Liquidity Risk and Trading – Is it Profitable?

470578

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Abstract

This study investigates whether the market-wide liquidity risk is priced. The data I used in this paper is the CRSP daily stock files, from 2002 to 2017. I find that the market liquidity factors are related to the excess return in both cross-sectional and time-series study. The measurement of illiquidity I used in this paper is the Amihud's *ILLIQ*, and the market-factor I used is the innovation of market *ILLIQ* and the difference of quantile illiquidity portfolio, *IML*. The result suggests the market liquidity was indeed priced. I also compared the Sharpe ratio of each quantile portfolios in the later empirical study. The empirical study gives evidence that the most and least illiquidity portfolios outperform during the sample period.

Keywords: Amihud's *ILLIQ*, liquidity risk, asset pricing

1. Introduction

Liquidity is a good candidate for a priced state variable (Pastor et al., 2003). Liquidity is risky and has a commonality: it varies over time both for individual stocks and for the market as a whole (*Chordia et al.*, 2000; *Hasbrouck and Seppi*, 2001; *Huberman and Halka*, 1999). After the financial crisis, people pay more attention to the liquidity risk than ever before. Given that situation, I would like to find the connection between liquidity and stock returns and try to make a liquidity-based trading strategy.

The main research question in this paper is whether the market liquidity risk is priced. There are two main benefits to find out what factor is considered by the market. Theoretically, this leaves us trace to investigate what risks do investors or the market care more, and the effect of each risk factor on the return of financial products. In empirical work, a precise pricing model yields typically better risk management level, better profitability, and more opportunity of arbitrage for investors, and can help policy maker to establish more pinpoint regulatory policies.

In this paper, the liquidity risk is proxied using the most famous and widely used illiquidity measure, *ILLIQ*, which is the daily ratio of absolute stock return to its dollar volume, averaged over the required period (usually monthly or annually). The *ILLIQ* could be interpreted as the daily price response associated with the dollar trading volume. (*Amihud*, 2002). Some other illiquidity measurement, such as bid-ask spread, is not always as easy-to-get as the *ILLIQ* in many stock markets, as the calculation of *ILLIQ* needs only 3 very common public information: price, volume and return of one stock.

This paper employs the traditional capital asset pricing model(*CAPM*), Fama-French factors and momentum factors to find out if there exist alphas, which indicates whether new pricing factor should be introduced; then add liquidity factors in the 4-factor model to show if the liquidity risk is priced.

The regression results show that both cross-sectional and over time effect of liquidity risk factors on the excess stock return is significantly negative. Investors realised and priced the liquidity risk. I also provide evidence that among all 10 quantile illiquidity portfolios, the one with the largest illiquidity outperforms during the whole sample period.

The main contribution of this paper is that this paper examined the liquidity factor still valid in the latest 15 years. Moreover, the Sharpe ratio of each portfolio suggests that the most illiquid portfolio perform the best monthly over 15 years, especially when the market is not extraordinarily liquid or illiquid. This fact indicates that with a stable market liquidity risk level, an illiquidity-stocks-based trading strategy can be considered.

This paper proceeds as follows. Section 2 introduces the data and methodology I used. Section 3 gives the time-series result for univariate regression, regress return on illiquidity. Section 4 presents the empirical study of if illiquidity sorted portfolio is profitable.

2. Data and methodology

2.1 Data

The data I used is daily return and volume data of daily stock files from the CRSP database in WRDS[1], from 01/Jan/2002 to 31/Dec/2017, for all common shares listed on *NYSE* and *AMEX*. The deliberately omit of *NASDAQ* is because there are some indexes (e.g. volume) includes interdealer trades. The other pricing factors, *SMB* (small minus big), *HML* (high minus low) and *UMD* (momentum)[2].

2.2 Measurement of illiquidity

Liquidity is an elusive concept. It is not observed directly but instead has some aspects that cannot be captured in a single measure.[3] Illiquidity reflects the impact of order flow on price- the discount that a seller concedes or the premium that a buyer pays when executing a market order- that results from adverse selection costs and inventory costs (*Amihud and Mendelson*, 1980; *Glosten and Milgrom*, 1985).

If a stock is illiquid, stock's price moves a lot in response to little volume. In my model, illiquidity is the cost of selling, and real markets have several different selling costs including

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[1] source site: https://wrds-web.wharton.upenn.edu/wrds
[2] Source site: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[3] See discussion in *Amihud* and *Mendelson*(1991b)

bid-ask spread, broker fees, market impact, and search costs such as get a counterpart. The empirical strategy is based on the assumption that *ILLIQ* is a valid instrument for the costs of selling. *Amihud*(2002) shows in practical, *ILLIQ* is positively related to measures of price impact and fixed trading costs over the period in which he has the microstructure data.

The return of each stock is given by holding period return(*ret*), and dollar volume is calculated by the volume of each stock(*vol*) times its daily closing price(*prc*).

The illiquidity of each stock is computed as follow,

$$ILLIQ_t^i = \frac{1}{Days_t^i}\sum_{d=1}^{Days_t^i}\frac{\left|R_{td}^i\right|}{V_{td}^i} \tag{1}$$

Where R_{td}^i and V_{td}^i are, respectively, the return and dollar volume (in millions) on day *d* in month *t,* and $Days_t^i$ is the number of valid observation days in month *t* for stock *i*. The dollar volume is calculated by one stock's daily volume times its average daily price.

Note that I followed *Amihud* (2002), selecting the data I use to follow these criteria:

1. Only consider a stock with its trading date larger than 200 days in one year. This criterion is to prevent the abnormal illiquidity outcome caused by the irregular trading situation.

2. At the same time, only the stocks with its price higher than \$5 are considered. For returns on low-priced stocks are much affected by the minimum tick of \$1/8, which adds noise to the estimations

3. After satisfied criteria 1 and 2, stocks whose estimated annual $ILLIQ_t^i$ lies at highest or lowest 1% tails are considered outliers – they are eliminated.

The intuition behind this illiquidity measure follows *Amihud* (2002) and *Archaya et al.* (2005). Stock illiquidity is defined as the average ratio of the absolute daily return to the dollar trading volume on that day. The table below presents the summary statistics for the variables I after selected following above criteria, and the calculated monthly illiquidity.

Table 1 Summary statistics for the variables

This table reports the summary statistics of variables I used to calculate illiquidity, and the equal-weighted illiquidity each year during 2002-2017. The *ILLIQ*_month represent monthly illiquidity. N is the number of observations.

Variable	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**
Return	983,892	0.010985	0.122741	-0.98388	15.98446
Volume	985,312	219247.5	1062135	3	2.01E+08
Price	984,689	57.94127	2052.36	-343.5	297600
***ILLIQ*_month**	985,312	0.065637	0.184555	6.61E-06	1.769078

2.3 Portfolios

At each end of the month, stocks are sorted by their previous year's illiquidity and assigned 10 illiquidity portfolios for each year *y* during the period 2002 to 2017. I compute the monthly illiquidity for each eligible stock as the average over the last period. I calculate the monthly illiquidity for each eligible stock as the average over the entire month *m-1* of daily illiquidity.

Although some authors prefer value-weighted illiquidity and returns for the market portfolio, I followed *Amihud* (2002) and *Chordia et al.* (2000), that focus on equal-weighted return and illiquidity measures. The reason is that computing the market return and illiquidity as equal-weighted averages is a way of compensating for the over-representation in the value-weighted sample.

The return *r* in a year of a month of the portfolio is calculated by following for each portfolio *p* as

$$r_t^p = \sum_{i=1}^{p} w_t^{ip} r_t^i \tag{2}$$

Where the sum is taken over the stocks included in portfolio *p* in period *t*, and where w_t^{ip} are either equal weights or value-based weights. In this paper, it's equal weights, so in another words, it's N_{it}, the number of valid trading the day in the portfolio.

Similarly, the illiquidity of the portfolio is calculated as:

$$c_t^p = \sum_{i=1}^{p} w_t^{ip} c_t^i \tag{3}$$

where w_t^{ip} are either equal weights or value-based weights, depending on the specification. In this paper, I will report equal-weighted portfolio outcome. The market illiquidity in month t is the average of the illiquidity of all trading stocks in the same month.

The table below shows the statistics for the variables I used to calculate illiquidity, and also the illiquidity outcome.

Table 2 Summary statistics for the portfolios

This table reports the summary statistics about the portfolios over the sample period (2002-2017). The CAPM means regress portfolio excess return on the market excess return: $\mathrm{E}(r_t^p - r_t^f) = a + \beta_1 * (r_t^m - r_t^f)$; and the 4-factor model is $\mathrm{E}(r_t^p - r_t^f) = a + \beta_1 * (r_t^m - r_t^f) + \beta_2 * SMB + \beta_3 * HML + \beta_4 * UMD$. The alpha refers to the constant term of each regression model. Where $E(r_t^p)$ represents average monthly return of the portfolio, $\sigma(r_t^p)$ is the standard deviation of each portfolio's monthly return, $E(c_t^p)$ and $\sigma(c_t^p)$ report the average monthly illiquidity and standard deviation of portfolio's monthly illiquidity respectively. N is the number of stocks over the whole sample period. The variable r_t^p and c_t^p are calculated following formula (2) and (3).

Portfolio	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**10-1**
CAPM Alpha	-0.00145	-0.000114	0.000509	0.000428	0.00110	0.00133	0.00266	0.00417	0.00482	0.00822	0.0208
	(-1.95)	(-0.11)	(0.47)	(0.37)	(0.90)	(1.00)	(1.87)	(2.92)	(3.50)	(5.94)	(164.64)
4-Factor Alpha	-0.000994	0.000132	0.000633	0.000511	0.000979	0.00122	0.00258	0.00378	0.00457	0.00805	0.0197
	(-1.55)	(0.16)	(0.87)	(0.70)	(1.38)	(1.56)	(2.84)	(3.98)	(4.34)	(6.95)	(149.97)
$\boldsymbol{E(r_t^p)}$	0.005244	0.006931	0.007366	0.007495	0.008408	0.007768	0.010007	0.01139	0.012019	0.015901	-
$\boldsymbol{\sigma(r_t^p)}$	4.11E-02	0.048941	0.049313	0.050987	0.048624	4.73E-02	0.0466	0.044116	0.042256	0.037926	-
$\boldsymbol{E(c_t^p)}$	0.000103	0.000413	0.001057	0.002395	0.004674	0.009123	0.018556	0.039353	0.103465	0.379964	-
$\boldsymbol{\sigma(c_t^p)}$	0.000289	0.000461	0.001367	0.003555	0.007676	0.012116	0.028055	0.05286	0.126449	0.344516	-
N	1179	2136	2780	3208	3507	3677	3706	3553	3359	2877	-

3. Empirical results

3.1 Building a liquidity risk factor

This section investigates whether a stock's expected return is related to the sensitivity of its return to the innovation in aggregate liquidity. I used the 10 portfolios I formed in the previous section.

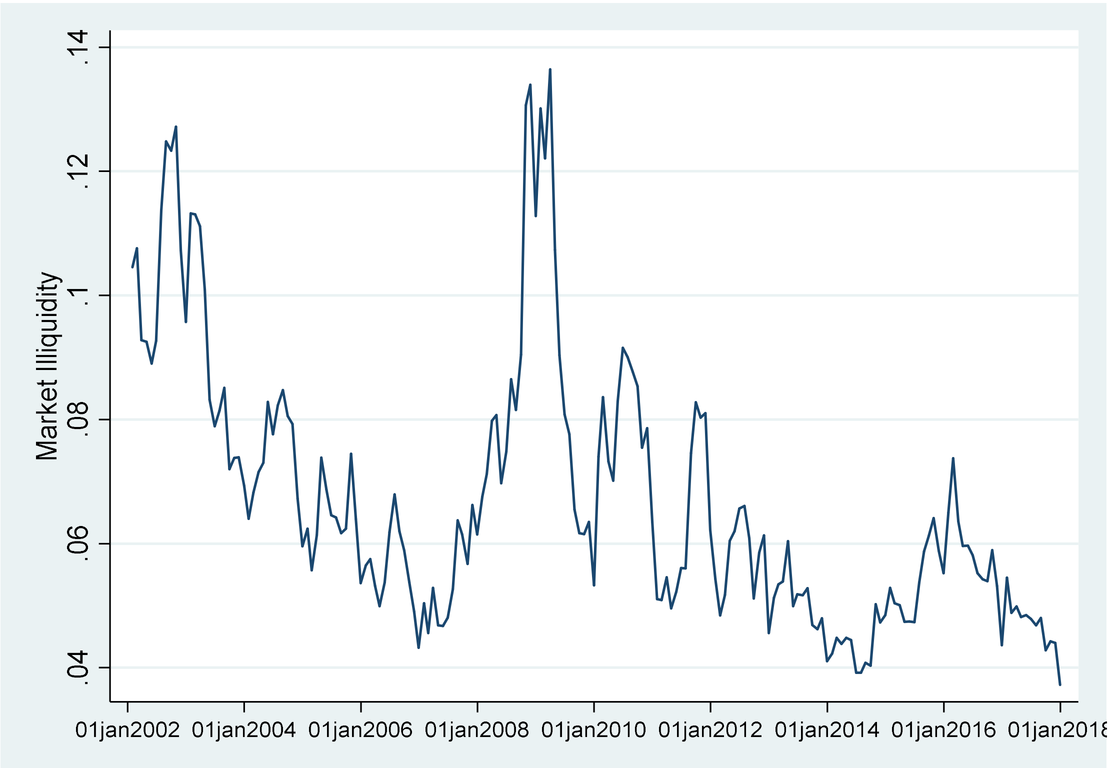
Firstly, I calculated the market illiquidity by

$$c_t^M = \frac{1}{N}\sum_{i=1}^{k} c_t^i \tag{4}$$

where c_t^M is the market illiquidity in month t. The distribution of market illiquidity is shown in the figure below:

Figure. 1 Market illiquidity

This figure shows the distribution of *NYSE* and *AMEX* market illiquidity. It is noticeable that a sky-rocketing of illiquidity burst during the subprime crisis, and the dot-com bubble as well.



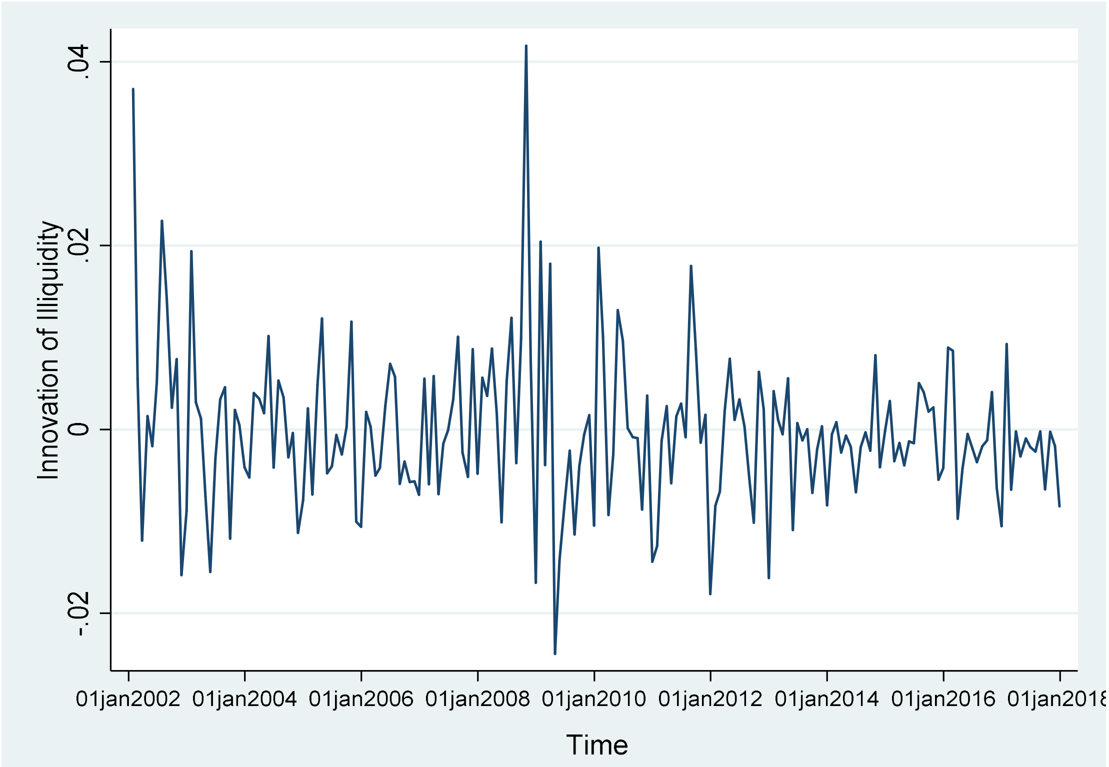
Then I followed *Acharya et al.* (2005) to form a liquidity risk factor. To predict market illiquidity, I run the following regression:

$$ILLIQ_t^M = a + \beta_1 * ILLIQ_{t-1}^M + C_t^{inov} \tag{5}$$

Where $ILLIQ_t^M$ is the average $ILLIQ$ of each portfolio in month t. Then I extract the innovation term, C_t^{inov}, and use it as the factor of illiquidity of the market. The distribution of innovation over time is shown below.

Figure. 2 Innovation of Illiquidity

The figure below plots the innovation of illiquidity. This term is calculated by extract the residual term of this time series regression: $ILLIQ_t^M = a + \beta_1 * ILLIQ_{t-1}^M + C_t^{inov}$.



Then a new illiquidity-related factor was built up and used as a pricing factor combined with traditional Fama-French factors model (1993):

$$\mathrm{E}\left(r_t^i - r_t^f\right) = a + \beta_1 * \left(r_t^m - r_t^f\right) + \beta_2 * SMB + \beta_3 * HML + \beta_4 * UMD + \beta_5 * C_t^{inov} \quad (6)$$

where *SMB* is small minus big, *HML* is high minus low, and *UMD* is the momentum factor. r_t^m is the market return. All the 4 above factors are given by Fama-French's website.

Table 3 Correlation matrix

This table reports the correlation between different pricing factors. Where is the monthly illiquidity measured using formula 5. *MKT* represents the market excess return (market return minus risk-free return). *SMB*, *HML* and *UMD* represent small minus big, high minus low and momentum factors.

	C_t^{inov}	**MKT**	**SMB**	**HML**	**UMD**
C_t^{inov}	1				
MKT	-0.3593	1			
SMB	-0.0181	0.3091	1		
HML	-0.3102	0.2074	0.1767	1	
UMD	0.1176	-0.4256	-0.0641	-0.2797	1

To check the effect of I run the regression on the return of each stock, and get the following result:

$\mathrm{E}(r_t^i - r_t^f) = 0.00315 + 0.878 * (r_t^m - r_t^f) + 0.511 * SMB + 0.0575 * HML - 0.0904 * UMD - 0.339 * C_t^{inov}$, all the betas are significant under 1 percent significance level.

From the result, we can find out that the illiquidity factor has a significant negative coefficient of the excess return for individual stocks. The increase of market illiquidity will lead to a decrease in individual stock's excess return.

3.2 Portfolio study—sorting by illiquidity

As discussed earlier, the liquidity risk is priced for individual stocks. Now I'm going to find out if it also works for portfolios. In this section, I'll assign 10 portfolios based on quantile of illiquidity. The portfolio's return is measured by formula (2). Firstly, I'll run the time-series regression of traditional capital asset pricing model (CAPM) and 4-factor model that combined the Fama-French factors *MKT* (market excess return), *SMB* (small minus big) and *HML* (high minus low), and the *MOM* (momentum). If the liquidity risk factor is priced, it could be seen that systematic differences occur in the average returns of the illiquidity-based portfolios. The equal-weighted portfolios' alphas were shown in table 2.

From table 2 we can see that both the value and the significance of alpha monotonically increases along with the increase of illiquidity, which suggests that the pricing of liquidity risk.

Then I regress excess return of portfolio on the Fama-French factors and liquidity risk factor. I here use *IML*, illiquidity minus liquidity, as a robustness check. The regression formula is as follows: $\mathrm{E}(r_t^p - r_t^f) = a + \beta_1 * (r_t^m - r_t^f) + \beta_2 * SMB + \beta_3 * HML + \beta_4 * UMD + \beta_5 * ILLIQUIDITY$

Where the *ILLIQUIDITY* could be either *IML* or C_{inov}, the innovation of market illiquidity that is discussed in the previous section. The *IML* factor, introduced by *Amihud et. al*[4](2015), is measured by the difference of the top 10 quintile and least 10 quintile portfolios of stocks. If the illiquidity factor is priced, it is expected that the alpha of each portfolio will be no difference from 0 when the relative factors are introduced. So I use GRS-test to find out if there's alpha exist in each portfolio. The regression outcome presents below:

Table 4 Properties of illiquidity portfolios

This table reports the pricing model based on the Fama-French 3 factor model and an illiquidity measure C_{inov} or *IML*. Where R_p represents the return of each equal-weighted portfolio, C_{inov} represents the innovation of market illiquidity, and *IML* represents the illiquid minus liquid factor. GRS is the p-value of GRS-test for each regression equation. The GRS-test is calculated by:

$z = \frac{T-n-1}{n(T-2)} \frac{1}{q1} \hat{\alpha}' \widehat{\Sigma^{-1}} \hat{\alpha} \sim F_{n,T-n-1}$. The observation of each portfolio is 192(months).

Portfolio	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**10-1**
Alpha	-0.000955	0.000235	0.000664	0.000574	0.00111	0.00128	0.00267	0.00389	0.00465	0.00820	0.0195
	(-1.50)	(0.30)	(0.93)	(0.79)	(1.67)	(1.61)	(2.95)	(4.14)	(4.42)	(7.26)	(148.75)
MKT	1.002	1.010	1.001	1.012	0.934	0.891	0.819	0.795	0.753	0.632	-0.929
	(40.97)	(37.07)	(47.34)	(44.18)	(45.21)	(34.92)	(31.66)	(27.27)	(21.67)	(16.44)	(-220.35)
SMB	0.0326	0.325	0.477	0.536	0.591	0.631	0.632	0.633	0.522	0.431	0.553
	(1.09)	(9.09)	(15.81)	(14.76)	(16.77)	(17.27)	(14.50)	(14.77)	(10.53)	(7.63)	(99.56)
HML	-0.125	0.0208	0.0325	0.0915	0.0820	0.0749	0.0949	0.0779	0.0866	0.0881	0.307
	(-4.63)	(0.68)	(1.08)	(3.04)	(2.32)	(1.70)	(1.82)	(1.23)	(1.14)	(1.25)	(52.15)
UMD	-0.111	-0.139	-0.147	-0.154	-0.118	-0.131	-0.138	-0.0635	-0.0714	-0.0666	0.137
	(-5.03)	(-7.13)	(-6.63)	(-4.11)	(-4.38)	(-4.43)	(-5.05)	(-2.12)	(-2.44)	(-2.32)	(32.91)
C_{inov}	-0.125	-0.325	-0.0997	-0.201	-0.412	-0.171	-0.298	-0.338	-0.245	-0.502	0.551
	(-1.07)	(-2.39)	(-0.93)	(-1.93)	(-4.22)	(-1.63)	(-2.27)	(-2.42)	(-1.66)	(-2.51)	(27.54)
GRS	0	0	0	0	0	0	0	0	0	0	0

[4] *The illiquidity premium: International evidence.* Amihud et.al., 2015

Portfolio	1	2	3	4	5	6	7	8	9	10	10-1
Alpha	0.00332	0.00211	0.00215	-0.000912	0.00156	0.00140	0.00505	0.00824	0.0155	0.0295	0.0349
	(1.01)	(0.53)	(0.61)	(-0.28)	(0.54)	(0.37)	(1.50)	(2.07)	(4.04)	(7.81)	(62.28)
MKT	1.003	1.034	1.006	1.033	0.969	0.906	0.839	0.814	0.750	0.627	-1.012
	(43.87)	(36.61)	(46.75)	(48.45)	(44.90)	(40.58)	(32.26)	(28.66)	(22.00)	(18.55)	(-254.08)
SMB	0.0398	0.342	0.482	0.546	0.612	0.640	0.648	0.651	0.537	0.460	0.530
	(1.28)	(9.08)	(15.73)	(14.63)	(16.48)	(17.16)	(15.29)	(15.44)	(11.58)	(9.02)	(95.54)
HML	-0.131	0.0234	0.0315	0.0984	0.0891	0.0779	0.0960	0.0759	0.0698	0.0555	0.267
	(-5.15)	(0.78)	(1.05)	(3.31)	(2.29)	(1.83)	(1.88)	(1.23)	(0.93)	(0.84)	(45.27)
UMD	-0.119	-0.146	-0.151	-0.155	-0.124	-0.133	-0.146	-0.0744	-0.0907	-0.105	0.123
	(-5.82)	(-6.85)	(-6.39)	(-4.07)	(-4.13)	(-4.40)	(-4.97)	(-2.57)	(-3.15)	(-3.40)	(29.52)
IML	-0.0106	-0.00486	-0.00374	0.00350	-0.00144	-0.000449	-0.00608	-0.0110	-0.0269	-0.0529	-0.0374
	(-1.25)	(-0.47)	(-0.43)	(0.43)	(-0.20)	(-0.05)	(-0.74)	(-1.10)	(-2.88)	(-5.79)	(-26.74)
GRS	0	0	0	0	0	0	0	0	0	0	0

From the result we can find out for each portfolio, the result of GRS test is 0. This means that the illiquidity factor indeed priced, no matter which one proxy of illiquidity is used. From the beta of C_{inov} and IML are all negative, this in line with the hypothesis that the illiquidity has negative effect against portfolio's excess return.

4. Empirical application

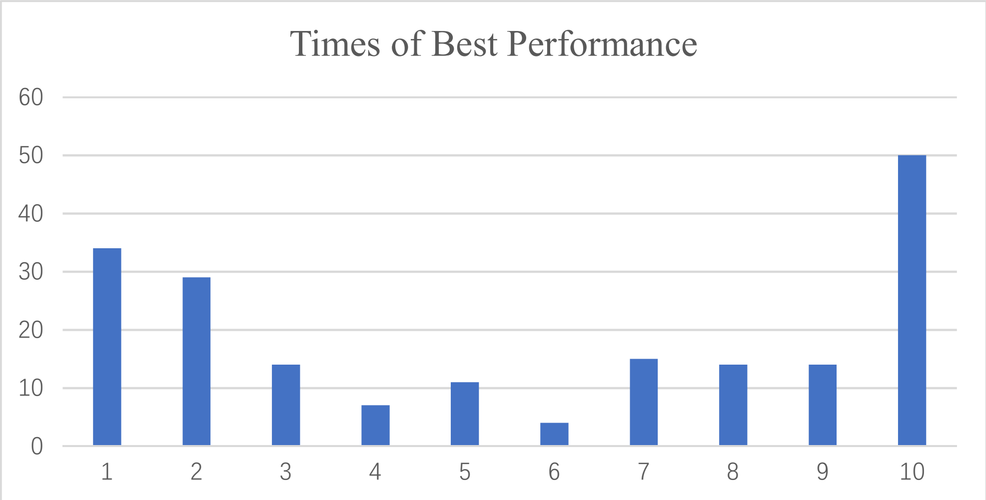
Now we know the liquidity risk is priced. But to use it in our empirical work, we need to see if it is possible to profit from the liquidity risk. In this section, I'll study the profitability of liquidity portfolios by performing testing the performance of each portfolio.

4.1 Portfolio performance over time

To study how liquidity portfolios performed, I calculated the Sharpe ratio of each portfolio over 15 years (2002-2017). The best performance portfolio will earn the portfolio of the month.

Figure 3. Times of portfolios best perform in the monthly time scale

The figure below shows the times of each portfolio outperform over a monthly time period. For the monthly competition, portfolio 1 wins 34 and portfolio 10 get 50 among all the 192 months.



The figure above gives the times of different portfolios earned the best performer among all the combinations. It is shown that the most illiquid portfolio (portfolio 10) is relatively best performed over the last 15 years on a monthly scale. The exposure to liquidity risk somewhat generates extra return than others.

4.2 Portfolio performance when anomalies appear

In the previous section, I showed that in a monthly scale, the portfolio with large liquidity risk exposure performed best over the whole sample period. Does this because of the market anomalies? To study this question, I ranked the monthly market illiquidity, and extract most and least 12 scenarios, then listed the best perform portfolio when anomalies happen.

Table 5 Anomalies and portfolio of the month

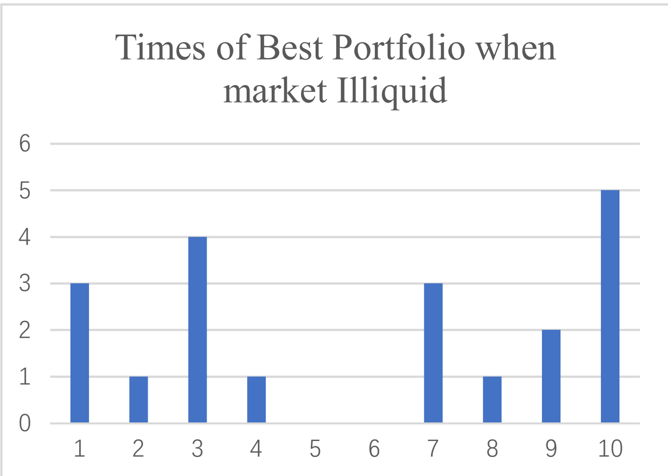
The table below lists the top 20 and least 20 market illiquid scenario, and the best performing portfolio of that specific month. Rank is the rank of monthly market illiquidity over the whole 192 periods.

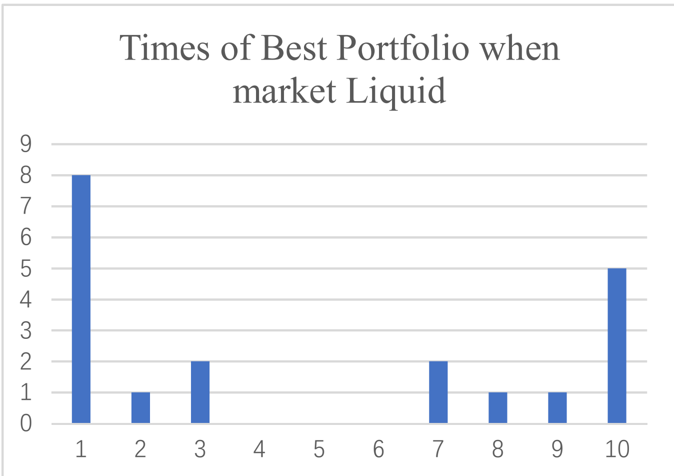
Month	Rank	Best Portfolio		Month	Rank	Best Portfolio
Nov-08	1	10		Dec-13	192	1
Oct-08	2	9		Dec-17	191	1
Nov-09	3	1		Oct-13	190	1
Jan-09	4	9		Jul-14	189	10
Dec-08	5	2		Jun-14	188	3
Feb-09	6	10		Aug-14	187	1
Aug-02	7	8		Sep-17	186	3
Oct-02	8	1		Sep-14	185	10
Sep-02	9	7		Sep-13	184	7

Feb-03	10	10		Feb-07	183	10
Apr-09	11	3		Oct-17	182	8
Mar-03	12	7		Dec-16	181	10
Jan-03	13	10		Nov-13	180	7
Jul-02	14	3		Dec-06	179	9
Sep-08	15	3		May-07	178	1
Apr-03	16	1		Nov-17	177	1
Nov-02	17	4		Jan-14	176	10
Jul-08	18	7		Apr-07	175	1
Feb-02	19	3		Dec-10	174	2
Sep-11	20	10		Feb-17	173	1

Figure 4 Anomalies and portfolio of the month

The figure below plots the times of each portfolio ranked the best during anomalies months. The left figure presents the times of each portfolio earned the best portfolio during the 20 most illiquid months, and the right-hand one presents those outperform during the 20 most liquid months.





From the figure above, it is clear that portfolio 10 perform best during most illiquid months and portfolio 1 outperform when market abundant liquidity scenarios happen. This fact indicates that when the investor expects an anomaly, stocks with extreme (either most or least) illiquidity can be considered to balance the invest basket to gain an excess return. Besides, from the total 192 months, portfolio 10 only outperform 10 times during the extreme 40 market liquid or illiquid scenarios, that indicates when the market liquidity risk level fluctuates within a small range, the most illiquid portfolio should be preferred.

5. Conclusion

In this paper, I studied the impact of liquidity risk on stocks' return. I find that for both individual stocks and the illiquidity-based portfolios, the liquidity risk factor always plays a crucial role in the excess return.

In this paper, I used Amihud's *ILLIQ* to depict the liquidity risk exposure of each stock. And then I formed 10 equal-weighted *ILLIQ* sorted portfolios and tried to use the innovation of market illiquidity and the *IML* factor to study the effect of liquidity risk. I use equal-weighted way to avoid the over-representative issue. The regression results suggest both factors, innovation and the *IML*, have a significant adverse effect on the excess return of portfolios.

For the profitability of each portfolio, I find that the portfolio with most liquidity risk exposure outperforms than other portfolios for more than 25% of all periods, especially when the market is not extremely liquid or illiquid. This suggests that with a stable market liquidity risk level, an illiquidity-stocks-based trading strategy can be considered.

For the further research, there are two interesting points can be dig in. First is the coefficient between illiquidity factors and the excess return. The illiquidity betas are not all significant as expected. Maybe some conditions need to be considered, or only need to change the proxy of illiquidity from level to the logarithm, or using the innovation of second-order difference. The second one is when the market is liquid; the most liquid portfolio performs best during the sample period. The fact does not meet the expectation that when the market provides an abundant liquid, the investors shall pursue substantial risk exposure to generate more premium.

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