are revised and the rest are carried over from the previous month. The monthly rebalanced equally-weighted portfolio returns are then recorded. I use 6/0/6 and 12/0/3 momentum portfolios as these are most successful strategies according to Jegadeesh and Titman (1993).

I first investigate the extent to which the abnormal return of the momentum spread is reduced by including the liquidity risk factor. Since I am running time-series regression, I use the liquidity spread LIQ controlling for size as the liquidity risk factor. Table 7 reports the liquidity loadings and alphas for the momentum decile portfolios when regressed on the Fama-French three factors plus LIQ. Interestingly, with the exception of the two most winner portfolios (deciles 9-10), loadings on the liquidity factor increase monotonically from the loser portfolio (decile 1) to decile 8. The negative weight of the loser portfolio indicates that it pays off positively when the market liquidity is low. Hence, this is consistent with a positive price of liquidity risk. People do not like stocks that have $\rho(r, L1) > 0$, i.e., the stocks that have low payoffs in illiquidity states. Thus investors demand a higher risk premium for those stocks whose returns are positively correlated with the common liquidity

[9]The results are robust to model specification of $FF3 + UMD +$ Liquidity Factor.

factor. This goes to the correct direction in explaining the positive abnormal returns of the winner portfolios and negative abnormal returns of the loser portfolios. As a result, the Winner-Minus-Loser spread loads significantly positively on the liquidity factor LIQ (0.77 for the 6/0/6 momentum spread and 0.84 for the 12/0/3 momentum spread). Comparing the alphas with respect to the FF3 factors and $FF3 + LIQ$, we can see that adding LIQ generally reduces the magnitude of abnormal returns across the decile portfolios. As a result, the 10-1 momentum spread's annualized alpha is reduced by adding the liquidity factor LIQ. The 6/0/6 momentum spread's alpha is reduced from 14.46% to 12.13%, and the alpha for the 12/0/3 momentum spread is reduced from 16.68% to 14.12%. The alphas for the momentum spreads remain significantly different from zero after including the liquidity factor LIQ. This evidence indicates that liquidity risk provides a partial explanation for momentum.

Table 8 presents the results testing whether the common liquidity factor can drive out the momentum factor. In order to evaluate and compare the performance of different model specifications, I perform Hansen's (1982) over-identification J-test, and compute Hansen and Jagannathan (1997) distance measure (HJ-distance). Let $g_T(b)$ be the model implied moment conditions, S be the covariance matrix for $g_T(b)$, the over-identification J-test is

$$TJ_T = Tg_T(\hat{b})'S^{-1}g_T(\hat{b}) \longrightarrow \chi^2(\#moments - \#paramters) \tag{14}$$

Assuming an asset pricing model provides a pricing kernel proxy y, and m is the true pricing kernel, the HJ-distance is defined as

$$\delta = min_{m \in L^2}||y - m||,\ s.t.\ E(mR) = P, \tag{15}$$

where R is the asset return, and P is the corresponding price. Solving the minimization problem, the HJ-distance is

$$\delta = [E(yR - p)'E(RR')^{-1}E(yR - p)]^{1/2} \tag{16}$$

The HJ-distance uses the inverse of the covariance matrix of asset returns as the weighting matrix. It is invariant across models, making HJ-distance suitable for model comparisons. To examine explicitly the ability of the liquidity factor $L1$ to absorb the pricing information in the the momentum factor UMD, I also perform Newey-West's (1987) ΔJ test. I call the model specification that includes both $L1$ and UMD as the "unrestricted model". The "restricted model" is the one that includes only the liquidity factor $L1$. The difference in the J functions from the two model specifications is chi-square distributed:

$$TJ(restricted) - TJ(unrestricted) \sim \chi^2(\#\text{ of restrictions}). \tag{17}$$

Considering the 6/0/6 momentum portfolios in Panel A of Table 8, we notice that both the common liquidity factor and the momentum factor are rewarded with significant risk premiums respectively. Interestingly, the model specification of $FF3 + L1$ passes both the optimal GMM over-identification J test and the test of HJ-distance equals zero, while the model $FF3 + UMD$ fails to pass either of the over-identification J test or HJ-distance test. When I include both the liquidity factor $L1$ and the momentum factor UMD, the momentum factor's risk premium becomes insignificantly different from zero. The ΔJ test indicates that once we take into account the liquidity risk factor, adding momentum factor does not improve the model performance in pricing the 6/0/6 momentum portfolios. As for the 12/0/3 momentum portfolios in Panel B, the situation is somehow different. First of all, the liquidity factor $L1$ and the momentum factor UMD still have significant risk premiums, individually. But now, in pricing the 12/0/3 momentum portfolios, all the model specifications in the table are rejected by both the optimal GMM over-identification J test and HJ-distance test. Second, although the momentum factor UMD is still rewarded with a significant premium in the presence of the liquidity factor $L1$, the ΔJ statistic is not significantly different from zero, indicating the redundancy of the momentum factor in improving the model performance. $FF3 + L1$ has a smaller HJ-distance than $FF3 + UMD$ for both the 6/0/6 and 12/0/3 momentum portfolios. This clearly shows that $FF3 + L1$ is superior to $FF3 + UMD$ in pricing the momentum portfolios.

This evidence shows that liquidity risk is priced significantly in the cross-section of momentum portfolios, and provides a partial explanation for momentum.

4.2.6 Examination of Individual Liquidity Proxies

Since the common liquidity factor captures the common source of liquidity variation from seven liquidity proxies, it is natural to address how individual liquidity measures affect the cross-section of stock returns. Moreover, once we account for the common liquidity factor $L1_t$, do other liquidity measures matter?

One can argue that the constructed 5×5 size and liquidity beta portfolios are biased toward $L1$. For the investigation purpose, I use the 6/0/6 momentum portfolios as testing assets.[10] From Table 2, we notice that the individual liquidity measures are highly correlated with the common liquidity factor. When I include both individual liquidity measures and the common liquidity factor in the model specifications, I orthogonalize them against the common liquidity factor $L1_t$ and use the orthogonalized part. Table 9 presents the risk premiums estimated by GMM. The model specifications are $FF3 +$ Liquidity Measures.[11] With the exception of the $PSPR$, all of the individual liquidity measures are priced in

[10] The results are robust to 5×5 size and liquidity beta portfolios.

[11] The results are robust to model specifications of $FF3 + UMD +$ Liquidity Measures.

the cross-section of 6/0/6 momentum portfolios. $STOV$ has a significant risk premium of 0.27% with a t-statistic of 2.56. $PS_{\$}$ and BHK_{to} are priced significantly with a t-statistic of 2.59 and 2.42 respectively, and $ILLIQ$, PS_{to} and $BHK_{\$}$ are priced at the 6% level. This evidence confirms the findings in the previous subsection that liquidity risk provides a partial explanation for momentum. In contrast, the FF3 factors MKT, SMB, and HML perform poorly in pricing the momentum portfolios, confirming a well-known result. After we account for the common liquidity factor $L1$, all of the seven individual liquidity measures lose their significance, while the common liquidity factor remains significant.

The results provide direct evidence that the common liquidity factor captures the common source of liquidity variation, and apart from this common liquidity part, the remaining parts of the individual liquidity measures are not priced in the cross-section of 6/0/6 momentum portfolios.

4.2.7 Liquidity and Volatility

Increases in aggregate uncertainty tend to decrease liquidity, increase risk aversion, and cause stock prices to fall as risk premiums rise. Note from Section 3, the correlation of the first principal component $L1$ with stock price volatility *mktvol* is -52.8%, and is -66.7% with VIX. Pastor and Stambaugh note that periods experiencing extreme adverse liquidity shocks always coincide with high market volatility. One concern therefore is whether the extracted liquidity factor captures only a market volatility effect. Ang, Hodrick, Xing and Zhang (2004) (AHXZ) develop a risk factor based on aggregate volatility. I thus move forward to examining the role of liquidity in cross-sectional pricing effect as opposed to different responses to the increasing volatility. More specifically, I investigate the relationship between cross-sectional effect of the common liquidity factor and AHXZ aggregate volatility measure by examining whether the common liquidity factor $L1$ is still priced significantly after controlling for the volatility factor.

To construct a set of test assets which have sufficient dispersions in the factor loadings, I form 25 investible portfolios sorted by volatility beta $\beta_{\Delta VIX}$ and liquidity beta β^L as follows. At the beginning of each month from 1986 to 2002, common stocks are first sorted into five quintiles based on their past $\beta_{\Delta VIX}$. Within each quintile, stocks are then sorted into five groups on the basis of their historical liquidity beta β^L. The portfolios are value-weighted and rebalanced monthly. β^L is computed by the regression (11) using most recent five years' data. $\beta_{\Delta VIX}$, which measures the sensitivity to aggregate volatility risk, is estimated by the regression

$$r_t^i = \beta_0 + \beta_{MKT}^i \cdot MKT_t + \beta_{\Delta VIX}^i \cdot \Delta VIX_t + \varepsilon_t^i, \tag{18}$$

using daily data over the past month, where ΔVIX is the daily changes in VIX.

To estimate the factor premiums, the model specifications are $FF3 + FVIX + OL1$ and $FF3+UMD+FVIX+OL1$. $FVIX$ is the mimicking factor to track innovations in VIX. According to AHXZ (2004), $FVIX$ is constructed by estimating the coefficient b in the following regression:

$$\Delta VIX_t = c + b'X_t + u_t, \tag{19}$$

where X_t represents the returns on the quintile portfolios sorted on past $\beta_{\Delta VIX}$. The return on the portfolio, $b'X_t$, is the factor $FVIX$ that mimics innovations in market volatility. $OL1$ is the orthogonalized liquidity factor against the volatility factor $FVIX$. In this way, I purge the liquidity factor $L1$ of potential volatility effect. The premiums are estimated by GMM. Table 10 reports the results. Since $FVIX$ is available from 1986, the sample period is from Jan 1986 to Dec 2002. In model I, I estimate factor premiums from model specification of $FF3 + FVIX + OL1$. Model II includes the additional momentum factor UMD. Panel A shows that after controlling the volatility effect $FVIX$, the orthogonalized liquidity factor is still rewarded a significant risk premium. When adding the momentum factor, the estimate of the risk premium on $OL1$ is slightly changed, moving from 1.06% in model I to 0.8% in model II. The volatility factor $FVIX$ is also significantly priced both in model I and model II. The insignificance of the premiums on SMB and HML indicates the poor performance of these two factors during the sample period. When adding UMD, both MKT and UMD are significantly priced. Panel B of Table 10 reports the factor loadings on OL1 estimated from $FF3 + FVIX + OL1$.[12] In general, all the $OL1$ loadings increase monotonically from low β^L to high β^L portfolios, and the sorted portfolios provide disperse in the ex-post liquidity loadings.

The evidence from this subsection indicates that although the extracted liquidity measure is intimately related to the volatility, the role of liquidity in cross-sectional pricing effect is not due to the volatility effect.

4.3 Is Common Liquidity Risk Priced in the Bond Market?

Pastor and Stambaugh (2003) document "flight-to-quality" effect in months with exceptionally low liquidity. By classifying samples according to their return reversal liquidity measure, they find that months with severe liquidity drops tend to be months in which returns on stocks and fixed-income assets move in opposite directions. Using high frequency data, Chordia, Sarkar, and Subrahmanyam (2003) explore liquidity movements in stock and Treasury bond markets and find that a shock to quoted spreads in one market affects the spreads in both markets. Motivated by this empirical evidence, it is natural to seek whether stock market liquidity risk also exerts an effect on bond markets.

[12] The loading patterns remain same when estimated from $FF3 + UMD + FVIX + OL1$.

4.3.1 Treasury Bond Market

I first explore $L1_t$ as a pricing factor in the Treasury bond market. The reason that this question is worth investigating is that if stock market liquidity risk is priced in the Treasury bond market, it will be an important potential state variable for the modelling of the yield curve.

I use CRSP Fama bond portfolio data. There are eight portfolios and the portfolio maturity interval is six months. Only non-callable, non-flower notes and bonds are included in the portfolios. The sample period is from May 1971 to Dec 2002. Panel A of Table 11 presents loadings on the stock liquidity risk factor and the estimated risk premiums. The liquidity loadings are estimated in the presence of the Fama-French three factors. Interestingly, the loadings on the stock liquidity factor increase monotonically from shorter maturity portfolios to longer maturity portfolios, indicating higher liquidity risk in longer maturity bonds. Five of the eight liquidity loadings are significant at the 6% level. The stock liquidity factor $L1$ is priced in the treasury bond market at the 8% significance level. The premium is 0.0132 with a t-statistic of 1.73. When pricing stocks and bonds simultaneously, I use the 6/0/6 stock momentum portfolios for the stock market.[13] Now the common stock liquidity factor is significantly priced in the joint markets. The associated premium is 0.0107 with a t-statistic of 3.35.[14]

4.3.2 Corporate Bond Market

Jong and Driessen (2004) investigate the role of liquidity risk in the pricing of corporate bonds and find that the exposures of corporate bond returns to fluctuations in treasury bond liquidity and equity market liquidity (proxied by illiqudity ratio) help to explain the credit spread puzzle. Corporate bond market is a natural testing ground for the role of liquidity in asset pricing because the returns on corporate bonds are correlated with both the returns on the treasury bond market, and with returns on the stock market. I collect data from Datastream on Lehman corporate bond indices. The credit rates range from BAA to AAA. I use the 'intermediate maturity' (average about 5 years) indices and the 'long maturity' (average about 22 years) indices. The sample period is from Jan 1975 to Dec 2002.

Using these corporate bond data, Panel B of Table 11 presents the test results. Consistent with the findings of the treasury bond data, the corporate bond portfolios generally have significant loadings on the stock liquidity risk factor. Five of the seven portfolios load significantly on the stock liquidity factor at the 8% level. The stock market liquidity factor $L1$ is significantly priced in the corporate bond market. The associated risk premium is

[13]The result is robust to other stock portfolios in the previous subsection.

[14]To conserve space, I do not report these numbers in the table.

0.0095 with a t-statistic of 2.33. When we estimate the model simultaneously with stock portfolios, the common stock liquidity factor again receives significant risk premium.

The evidence in this subsection provides support that stock market liquidity risk exerts an effect on bond markets as well.

5 Reexamination of the Relation Between the Expected Value and the Volatility of the Nominal Excess Return on Stocks

Fujimoto and Watanabe (2003) find a significant positive relation between illiquidity and the conditional variance of monthly stock returns using three liquidity proxies ($PSPR$, $ILIQ$, and $PS_{\$}$) respectively. Moreover, the illiquidity measures subsume traditional GARCH coefficients in the conditional variance of the stock returns. This means that stock liquidity is important in the dynamics of the conditional variance. In the literature, there has been a long-standing debate on the tradeoff between risk and return. The empirical evidence on this topic is conflicting. Standard GARCH-M models generally support for a zero or positive relation. Using a modified GARCH-M model, Glosten, Jagannathan, and Runkle (1993) document a negative relation between conditional expected monthly return and the conditional variance of monthly return. It is possible that the models for the conditional volatility may not capture the time series properties of the excess stock returns correctly. Given the evidence that market liquidity is important in the modelling of the conditional variance of stock returns, I reexamine the risk-return relation by including the market liquidity in the modelling of the conditional variance.

I revise the Glosten, Jagannathan, and Runkle (1993) modified GARCH-M model by incorporating the stock liquidity measure $PC1$ in the dynamics of the conditional variance. Let r_t be the continuously compounded excess return on the CRSP value-weighted index of stocks. The general GARCH-M model of the risk-return relation is given by:

$$r_t = a_0 + a_1 h_{t-1} + \epsilon_t \tag{20}$$

$$h_{t-1} = b_0 + b_1 h_{t-2} + \beta' x_{t-1} + g_1 \epsilon_{t-1}^2 + g_2 \epsilon_{t-1}^2 I_{\{\epsilon_{t-1}<0\}} \tag{21}$$

where $E_{t-1}[\epsilon_t] = 0$ and $E_{t-1}[\epsilon_t^2] = h_{t-1}$. x_{t-1} is a vector of instrument variables which are important in the conditional variance process. Here, I use continuously compounded return on Treasury bills from Ibbotson & Associates and the common liquidity measure $PC1$ in x_{t-1}. Glosten, Jagannathan, and Runkle (1993) show that the risk-free rate contains information about future volatility within the GARCH-M framework. When including the liquidity measure $PC1$ in the vector x_{t-1}, I orthogonalize it against the market excess return. The indicator $I_{\{\epsilon_{t-1}<0\}}$ is 1 when $\epsilon_{t-1} < 0$, and 0 otherwise. It is meant to capture the asymmetric effect that positive and negative innovations to returns may have different impacts on the conditional volatility.

Table 12 presents the estimate results from various model specifications. The first two models demonstrate the importance of stock liquidity on the conditional variance of stock returns. Model 1 is the standard GARCH(1,1) model without exogenous variables. As what is usually found in the literature, both the ARCH and GARCH coefficients are significant and their sum is close to but smaller than 1, indicating stationarity and high persistence. The value of the GARCH coefficient 0.87 is much larger than the value of the ARCH coefficient 0.05, implying long memory in the conditional variance. Model 2 incorporates the orthogonalized liquidity measure in the conditional variance equation. The liquidity measure turns out to be significant at the 1% level and completely subsumes the significance of the two GARCH related coefficients b_1 and g_1. The negative coefficient of $PC1$ (β_2) indicates that lower market liquidity results in upward revisions of the conditional variance. These results are consistent with Fujimoto and Watanabe (2003) Table 6 results, and imply that the liquidity measure provides useful information about the variability of the market return. I examine the risk-return relation from Model 3 onwards. The coefficient we are focusing on is a_1. In Model 3, when I include both $PC1$ and rf in the conditional variance process, only $PC1$ is significant. The risk-return relation a_1 is positive but not significantly different from zero. I encountered some problem in estimating the GARCH-M models with asymmetric effect. So I only present part of the results for asymmetric GARCH-M models. Model 4 is a standard asymmetric GARCH-M model. The negative sign of g_1 indicates that unexpected positive return decreases the conditional variance. The t-statistic for g_2 is 1.75, indicating weak evidence of asymmetric effect in the conditional variance during our sample period. Model 5 is an extension of Model 4 by adding the risk-free rate in the conditional variance process, and the results are qualitatively same.

In conclusion, by including the common liquidity measure $PC1$ in the dynamics of the conditional variance of the stock return, I document zero or insignificantly positive relation between risk and return. Note we should be cautious in interpreting this result because there is always possibility that the model specifications used here are misspecified.

6 Conclusions

This paper demonstrates that a common liquidity factor, extracted from seven liquidity proxies using principal component analysis, captures the common source of liquidity variation. My first contribution is providing a unique liquidity risk measure and resolving the debate of whether and to what extent liquidity has an important bearing on asset pricing.

Armed with the extracted unique liquidity risk measure, I find that liquidity does matter in asset pricing. Moreover, I find that from 1971 through 2002, a difference in liquidity risk contributes 3.70% to the difference in annualized expected return between high β^L and low β^L portfolios.

I investigate the extent to which liquidity can explain the cross-sectional momentum effect. With the exception of the two most winner portfolios (deciles 9-10), loadings on the liquidity factor increase monotonically from the loser portfolio (decile 1) to decile 8. Adding liquidity spread to the Fama-French three factors reduces momentum spread's alpha from 14.46% to 12.13% for 6/0/6 momentum portfolios, and from 16.68% to 14.12% for 12/0/3 momentum portfolios. Models with the common liquidity factor are superior to models with momentum factor in pricing the momentum portfolios. The common liquidity factor drives out the momentum factor in the pricing of 6/0/6 momentum portfolios.

I also examine the role of liquidity in cross-sectional pricing effect as opposed to different responses to the increasing volatility. Using Ang, Hodrick, Xing and Zhang (2004) aggregate volatility measure, I find that the liquidity effect is robust to controlling for the volatility effect. This evidence implies that although liquidity and volatility are intimately related to each other, they have different cross-sectional pricing effect.

I find that the stock liquidity risk is also priced in the bond markets. I interpret this result as evidence for "flight to quality" effect, which is consistent with Pastor and Stambaugh's (2003) findings.

Finally, by including the market liquidity measure in the conditional variance process of GARCH-M models, I reexamine the risk-return relation and document insignificantly positive relation.

The evidence presented in this paper suggests that liquidity risk is a pervasive risk factor, and it is priced in both stock markets and bond markets. The future research agenda will be incorporating the pervasive liquidity factor in the pricing kernel, and modelling the term structure and stock markets jointly.

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Table 1: **Descriptive Statistics for Monthly Aggregate Liquidity Measures.** This table presents descriptive statistics for seven scaled aggregate liquidity proxies: proportional bid-ask spread ($PSPR$), turnover ($STOV$), illiquidity ratio ($ILLIQ$), Pastor and Stambaugh return reversal ($PS_{\$}$ and PS_{to}), and Breen, Hodrick, and Korajczyk measure ($BHK_{\$}$ and BHK_{to}). The aggregate proxies are given by the cross-sectional average of the corresponding individual-stock liquidity measures and then scaled for stationarity concern. The construction of each measure is explained in Section 2. The sample period is from Jan 1963 to Dec 2002.

	$PSPR$	$STOV$	$ILLIQ$	$PS_{\$}$	$BHK_{\$}$	PS_{to}	BHK_{to}
A. Correlations							
$PSPR$	1.00						
$STOV$	0.30	1.00					
$ILLIQ$	0.37	0.29	1.00				
$PS_{\$}$	0.18	0.15	0.29	1.00			
$BHK_{\$}$	0.30	0.23	0.82	0.43	1.00		
PS_{to}	0.22	0.24	0.34	0.85	0.40	1.00	
BHK_{to}	0.27	0.44	0.55	0.40	0.68	0.47	1.00
B. Autocorrelations							
Lag							
1	0.9311	0.6662	0.8885	0.1854	0.7969	0.2607	0.9126
2	0.8673	0.4914	0.8563	0.2803	0.8016	0.2367	0.8222
3	0.8144	0.3841	0.8300	0.2036	0.7806	0.1690	0.7634
4	0.7452	0.2611	0.7780	0.1229	0.6957	0.0908	0.7048
5	0.6884	0.2171	0.7611	0.1902	0.7231	0.1315	0.6651

Table 2: **Principal Component Analysis.** This table presents the Principal Component analysis result from the seven liquidity proxies: proportional bid-ask spread ($PSPR$), turnover ($STOV$), illiquidity ratio ($ILLIQ$), Pastor and Stambaugh return reversal ($PS_{\$}$ and PS_{to}), and Breen, Hodrick, and Korajczyk measure ($BHK_{\$}$ and BHK_{to}). The construction of the seven liquidity proxies is explained in Section 2. The columns list the principal components corresponding to the first to smallest eigenvalues. The loadings of the principal components and the corresponding weighting percentage for each principal component to explain the total liquidity variation are reported. The right panel reports the selected correlations for the first principal component $PC1$ with the seven liquidity proxies, market return ($mktret$), market volatility ($mktvol$ and VIX) and market trading volume ($volume$). The sample period is from Dec 1965 to Dec 2002.

Principal Component Analysis									
	$PC1$	$PC2$	$PC3$	$PC4$	$PC5$	$PC6$	$PC7$	$corr$	$PC1$
$PSPR$	0.3071	0.1182	-0.2680	0.2504	-0.4593	0.0593	-0.0256	$PSPR$	0.4893
$STOV$	0.3946	-0.0898	0.1703	-0.2568	-0.0303	0.0470	-0.0159	$STOV$	0.5447
$ILLIQ$	0.3397	0.1569	-0.3237	-0.1979	0.0680	-0.1033	0.1235	$ILLIQ$	0.7355
$PS_{\$}$	0.3527	-0.0435	0.2630	-0.1070	-0.0054	0.1821	0.0118	$PS_{\$}$	0.6644
$BHK_{\$}$	0.3857	0.1329	-0.3810	-0.1435	0.2646	0.0169	-0.0853	$BHK_{\$}$	0.8087
PS_{to}	0.3872	-0.0727	0.3718	-0.0115	-0.0365	-0.1588	-0.0124	PS_{to}	0.7129
BHK_{to}	0.4306	-0.1027	0.1627	0.3975	0.1147	-0.0450	0.0176	BHK_{to}	0.8292
% variance								$mktret$	0.3216
explained	0.6172	0.1535	0.1004	0.0669	0.0379	0.0175	0.0064	$mktvol$	-0.5281
								VIX	-0.6671
								$volume$	0.4446

Table 3: **Average Market Liquidity at Different Stock Market and Economic States.** This table reports the average monthly liquidity levels at different stock market and economic states. The market liquidity proxy is the extracted 1st principal component $PC1$ as described in Section 3. Down (up) markets are the months with negative (zero or positive) market return (*mktret*). High (low) volatility months are those with greater than (equal to or less than) average market volatility (*mktvol*). High (low) trading activity months are those with greater than (equal to or less than) average market trading volume (*volume*). *mktret*, *mktvol* and *volume* are described in Section 3. The business cycle classification is based on the NBER business cycle dates. Expansionary (contractionary) monetary regimes are the months with falling (rising) Federal Reserve discount rates. Sample months are also classified into months with high (low) probability of recession if the probability of future recession based on Stock and Watson's (1989) Experimental Recession Index exceeds 20% and otherwise. Robust p-values for difference in means are reported. The sample period is from Dec 1965 to Dec 2002.

	$PC1$
Market Return	
(1) Down (N.Obs.=187)	-0.7998
(2) Up (N.Obs.=293)	0.3039
P((2)-(1)=0)	0.01
Market Volatility	
(1) High (N.Obs.=191)	-1.0199
(2) Low (N.Obs.=289)	0.5138
P((2)-(1)=0)	0.001
Market Volume	
(1) Low (N.Obs.=263)	-0.6687
(2) High (N.Obs.=217)	0.4957
P((2)-(1)=0)	0.01
NBER Business Cycles	
(1) Recessions (N.Obs.=66)	-1.5616
(2) Expansions (N.Obs.=414)	0.1104
P((2)-(1)=0)	0.06
Monetary Policy Regimes	
(1) Contractionary (N.Obs.=234)	-0.7181
(2) Expansionary (N.Obs.=246)	0.3629
P((2)-(1)=0)	0.02
Experimental Recession Index	
(1) High (N.Obs.=104)	-1.0946
(2) Low (N.Obs.=376)	0.1543
P((2)-(1)=0)	0.07

Table 4: **Properties of 5×5 Size and Liquidity Beta Portfolios.** 5×5 size and liquidity beta sorted portfolios are formed as follows. At the beginning of each month, firms are first sorted into five groups by size. Within each size quintile, firms are sorted into quintile portfolios according to their historical liquidity beta with respect to the constructed liquidity factor $L1$, which is computed using the most recent five years of monthly data. Panel A reports the risk diagnostics of the portfolios. The annualized Fama-French alpha are reported in percentage. The loadings on the Fama-French three factors, MKT, SMB, HML, and the non-traded liquidity factor $L1$ are computed through a time-series multiple regression of each portfolio on these factors. The numbers in square brackets are robust Newey-West t-statistics. Panel B reports corresponding liquidity characteristics. size is the logarithm of the market capitalization in millions of dollars. Turnover is reported in percentage. The sample period is from Jan 1971 to Dec 2002.

Panel A: Risk Diagnostics							
		Low		β^L		High	High-Low
	Size						
	Small	7.49	8.50	7.64	7.56	10.31	2.82
		[2.15]	[3.35]	[3.24]	[3.12]	[3.70]	[1.13]
Fama-French		-5.19	-0.23	0.33	0.42	-1.22	3.97
		[-2.90]	[-0.19]	[0.24]	[0.32]	[-0.71]	[2.59]
alpha		-3.42	0.91	1.52	1.79	0.48	3.90
		[-2.77]	[0.98]	[1.68]	[1.95]	[0.43]	[2.57]
		-2.30	2.06	1.15	2.32	1.09	3.39
		[-2.13]	[2.41]	[1.31]	[2.61]	[1.11]	[2.26]
	Big	-1.78	0.07	0.43	0.26	0.51	2.29
		[-1.63]	[0.09]	[0.54]	[0.29]	[0.58]	[1.55]
	Small	-1.12	-0.59	-0.28	-0.32	-0.51	0.60
		[-2.11]	[-1.54]	[-1.11]	[-1.18]	[-1.08]	[2.23]
		-0.67	0.00	0.17	0.17	-0.08	0.58
		[-2.62]	[0.04]	[1.15]	[1.20]	[-0.40]	[3.23]
L1		-0.44	-0.05	0.18	0.23	0.03	0.47
		[-3.02]	[-0.49]	[1.59]	[2.02]	[0.20]	[2.93]
loading		-0.41	0.12	0.18	0.25	0.15	0.56
		[-2.97]	[0.94]	[1.41]	[1.80]	[1.14]	[3.01]
		-0.32	0.14	0.20	0.29	0.22	0.54
	Big	[-2.23]	[1.04]	[1.52]	[2.14]	[1.82]	[2.79]

Table 4-*Continued*

Panel B: Liquidity Characteristics						
		Low		β^L		High
	Size					
size	Small	1.59	1.69	1.74	1.73	1.65
		3.15	3.18	3.18	3.18	3.15
		4.26	4.28	4.30	4.30	4.27
		5.48	5.52	5.52	5.51	5.48
		7.33	7.49	7.53	7.45	7.24
turnover	Small	3.98	3.30	3.12	3.45	4.42
		5.38	4.14	3.94	4.18	5.59
		7.51	5.33	4.78	4.89	7.07
		8.89	6.16	5.59	5.86	8.24
		9.03	6.11	5.70	5.80	7.05
illiquidity ratio	Small	74.69	62.18	48.86	49.34	61.63
		5.89	4.90	4.64	4.43	4.88
		0.90	0.93	0.92	0.95	0.88
		0.21	0.19	0.23	0.22	0.18
		0.03	0.02	0.03	0.03	0.03

Table 5: **Pricing Common Liquidity Risk with Cross-sectional Testings.** This table reports the factor premiums on 25 portfolios sorted first on size and then on liquidity beta β^L. β^L is computed from the regression $r_{i,t} = \beta_i^0 + \beta_i^M MKT_t + \beta_i^S SMB_t + \beta_i^H HML_t + \beta_i^L L1_t + \epsilon_{i,t}$ using the most recent five years of monthly data. MKT is the excess return on the market portfolio, SMB and HML are the Fama-French (1993) size and value factors, UMD is the momentum factor constructed by Kenneth French, and $L1$ is the common liquidity factor constructed in Section 4.1. The risk premiums are estimated by GMM method. Robust t-statistics are reported in square brackets. The sample period is from Jan 1971 to Dec 2002.

	MKT	SMB	HML	UMD	$L1$
Model I	0.0058	0.0024	0.0101		0.0056
	[1.6016]	[0.9303]	[2.8660]		[3.3154]
Model II	0.0044	0.0030	0.0080	-0.0186	0.0070
	[1.2180]	[1.0598]	[2.0253]	[-1.9121]	[3.0945]

Table 6: **Examination of the Other Principal Components in the Pricing of Stock Returns.** This table reports the factor premiums on 25 portfolios sorted first on size and then on liquidity beta β^L. β^L is computed from the regression $r_{i,t} = \beta_i^0 + \beta_i^M MKT_t + \beta_i^S SMB_t + \beta_i^H HML_t + \beta_i^L L_t + \epsilon_{i,t}$ using the most recent five years of monthly data. MKT is the excess return on the market portfolio, SMB and HML are the Fama-French (1993) size and value factors, and $L2 - L7$ are the innovation series for the 2nd principal component to the 7th principal component. The risk premiums are estimated by GMM method. Robust t-statistics are reported in square brackets. The sample period is from Jan 1971 to Dec 2002.

Risk Premiums			
2nd Principal Component			
MKT	SMB	HML	$L2$
-0.0053	-0.0025	0.0181	-0.0014
[−2.0915]	[-1.0288]	[3.9935]	[-0.7259]
3rd Principal Component			
MKT	SMB	HML	$L3$
0.0035	0.0005	0.0167	-0.0021
[1.1547]	[0.2056]	[4.2634]	[-1.3308]
4th Principal Component			
MKT	SMB	HML	$L4$
-0.0030	-0.0034	0.0251	0.0016
[−0.8893]	[-1.2955]	[4.9509]	[1.4290]
5th Principal Component			
MKT	SMB	HML	$L5$
0.0020	-0.0008	0.0138	-0.0007
[0.6970]	[-0.3374]	[3.6328]	[-0.6437]
6th Principal Component			
MKT	SMB	HML	$L6$
-0.0024	0.0005	0.0185	0.0006
[−0.8109]	[0.2318]	[4.9603]	[0.8876]
7th Principal Component			
MKT	SMB	HML	$L7$
0.0018	0.0006	0.0151	-0.0002
[0.5711]	[0.2668]	[3.6485]	[-0.4247]

Table 7: **Alphas of Momentum Portfolios.** This table reports the liquidity loadings and alphas for the momentum decile portfolios when regressed on the three Fama-French factors plus liquidity spread LIQ. LIQ is the liquidity spread controlling for size, which is constructed from the 5×5 size and liquidity beta sorted portfolios. Alphas are annualized and reported in percentage. The construction of 6/0/6 momentum portfolios in Panel A and 12/0/3 portfolios in Panel B is described in Section 4.2.5. The sample period is from Jan 1971 to Dec 2002.

	DECILE PORTFOLIO										
	1	2	3	4	5	6	7	8	9	10	10-1
	A. Momentum 6/0/6										
FF3-α	-8.91	-8.34	-4.71	-2.77	-0.76	0.23	1.39	2.27	3.81	5.55	14.46
	[-3.05]	[-4.89]	[-4.00]	[-3.07]	[-0.96]	[0.30]	[1.71]	[2.53]	[3.47]	[3.56]	[4.66]
FF3+LIQ α	-6.55	-7.35	-4.24	-2.62	-0.83	0.00	1.02	1.89	3.58	5.58	12.13
	[-2.17]	[-4.14]	[-3.45]	[-2.80]	[-1.01]	[0.00]	[1.28]	[2.10]	[3.10]	[3.34]	[3.77]
LIQ loading	-0.77	-0.32	-0.15	-0.05	0.02	0.07	0.12	0.13	0.07	-0.01	0.77
	[-3.04]	[-2.72]	[-2.14]	[-0.94]	[0.46]	[1.47]	[2.26]	[2.00]	[0.86]	[-0.07]	[3.38]
	B. Momentum 12/0/3										
FF3-α	-8.77	-9.74	-5.96	-2.74	-0.86	0.60	2.06	3.36	5.48	7.91	16.68
	[-2.81]	[-5.56]	[-4.84]	[-2.89]	[-1.05]	[0.76]	[2.40]	[3.42]	[4.33]	[4.62]	[4.79]
FF3+LIQ α	-6.29	-8.81	-5.55	-2.57	-1.00	0.26	1.72	3.03	5.17	7.83	14.12
	[-1.98]	[-4.95]	[-4.39]	[-2.59]	[-1.20]	[0.34]	[2.00]	[2.96]	[3.83]	[4.20]	[4.00]
LIQ loading	-0.81	-0.30	-0.14	-0.06	0.04	0.11	0.11	0.11	0.10	0.03	0.84
	[-2.99]	[-2.72]	[-1.98]	[-1.10]	[0.99]	[2.50]	[1.65]	[1.43]	[1.05]	[0.21]	[3.33]

Table 8: **Liquidity and Momentum.** This table investigates the relation between liquidity and momentum in the cross-section of stock returns. $L1$ is the common liquidity factor described in Section 4.1. UMD is the momentum factor constructed by Kenneth French. Risk premiums and associated t-statistics are presented. Optimal GMM over-identification test statistics, HJ-distance, and associated p-values are also reported. ΔJ test statistic and associated p-value are for the null hypothesis that adding momentum factor UMD to $FF3 + L1$ does not help model performance in the pricing of momentum portfolios. Panel A uses the 6/0/6 momentum portfolios as testing assets, while Panel B uses the 12/0/3 momentum portfolios. The sample period is from Jan 1971 to Dec 2002.

Panel A: 6/0/6 momentum decile portfolios							
MKT	SMB	HML	$L1$	UMD	over-identification test	HJ Distance	ΔJ
-0.0042	0.0112	-0.0007	0.0082		7.8210	0.1746	
[−0.5136]	[1.5121]	[-0.1599]	[2.3858]		(0.2515)	(0.4425)	
0.0087	-0.0026	-0.0016		0.0075	16.8613	0.2347	
[1.3435]	[-0.4836]	[-0.3681]		[2.6105]	(0.0098)	(0.0066)	
-0.0062	0.0131	0.0025	0.0081	0.0073	6.1212	0.1544	1.2183
[−0.7128]	[1.6471]	[0.4856]	[2.2418]	[1.5674]	(0.2946)	(0.4528)	(0.2697)
Panel B: 12/0/3 momentum decile portfolios							
MKT	SMB	HML	$L1$	UMD	over-identification test	HJ Distance	ΔJ
0.0078	-0.0008	-0.0067	0.0081		16.3158	0.2905	
[1.1964]	[-0.1160]	[-1.5699]	[3.5158]		(0.0122)	(0.0141)	
-0.0015	0.0050	0.0057		0.0105	24.6917	0.3203	
[−0.2896]	[1.3025]	[1.5074]		[3.7515]	(0.0004)	(0.0000)	
0.0022	0.0053	0.0002	0.0068	0.0098	15.4812	0.2705	2.6976
[0.3633]	[0.9282]	[0.0532]	[3.1026]	[2.6193]	(0.0085)	(0.0086)	(0.1005)

Table 9: **Common Liquidity Factor and Individual Liquidity Measures.** This table investigates the relation between the common liquidity factor and individual liquidity measures in the cross-section of stock returns. $L1$ is the common liquidity factor described in Section 4.1. The seven individual liquidity measures are proportional bid-ask spread ($PSPR$), turnover ($STOV$), illiquidity ratio ($ILLIQ$), Pastor and Stambaugh return reversal ($PS_{\$}$ and PS_{to}), and Breen, Hodrick, and Korajczyk measure ($BHK_{\$}$ and BHK_{to}). The prefix "O" before each measure stands for the orthogonalized measure against the common liquidity factor $L1$. Risk premiums and associated t-statistics are presented. The 6/0/6 momentum portfolios are used as testing assets. The sample period is from Jan 1971 to Dec 2002.

MKT	SMB	HML	$PQSPR$	$L1$	$OPQSPR$
0.0114	-0.0034	-0.0053	0.0002		
[1.5147]	[-0.5030]	[-1.2182]	[0.2404]		
0.0042	0.0025	-0.0056		0.0086	-0.0014
[0.3444]	[0.2230]	[-0.8031]		[2.4274]	[-1.0991]
MKT	SMB	HML	$STOV$	$L1$	$OSTOV$
0.0161	-0.0107	-0.0054	0.0027		
[2.2678]	[-1.6086]	[-1.1002]	[2.5571]		
-0.0006	0.0050	-0.0014		0.0079	0.0009
[-0.0621]	[0.4825]	[-0.2545]		[2.1896]	[0.7292]
MKT	SMB	HML	$ILLIQ$	$L1$	$OILLIQ$
0.0066	-0.0005	-0.0082	0.0027		
[0.8510]	[-0.0760]	[-1.6605]	[1.8364]		
-0.0050	0.0118	0.0015		0.0096	-0.0014
[-0.5158]	[1.3595]	[0.2653]		[2.6067]	[-0.6883]
MKT	SMB	HML	$PS_{\$}$	$L1$	$OPS_{\$}$
0.0006	0.0120	-0.0015	0.0006		
[0.0640]	[1.5683]	[-0.2986]	[2.5886]		
-0.0058	0.0128	-0.0002		0.0098	0.0000
[-0.6099]	[1.5119]	[-0.0371]		[2.8546]	[0.0854]
MKT	SMB	HML	$BHK_{\$}$	L	$OBHK_{\$}$
0.0054	0.0013	-0.0057	0.0012		
[0.6163]	[0.1708]	[-1.2620]	[1.9364]		
-0.0062	0.0132	0.0018		0.0100	-0.0009
[-0.5695]	[1.3584]	[0.2441]		[2.5125]	[-1.0047]
MKT	SMB	HML	PS_{to}	L	OPS_{to}
0.0041	0.0055	-0.0021	0.0079		
[0.5516]	[0.8570]	[-0.5097]	[1.9787]		
-0.0062	0.0121	0.0005		0.0097	-0.0037
[-0.6589]	[1.3892]	[0.0951]		[2.7982]	[-1.0336]
MKT	SMB	HML	BHK_{to}	L	$OBHK_{to}$
0.0042	0.0043	-0.0031	0.0003		
[0.5486]	[0.6092]	[-0.7044]	[2.4169]		
-0.0057	0.0127	-0.0002		0.0097	-0.0000
[-0.5943]	[1.5310]	[-0.0370]		[2.8524]	[-0.3193]

Table 10: **Liquidity and Volatility.** This table reports the factor premiums on 25 portfolios sorted first on volatility beta $\beta_{\Delta VIX}$ and then on liquidity beta β^L. β^L is computed from the regression $r_{i,t} = \beta_i^0 + \beta_i^M MKT_t + \beta_i^S SMB_t + \beta_i^H HML_t + \beta_i^L L1_t + \epsilon_{i,t}$ using the most recent five years of monthly data. $\beta_{\Delta VIX}$ is estimated by the regression $r_t^i = \beta_0 + \beta_{MKT}^i \cdot MKT_t + \beta_{\Delta VIX}^i \cdot \Delta VIX_t + \varepsilon_t^i$ using daily data over the past month. MKT is the excess return on the market portfolio, SMB and HML are the Fama-French (1993) size and value factors, UMD is the momentum factor constructed by Kenneth French, $FVIX$ is the mimicking factor for aggregate volatility innovations, $L1$ is the common liquidity factor, and $OL1$ is the orthogonalized liquidity factor against $FVIX$. The risk premiums are estimated by GMM method. Robust t-statistics are reported in square brackets. The sample period is from Jan 1986 to Dec 2002.

Panel A: Factor Premiums						
	MKT	SMB	HML	UMD	$FVIX$	OL1
Model I	0.0110	-0.0024	-0.0046		-0.0957	0.0106
	[1.5077]	[-0.6034]	[-1.0430]		[-2.0172]	[4.4660]
Model II	0.0186	0.0030	-0.0070	0.0243	-0.1406	0.0081
	[2.1919]	[0.7332]	[-1.6575]	[3.1341]	[-2.6302]	[3.4371]

Panel B: Ex-Post Factor Loadings on OL1						
		Pre-ranking on β^L				
		1 low	2	3	4	5
Pre-ranking on $\beta_{\Delta VIX}$	Low 1	-0.76	-0.14	0.12	0.17	0.57
		[-4.44]	[-0.97]	[1.06]	[1.81]	[2.36]
	2	-0.36	-0.07	0.09	0.18	0.23
		[-3.64]	[-0.70]	[1.18]	[2.48]	[2.59]
	3	-0.41	0.08	0.07	0.17	0.32
		[-4.92]	[0.92]	[0.76]	[1.96]	[3.65]
	4	-0.61	-0.04	0.09	0.00	0.44
		[-4.07]	[-0.35]	[0.82]	[0.04]	[3.17]
	5	-0.76	-0.38	-0.02	0.25	0.53
		[-3.76]	[-3.26]	[-0.16]	[1.35]	[2.77]

Table 11: **Pricing Stock Market Liquidity Risk in the Bond Markets.** This table reports loadings on the stock liquidity risk factor and the estimated risk premiums. Panel A uses the CRSP Fama bond portfolios, and Panel B uses the Lehman corporate bond indices from Datastream. The suffix "s" stands for "intermediate maturity", while "l" stands for "long maturity". The liquidity risk factor $L1$ is the extracted common liquidity factor from stock market. The construction is described in Section 4.1. The liquidity loadings are estimated in the presence of the Fama-French three factors. Robust t-statistics are reported in square brackets. The sample period is from May 1971 to Dec 2002 for Fama bond portfolios, and from Jan 1975 to Dec 2002 for Lehman corporate bond indices.

Panel A: CRSP Fama bond portfolios								
	6m	12m	18m	24m	30m	36m	42m	48m
Loading	0.60	1.17	1.82	2.77	3.98	5.06	5.78	6.29
	[1.91]	[1.47]	[1.44]	[1.65]	[1.93]	[2.12]	[2.14]	[2.05]
			MKT			$L1$		
Premium			0.0151			0.0132		
			[1.1047]			[1.7348]		

Panel B: Lehman corporate bonds							
	AAA(s)	AAA(l)	AA(s)	AA(l)	A(s)	A(l)	BAA(s)
Loading	0.0755	0.1164	0.0770	0.1238	0.0768	0.1085	0.0645
	[2.21]	[1.73]	[2.26]	[1.86]	[2.22]	[1.62]	[1.81]
			MKT			$L1$	
Premium			0.0155			0.0095	
			[1.7929]			[2.3259]	

Table 12: **Estimated GARCH-M models for the Risk-return Relation.** This table presents the parameter estimates of the market-level GARCH-M models. r_t is the continuously compounded excess return on the CRSP value-weighted index of stocks. The general GARCH-M model of the risk-return relation is given by $r_t = a_0 + a_1 h_{t-1} + \epsilon_t$, $h_{t-1} = b_0 + b_1 h_{t-2} + \beta_1 rf + \beta_2 PC1_{t-1} + g_1 \epsilon_{t-1}^2 + g_2 \epsilon_{t-1}^2 I_{\{\epsilon_{t-1}<0\}}$, where $E_{t-1}[\epsilon_t] = 0$ and $E_{t-1}[\epsilon_t^2] = h_{t-1}$. rf is continuously compounded return on Treasury bills from Ibbotson & Associates, and $PC1$ is the common liquidity measure. The indicator $I_{\{\epsilon_{t-1}<0\}}$ is 1 when $\epsilon_{t-1} < 0$, and 0 otherwise. Robust t-statistics are shown in square brackets. The sample period is from Dec 1965 to Dec 2002.

	Model 1	Model 2	Model 3	Model 4	Model 5
a_0	0.0623	0.0433	0.0056	0.1055	0.1360
	[1.26]	[1.00]	[0.05]	[0.59]	[1.43]
a_1			0.0533	-0.0370	-0.0647
			[0.41]	[-0.21]	[-0.69]
b_0	0.0763	0.9420	0.6165	0.4163	0.0771
	[1.47]	[4.89]	[3.25]	[1.11]	[0.71]
b_1	0.8728	0.0458	0.1246	0.5215	0.5386
	[11.6]	[0.269]	[0.80]	[1.36]	[2.82]
β_1			0.0997		0.1309
			[1.58]		[1.83]
β_2		-0.4265	-0.3770		
		[-4.61]	[-4.53]		
g_1	0.0537	-0.0028	0.0031	-0.0931	-0.1057
	[2.01]	[-0.18]	[0.17]	[-3.98]	[-4.00]
g_2				0.2819	0.3640
				[1.75]	[1.94]

Figure 1: **Aggregate Liquidity Measures.** The figure plots the scaled time series of seven aggregate market-wide liquidity measures: proportional spread ($PSPR$), turnover ($STOV$), illiquidity ratio ($ILLIQ$), PS return reversal ($PS_{\$}$ and PS_{to}), and BHK measure ($BHK_{\$}$ and BHK_{to}). Each series is given by the cross-sectional average of the corresponding individual-stock measures and then scaled for stationarity concern. The signs of $PSPR$, $ILIQ$, $BHK_{\$}$ and BHK_{to} have been flipped to represent liquidity. The sample period is from Jan 1963 to Dec 2002.

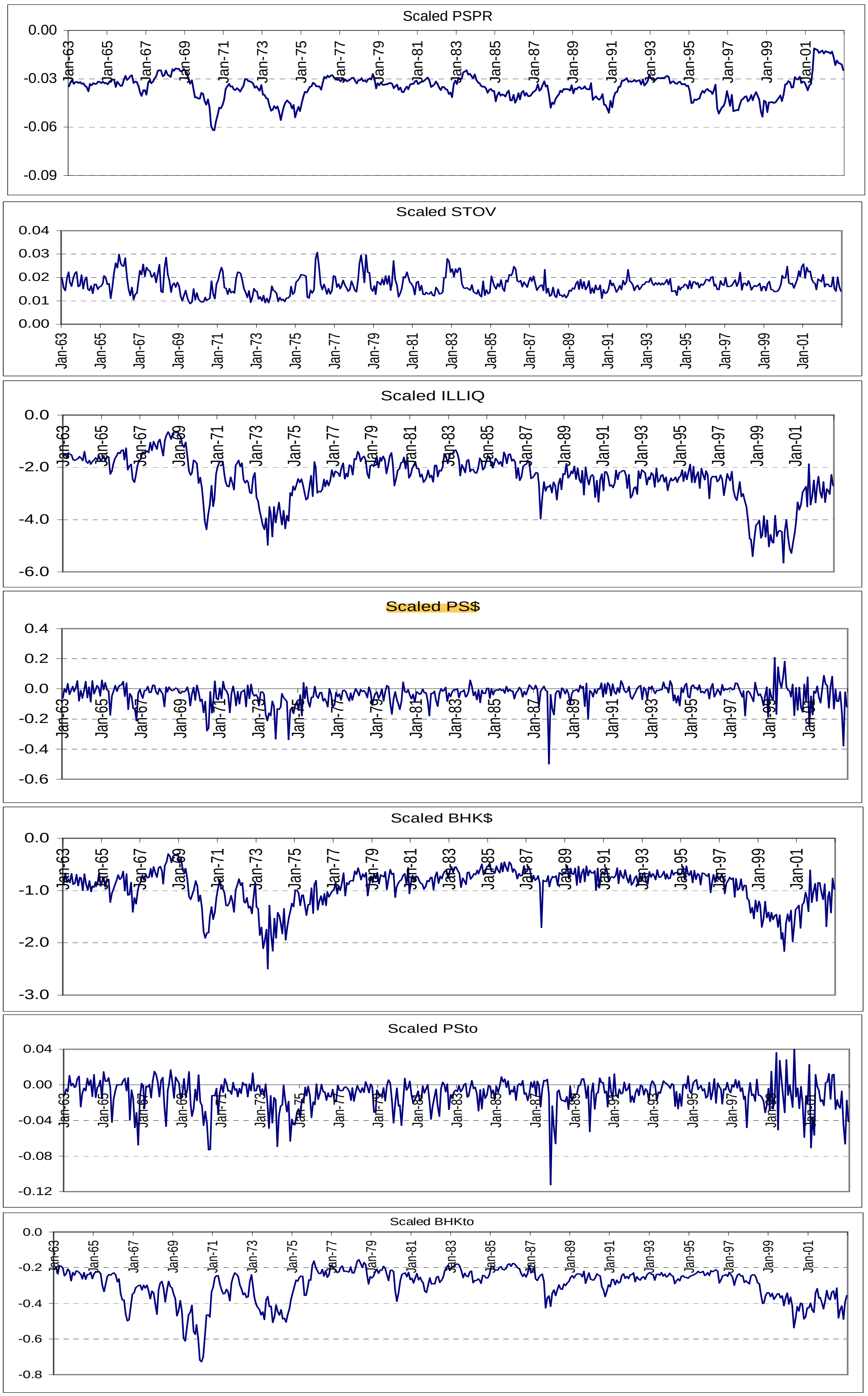

Figure 2: **First Principal Component.** The figure plots the time series of the first principal component extracted from the seven aggregate market-wide liquidity proxies. The sample period is from Dec 1965 to Dec 2002.

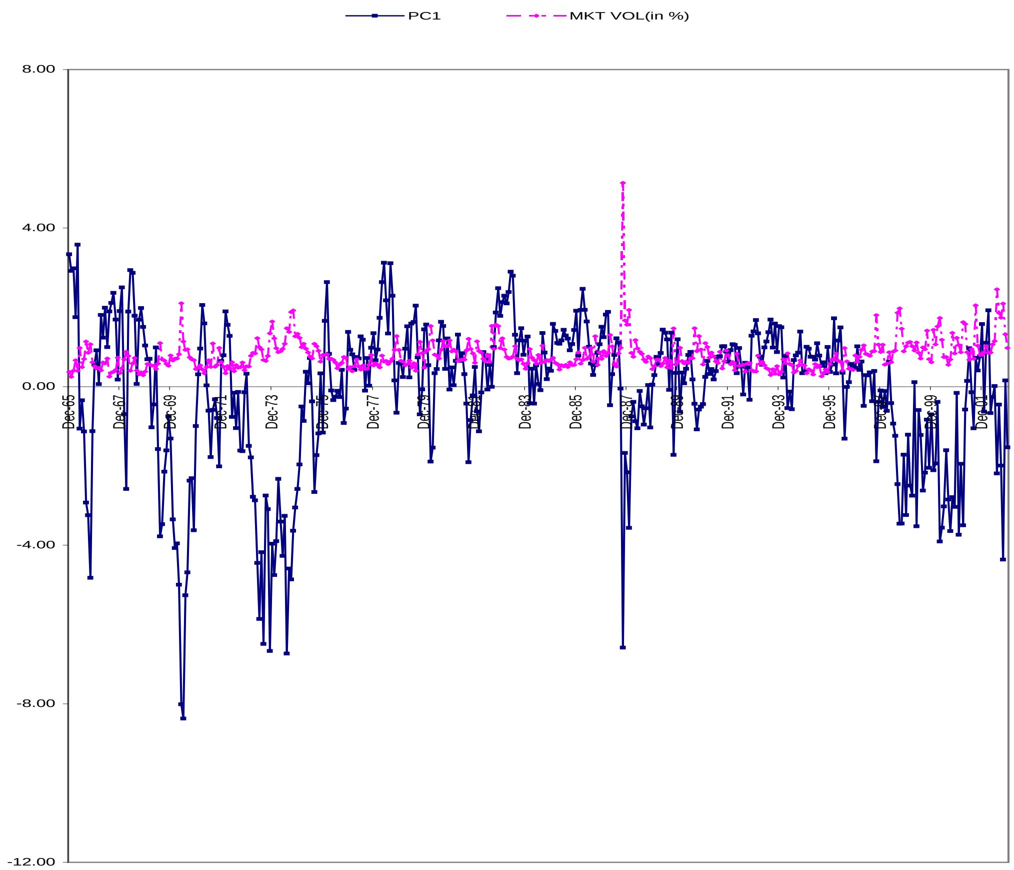

Figure 3: **Innovations in First Principal Component.** The figure plots the time series of innovations to the first principal component. The innovations are computed as residuals from $AR(3)$ model in equation (10). The sample period is from Mar 1966 to Dec 2002.