Asset Pricing with Extreme Liquidity Risk*

(Job Market Paper)

by

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Abstract

Defining extreme illiquidity as the tails of illiquidity for all stocks, I propose a direct measure of market-wide extreme liquidity risk and find that extreme liquidity risk is priced cross-sectionally in the U.S. equity market. From 1973 through 2011, stocks in the highest quintile of extreme liquidity risk loadings earned value-weighted average returns 6.6% per year higher than stocks in the lowest quintile. The extreme liquidity risk premium is robust to common risk factors related to size, value and momentum. The premium is different from that on aggregate liquidity risk documented in Pástor and Stambaugh (2003) as well as that based on tail risk of Kelly (2011). Extreme liquidity estimates can offer a warning sign of extreme liquidity events. Predictive regressions show that the extreme liquidity measure reliably outperforms aggregate liquidity measures in predicting future market returns. Finally, I incorporate the extreme liquidity risk into Acharya and Pedersen's (2005) framework and find new supporting evidence for their liquidity-adjusted capital asset pricing model.

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I. Introduction

The "liquidity crunch of 2007-2008" (Brunnermeier, 2009) highlights the need to measure and model liquidity risk, which, in its extreme form, arises from the simultaneous drying up of liquidity across assets and can lead to the freezing up of the markets. Liquidity risk is not continuous, but is subject to abrupt changes. Investors might not worry about liquidity risk in normal market climates, but it can become a concern in the case of liquidity crises. After liquidity risk exceeds a certain threshold, it doesn't follow a mean-reversion pattern; instead, it feeds on itself, gathers momentum, and causes more severe market declines than would occur in normal occurrences (Brunnermeier and Pedersen, 2009). Despite the intuitive appeal of a threshold-based measure of liquidity risk, there has been little empirical research into how liquidity risk in its extreme form is priced in the cross-section of stock returns. Prior research has found that a stock's exposure to systematic liquidity risk and whether its liquidity dries up at inopportune times does matter for investors (e.g., Pástor and Stambaugh, 2003; Acharya and Pedersen, 2005; Sadka, 2006; Korajczyk and Sadka, 2008; Lee, 2011). However, because most studies focus on the aggregate level of market liquidity in which extreme liquidity events are rarely observed, this research could not accurately measure extreme liquidity risk, which is the risk that market liquidity worsens to the extent that dealers are shutting down when the trader needs to unwind (Pedersen, 2008).

In this paper, I propose a direct and viable measure of economy-wide extreme liquidity risk by taking a panel approach. The nature of extreme liquidity risk is that the market experiences infrequent liquidity events of extreme magnitude, although it is in a normal liquidity state most of the time. The arrival of such liquidity crises is often unexpected, so an investor may have little or no clue as to when the market will seize up. The fear that market liquidity could dry up precipitously could have a significant impact on investors' trading behaviors and on equilibrium asset prices, even before the realization of such an event. Rather than waiting to accumulate extreme observations in market-wide liquidity dry-ups, I assume that extreme liquidity risks of individual stocks are driven by a common underlying dynamic.[1]

[1] One example for this assumption is the limited number of liquidity suppliers (Comerton-Forde, Hendershott, Jones, Moulton, and Seasholes, 2010). Another reason is the correlated trading among institutionals (Koch, Ruenzi, and Starks, 2009).

Therefore, information about the likelihood of a market-wide extreme liquidity event could be extracted from the cross section of extreme liquidity events occurring for different individual stocks at each point in time. Based on this approach, I build my extreme liquidity estimate from the Amihud (2002) illiquidity measure for individual firms on a daily basis. I find that the cross-section of expected stock returns reflects a premium for extreme liquidity risk. From 1973 through 2011, stocks in the highest quintile of extreme liquidity risk loadings earned value-weighted average returns of 0.55% per month higher than stocks in the lowest quintile. The extreme liquidity risk premium remains robust after controlling for a number of common risk factors, including the Fama and French (1993) three factors, the Carhart (1997) momentum factor, the Pástor and Stambaugh (2003) traded liquidity factor, Kelly's (2011) traded tail risk factor, and Acharya and Pedersen's (2005) liquidity-adjusted capital asset pricing model (CAPM). Extreme liquidity estimates can offer a warning sign of extreme liquidity events[2]. Predictive regressions also show that my extreme liquidity risk estimates forecast market returns consistently and outperforms aggregate liquidity measures. I incorporate my measured extreme liquidity risk into Acharya and Pedersen's (2005) framework and provide new evidence to support their liquidity-adjusted CAPM. The cross-sectional return premium corresponding to their three liquidity betas, using my measure of extreme liquidity risk, is statistically and economically significant.

My analysis focuses on the tail distribution of liquidity risk. This intuition comes from the recent financial crisis, which has reinforced the importance of the risk of infrequent, but severe, market events, and from a long standing literature on how tail risk plays a special role in determining expected return. Early studies analyzed the behavior of the tails in stock returns, following seminal work by Mandelbrot (1963) and Fama (1965) that documented that stock returns are not Gaussian but have univariate heavy tails. In the past decade, focus has shifted to the role of heavy-tailed shocks to economic fundamentals in pricing securities. Researchers, including Eraker and Shaliastovich (2008), Bansal and Shaliastovich (2011), Drechsler and Yaron (2011), Gabaix (2012), and Wachter (2012), have built asset pricing models

[2] Examples include the Mideast oil embargo in 1973, the stock market crash in 1987, the Long Term Capital Management (LTCM) crisis in 1999, the stock market downturn of 2002, and the "liquidity crunch of 2007–2008" (Brunnermeier, 2009). I later discuss these events in detail.

in which fat-tailed processes are used to explain the equity premium, excess volatility, and risk free rate puzzles. Empirical studies, such as Ang, Chen and Xing (2006), Kelly (2011), and Ruenzi and Weigert (2011), investigate the impact of downside risk and tail risk on the cross-section of expected stock returns. They find that investors demand additional compensation for stocks that are crash-prone, that is, stocks that have particularly bad returns exactly when the market crashes. None of these papers, however, investigates the implication of extreme liquidity risk for asset pricing. Although the study of liquidity considers the factors impacting the cost of trading, rarely are the contagion and correlation of liquidity demands, such as those observed in the most recent global financial crisis, taken into account in security risk measures. In order for a measurement of liquidity to be meaningful to market participants, it needs to include, not just the aggregate level of liquidity, but also the possibility of extreme liquidity event that leads investors to withdraw from markets they would otherwise be prepared to invest in. This serves as the primary motivation for my paper.

My investigation differs from numerous earlier studies that question whether systematic liquidity risk is a priced factor.[3] Pástor and Stambaugh (2003) find that stocks with high loadings on the market liquidity factor outperform stocks with low loadings by 7.5% annually. Acharya and Pedersen (2005) derive an equilibrium model for returns that includes the liquidity level and a stock's liquidity co-variation with market liquidity and the market return. Hasbrouck (2009), however, finds only weak evidence of liquidity risk as a priced factor during a long horizon, 1926–2006. Pástor and Stambaugh (2003) leave the question of "whether expected returns are related to stocks' sensitivities to fluctuations in other aspects of aggregate liquidity" as one direction for future research. I seek to answer this question by focusing on a new dimension of liquidity risk: the likelihood of market liquidity at its extremes. My extreme liquidity measures can offer a warning sign of extreme liquidity events. The measured extreme liquidity index has hit its three-year high jump before periods characterized by liquidity crises. High extreme liquidity risk is associated with bad market states. It implies that stocks that hedge extreme liquidity risk are more

[3] Among many others, I include Amihud and Mendelson (1986), Brennan and Subrahmanyan (1996), Brennan, Chordia, and Subrahmanyan (1998), Jacoby, Flower, and Gottesman (2000), Jones (2002), Pástor and Stambaugh (2003), Acharya and Pedersen (2005), Sadka (2006), Chordia, Huh, and Subrahmanyam (2009), and Brennan, Chordia, Subrahmanyam, and Tong (2012).

valuable than those adversely exposed to extreme liquidity risk, and therefore have lower expected returns. I find strong evidence that the market-wide extreme liquidity risk is positively priced in the cross-section. I also implement Acharya and Pedersen's (2005) liquidity-adjusted CAPM using extreme liquidity risk and provide consistent evidence for the return premium related to all three liquidity-related betas in their model.

My inspiration for this particular extreme liquidity risk choice is also drawn from important new literature on how commonality in liquidity – also known as liquidity black holes – intensifies during large market downturns. Brunnermeier and Pedersen (2009) and other models predict that the large market declines affect the funding liquidity of financial intermediaries. As a consequence, these intermediaries reduce the provision of liquidity across many securities. The resulting decrease in market liquidity and the increase in commonality in liquidity lead to further losses and/or margin increase, creating an "illiquidity spiral" that further tightens the funding liquidity and pushes down the price. Empirical studies have found consistent evidence that commonality in liquidity increases during market downturns, such as those of Comerton-Forde *et al.* (2010), and Hameed, Kang, and Viswanathan (2010), with regard to the U.S., and that of Karolyi, Lee, and van Dijk (2012) regarding global markets. Given the close relation between large market declines and liquidity dry-ups, a logical question is whether extreme liquidity risk is a state variable important for asset pricing. I find that the cross-section of expected stock returns does reflect a premium for extreme liquidity risk, which may shed light on the source of tail risk, specifically during episodes of panic liquidation.

How I measure the level of extreme liquidity risk is critical for my exercise. My empirical estimate is based on the assumption that extreme liquidity risks of individual stocks are driven by a common underlying process. Given this assumption, the rich variation in the cross section of extreme liquidity events occurring for individual stocks could be used to provide accurate information about the prevailing market-wide level of extreme liquidity risk for each point in time. This avoids having to accumulate years of extreme liquidity events from the aggregate market time series in order to estimate extreme liquidity risk, and therefore avoids using stale observations that carry little information about current extreme liquidity risk. My approach applies Hill's (1975) power law estimator to the cross section of extreme liquidity events across stocks in the market. It is distinct from a large volume of literature that has modeled extreme returns using jump processes (e.g., Duffie, Pan and Singleton, 2000) and copulas (e.g., Ané and Kharoubi, 2003; Ruenzi and Weigert, 2011). Instead, my approach models conditional liquidity tails in discrete time and uses dynamic extreme value theory. This procedure has been adopted as a measure of systemic banking sector risk by Allen, Bali, and Tang (2011), as a measure of return tail risk by Kelly (2011), and as a measure of hedge fund tail risk by Jiang and Kelly (2011).

The remainder of the paper is organized as follows: Section II explains the construction of the extreme liquidity measure, presents the data and summary statistics, and furnishes empirical features of extreme liquidity measure. Section III examines the significance of a cross-sectional relation between extreme liquidity risk and expected stock returns. Section IV lays out several robustness checks, and Section V concludes.

II. Measuring Extreme Liquidity Risk

A. The Tail Distribution of Liquidity

A stock is in a normal liquidity state most days, but can experience liquidity events of extreme magnitude, so the nature of extreme liquidity risk is that it is infrequent, comes suddenly, and is somewhat unpredictable. Investors might care little about liquidity in normal conditions, but high transaction costs might become a first order concern if the market hits a disaster liquidity state; that is, its illiquidity cost lies at the right tail of the distribution. The arrival of such liquidity crises is often unexpected, so an investor may have little or no clue as to when the market will seize up. The fear that market liquidity could dry up precipitously could have a significant impact on investors' trading behaviors and on equilibrium asset prices, even before the realization of such events.

Extreme value theory provides a statistical framework characterizing the asymptotic extreme characteristics of stationary distributions. The theory allows us to obtain an adequate characterization of the extreme behavior and, to this end, the estimation of the so-called tail index is essential, for which theory offers a variety of different approaches.

Originally Mandelbrot (1963), and later Fama (1965), pointed out that the distribution of the empirical returns is often leptokurtic and frequently positively skewed, which implies that it is peaked and fat-tailed. Since these observations were made, extreme value theory has been increasingly used in the modeling of the tail of stock returns.[4] More recent studies (Plerou, Gopikrishnan, Amara, Gabaix, and Stanley, 2000; Gabaix, Gopikrishnan, Plerou, and Stanley, 2006; and Gabaix, 2009) have argued that the power law applies not only to the tail distribution of returns but also to the tail distributions of other critical financial time series, including price impact, trading volume, the number of trades, and the size of large investors. Among them, the unconditional tail distribution of price impact is aptly described by a power law, which yields a concave price impact function (Hasbrouck, 1991; Hasbrouck and Seppi, 2001; and Plerou, Gopikrishnan, Gabaix, and Stanley, 2002). The power law parameterization is often used, for example, by Barra (1997); Grinold and Kahn (1999); Hasbrouck and Seppi (2001); and Gabaix, Gopikrishnan, Plerou, and Stanley (2003).

Given the power law of price impact, I use Amihud (2002) illiquidity measure as my measure of price impact[5] and therefore propose a novel specification for equity liquidities in which the tail distribution obeys a power law that potentially changes over time,

$$P\left(ILLIQ_{t,d}^{i} > x \middle| ILLIQ_{t,d}^{i} > p_t^*, \mathcal{F}_{\mathrm{t}}\right) \sim (x/p_t^*)^{-a^i \gamma_t} \tag{1}$$

Equation (1) states that the right tail of stock illiquidity is defined as the set of liquidity events, that is, the observations $ILLIQ_{t,d}^{i}$ in terms of Amihud (2002) illiquidity measure, exceeding some high threshold p^*_t and it follows a power law. The term of $ILLIQ_{t,d}^{i}$ takes the form of stock *i* available on day *d* in month *t*

[4] Consider, among many others, studies by Quintos, Fan, and Phillips (2001), Wagner (2003), Galbraith and Zernov (2004), and Werner and Upper (2004).

[5] Amihud's (2002) illiquidity measure has been extensively used in the literature on stock market liquidity and asset pricing. As suggested by Goyenko, Holden and Trzcinka (2009), it does well in measuring price impact.

$$ILLIQ^{i}_{t,d} = |R^{i}_{t,d}| / V^{i}_{t,d} \tag{2}$$

in which $R^{i}_{t,d}$ and $V^{i}_{t,d}$ are, respectively, the return and dollar volume (in millions) on day d in month t. The second term in the exponent, γ_t, varies with the conditioning information set $\mathcal{F}_t$. While different assets have different levels of extreme liquidity risk (determined by the constant a^i), dynamics are the same for all assets because they are driven by a common conditional process. Thus, I refer to $-\gamma_t$ as economy-wide extreme event risk in liquidity. The focus of this paper is the right tail of the liquidity distribution. The convention in extreme value theory is to represent a tail distribution as the right tail, and I follow this convention closely.

The threshold parameter p^*_t is set to define where the center of the distribution ends and the tail begins. It is necessary to have enough observations in the tail to make inferences. On the other hand, using data points from the center of the sampling distribution tends to reduce the effectiveness of the tail estimates. Here I follow Gabaix *et al.* (2006) and Kelly (2011) by fixing the threshold at the 95th percentile of the cross section distribution month-by-month.[6] Consequently, the threshold varies as the cross-sectional distribution fans out and compresses over time, which is a convenient way of mitigating undue effects of aggregate market liquidity level on the tail risk estimates.

The Hill (1975) estimator is established as one of the most suitable methods for financial applications: the semi-parametric estimation approach is based on the assumption that the underlying distribution is in the maximum domain of attraction of the Fréchet extreme value distribution. This generally holds for fat-tailed distributions as analyzed in finance. Unlike, for example, the estimation approach based on the generalized extreme value distribution, the assumption for the Hill estimator does not require that exact asymptotic limits be met. I therefore apply the Hill (1975) estimator for the tail exponent of economy-wide liquidity for each month by employing the pooled set of daily Amihud (2002) liquidity observations for all stocks in month t. The extreme liquidity index based on the method of Hill (1975) is defined as

[6] Similar empirical results are obtained when the thresholds are set to be between the 90th and 99th percentiles. I later discuss the robustness check on the threshold choice.

$$1/\gamma_t \quad = (1/N_t)\sum^{Nt}_{k=1} ln\, (\, ILLIQ^{(k)}_{t,d} / p^*_t\,)$$

(3)

where N_t is the number of daily illiquidity observations that exceed the threshold p^*_t for month t, and $ILLIQ^{(k)}_{t,d}$ is a daily Amihud (2002) illiquidity measure during that month if it is larger than p^*_t.

Given that for stock i,

$$E_{t-1}[ln(\, x^i_{k,t} / p^*_t\,)] = 1 / (a^i \gamma_t)$$

(4)

the expected value of $1/\gamma_t$ is the cross-sectional average tail exponent,

$$E_{t-1}[\ (1/N_t)\sum^{Nt}_{k=1} ln\, (\, x_{k,t} / p^*_t\,) \mid \gamma_t\ ] \ = \ 1 / (\bar{a}\, \gamma_t)\ ,$$

$$\text{where}\ \ \bar{a} \equiv n/\sum^{Nt}_{k=1}(1/a^i)$$

(5)

Different stocks will experience extreme liquidity events in different periods. The heterogeneity in the set of a^i coefficients entering in the tail calculation over time will affect the estimation of the market-wide extreme liquidity risk. However, the conditional expectation of the Hill (1975) measure is unaffected by this heterogeneity since *ex ante* it is unknown which stocks will be in the tail part. Equation (5) states that the Hill estimator is expected to be equal to the true common tail component $1/\gamma_t$ times a constant multiple; therefore, the expected value of month-by-month Hill estimates is perfectly correlated with the true economy-wide tail process $1/\gamma_t$.

B. Data and Summary Statistics

I collect daily Center for Research in Security Prices (CRSP) data from July 1967 to December 2011 from NYSE stocks with share codes 10 and 11. To keep the liquidity measure consistent across stocks, I exclude NASDAQ because the NASDAQ returns and volume data are available from CRSP for only part of this period (beginning in 1972). Also the volume data of NASDAQ includes interdealer trades, unlike those reported on the NYSE and the AMEX. On the other hand, the CRSP sample covers all size groups, and indeed very small, microcap stocks produce challenging results (Fama and French, 2008), especially those with strong idiosyncratic liquidity shocks. Incorporating the observations from these micro-cap stocks would contaminate the estimation of systematic extreme liquidity risk. I therefore control for the potential influence of microcap stocks by excluding stocks on the AMEX. [7]

On the other hand, because the accuracy of my approach relies on the quantity of observations in the right tail distribution, I require the liquidity observations from a large panel of stocks to gain sufficient information about the tail at each point. Figure 1 plots the effective number of stocks in NYSE from CRSP each month. The sample has fewer than 1,000 stocks until 1951 and, in July 1968, the sample size roughly rises to more than 1,200 stocks. I therefore focus my sample on the 1968 to 2011 period to prevent the issue of noisy estimates due to too few data points.

All existing NYSE common stocks are considered for the whole sample period. However, in each month, I eliminate the stocks for which some data are missing.[8] Also removed from a trading day are all the stocks for which the firm experienced a merger, delisting, partial liquidation, or seasoned equity offerings during that month. The stocks with less than one year of trading history on the NYSE at the start of the month are similarly discarded from that month. Finally, I eliminate from a trading day within that month any stock whose trading volume is zero.

I form twenty equal-weighted portfolios based on the cross-section distribution of Amihud (2002) illiquidity measures month-by-month, and Table 1 reports the summary statistics on the cross-sectional properties of the whole NYSE sample. Here the sorting is based on the stock-date observations within each month: a stock is included in one particular portfolio as long as it has at least one daily Amihud (2002) illiquidity observation lying in the illiquidity range specified for that portfolio. It is possible for one stock to be included in both the most illiquid portfolio and the most liquid one during the same month. Not surprisingly, we see that illiquid stocks, that is, stocks with high average illiquidity cost, tend to have a lower return, a high volatility of returns, a lower turnover, and a small market capitalization. The most illiquid stocks in the last of twenty portfolios yield a much lower level of simple average monthly return, 0.51%, compared with 1.60% for the most liquid stocks in the first of twenty portfolios. Their simple

[7] Stocks on the NASDAQ and AMEX will be considered in the asset pricing tests of section III.
[8] For example, if a stock's trading volume is missing in CRSP on any day, we simply remove that stock from that day.

average monthly volatility is 3.46%, higher than that for the most liquid stocks, 1.89%. At the same time, the simple average monthly turnover is 4.10%, lower than 11.39% for the most liquid stocks. The simple average size for the most illiquid stocks, \$0.12 billion, is also smaller than that for most liquid stocks, \$11.77 billion.[9]

The tail index measure in (5) only uses the observations that exceed the tail threshold p^*_t, that is, the observations of the most illiquid portfolios. And the extreme liquidity estimate accesses the average distance between the most extreme observations and the benchmark. Therefore, when the index is applied to the cross section of liquidity, it varies monotonically with the average frequency of extreme realizations. For example, when applied to the liquidity of various firms each month, the index will be larger when more firms experience extremely low liquidity. This monotonic property with the likelihood of extreme liquidity events is what makes the extreme liquidity index an attractive empirical proxy for tail risk in liquidity. The more positive the power law exponent $1/\gamma_t$, the heavier the tails of the particular stock illiquidity costs, the higher extreme liquidity risk. In practice, I follow Kelly (2011) and normalize the extreme liquidity estimates (subtract mean and divide by standard deviation), which is denoted by *ELR* for later analysis[10].

C. Empirical Features of the Extreme Liquidity Risk Measure

Figure 2 plots the estimated extreme liquidity risk series along with the NBER recessions. My sample starts around the late 1960's bull market peak. Estimated extreme liquidity risk is low at the starting point, and continues to fall sharply until the midpoint of 1969, when it reaches its lowest level for the whole period. Extreme liquidity risk starts to rise sharply in the recession of 1969–1970 when the U.S. stock market experienced a severe bear market. The risk index then fluctuates for several years, with obvious jumps during three recessions: from November 1973 through March 1975, from January 1980 through July 1980, and from July 1981 through November 1982. Extreme liquidity risk begins to go up

[9] The summary statistics are similar in terms of value-weighted returns and value-weighted illiquidity for these twenty portfolios. Quite a few studies focus on equal-weighted return and illiquidity measures, such as Chordia *et al.* (2000), Amihud (2002), and Acharya and Pedersen (2005), to name just a few. As suggested in Acharya and Pedersen (2005), computing the return and illiquidity as equal-weighted average can compensate for the over-representation in the sample of large liquid stocks, as compared to the "true" portfolios in the economy.

[10] The results for unnormalized estimates are very close and available upon request in an internet appendix.

quickly in the months following the 1987 October crash and reaches its highest level in the 1990 liquidity crisis. The technology boom that follows then pushes down the market-wide extreme liquidity risk until the LTCM collapse and the Russian debt crisis. Throughout the last half of the decade, extreme liquid risk rises quickly to another peak, especially during the 2007–2009 financial crisis and recession.

Although aggregate illiquidity measures[11] also increase during periods characterized by liquidity crises, the extreme liquidity risk index is weakly associated with aggregate liquidity measures. As shown in Appendix I, my extreme liquidity measures have correlations of 0.12, -0.07, 0.15, and 0.01 with Pástor and Stambaugh (2003) aggregate liquidity innovations, Acharya and Pedersen's (2005) aggregate illiquidity innovations, Hu, Pan, and Wang (2012) market-wide liquidity measures, and Sadka (2006) permanent liquidity factor, respectively. This suggests that my extreme liquidity captures a dimension of liquidity risk which is different from the aggregate level. On the other hand, extreme liquidity measure has a relatively high correlation of 0.48 with the average commonality in liquidity. Extreme liquidity risk appears fairly closely associated with credit risk, having the correlations of 0.41 and -0.22 with the term spread (the difference between yields on long- and short-term government bonds) and the default spread (the difference in yields on BAA and AAA corporate bonds). Compared with supply-side sources for commonality in liquidity, extreme liquidity index appears more closely associated with demand-side factors[12]. In particular, it shares a monthly correlation of 0.63 with ETFs volume, as a measure of index-related basket trading in Karolyi, Lee, and van Dijk (2012). It is also closely correlated with NYSE margin debt outstanding (0.50) in which high levels of margin debt shows the effect of over-leveraging and makes the market vulnerable to nasty tumbles.

[11] Consider, for example, the innovation of market liquidity in Pástor and Stambaugh (2003) and the innovation of market illiquidity in Acharya and Pedersen (2005).

[12] Some empirical studies have found support for supply-side sources of commonality in liquidity related to the funding constraints of financial intermediaries (e.g., Coughenour and Saad, 2004; Comerton-Forde *et al.* 2010; Hameed, Kang, and Viswanathan, 2010). Other work has explored demand-side sources, for example those driven by correlated trading activity (e.g., Chordia, Roll, and Subrahmanyam, 2000; Hasbrouck and Seppi, 2001; Koch, Ruenzi, and Starks, 2009).

It is hard to predict liquidity dry-ups in that liquidity risk is often high after a long period of abundant liquidity. But my extreme liquidity measures can offer a warning sign of possible financial panics in that the sharp increase in extreme liquidity measure gives rise to the financial vulnerability and the likelihood of a liquidity crisis. The measured extreme liquidity index has hit its three-year high jump before periods that were characterized by liquidity crises, for example, the Mideast oil embargo in November 1973, the stock market crash in October 1987, the 1991 Japanese asset price bubble bursts, the LTCM collapse in 1999, the stock market downturn of 2002, the "liquidity crunch of 2007–2008" (Brunnermeier, 2009), and the European sovereign debt crisis in 2009. Compared with the abrupt changes in aggregate liquidity measures, the relatively persistent movement of extreme liquidity series, with the autocorrelation of 0.98, suggests that extreme liquidity risk has the potential to impact returns. To investigate this hypothesis, I estimate a series of predictive regressions for market returns based on the estimated extreme liquidity series. The dependent variable is the return on the CRSP value-weighted index at frequencies of one month, three months, six months, one year, three years, and five years. I compare the performance of my extreme liquidity risk measure with those of Pástor and Stambaugh (2003) liquidity measure and Acharya and Pedersen's (2005) illiquidity measure. Extreme liquidity risk forecasts returns consistently over all horizons and outperforms the aggregate liquidity measures. For example, in the five-year horizon, extreme liquidity risk yields R^2 value of 7.12%, higher than 0.21% for Pástor and Stambaugh (2003) liquidity level measure and 1.81% for Acharya and Pedersen's (2005) illiquidity level measure.

My measure of extreme liquidity tends to be high when market volatility is high. This positive association between volatility and the extreme liquidity measure, reported in Appendix I, is reasonable, because the compensation required to providers of liquidity for a given level of order flow could well be greater when volatility is higher. A kind of "flight-to-quality" effect appears in months with exceptionally high extreme liquidity risk[13]. That is, months in which extreme liquidity rises severely tend to be months

[13] In crisis periods, the flight-to-quality phenomenon is well documented in the U.S. markets, for example, by Longstaff (2004) and Vayanos (2004), and with the global empirical evidence of Hund and Lesmond (2008) and Goyenko and Sarkissian (2008), among others.

in which stocks and fixed-income assets move in opposite directions. During the months when extreme liquidity measure is at least two standard deviations above its mean, the correlation between the return on the CRSP value-weighted index and the return on long-term government bonds is -0.16. In addition, extreme liquidity risk shares a monthly correlation of -0.52, -0.14, -0.48 and -0.17 with dividend-price ratio, unemployment, inflation, and the Chicago Fed National Activity Index (CFNAI).

III. Extreme Liquidity Risk and the Cross Section of Expected Returns

A. Is Extreme Liquidity Risk Priced?

My extreme liquidity risk measure relies on a large cross section of stocks and yields a monthly series spanning almost 40 years. As such, the series is well suited for this study's focus on extreme liquidity risk and asset pricing. In this section, I test whether a stock's expected return is related to the sensitivity of its return to extreme liquidity risk. Stocks with high predictive loadings on extreme liquidity risk are discounted more steeply and thus have higher expected returns going forward. On the other hand, stocks with low or negative extreme liquidity risk loadings serve as effective hedges and therefore have comparatively higher prices and lower expected returns. At the end of each year, I estimate extreme liquidity risk sensitivities of individual stocks with respect to extreme liquidity risk by the form

$$E_t\,[r_{i,t+1}\,] = \mu_i + \beta_i\, ELR_t \tag{6}$$

Here the regression uses only data available at that time. And eligible stocks are defined as ordinary common shares traded on the NYSE, AMEX, or NASDAQ with at least four years of non-missing monthly returns out of five years and with stock prices between $5 and $1,000. Stocks are then sorted into quintile portfolios based on their estimated extreme liquidity risk loadings. In addition, I follow Pástor and Stambaugh (2003) and construct decile portfolios to assess the robustness. The post-formation returns on these portfolios during the next 12 months are linked across years to form a single return series for each portfolio, which covers the period from July 1973 to December 2011.

Panel A of Table 2 reports the preceding loadings, the post-ranking loadings, and additional properties for quintile portfolios formed on an annual basis. The upper part of Panel A presents summary statistics in which stocks are value-weighted, and those for the equal weighting are shown in the lower part. Taking the value-weighted returns as an example, both the preceding extreme liquidity loadings and the post-ranking loadings increase across quintiles.[14] The "5–1" spread is comprised of longing quintile 5 (stocks with the highest preceding extreme liquidity loadings) and shorting quintile 1 (stocks with the lowest preceding extreme liquidity loadings). It has an overall-period post-ranking extreme liquidity loading of 0.58 (t = 2.33), even larger than its preceding loading, 0.22. Additional properties are reported: The lowest quintile portfolio contains stocks of smaller firms, the value-weighted size (averaged over time) is $22.93 billion, as compared to $27.70 billion in quintile 5. Stocks in the lowest loading portfolios tend to be less liquid, as measured by the value-weighted Amihud (2002) illiquidity measure, although this pattern is also not monotonic. Table 2 also reports the quintile portfolios' betas with respect to the Fama-French (1993) three factors (MKT, SMB, and HML), the Carhart (1997) momentum factor (MOM), the Pástor and Stambaugh (2003) traded liquidity factor (PS-Liquidity), and Kelly's (2011) tail risk factor (K-Tail)[15]. The betas are estimated by regressing the quintile excess returns on all of the six factor portfolio returns. The MKT beta of the "5–1" spread is statistically significant. The SMB beta (-0.26) confirms the pattern in average market capitalizations. The momentum beta for the "5–1" spread is significantly positive (0.22, t = 4.87), suggesting some tilt toward past winners. The liquidity beta (-0.08) is consistent with the pattern in the Amihud (2002) illiquidity measure. The "5–1" spread's tail beta is significantly positive (0.21, with a t-statistic of 4.17), indicating some tilt toward stocks with high loadings on the tail risk in return.

The empirical features of quintile portfolios sorted on extreme liquidity risk are robust to the weighting scheme and rebalancing frequency. Changing from value weighted portfolios to equally

[14] Here the preceding loadings are the β_i in the regression (6). The post-ranking extreme liquidity loadings are estimated by regressing the portfolio excess returns on the extreme liquidity risk estimate and the market excess return factor over the whole sample period.

[15] The MKT, SMB, HML, and MOM data are obtained from Prof. Kenneth R. French's data library, the PS-Liquidity data is obtained from Prof. Robert F. Stambaugh's website, and the K-Tail data is constructed by Kelly (2011).

weighted portfolios does not qualitatively change these properties except that the average portfolio sizes shrink and the average Amihud (2002) illiquidity cost for quintile 1 becomes much higher than that for quintile 5. Panel B of Table 2 reports summary statistics for the one-month post-formation experiments,[16] which are nearly identical to those in Panel A in which the post formation period is one year.

Asparouhova, Bessembinder and Kalcheva (2010) document that noisy prices lead to biases in intercept and slope coefficients obtained in any ordinary least squares (OLS) regression using rates of return as the dependent variable.[17] To mitigate such bias, Asparouhova, Bessembinder and Kalcheva (2012), in particular, assess the effects of value-weighted returns, when weights are based on prior-month market values and on prior-December market values. Their analysis provides strong reason to prefer the weighting by the prior-month size to the weighting by prior-December size, since "the latter method does not correct for bias in months other than the first month after portfolio formation" (Asparouhova, Bessembinder and Kalcheva, 2012). Given the possibility of noise existence in portfolios sorted on extreme liquidity risk, I focus on the value-weighted returns in which weights are based on prior-month market values[18].

Table 3 illustrates the systematic differences in the average returns of portfolios sorted on the extreme liquidity risk loadings. From 1973 through 2011, stocks in the highest quintile of extreme liquidity risk loadings earned value-weighted average returns 6.6% per year higher than stocks in the lowest quintile, with a *t*-statistic of 2.73. The equal-weighted average return on the high-minus-low extreme liquidity risk portfolio was 5.52% per annum (t = 3.15). Average portfolio returns demonstrate a stable monotonic pattern that increases in tail risk. Table 3 also reports the post-ranking alphas for the value-weighted (and equal-weighted) portfolios from regressing portfolio returns on the Fama and French

[16] Each month, I estimate the extreme liquidity loading for each stock in the regression (6) that uses the most recent 60 months of data. Stocks are then sorted into quintile portfolios and decile portfolios based on their estimated extreme liquidity risk loadings. One month post-formation value-weighted and equal-weighted portfolio returns are tracked. Portfolios are reconstituted each month.

[17] Asparouhova, Bessembinder and Kalcheva (2010) follow Blume and Stambaugh (1983) in referring to the underlying security value as the true price, and interpret noise to mean any temporary deviation of transaction prices from true prices. The sources of noise in price, in their study, include, but are not limited to, microstructure-based frictions, the presence of irrational traders, and the inelasticity of short-run liquidity supply.

[18] The results for the value-weighted returns in which weights are based on prior-December market value, available in an appendix, are similar to those reported in Tables 2-8.

three-factor model and three additional extended models: 1) alphas with respect to the Fama and French three-factor model; 2) alphas with respect to the Carhart four-factor model; 3) alphas with respect to the Carhart four-factor plus Pástor and Stambaugh (2003) traded liquidity factor as a fifth control; 4) alphas after considering Kelly's (2011) tail risk factor as a sixth control beyond the Carhart four-factor and the Pástor and Stambaugh (2003) traded liquidity factor. Alphas of the high-minus-low quintile portfolio are large and statistically significant for all of the models: in terms of value-weighted returns, the Fama-French alpha is 8.40%[19] per year (t = 3.56), the four-factor alpha is 6.72% per year (t = 2.84), the five-factor alpha is 7.32% per year (t = 3.05), and the six-factor alpha is 6.60% per year (t = 2.81). When Acharya and Pedersen's (2005) liquidity-adjusted CAPM is used as the benchmark model, the alpha is still significantly positive and economically large, with the value of 7.92% (t = 3.39) per year. Adding more factors, such as SMB, HML, and MOM, to Acharya and Pedersen's (2005) liquidity-adjusted CAPM doesn't change the magnitudes and statistical significances of the alphas, which remain 6.72% (t = 2.84) per year for the "5–1" spread and 9.72% (t = 3.15) per year for the "10–1" spread. The same is true for equal-weighted returns, for example, in which the "5–1" spread alpha is 5.40% (t = 3.28) for the six-factor model. Regression alphas retain the same stable monotonicity that is observed for the raw average portfolio returns.

Panel B of Table 3 presents the results under alternative portfolio construction, monthly rebalance. These results show that monthly-rebalancing portfolio returns have the same qualitative behavior with the annual-rebalancing portfolio returns. Value-weighted return for the "5–1" spread portfolio is 0.44% per month (5.28% annualized, t = 2.39), and equal-weighted return yields 0.38% per month (4.56% annualized, t = 2.13). Compared with the results when portfolios are value-weighted, evidence of the extreme liquidity risk premium is slightly stronger for equally-weighted portfolios. When portfolios are monthly rebalanced, the regression alphas of the "5–1" spread portfolio are 0.49% (5.88% annualized, t = 3.01) per month for the Fama and French three-factor model, 0.44% (5.28% annualized, t = 2.66) per month for the Carhart four-factor model, 0.39% (4.68% annualized, t = 2.47) per month for the extended

[19] Annual alphas are computed as 12 times the monthly estimates.

six-factor model, and 0.52% (6.24% annualized, t = 3.00) per month for Acharya and Pedersen's (2005) liquidity-adjusted CAPM, respectively.

Table 4 reports Fama-MacBeth regression results of excess (risk-unadjusted) returns on characteristics best known to be associated with expected returns: SIZE, B/M, Mom, Turnover, Amihud (2002) liquidity measure, and betas on both normal liquidity risk constructed by Pástor and Stambaugh (2003) and tail risk in return by Kelly (2011). The average slopes on the extreme liquidity risk beta are all economically large (varies from 0.36 to 0.66) and always highly significant (t-statistics all above 2.08). In contrast, the average slopes on normal liquidity risk beta are rather small (around 0.22) and not statistically distinguishable from zero for most of the scenarios listed in Table 4, especially when the factor of turnover or the beta on extreme liquidity risk is considered. The coefficients of SIZE, B/M and Mom are, respectively, negative, and positive, and positive, corresponding with similar studies such as Fama and French (1992) and Lewellen (2012). Lee and Swaminathan (2000) show that the turnover of the past 3 to 12 months is negatively related to subsequent returns, especially among stocks that performed poorly over the same past 3 to 12 months. The effect persists after controlling for size and B/M factors and the negative coefficients for the lag of turnover confirms their findings. The positive coefficients for the lag of Amihud (2002) liquidity measure confirm Spiegel and Wang (2005).

Results from two-way portfolio sorts are reported in Appendix II. Stocks are independently sorted by size[20] and their preceding extreme liquidity risk loadings. Portfolios are rebalanced at the end of each year. Value-weighted returns for the one month post-formation portfolios are reported in Panel A and equal-weighted returns are presented in Panel B. Within each size quintile I calculate the average returns (value-weighted and equal-weighted) on the high-minus-low portfolio on extreme liquidity risk. Value-weighted "5–1" spreads within size quintiles range from 0.37% to 0.72% per month (t-statistics are 2.49 and 3.63, respectively). All of the alphas are significant with respect to a variety of benchmark models. Using the alphas corresponding to the Acharya and Pedersen's (2005) liquidity-adjusted CAPM as an

[20]The size breakpoints come from Prof. Kenneth R. French's data library. The breakpoints use all NYSE stocks with available market equity.

example, the alphas (per month) of the "5–1" spreads are 0.47% for the smallest stocks, 0.72% for the second smallest stocks, 0.69% for the middle size stocks, 0.82% for the second biggest stocks, and 0.57% for the biggest stocks. The extreme liquidity risk premium retains economically large in big stocks and there is only weak evidence of size effect for the premium. In Panel B, equal-weighted returns on high-minus-low extreme liquidity risk loading portfolio are slightly smaller than the value-weighted returns, but still more than 0.30% per month in all cases. Almost all of the alphas are significant, robust to considering alternative priced factors.

Appendix III summarizes the mean returns for the 80 ($4 \times 4 \times 5$) triple-sorted portfolios. Sorts are performed sequentially, first sorting on size and then again, within each group, on the basis of the Amihud (2002) illiquidity measure. Finally each of the sixteen sub-groups is subdivided into five portfolios according to their preceding extreme liquidity loadings. The average return monotonically increases from the lowest quintile of extreme liquidity loading (0.37% per month) to the highest quintile (0.92% per month), and so does the six-factor alpha (the results for other regression models, not shown, are nearly identical.) Even within each size and liquidity cost category, the patterns of cross-sectional returns related to the extreme liquidity risk loading are discernible. All of the sixteen "5–1" spread portfolios have positive mean returns and regression alphas. On average, the return spread of the hedge portfolio on the extreme liquidity loading is 54 basis points per month across the sixteen size/liquidity-cost portfolios, with its regression alpha for the six-factor model of 0.62% per month (t = 3.09). As shown in Panel B of Appendix III, the results are similar when the portfolios are equally weighted: Almost all of the "5–1" return spreads are beyond 0.23% per month and most of the regression alphas are above 0.21% per month.

Next I test the hypothesis that all of the alphas in each set of test asset portfolios are jointly equal to zero, using the test of Gibbons, Ross, and Shanken (1989). The hypothesis is always rejected at a 1% significant level, for both equally weighted and value-weighted portfolios; for all quintile, decile, double, and triple-sorted portfolios; and for all of the six benchmark models.

The possible presence of industry clustering raises concern about the interpretation of abnormal returns from methods that do not explicitly account for industry effects. I then examine to what extent the industry rotation matters in measuring the long-term abnormal returns for extreme liquidity risk. An industry-neutral strategy is therefore employed: I identify all of the stocks by their Fama-French 30 industries, and within each industry I sort the target stocks in five quintile groups. I then form industry-neutral portfolios by combining the stocks in quintile 1 from all 30 of the Fama-French industries into a single quintile 1 portfolio, and similarly with the remaining four groups to form the five industry-neutral portfolios. Untabulated results (available upon request in an internet appendix) show that the industry-neutral quintile hedge portfolio on extreme liquidity risk has the alpha of 39 basis points (t = 3.12) per month for the Carhart four-factor model, the alpha of 40 basis points (t = 3.07) per month for the Carhart four-factor model plus both the Pástor and Stambaugh (2003) traded liquidity factor and Kelly's (2011) tail risk factor, and the alpha of 41 basis points (t = 3.16) per month for Acharya and Pedersen's (2005) liquidity-adjusted CAPM. The extreme liquidity risk premium is not driven by industry clustering as industry neutrality is maintained in this strategy[21].

To better understanding the extreme liquidity risk premium, I apply the Hill (1975) estimator for the left tail exponent, that is, the most liquid observations, of the pooled set of daily Amihud (2002) illiquidity observations for all stocks month-by-month. I then test the hypothesis that the extreme liquidity risk measure is merely a manifestation of the fat-tail distribution underlying the price impact measures. If the beta based on the new Hill (1975) estimator also helps explain the cross section of stock returns, it will lead us not to reject the null hypothesis. The portfolios sorted on the betas with respect to the new estimator behaviors differently from the main experiment: Average raw returns neither increase nor decrease with the loadings. Although the "5–1" spread portfolio earns, on average, 0.11% per month throughout the sample period, it is with a t-statistic of only 0.59, which indicates that the spread return is statistically indistinguishable from zero. Moreover, the positive average return for the hedge portfolio is not robust to considering alternative priced factors. For example, the alpha for the Fama-French three-factor model is -0.01% (t = -0.05). Such weak evidence on the extreme liquid measure suggests us to

[21] Another experiment I investigated was to exclude financial firms when quintile/decile portfolios are constructed. The results (available upon request) are quantitatively similar to those reported in Table 2 and 3.

reject the hypothesis and validates that extreme liquidity risk premium found in the main experiment indeed captures, to some extent, the market-wide liquidity pressure which is important for asset pricing.

I also investigate whether the empirical validity of extreme liquidity risk premium is influenced by the purely mechanical way in which the tail threshold parameter, p^*_t, is chosen. I gradually adjust the threshold, from the 90th to the 99th percentile, and repeat the main experiment above. When the thresholds are set to be between the 91th and 99th percentiles, the empirical results are very similar with those for the 95th percentile. On the other hand, if the threshold is at the 90th percentile, the average value-weighted return of the "10–1" spread portfolio becomes statistically insignificant at the 95% confidence level although both the average return and regression alphas of the quintile spread are statistically significant. This examination suggests that an inappropriately low threshold is more likely to contaminate the estimation of extreme liquidity risk. In addition, I winsorize the effect of outliers by excluding all of the most illiquid observations beyond 99th percentile, set the 95th-percentile threshold for the new winsorized distribution, and then constructed the extreme liquidity risk estimate, the results (available upon request) based on the new extreme liquidity risk measure are quantitatively similar to those reported in Table 2 and 3.

In sum, there is strong evidence supporting the hypothesis that extreme liquidity risk is priced cross-sectionally. The premium for this risk is positive in that stocks highly sensitive to extreme liquidity shocks offer higher expected returns. This positive premium confirms the intuition that a sharp drop in extreme liquidity is undesirable for the representative investor, so that the investor might require compensation for holding such stocks with higher exposure to extreme liquidity risk.

B. Revisiting Acharya and Pedersen's (2005) Liquidity-adjusted CAPM

In Acharya and Pedersen's (2005) liquidity-adjusted CAPM, the required excess return is the expected relative illiquidity cost plus four betas times the risk premium. As in the standard CAPM, the required return on an asset increases linearly with the market beta. The model yields three additional effects: 1) return increases with the covariance between a security's liquidity and the market liquidity; 2) return decreases with the covariance between a security's return and the market liquidity; 3) return decreases with the covariance between a security's liquidity and the market return.

The previous sections focus on the second effect, and this section first tests the hypothesis that the two other effects also help explain the cross-section of average stock returns. To capture the first liquidity risk effect, at the end of each year, β^2 is estimated for each stock by regressing its Amihud (2002) illiquidity cost on the market illiquidity level, which is the same with Acharya and Pedersen (2005). Similarly, I calculate β^4, corresponding to the third liquidity risk effect, for each stock using the regression in which the independent variable is the return of market portfolio, measured by the return on the CRSP value-weighted index. I find a return premium associated with β^4 but no return premium on β^2. The lack of the return premium with respect to β^2 confirms the small magnitude of the first liquidity risk effect documented in Acharya and Pedersen (2005)[22]. Across quintile portfolios sorted on β^4, the return difference between the highest loading quintile and the lowest loading quintile is -19 basis points per month[23], with a *t*-statistic of -1.85. Compared with quintile portfolios, decile portfolios provide stronger evidence: Alphas of the high-minus-low β^4-sorted portfolio, for example, are statistically significant for all of the benchmark models. The risk-adjusted premium for the decile spread remains -15 basis points per month (t = -2.10) for the extended six-factor model. Even in terms of value-weighted returns, the decile spread alpha yields -29 basis points per month (t = -2.24) for the same model.

Table 5 presents the testing results for the hypothesis that the overall liquidity-related net beta is correlated with the difference of expected return cross-sectionally. Here I implement Acharya and

[22] As in Acharya and Pedersen (2005), β^2 is related to the return premium due to commonality in liquidity. I therefore follow Karolyi, Lee, and van Dijk (2011) and use the R^2 of regressions of the liquidity of individual stocks on market liquidity to obtain a measure of commonality in liquidity. Each month, I estimate the R^2 for each stock and then construct quintile portfolios based on the sorting on the level of R^2s. In this experiment, the value-weighted return premium monotonically increases from the lowest R^2 quintile (0.82%) to the highest quintile (1.07%). Both the "5–1" spread and "10–1" spread are robust to considering alternative priced factors. The results are close when the portfolios are equally weighted, but slightly weaker when the portfolios are rebalanced annually.

[23] Note that this effect stems from the willingness of investors to accept a lower expected return on a security that is liquid in a down market.

Pedersen's (2005) liquidity-adjusted CAPM, using the extreme liquidity risk[24], and find consistent evidence for return premium on the liquidity-related net beta. Table 5 reports mean returns and regression alphas for the portfolios sorted on the liquidity-related net beta[25], β^{net}, against all of the six benchmark models For the quintile portfolios, stocks in the highest quintile earn higher returns and have higher Amihud (2002) illiquidity cost than those in the lowest quintile. The mean return of the "5-1"spread is 0.79% per month in terms of value weighting (t = 3.84) and 0.37% per month in terms of equal weighting (t = 3.44). After controlling a variety of common risk factors, risk-adjusted premiums still increase with the liquidity-related net beta. For example, when portfolios are annually rebalanced, stocks in quintile 5 outperform stocks in quintile 1 by earning an additional 0.78% per month (9.36% per year) after benchmarking the raw returns against the Carhart four-factor model plus the Pástor and Stambaugh (2003) traded liquidity factor as the fifth control. Again, both the "5–1" spread and the "10–1" spread are significant at the 10% level.

To conclude, I implement Acharya and Pedersen's (2005) liquidity-adjusted CAPM, using my extreme liquidity risk measures, and find consistent evidence that the liquidity-related net beta helps explain the cross-sectional differences in expected returns across stocks.

IV. Robustness Check

Appendix IV indicates that extreme liquidity risk traded factor has low correlations with other common risk factors. The correlations between the extreme liquidity risk traded factor and the market return, the size factor, the value factor, and the momentum factor are -0.26, -0.20, 0.10, and 0.19, respectively. We can also notice that the extreme liquidity risk traded factor is weakly correlated with the Pástor and Stambaugh (2003) traded liquidity factor and Kelly's (2011) tail risk factor, which again suggests that extreme liquidity risk is a distinct type of risk compared with the aggregate liquidity risk and the tail risk in return.

24 I also estimate the liquidity-related net beta by using the innovation in aggregate market illiquidity as the proxy for market illiquidity, and construct quintile portfolios in a similar way with previous experiments. However it is hard to find clear evidence in the way that Acharya and Pedersen (2005) predicts.

25 $\beta^{net} = \beta^2 - \beta^3 - \beta^4$

A. Sub-period Analysis

Given the evidence above that market-wide extreme liquidity risk is a state variable important for asset pricing, a logical question is whether the magnitude of extreme liquidity risk premium varies over time. Section II notes extreme liquidity risk measure goes up during recessions. A natural comparative sub-period analysis reveals the difference of extreme liquidity risk premiums between normal times and times of crisis.

I first separate the entire sample period into two sub-periods and Table 6 distinguishes the return premiums on extreme liquidity risk during economic recessions and those in economic expansions. Regression alphas decrease noticeably for the recession periods. In terms of value-weighted returns and annual rebalance, the regression alpha of the spread falls sharply from 0.61% per month to 0.37% per month when the extended six-factor model is the benchmark.

I next look into another set of two sub-periods, one with sudden market downturns and the other without market downturns. The alphas decrease more obviously in this experiment. All of the risk-adjusted returns of the quintile spreads, either value-weighted or equal-weighted, are negative during the times with sudden market downturns, and the magnitudes are larger. For instance, the alpha of the "5–1" spread portfolios is -1.12% per month during the downturn period, much lower than the 0.65% per month for the period without downturns, and here the benchmark model includes Acharya and Pedersen's (2005) liquidity-adjusted CAPM and three additional factors (SMB, HML, and MOM).

Another example for the financial crisis is a liquidity dry-up event. I then check the periods with liquidity dry-ups and those without liquidity dry-ups. Here liquidity dry-ups includes months when the average liquidity is at least two standard deviations below its means measured by Pástor and Stambaugh (2003) liquidity innovations or the average illiquidity is at least two standard deviations above its means evaluated by Acharya and Pedersen (2005). The spread portfolio, which longs stocks with higher beta of extreme liquidity risk and shorts stocks with lower beta, performs also worse among the months of liquidity dry-ups.

B. Out of Sample Test

Given the positive evidence on the pricing of extreme liquidity risk, I try to pin down the positive risk premium more precisely into two sub-samples traded on different exchanges: NYSE&AMEX and NASDAQ. After all, my extreme liquidity risk estimate is based on the information extracted from the NYSE stocks while the portfolios incorporate all NYSE/AMEX/NASDAQ stocks. The experiment on the NASDAQ stock serves as an out-of-sample test[26] and Table 7 provides another indication of the robustness of my results.

Both the NASDAQ sample and the NYSE/AMEX sample deliver strong results not only for the average returns of spread portfolios but also for the regression alphas estimated under different factor specifications. With annual rebalancing, the "5–1" spread from the sample of NASDAQ stocks earn value-weighted average return 0.71% per month, with a t-statistic of 3.15, higher than the 0.52% per month (t = 2.81) for the NYSE/AMEX sample. The equal-weighted "5–1" spread portfolio earns average returns of 0.58% (t = 3.23) per month for the NASDAQ sample and 0.46% (t = 3.59) per month for the NYSE/AMEX sample. Both of the sub-samples have large and statistically significant alphas of the value-weighted "5–1" spread portfolio. When the extended six-factor model is considered, the quintile spread for the NYSE/AMEX stocks earns a risk-adjusted return of 0.55% per month (t = 3.05) while the NASDAQ stocks yield a risk-adjusted return of 0.60% per month (t = 2.69). In terms of equal-weighted returns, the regression alphas are 0.42% per month (t = 3.35) for NYSE/AMEX stocks and 0.46% per month (t = 2.72) for NASDAQ stocks, using the same benchmark model.

C. Alternative Liquidity Measure

My extreme liquidity risk estimate in the previous analyses is based on the Amihud (2002) illiquidity measure. In this section I try another proxy for the price impact, the Roll Impact, which is "a close second behind Amihud" suggested by Goyenko, Holden and Trzcinka (2009). The Roll Impact for time interval t is defined as follows:

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[26] I also check another set of two sub-samples: NYSE, and NASDAQ/AMEX, and it produces almost identical results.

$$\textit{Roll Impact}_t = \textit{Roll}_t \,/\, \textit{Average Daily Dollar Volume}_t \qquad (7)$$

where $Roll_t$ takes the form

$$Roll = \begin{cases} 2\sqrt{-cov(\Delta P_t, \Delta P_{t-1})} & when\ cov(\Delta P_t, \Delta P_{t-1}) < 0 \\ 0 & when\ cov(\Delta P_t, \Delta P_{t-1}) \geq 0 \end{cases} \qquad (8)$$

There is one problem with using the Roll Impact as the basis for the estimation of extreme liquidity risk. It is measured over a number of day observations, which are then averaged, while my estimate requires a large panel of day-stock observations within each month. To solve this problem, I make an adjustment on the measure of the Roll Impact: for each stock *i* and each day *d* in month *t*, I select a reference period which consists of the preceding 22 days (*d-22*, *d-21, …, d-1*) and the day *d*. The reference period is used to measure the Roll Impact for the stock on that day. On a given trading day *d*, the stock *i*'s daily trading dollar volumes in the reference period are used to measure the average daily dollar volume in the denominator of the Roll Impact. The serial covariance of the trade prices, which appears in the numerator of the Roll Impact, is also based on the trading data during the same reference period. For each stock with valid observations in month *t*, its trailing 23-day measure of the Roll Impact is accordingly estimated for each day in month *t*. Similar to the previous sections, I apply Hill's (1975) estimator to the cross section of illiquidity observations in terms of the Roll Impact for all of the qualified NYSE stocks month-by-month. I acknowledge several limitations in the implementation. It might not be able to incorporate the new information promptly by the trailing method. I also cannot disregard the fact that the Roll Impact is set to be zero whenever the serial covariance of traded price is larger than or equal to zero. I expect that the noisy estimates built on the Roll Impact most likely will fail to provide supporting evidence for the hypothesis that extreme liquidity risk is priced cross-sectionally in the U.S. stock market, and interpret this experiment as a sensitivity test to gauge the robustness of my results.

When portfolios are annually rebalanced and the stocks within each portfolio are equally-weighted, stocks in the highest decile of extreme liquidity risk loading earn value-weighted average return 0.45% per month higher than stocks in the lowest decile, with the *t*-statistic of 3.31. The equal-weighted "5–1" spread portfolio average return is 0.36% per month (t = 3.23). I next test if the risk premium survives a number of common risk factors. Taking the “5–1” spread as an example, the alphas are 0.30% per month (t = 2.65) for the Fama-French three-factor model, 0.24% per month (t = 2.07) for the Carhart four-factor model, 0.21% per month (t = 1.82) for the Carhart four-factor model plus the Pástor and Stambaugh (2003) traded liquidity risk factor, 0.35% per month (t = 3.08) for the Acharya and Pedersen’s (2005) liquidity-adjusted CAPM, and 0.23% per month (t = 1.98) for the Acharya and Pedersen’s (2005) liquidity-adjusted CAPM plus three additional common risk factors. The alpha with respect to the most extensive six-factor model, however, is less statistically significant, with the t-statistic of just 1.73, despite that it is large, 0.20% per month. When stocks within each portfolio are value-weighted, the high average return for the “10–1” spread is robust to controlling for a variety of risk factors while the performances on the “5–1” spread get less desirable. Compared to extreme liquidity measure based on the Amihud (2002) illiquidity measure, the Roll Impact appears more related to the level of illiquidity cost. The value-weighted Amihud (2002) illiquidity is 0.13% for the highest loading quintile, much higher than 0.06% reported in Table 2 for the quintile 5. The same is also true for equal-weighted portfolios. In addition, the high loading portfolios contain stocks of small size and growth tilt. The complete set of portfolio properties and returns are reported in Table 8.

Overall, the experiment on the alternative price impact measure produces the most disappointing results among all of the robustness tests. But, even with this challenge, there is still evidence suggesting that stocks more exposed to extreme liquidity risk tend to be more heavily discounted.

V. Conclusions

I propose a direct measure of market-wide extreme liquidity risk and find that the cross-section of expected stock returns reflects a premium for extreme liquidity risk. From 1973 through 2011, stocks in the highest quintile of extreme liquidity risk loadings earned value-weighted average returns 0.55% per month higher than stocks in the lowest quintile. The extreme liquidity risk premium is robust to common risk factors related to size, value and momentum. The premium is different from that on aggregate liquidity risk documented in Pástor and Stambaugh (2003) as well as that based on the extreme market-wide return of Kelly (2011). Predictive regressions show that my extreme liquidity measure reliably outperforms aggregate liquidity measures in predicting future market returns. Finally, I incorporate the extreme liquidity risk into Acharya and Pedersen’s (2005) framework and find new supporting evidence for their liquidity-adjusted capital asset pricing model.

My findings underscore the empirical relevance of extreme liquidity risk for the U.S. equity market. One direction for future research is to construct the higher frequency measures of extreme liquidity risk by utilizing high frequency liquidity benchmarks. Future work could investigate how the pricing of aggregate liquidity risk documented in Pástor and Stambaugh (2003) is related to the pricing of extreme liquidity risk in this study. It would also be useful to explore whether extreme liquidity risk is priced in other financial markets, such as international equity markets or fixed income markets, and whether information on the extreme liquidity risk of other non equity securities is helpful for the study of equity returns.

References

Acharya, V., and L. H. Pedersen, 2005, Asset Pricing with Liquidity Risk, *Journal of Financial Economics*, 77, 375-410.

Allen, L., T. Bali, and Y. Tang, 2011, Does Systemic Risk in the Financial Sector Predict Future Economic Downturns? Baruch College Working Paper.

Amihud, Y., 2002, Illiquidity and Stock Returns: Cross-section and Time-series Effects, *Journal of Financial Markets*, 5, 31-56.

Amihud, Y., and H. Mendelson, 1986, Asset pricing and the Bid-ask Spread, *Journal of Financial Economics*, 17, 223-249.

Ané, T., and Kharoubi, C., 2003, Dependence Structure and Risk Measure, *Journal of Business*, 76, 411-438.

Ang, A., J. Chen, and Y. Xing, 2006, Downside Risk, *Review of Financial Studies*, 19, 1191-1239.

Asparouhova, Elena N., Hendrik Bessembinder, and Ivalina Kalcheva, 2010, Liquidity Biases in Asset Pricing Tests, *Journal of Financial Economics*, 96, 215-237.

Asparouhova, Elena, Hendrik Bessembinder, and Ivalina Kalcheva, 2012, Noisy Prices and Inference Regarding Returns, *Journal of Finance*, Forthcoming.

Baker, M., Wurgler, J., 2006, Investor Sentiment and the Cross-section of Stock Returns. *Journal of Finance*, 61, 1645-1680.

Bansal, R., and I. Shaliastovich, 2011, Learning and Asset-Price Jumps, *Review of Financial Studies*, 24, 2738-2780.

Barra, Market Impact Model Handbook (Berkeley, CA: Barra, 1997).

Blume, Marshall E., and Robert F. Stambaugh, 1983, Biases in Computed Returns: an Application to the Size Effect, *Journal of Financial Economics*, 12, 387-404.

Brennan, M., and A. Subrahmanyam, 1996, Market Microstructure and Asset Pricing: On the compensation for Illiquidity in Stock Returns, *Journal of Financial Economics*, 41, 441-464.

Brennan, M., Chordia, T., and A. Subrahmanyam, 1998, Alternative Factor Specifications, Security Characteristics, and the Cross-section of Expected Returns, *Journal of Financial Economics*, 49, 345-373.

Brennan, M., Chordia, T., A. Subrahmanyam, and Qing Tong, 2012, Sell-Order Liquidity and the Cross-Section of Expected Stock Returns, *Journal of Financial Economics*, Forthcoming.

Brunnermeier, M. K., 2009. Deciphering the Liquidity and Credit Crunch 2007–08, *Journal of Economic Perspectives*, 23, 77-100.

Brunnermeier, M. K., and Pedersen, L. H., 2009, Market Liquidity and Funding Liquidity, *Review of Financial Studies*, 22, 2201–2238.

Carhart, Mark M., 1997, On Persistence in Mutual Fund Performance, *Journal of Finance*, 52, 57-82.

Chordia, T., Roll, R., and Subrahmanyam, A., 2000, Commonality in Liquidity, *Journal of Financial Economics*, 56, 3-28.

Chordia, T., Huh Sahn-Wook and Subrahmanyam, A., 2009, Theory-Based Illiquidity and Asset Pricing, *Review of Financial Studies*, 22, 3629-3668.

Comerton-Forde, Carole, Terrence Hendershott, Charles M. Jones, Pamela C. Moulton, and Mark S. Seasholes, 2010, Time Variation in Liquidity: The Role of Market Maker Inventories and Revenues, *Journal of Finance*, 65, 295–331.

Coughenour, J. F., and Saad, M. M., 2004. Common Market Makers and Commonality in Liquidity, *Journal of Financial Economics*, 73, 37-69.

Drechsler, I., and A. Yaron, 2011, What's Vol Got to do with It? *Review of Financial Studies*, 24, 1-45.

Duffie, D., J. Pan, and K. Singleton, 2000, Transform Analysis and Asset Pricing for Affine Jump-diffusions, *Econometrica*,1343-1376.

Dupuis, DJ., 1999, Exceedances over High Thresholds: A Guide to Threshold Selection, *Extremes*, 1, 251-261.

Eraker, B., and I. Shaliastovich, 2008, An Equilibrium Guide to Designing Affine Pricing Models, *Mathematical Finance*, 18, 519-543.

Fama, E. F., 1965, The Behavior of Stock-market Prices, *Journal of Business*, 38, 34-105.

Fama, E. F., and Kenneth R. French, 1993, Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics*, 33, 3-56.

Fama, E. F., and Kenneth R. French, 2008, Dissecting Anomalies, *Journal of Finance*, 63, 1653-1678.

Gabaix, X., 2009, Power Laws in Economics and Finance, *Annual Review of Economics*, 1, 255-293.

Gabaix, X., 2012, Variable Rate Disasters: An Exactly Solved Framework for Ten Puzzles in Macro-finance, *Quarterly Journal of Economics*, 127, 645-700.

Gabaix, X., P. Gopikrishnan, V. Plerou, and H. Stanley, 2003, A Theory of Power Law Distributions in Financial Market Fluctuations, *Nature*, 423, 267–230.

Gabaix, X., P. Gopikrishnan, V. Plerou, and H. Stanley, 2006, Institutional Investors and Stock Market Volatility, *Quarterly Journal of Economics*, 121, 461-504.

Galbraith, J.W., and S. Zernov, 2004, Circuit Breakers and the Tail Index of Equity Returns, *Journal of Financial Econometrics*, 2, 109-129.

Gibbons, Michael R., Stephen A. Ross, and Jay Shanken, 1989, A Test of the Efficiency of a Given Portfolio, *Econometrica*, 57, 1121-1152.

Goyenko, R., Holden, C., and Trzcinka C., 2009, Do Liquidity Measures Measure Liquidity? *Journal of Financial Economics*, 92, 153-181.

Goyenko, R., and Sergei Sarkissian, 2008, Flight-to-liquidity and Global Equity Returns, working paper, McGill University

Grinold, Richard C., and Ronald N. Kahn, Active Portfolio Management, Boston, MA; London: Irwin/McGraw-Hill, 1999.

Hameed, A., Kang,W., and Viswanathan, S., 2010, Stock Market Declines and Liquidity, *Journal of Finance*, 65, 257–293.

Hasbrouck, J., 1991, Measuring the Information-Content of Stock Trades, *Journal of Finance*, 46, 179–207.

Hasbrouck, J., 2009, Trading Costs Returns for U.S. Equities: Estimating Effective Costs from Daily Data, *Journal of Finance*, 64, 1445-1477.

Hasbrouck, J., and Duane Seppi, 2001, Common Factors in Prices, Order Flows and Liquidity, *Journal of Financial Economics*, 59, 388–411.

Hill, B. 1975, A Simple General Approach to Inference about the Tail of a Distribution, *The Annals of Statistics*, 3, 1163-1174.

Hu, Xing, Jun Pan, and Jiang Wang, 2012, Noise as Information for Illiquidity, working paper, MIT.

Hund, John, and David Lesmond, 2008, Liquidity and credit risk in emerging debt markets, 14th Annual Conference on Financial Economics and Accounting, working paper.

Jacoby, G., D. Fowler, and A. Gottesman, 2000, The Capital Asset Pricing Model and the Liquidity Effect: A Theoretical Approach, *Journal of Financial Markets*, 3, 69-81.

Jiang, H., and B. Kelly, 2011, Tail Risk and Hedge Fund Returns, Chicago Booth Working Paper.

Jones, C., 2002, A century of stock market liquidity and trading costs, working paper, Columbia University.

Karolyi, G. A., Lee, K., and M. A. Van Dijk, 2012, Understanding commonality in liquidity around the world, *Journal of Financial Economics*, 105, 82-112.

Kelly, B., 2011, Tail Risk and Asset Prices, Chicago Booth Working Paper.

Koch, A., Ruenzi, S., Starks, L., 2009, Commonality in Liquidity: A Demand-side Explanation, working paper, University of Texas at Austin.

Korajczyk, R. A., and Sadka, R., 2008, Pricing the Commonality across Alternative Measures of Liquidity, *Journal of Financial Economics*, 87, 45-72.

Lee, K. H., 2011, the World Price of Liquidity Risk, *Journal of Financial Economics*, 99, 136-161.

Lewellen, J. 2012, the Cross Section of Expected Stock Returns, working paper, Dartmouth College.

Longstaff, F. A., 2004, The Flight-to-liquidity Premium in US Treasury Bond Prices, *Journal of Business*, 77, 511–526.

Mandelbrot, B., 1963, The Variation of Certain Speculative Prices, *Journal of Business*, 36, 394-419.

Matthys, G., and J. Beirlant, 2000, Adaptive Threshold Selection in Tail Index Estimation, *Extremes and Integrated Risk Management*, 37-49.

Menkveld, A., and Wang, T., 2011, Liquileaks, VU University Amsterdam, working Paper.

Pástor, L., and R. F. Stambaugh, 2003, Liquidity Risk and Expected Stock Returns, *Journal of Political Economy* 111, 642-685.

Pedersen, L. H., 2008, Liquidity Risk and the Structure of Financial Crises, Talks at IMF and Federal Reserve Board on the liquidity crisis, slides, New York University.

Plerou, V., P. Gopikrishnan, L. Amaral, X. Gabaix, and H. Stanley, 2000, Economic Fluctuations and Anomalous Diffusion, *Physical Review E*, 62, R3023–R3026.

Plerou, V., P. Gopikrishnan, X. Gabaix, and H. Stanley, 2002, Quantifying Stock Price Response to Demand Fluctuations, *Physical Review E*, 66, 027104-1–027104-4.

Plerou, V., P. Gopikrishnan, X. Gabaix, and H. Stanley, 2004, On the Origins of Power-Law Fluctuations in Stock Prices, *Quantitative Finance*, 4, C11–C15.

Quintos, C., Z. Fan, and P.C.B. Philips, 2001, Structural Change Tests in Tail Behavior and the Asian Crisis, *Review of Economic Studies*, 68, 633-663.

Roll, R., 1984, A Simple Implicit Measure of the Effective Bid–ask Spread in an Efficient Market, *Journal of Finance*, 39, 1127–1139.

Ruenzi, S., and Weigert, F., 2011, Extreme Dependence Structures and the Cross-Section of Expected Stock Returns, working paper.

Sadka, R., 2006. Momentum and Post-earnings-announcement Drift Anomalies: The Role of Liquidity Risk, *Journal of Financial Economics*, 80, 309-349.

Spiegel, M.I., and Wang, X., 2005, Cross-sectional Variation in Stock Returns: Liquidity and Idiosyncratic Risk, working paper, Yale University.

Vayanos D., 2004. Flight to Quality, Flight to Liquidity, and the Pricing of Risk, working paper, London School of Economics.

Wachter, J., 2012, Can Time-varying Risk of Rare Disasters Explain Aggregate Stock Market Volatility? Forthcoming in *Journal of Finance*.

Wagner, N., 2003, Estimating Financial Risk under Time-varying Extremal Return Behavior, *OR Spectrum*, 25, 317-328.

Werner, T., and C. Upper, 2004, Time Variation in the Tail Behavior of Bund Future Returns, *Journal of Futures Markets*, 24, 387-398.

Table 1
Summary Statistics: 1973-2011

Group	$E(r^m)$	$E(r^d)$	$\sigma(r)$	$E(c^m)$	$E(c^d)$	$\sigma(c)$	size	trn	price	shares outstanding
	monthly	daily	monthly	monthly	daily	monthly	per stock	monthly	monthly	monthly
	(%)	(%)	(%)	(%)	(%)		(\$billion)	(%)	(\$)	(million)
<5th	1.60	0.02	1.89	0.01	0.00	0.01	11.77	11.39	115.58	264.15
5th~10th	1.55	0.04	1.92	0.01	0.00	0.01	8.57	11.19	105.85	206.64
10th~15th	1.54	0.06	1.96	0.01	0.00	0.02	6.10	11.14	101.62	156.64
15th~20th	1.53	0.08	1.99	0.02	0.01	0.02	4.68	11.08	98.21	127.95
20th~25th	1.51	0.09	2.02	0.02	0.01	0.03	3.68	11.02	93.09	106.51
25th~30th	1.54	0.10	2.05	0.03	0.01	0.03	2.94	10.87	89.60	90.10
30th~35th	1.50	0.10	2.08	0.04	0.01	0.04	2.38	10.73	80.67	77.20
35th~40th	1.50	0.11	2.11	0.04	0.02	0.05	1.93	10.56	72.11	66.28
40th~45th	1.50	0.11	2.14	0.06	0.03	0.07	1.57	10.31	57.61	57.20
45th~50th	1.50	0.11	2.18	0.07	0.03	0.08	1.28	10.01	47.22	49.64
50th~55th	1.47	0.10	2.22	0.09	0.05	0.11	1.05	9.67	38.49	43.46
55th~60th	1.46	0.11	2.26	0.11	0.06	0.13	0.87	9.29	31.31	38.32
60th~65th	1.44	0.10	2.30	0.14	0.08	0.17	0.73	8.86	27.13	33.96
65th~70th	1.40	0.10	2.35	0.18	0.11	0.22	0.60	8.40	24.17	30.15
70th~75th	1.35	0.09	2.42	0.22	0.16	0.29	0.49	7.90	21.32	26.82
75th~80th	1.28	0.08	2.51	0.29	0.22	0.39	0.40	7.34	19.64	24.13
80th~85th	1.19	0.06	2.60	0.39	0.33	0.54	0.32	6.74	17.47	21.59
85th~90th	1.05	0.04	2.74	0.56	0.53	0.81	0.25	6.00	15.50	19.36
90th~95th	0.86	-0.01	2.96	0.97	1.03	1.52	0.18	5.17	13.25	17.23
>95th	0.51	-0.05	3.46	6.99	20.43	13.43	0.12	4.10	10.21	15.17

This table reports the properties of twenty equal-weighted portfolios based on the cross-section distribution of extreme liquidity risk involved in each stock on the NYSE each month during 1973-2011. The average monthly return $E(r^m)$, the average daily return $E(r^d)$, the average monthly illiquidity $E(c^m)$, the average daily illiquidity $E(c^d)$, the market capitalization (Size), the turnover (trn), the trading volume (volume), the price (Price), and the shares outstanding (Shares Outstanding) are computed for each group as time-series averages of the respective characteristics. Finally, $\sigma(r)$ is the average of the standard deviation of daily returns for the group's constitute stocks computed each month, and $\sigma(c)$ is the average of the standard deviation of daily illiquidity for the group's constitute stocks computed each month.

Table 2
Properties of Extreme Liquidity Loading-sorted Portfolios: 1973-2011

Extreme Liquidity Loading	Low				High				
	1	2	3	4	5	**5–1**	*t-stat.*	**10–1**	*t-stat.*
Panel A: Annual Rebalance									
Value-weighted									
Preceding loadings	-0.12	-0.03	0.00	0.03	0.10	**0.22**	*9.69*	**0.30**	*9.65*
Post-ranking loadings	-0.46	-0.01	0.05	0.11	0.12	**0.58**	*2.33*	**0.61**	*1.90*
<u>Additional Properties</u>									
Market cap	22.93	35.96	34.01	31.83	27.70	**4.77**	*2.37*	**3.57**	*1.85*
(Il)liquidity	0.09	0.05	0.04	0.03	0.06	**-0.04**	*-8.50*	**-0.08**	*-8.71*
MKT beta	1.17	1.06	0.95	0.94	0.94	**-0.24**	*-5.16*	**-0.31**	*-5.36*
SMB beta	0.22	-0.09	-0.12	-0.15	-0.04	**-0.26**	*-4.00*	**-0.43**	*-5.21*
HML beta	-0.09	0.10	0.22	0.12	-0.03	**0.07**	*0.98*	**0.04**	*0.51*
MOM beta	-0.15	-0.05	0.01	0.05	0.06	**0.22**	*4.87*	**0.19**	*3.32*
PS-Liquidity beta	0.03	0.00	0.01	-0.01	-0.05	**-0.08**	*-1.50*	**-0.10**	*-1.53*
K-Tail beta	-0.06	-0.05	0.05	0.06	0.15	**0.21**	*4.17*	**0.37**	*5.80*
Equal-weighted									
Preceding loadings	-0.12	-0.03	0.00	0.03	0.10	**0.22**	*10.06*	**0.30**	*9.91*
Post-ranking loadings	-0.47	-0.07	0.05	0.17	0.08	**0.55**	*3.08*	**0.59**	*2.61*
<u>Additional Properties</u>									
Market cap	1.28	2.22	2.38	2.45	1.85	**0.58**	*5.06*	**0.59**	*5.74*
(Il)liquidity	1.50	1.57	1.13	1.06	0.98	**-0.75**	*-11.81*	**-0.81**	*-12.17*
MKT beta	1.05	0.93	0.87	0.83	0.90	**-0.15**	*-4.62*	**-0.15**	*-3.67*
SMB beta	0.85	0.51	0.39	0.43	0.54	**-0.31**	*-7.07*	**-0.39**	*-6.93*
HML beta	0.09	0.36	0.41	0.33	0.24	**0.14**	*3.10*	**0.22**	*3.71*
MOM beta	-0.17	-0.08	-0.04	-0.02	0.00	**0.17**	*5.44*	**0.18**	*4.73*
PS-Liquidity beta	0.01	-0.01	0.00	0.00	-0.04	**-0.05**	*-1.51*	**-0.09**	*-1.91*
K-Tail beta	0.02	0.00	0.05	0.07	0.16	**0.14**	*4.08*	**0.17**	*3.86*

Table 2, continued

Extreme Liquidity Loading	Low				High				
	1	2	3	4	5	**5–1**	*t-stat.*	**10–1**	*t-stat.*
Panel B: Monthly Rebalance									
Value-weighted									
Preceding loadings	-0.13	-0.03	0.00	0.03	0.10	**0.22**	*33.01*	**0.31**	*32.65*
Post-ranking loadings	-0.53	-0.02	0.03	0.13	0.16	**0.68**	*2.45*	**0.71**	*2.13*
Additional Properties									
Market cap	21.75	35.42	34.87	30.69	29.88	**8.13**	*3.94*	**6.38**	*3.21*
(Il)liquidity	0.09	0.04	0.04	0.04	0.06	**-0.03**	*-6.43*	**-0.06**	*-7.28*
MKT beta	1.25	1.05	0.96	0.89	0.90	**-0.35**	*-7.20*	**-0.40**	*-6.82*
SMB beta	0.37	-0.03	-0.16	-0.17	-0.09	**-0.46**	*-6.71*	**-0.56**	*-6.86*
HML beta	-0.16	0.04	0.25	0.13	0.01	**0.17**	*2.37*	**0.18**	*2.09*
MOM beta	-0.15	-0.07	-0.01	0.03	0.08	**0.22**	*4.64*	**0.20**	*3.55*
PS-Liquidity beta	0.00	0.02	0.01	-0.01	-0.06	**-0.05**	*-0.97*	**-0.05**	*-0.80*
K-Tail beta	-0.18	-0.06	0.05	0.09	0.23	**0.41**	*7.58*	**0.56**	*8.81*
Equal-weighted									
Preceding loadings	-0.13	-0.03	0.00	0.03	0.10	**0.22**	*34.15*	**0.30**	*33.68*
Post-ranking loadings	-0.46	-0.02	0.08	0.09	0.11	**0.57**	*2.57*	**0.63**	*2.28*
Additional Properties									
Market cap	1.25	2.25	2.48	2.37	1.90	**0.64**	*5.46*	**0.63**	*5.83*
(Il)liquidity	1.41	1.27	1.15	1.08	1.00	**-0.41**	*-8.44*	**-0.49**	*-8.36*
MKT beta	1.11	0.94	0.88	0.85	0.92	**-0.19**	*-5.13*	**-0.21**	*-4.53*
SMB beta	1.02	0.55	0.41	0.40	0.50	**-0.52**	*-10.06*	**-0.64**	*-9.91*
HML beta	0.03	0.34	0.39	0.36	0.28	**0.25**	*4.61*	**0.33**	*4.87*
MOM beta	-0.11	-0.05	-0.02	0.02	0.03	**0.14**	*3.78*	**0.14**	*3.20*
PS-Liquidity beta	0.00	0.00	0.00	0.00	-0.04	**-0.04**	*-1.05*	**-0.06**	*-1.15*
K-Tail beta	-0.07	0.01	0.03	0.09	0.21	**0.28**	*6.90*	**0.35**	*6.85*

Table 2, continued

The table shows the properties for the extreme liquidity risk beta-sorted portfolios. At each year end between 1972 and 2010, I estimate extreme liquidity risk sensitivities of individual stocks with respect to extreme liquidity risk by the form

$$E_t\,[r_{i,t+1}] = \mu_i + \beta_i\,ELR_t$$

Here the regression uses only data available at that time. And eligible stocks are defined as ordinary common shares traded on the NYSE, AMEX, or NASDAQ with at least four years of non-missing monthly returns out of five years and with stock prices between \$5 and \$1,000. Stocks are then sorted into quintile portfolios and decile portfolios based on their estimated extreme liquidity risk loadings. The post-formation returns on these portfolios during the next 12 months are linked across years to form a single return series for each quintile portfolio and decile portfolio covering the period from July 1973 to December 2011. Panel A reports the quintile portfolios' preceding extreme liquidity loadings ("preceding loadings" in the table) and post-ranking extreme liquidity loadings ("post-ranking loadings" in the table). The post-ranking extreme liquidity loadings are estimated by regressing the portfolio excess returns on the extreme liquidity risk estimate and the market excess return factor over the sample period. Panel B reports the time-series averages of the quintile portfolios' market capitalization and liquidity, obtained as the average of the corresponding Amihud (2002) illiquidity measures across the stocks within each quintile. Market capitalization is reported in billions of U.S. dollars. A stock's liquidity in any given month is the Amihud (2002) illiquidity measure. Also reported are post-ranking betas with respect to the three Fama-French factors, the momentum factor, the Pástor and Stambaugh (2003) traded liquidity factor ("PS-Liquidity" in the table) and Kelly's (2011) tail risk factor ("K-Tail" in the table). The four right-most columns report results for two high-minus-low zero net investment portfolio, one that longs quintile portfolio 5 and shorts quintile 1 and the other longs decile 10 and shorts decile 1, as well as *t*-statistics for the hedge portfolios' corresponding measures.

Table 3
Extreme Liquidity Loading-sorted Portfolio Returns: 1973-2011

Extreme Liquidity Loading	Low				High				
	1	2	3	4	5	**5–1**	*t-stat.*	**10–1**	*t-stat.*
Panel A: Annual Rebalance									
Value-weighted									
Mean	0.74	0.84	0.94	1.12	1.29	**0.55**	*2.73*	**0.68**	*2.64*
Alpha: FF	-0.32	-0.13	-0.02	0.22	0.39	**0.70**	*3.56*	**0.89**	*3.49*
Alpha: FF + Mom	-0.19	-0.10	-0.01	0.19	0.37	**0.56**	*2.84*	**0.81**	*3.14*
Alpha: FF + Mom + PS-Liquidity	-0.21	-0.10	-0.02	0.19	0.40	**0.61**	*3.05*	**0.87**	*3.35*
Alpha: FF + Mom + PS-Liquidity + K-Tail	-0.20	-0.08	-0.03	0.18	0.36	**0.55**	*2.81*	**0.77**	*3.06*
Alpha: AP-CAPM	-0.29	-0.09	0.07	0.25	0.37	**0.66**	*3.39*	**0.82**	*3.23*
Alpha: AP-CAPM + FF + Mom	-0.19	-0.09	-0.01	0.19	0.37	**0.56**	*2.84*	**0.81**	*3.15*
Equal-weighted									
Mean	0.97	1.13	1.24	1.33	1.43	**0.46**	*3.15*	**0.58**	*3.19*
Alpha: FF	-0.30	-0.06	0.09	0.22	0.26	**0.56**	*4.13*	**0.68**	*3.94*
Alpha: FF + Mom	-0.14	0.01	0.14	0.25	0.31	**0.45**	*3.31*	**0.56**	*3.22*
Alpha: FF + Mom + PS-Liquidity	-0.15	0.01	0.14	0.25	0.33	**0.48**	*3.51*	**0.61**	*3.48*
Alpha: FF + Mom + PS-Liquidity + K-Tail	-0.16	0.01	0.12	0.24	0.29	**0.45**	*3.28*	**0.56**	*3.26*
Alpha: AP-CAPM	-0.15	0.13	0.29	0.39	0.42	**0.58**	*4.12*	**0.71**	*4.01*
Alpha: AP-CAPM + FF + Mom	-0.24	-0.09	0.05	0.17	0.24	**0.48**	*3.49*	**0.58**	*3.38*
Panel B: Monthly Rebalance									
Value-weighted									
Mean	0.75	0.91	0.91	1.08	1.19	**0.44**	*2.39*	**0.42**	*2.02*
Alpha: FF	-0.33	-0.05	-0.06	0.18	0.29	**0.62**	*2.84*	**0.6**	*2.27*
Alpha: FF + Mom	-0.25	0.00	-0.04	0.18	0.28	**0.53**	*2.38*	**0.56**	*2.10*
Alpha: FF + Mom + PS-Liquidity	-0.25	-0.02	-0.05	0.18	0.31	**0.57**	*2.53*	**0.6**	*2.23*
Alpha: FF + Mom + PS-Liquidity + K-Tail	-0.20	0.00	-0.06	0.16	0.25	**0.46**	*2.15*	**0.45**	*1.80*
Alpha: AP-CAPM	-0.32	-0.03	0.03	0.21	0.28	**0.60**	*2.73*	**0.58**	*2.18*
Alpha: AP-CAPM + FF + Mom	-0.25	0.00	-0.04	0.18	0.28	**0.53**	*2.38*	**0.56**	*2.10*
Equal-weighted									
Mean	1.04	1.24	1.26	1.35	1.43	**0.38**	*2.13*	**0.46**	*2.05*
Alpha: FF	-0.24	0.04	0.11	0.22	0.24	**0.49**	*3.01*	**0.56**	*2.77*
Alpha: FF + Mom	-0.17	0.09	0.13	0.23	0.27	**0.44**	*2.66*	**0.52**	*2.53*
Alpha: FF + Mom + PS-Liquidity	-0.17	0.09	0.14	0.23	0.30	**0.47**	*2.81*	**0.56**	*2.70*
Alpha: FF + Mom + PS-Liquidity + K-Tail	-0.15	0.09	0.13	0.21	0.24	**0.39**	*2.47*	**0.47**	*2.35*
Alpha: AP-CAPM	-0.11	0.23	0.30	0.39	0.41	**0.52**	*3.00*	**0.62**	*2.83*
Alpha: AP-CAPM + FF + Mom	-0.26	0.00	0.05	0.15	0.20	**0.46**	*2.80*	**0.55**	*2.67*

Table 3, continued

The table shows the statistics for the extreme liquidity risk beta-sorted portfolios. At each year end between 1972 and 2010, I estimate extreme liquidity risk sensitivities of individual stocks with respect to extreme liquidity risk by the form

$$E_t\,[r_{i,t+1}\,] = \mu_i + \beta_i\,ELR_t$$

Here the regression uses only data available at that time. And eligible stocks are defined as ordinary common shares traded on the NYSE, AMEX, or NASDAQ with at least four years of non-missing monthly returns out of five years and with stock prices between \$5 and \$1,000. Stocks are then sorted into quintile portfolios and decile portfolios based on their estimated extreme liquidity risk loadings. The post-formation returns on these portfolios during the next 12 months are linked across years to form a single return series for each quintile portfolio and decile portfolio covering the period from July 1973 to December 2011. Panel A reports monthly portfolio returns when portfolios are rebalanced annually and Panel B reports monthly returns when portfolios are rebalanced monthly. The table also reports portfolio regression alphas from regressions of portfolio returns using the Fama-French three-factor model as well as its extended four-, five- and six-factor models considering the momentum factor, the Pástor and Stambaugh (2003) traded liquidity factor ("PS-Liquidity" in the table), and Kelly's (2011) tail risk factor ("K-Tail" in the table) as additional controls. In addition, the table shows regression alphas from regressions of portfolio returns using Acharya and Pedersen's (2005) liquidity-adjusted CAPM ("AP-CAPM" in the table) as well as extended model controlling size, value and momentum factors. The four right-most columns report results for two high-minus-low zero net investment portfolios, one that longs quintile 5 and short quintile 1 and the other longs decile 10 and shorts decile 1, as well as *t*-statistics for the hedge portfolios' average returns and factor model alphas.

Table 4
Fama-Macbeth Regression Estimates Using Individual Security Data: 1973-2011

Panel A: Models with Extreme Liquidity Risk Betas

Model	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII	XIII	XIV	XV
Beta_Extreme Liquidity Risk	0.66 **	0.57 **	0.51 **	0.59 **	0.63 **	0.49 **	0.45 **	0.47 **	0.43 **	0.42 **	0.49 **	0.42 **	0.36 **	0.43 **	0.36 **
	(2.61)	*(2.39)*	*(2.17)*	*(2.23)*	*(2.42)*	*(2.48)*	*(2.22)*	*(2.41)*	*(2.15)*	*(2.48)*	*(2.62)*	*(2.55)*	*(2.08)*	*(2.27)*	*(2.16)*
SIZE	-0.16 *					-0.13	-0.10	-0.14	-0.10	-0.14	0.14	-0.15	-0.10	0.18	-0.13
	(-1.93)					*(-1.60)*	*(-1.30)*	*(-1.64)*	*(-1.33)*	*(-1.63)*	*(0.79)*	*(-1.14)*	*(-1.31)*	*(1.05)*	*(-0.96)*
B/M		0.62 **				0.47 **	0.48 **	0.47 **	0.48 **	0.41 **	0.50 **	0.43 **	0.42 **	0.50 **	0.44 **
		(3.81)				*(2.91)*	*(3.04)*	*(2.88)*	*(3.01)*	*(2.90)*	*(3.29)*	*(3.09)*	*(2.98)*	*(3.38)*	*(3.16)*
Mom			0.78 **			0.66 **	0.66 **	0.66 **	0.66 **	0.67 **	0.64 **	0.70 **	0.67 **	0.64 **	0.70 **
			(4.01)			*(3.47)*	*(3.56)*	*(3.48)*	*(3.57)*	*(3.64)*	*(3.41)*	*(3.85)*	*(3.72)*	*(3.51)*	*(3.92)*
Beta_ K-Tail Risk				0.44 **			0.28 **		0.28 **				0.29 **	0.27 **	0.28 **
				(2.61)			*(2.25)*		*(2.28)*				*(2.52)*	*(2.18)*	*(2.44)*
Beta_PS-Liquidity Risk					0.32 **			0.23	0.21				0.14	0.20	0.17
					(2.20)			*(1.61)*	*(1.51)*				*(1.04)*	*(1.48)*	*(1.24)*
Turnover _NYSE/AMEX										-0.35 **		-0.26 *	-0.36 **		-0.28 *
										(-2.83)		*(-1.71)*	*(-3.03)*		*(-1.93)*
Turnover _NASDAQ										-1.07		-0.20 **	-1.07		-0.19 **
										(-1.50)		*(-2.73)*	*(-1.48)*		*(-2.87)*
Amihud_ NYSE/AMEX											0.24 **	0.01		0.24 **	0.00
											(2.31)	*(0.09)*		*(2.40)*	*(0.03)*
Amihud _ NASDAQ											0.42	0.26		0.43	0.26
											(0.73)	*(0.45)*		*(0.75)*	*(0.44)*
	1.09 **	0.79 **	0.58 **	0.71 **	0.75 **	0.94 **	0.84 **	0.94 **	0.85 **	1.08 **	0.54	1.08 **	0.99 **	0.44	1.00 **
Intercept	*(2.72)*	*(2.93)*	*(2.25)*	*(2.76)*	*(2.78)*	*(2.41)*	*(2.29)*	*(2.43)*	*(2.31)*	*(2.96)*	*(1.05)*	*(2.78)*	*(2.84)*	*(0.90)*	*(2.66)*
Months	468														
Observations	1,003,683														

Table 4, continued

Panel B: Models without Extreme Liquidity Risk Betas

Model	I'	II'	III'	IV'	V'	VI'	VII'	VIII'	IX'	X'	XI'	XII'	XIII'	XIV'	XV'
SIZE	-0.15 *					-0.11	-0.08	-0.12	-0.08	-0.12	0.18	-0.12	-0.09	0.22	-0.10
	(-1.76)					*(-1.32)*	*(-0.95)*	*(-1.36)*	*(-0.99)*	*(-1.39)*	*(1.01)*	*(-0.91)*	*(-1.03)*	*(1.24)*	*(-0.74)*
B/M		0.67 **				0.53 **	0.53 **	0.52 **	0.52 **	0.44 **	0.54 **	0.46 **	0.44 **	0.54 **	0.46 **
		(3.84)				*(3.03)*	*(3.11)*	*(2.98)*	*(3.06)*	*(2.99)*	*(3.40)*	*(3.20)*	*(3.02)*	*(3.43)*	*(3.22)*
Mom			0.79 **			0.67 **	0.67 **	0.67 **	0.67 **	0.67 **	0.64 **	0.70 **	0.67 **	0.64 **	0.70 **
			(3.95)			*(3.44)*	*(3.51)*	*(3.45)*	*(3.52)*	*(3.61)*	*(3.38)*	*(3.82)*	*(3.67)*	*(3.47)*	*(3.88)*
Beta_ K-Tail Risk				0.53 **			0.34 **		0.34 **				0.33 **	0.33 **	0.32 **
				(2.97)			*(2.67)*		*(2.70)*				*(2.89)*	*(2.60)*	*(2.81)*
Beta_PS-Liquidity Risk					0.44 **			0.30	0.27 *				0.19	0.25 *	0.22
					(2.83)			*(2.06)*	*(1.90)*				*(1.35)*	*(1.81)*	*(1.57)*
Turnover _NYSE/AMEX										-0.36 **		-0.25 *	-0.37 **		-0.28 *
										(-2.91)		*(-1.66)*	*(-3.07)*		*(-1.88)*
Turnover _NASDAQ										-1.05		-0.20 **	-1.04		-0.18 **
										(-1.47)		*(-2.73)*	*(-1.44)*		*(-2.77)*
Amihud_ NYSE/AMEX											0.26 **	0.02		0.26 **	0.01
											(2.42)	*(0.20)*		*(2.47)*	*(0.10)*
Amihud _ NASDAQ											0.44	0.26		0.45	0.26
											(0.77)	*(0.45)*		*(0.77)*	*(0.45)*
Intercept	1.03 **	0.79 **	0.55 **	0.67 **	0.72 **	0.87 **	0.76 **	0.89 **	0.77 **	1.04 **	0.45	1.01 **	0.93 **	0.34	0.92 **
	(2.51)	*(2.86)*	*(2.13)*	*(2.54)*	*(2.65)*	*(2.19)*	*(1.99)*	*(2.22)*	*(2.02)*	*(2.78)*	*(0.85)*	*(2.56)*	*(2.59)*	*(0.67)*	*(2.42)*
Months	468														
Observations	1,003,683														

Table 4, continued

This table summarizes Fama-MacBeth (1973) monthly cross-section regressions. Coefficient estimates are time-series averages of cross-sectional OLS regressions. And the *t*-statistics (in parenthesis) are computed for the Fama-MacBeth (1973) regressions using the Newey-West (1987) adjustment for heteroskedasticity and autocorrelation. In the Newey-West procedure, I use a lag of three. In all regressions, the dependent variable is the monthly individual stock return in excess of the risk-free rate. Eligible stocks are defined as ordinary common shares traded on the NYSE, AMEX, or NASDAQ with at least four years of non-missing monthly returns out of five years and with stock prices between $5 and $1,000. Then, at each year end between 1972 and 2010, I estimate extreme liquidity risk sensitivities of individual stocks with respect to extreme liquidity risk (*ELR*) by the form

$$E_t\,[r_{i,t+1}\,] = \mu_i + \beta_i\,ELR_t$$

Stocks are then sorted into decile value-weighted portfolios based on their preceding extreme liquidity risk loadings. Beta is estimated for each of the ten portfolios over the sample period (post-ranking loading). The post-ranking beta of portfolio *p* is assigned to an individual stock *i*, which belongs to portfolio *p* in the given year. Betas for the Pástor and Stambaugh (2003) aggregate liquidity risk (“Beta PS-Liqidity Risk” in the table) and those for Kelly’s (2011) tail risk (“Beta K-Tail Risk” in the table) are constructed in a similar way. The independent variables also include: SIZE represents logarithm of the market capitalization of firms as defined in Fama and French (1992); B/M is the logarithm of the ratio of book value of equity plus deferred taxes to market capitalization as defined in Fama and French (1992); Mom is the stock return from month -12 to month -2; Turnover_NYSE/AMEX is the average monthly turnover from month -12 to month -1 at each year end if stocks trade on NYSE/AMEX, and zero otherwise; Turnover_NASDAQ is the average monthly turnover from month -12 to month -1 at each year end if stocks trade on NASDAQ, and zero otherwise. Amihud_NYSE/AMEX is the liquidity measure in Amihud (2002) based upon the prior calendar year's data at each year end if stocks trade on NYSE/AMEX, and zero otherwise; Amihud_NASDAQ is the liquidity measure in Amihud (2002) based upon the prior calendar year's data at each year end if stocks trade on NASDAQ, and zero otherwise. * and ** denote significance at the 10% and 5% levels, respectively.

Table 5
Liquidity-related Net Beta-Sorted Portfolio Returns: 1973-2011

Extreme Liquidity Loading	Low				High				
	1	2	3	4	5	**5–1**	*t-stat.*	**10–1**	*t-stat.*
Panel A: Properties									
Value-weighted									
Preceding loadings	-3.65	-0.13	0.11	0.37	2.72	**6.37**	*4.61*	**12.51**	*4.15*
Post-ranking loadings	-0.43	-0.08	-0.01	0.03	0.26	**0.70**	*2.66*	**0.63**	*2.00*
Market cap	20.74	35.51	34.12	30.18	17.67	**-3.07**	*-1.56*	**-4.91**	*-7.35*
(Il)liquidity	0.11	0.02	0.06	0.05	0.35	**0.24**	*11.20*	**0.57**	*12.19*
MKT beta	1.14	1.05	0.95	0.93	0.93	**-0.21**	*-4.32*	**-0.32**	*-5.40*
SMB beta	0.29	-0.12	-0.12	-0.07	0.24	**-0.05**	*-0.79*	**-0.04**	*-0.49*
HML beta	-0.13	0.08	0.19	0.08	-0.04	**0.10**	*1.40*	**0.16**	*1.88*
MOM beta	-0.17	-0.04	0.06	0.06	0.03	**0.20**	*4.24*	**0.16**	*2.75*
PS-Liquidity beta	0.05	-0.02	-0.03	-0.05	-0.03	**-0.08**	*-1.46*	**0.07**	*1.10*
K-Tail beta	-0.10	-0.01	0.12	0.11	0.18	**0.28**	*5.36*	**0.36**	*5.56*
Equal-weighted									
Preceding loadings	-4.31	-0.12	0.11	0.37	4.51	**8.82**	*7.00*	**16.29**	*6.57*
Post-ranking loadings	-0.30	-0.09	0.04	0.08	0.04	**0.00**	*2.66*	**0.00**	*1.94*
Market cap	1.00	2.80	3.06	2.55	0.76	**-0.24**	*-3.71*	**-0.27**	*-18.07*
(Il)liquidity	2.28	0.37	0.44	0.52	2.63	**0.35**	*2.92*	**0.35**	*1.52*
MKT beta	0.97	0.98	0.92	0.88	0.82	**-0.15**	*-6.40*	**-0.15**	*-5.91*
SMB beta	0.75	0.47	0.37	0.48	0.64	**-0.10**	*-3.10*	**-0.16**	*-4.63*
HML beta	0.13	0.32	0.38	0.34	0.26	**0.13**	*3.82*	**0.16**	*4.56*
MOM beta	-0.15	-0.10	-0.02	-0.03	-0.01	**0.14**	*6.05*	**0.13**	*5.48*
PS-Liquidity beta	0.00	0.00	0.00	-0.01	-0.02	**-0.03**	*-1.07*	**-0.02**	*-0.88*
K-Tail beta	0.01	-0.01	0.09	0.10	0.11	**0.10**	*3.84*	**0.06**	*2.18*
Panel B: Returns									
Value-weighted									
Mean	0.68	0.87	1.11	1.12	1.47	**0.79**	*3.84*	**0.58**	*2.31*
Alpha: FF	-0.36	-0.08	0.15	0.20	0.48	**0.84**	*4.02*	**0.63**	*2.49*
Alpha: FF + Mom	-0.24	-0.06	0.12	0.17	0.50	**0.74**	*3.48*	**0.58**	*2.27*
Alpha: FF + Mom + PS-Liquidity	-0.26	-0.05	0.14	0.19	0.52	**0.78**	*3.68*	**0.55**	*2.11*
Alpha: FF + Mom + PS-Liquidity + K-Tail	-0.24	-0.04	0.11	0.16	0.47	**0.71**	*3.41*	**0.45**	*1.80*
Alpha: AP-CAPM	-0.35	-0.06	0.22	0.22	0.49	**0.84**	4.11	**0.65**	2.62
Alpha: AP-CAPM + FF + Mom	-0.24	-0.05	0.13	0.17	0.48	**0.71**	3.38	**0.54**	2.08
Equal-weighted									
Mean	0.98	1.11	1.32	1.35	1.35	**0.37**	*3.44*	**0.30**	*2.61*
Alpha: FF	-0.23	-0.09	0.15	0.18	0.19	**0.43**	*4.19*	**0.37**	*3.48*
Alpha: FF + Mom	-0.10	0.00	0.19	0.23	0.23	**0.33**	*3.25*	**0.27**	*2.53*
Alpha: FF + Mom + PS-Liquidity	-0.10	0.00	0.20	0.24	0.25	**0.35**	*3.39*	**0.28**	*2.64*
Alpha: FF + Mom + PS-Liquidity + K-Tail	-0.10	0.00	0.17	0.21	0.22	**0.32**	*3.17*	**0.27**	*2.50*
Alpha: AP-CAPM	-0.14	0.14	0.39	0.41	0.28	**0.42**	4.15	**0.36**	3.32
Alpha: AP-CAPM + FF + Mom	-0.24	-0.03	0.17	0.19	0.05	**0.30**	2.92	**0.23**	2.13

Table 5, continued

The table shows the statistics for the liquidity-related net beta-sorted portfolios. At each year end between 1972 and 2010, I estimate the three liquidity betas in Acharya and Pedersen's (2005) liquididity-adjusted CAPM using extreme liquidity risk. Here the regressions use only data available at that time. And eligible stocks are defined as ordinary common shares traded on the NYSE, AMEX, or NASDAQ with at least four years of non-missing monthly returns out of five years and with stock prices between $5 and $1,000. Stocks are then sorted into quintile portfolios and decile portfolios based on their estimated liquidity-related net betas.The post-formation returns on these portfolios during the next 12 months are linked across years to form a single return series for each quintile portfolio and decile portfolio covering the period from July 1973 to December 2011. Panel A reports the preceding liquidity-related net loadings ("preceding loadings" in the table) and post-ranking liquidity-related net loadings ("post-ranking loadings" in the table) of the quintile portfolios and spread portfolios. The post-ranking liquidity-related net loadings are estimated by regressing the portfolio excess returns on the extreme liquidity risk estimate and the market excess return factor over the sample period. In addition, Panel A reports the time-series averages of the quintile portfolios' market capitalization and (il)liquidity, obtained as the average of the corresponding measures across the stocks within each quintile. Market capitalization is reported in billions of dollars. A stock's liquidity in any given month is the Amihud (2002) illiquidity measure. Also reported are post-ranking betas with respect to the three Fama-French factors, the momentum factor, the Pástor and Stambaugh (2003) traded liquidity factor ("PS-Liquidity" in the table) and Kelly's (2011) tail risk factor ("K-Tail" in the table). The four right-most columns report results for two high-minus-low zero net investment portfolio, one that longs quintile 5 and shorts quintile 1 and the other longs decile 10 and shorts decile 1, as well as *t*-statistics for the hedge portfolios' corresponding measures. Panel B shows the monthly mean returns for the liquidity-related net beta-sorted portfolios that are rebalanced annually. The panel also reports portfolio alphas from regressions of portfolio returns using the Fama-French three-factor model as well as its extended four-, five- and six-factor models considering the momentum factor, the Pástor and Stambaugh (2003) traded liquidity factor ("PS-Liquidity" in the table), and Kelly's (2011) tail risk factor ("K-Tail" in the table) as additional controls. In addition, the table shows portfolio alphas from regressions of portfolio returns using Acharya and Pedersen's (2005) liquidity-adjusted CAPM ("AP-CAPM" in the table) as well as its extended model controlling the size, value and momentum factors. The four right-most columns report results for two high-minus-low zero net investment portfolios, one that longs quintile 5 and shorts quintile 1 and the other longs decile 10 and shorts decile 1, as well as *t*-statistics for the hedge portfolios' average returns and factor model alphas.

Table 6
Extreme Liquidity Loading-sorted Portfolio Returns: Normal Times and Times of Crisis

	CASE I					CASE II					CASE III				
	Expansion Period (32 Years)		Contraction Period (6.5 Years)		**Diff. in**	Period w/o Market Downturn (29.5 Years)		Sudden Market Downturn (9 Years)		**Diff. in**	Period w/o Liquidity Dry-ups (35.5 Years)		Liquidity Dry-ups (3 Years)		**Diff. in**
	5–1	*t-stat.*	5–1	*t-stat.*	**5–1**	5–1	*t-stat.*	5–1	*t-stat.*	**5–1**	5–1	*t-stat.*	5–1	*t-stat.*	**5–1**
Panel A: Value-weighted															
Mean	0.54	*2.63*	0.60	*0.94*	**0.07**	0.49	*2.08*	0.75	*1.95*	**0.26**	0.51	*2.61*	0.97	*0.85*	**0.46**
Alpha: FF	0.68	*3.25*	0.64	*1.10*	**-0.04**	0.87	*3.64*	-1.59	*-2.75*	**-2.46**	0.89	*4.43*	-0.25	*-0.20*	**-1.13**
Alpha: FF + Mom	0.62	*2.95*	0.54	*0.97*	**-0.09**	0.74	*3.07*	-1.64	*-2.98*	**-2.38**	0.70	*3.42*	-0.26	*-0.21*	**-0.96**
Alpha: FF + Mom + PS-Liquidity	0.65	*3.03*	0.63	*1.13*	**-0.02**	0.80	*3.32*	-1.66	*-3.01*	**-2.46**	0.71	*3.46*	-0.25	*-0.20*	**-0.96**
Alpha: FF + Mom + PS-Liquidity + K-Tail	0.61	*2.91*	0.37	*0.68*	**-0.24**	0.73	*3.07*	-1.62	*-2.99*	**-2.36**	0.66	*3.27*	-0.02	*-0.01*	**-0.68**
Alpha: AP-CAPM	0.69	3.38	0.34	0.55	**-0.35**	0.85	3.57	-1.51	-2.65	**-2.36**	0.73	3.72	-0.72	-0.56	**-1.45**
Alpha: AP-CAPM + FF + Mom	0.62	2.95	0.54	0.97	**-0.08**	0.74	3.07	-1.64	-2.97	**-2.38**	0.70	3.41	-0.26	-0.21	**-0.96**
Panel B: Equal-weighted															
Mean	0.44	*2.88*	0.55	*1.31*	**0.11**	0.38	*2.24*	0.74	*2.54*	**0.36**	0.41	*2.88*	1.13	*1.29*	**0.72**
Alpha: FF	0.54	*3.65*	0.57	*1.50*	**0.03**	0.67	*4.13*	-0.80	*-1.84*	**-1.47**	0.70	*5.08*	0.43	*0.52*	**-0.27**
Alpha: FF + Mom	0.47	*3.14*	0.49	*1.38*	**0.02**	0.56	*3.44*	-0.83	*-2.01*	**-1.39**	0.55	*3.91*	0.43	*0.51*	**-0.12**
Alpha: FF + Mom + PS-Liquidity	0.49	*3.27*	0.54	*1.53*	**0.05**	0.61	*3.73*	-0.86	*-2.10*	**-1.47**	0.56	*4.00*	0.42	*0.49*	**-0.14**
Alpha: FF + Mom + PS-Liquidity + K-Tail	0.47	*3.15*	0.43	*1.18*	**-0.04**	0.56	*3.48*	-0.84	*-2.06*	**-1.40**	0.53	*3.82*	0.55	*0.68*	**0.02**
Alpha: AP-CAPM	0.61	4.05	0.39	0.98	**-0.22**	0.70	4.16	-0.62	-1.40	**-1.32**	0.61	4.41	0.01	0.01	**-0.60**
Alpha: AP-CAPM + FF + Mom	0.50	3.33	0.50	1.42	**0.00**	0.58	3.58	-0.79	-1.91	**-1.37**	0.57	4.10	0.43	0.52	**-0.14**

Table 6, continued

The table shows the statistics for extreme liquidity beta-sorted portfolios during normal times and times of crisis. At each year end between 1972 and 2010, I estimate extreme liquidity risk sensitivities of individual stocks with respect to extreme liquidity risk by the form

$$E_t\,[r_{i,t+1}\,] = \mu_i + \beta_i\, ELR_t$$

Here the regression uses only data available at that time. And eligible stocks are defined as ordinary common shares traded on the NYSE, AMEX, or NASDAQ with at least four years of non-missing monthly returns out of five years and with stock prices between $5 and $1,000. Stocks are then sorted into quintile portfolios and decile portfolios based on their extreme liquidity risk loadings. Panel A reports monthly value-weighted portfolio returns and Panel B reports monthly equally weighted portfolio returns. The panels also reports portfolio alphas from regressions of portfolio returns using the Fama-French three-factor (FF) model as well as its extended four-, five- and six-factor models considering the momentum factor, the Pástor and Stambaugh (2003) traded liquidity factor ("PS-Liquidity" in the table), and Kelly's (2011) tail risk factor ("K-Tail" in the table) as additional controls. In addition, the table shows portfolio alphas from regressions of portfolio returns using Acharya and Pedersen (2005)'s liquidity-adjusted CAPM ("AP-CAPM" in the table) as well as its extended model controlling the size, value and momentum factors. The left-most five columns of the table report the results for quintile extreme liquidity beta-sorted portfolios during the NBER recession periods and during the NBER expansion periods, respectively, which is denoted as CASE I. The statistics include the average returns of the "5–1" spread portfolio that longs quintile 5 and shorts quintile 1, as well as the *t*-statistic for the hedge portfolios' average returns. The factor model alphas and their *t*-statistics are also reported. The last column for CASE I reports results for differences between the two "5–1" spread portfolios, including the differences in mean returns and regression alphas. Similarly, CASE II, which is shown in the next five columns in the table, reports the results for quintile extreme liquidity beta-sorted portfolios during periods without market downturns and those with sudden market downturns. Here sudden market downturn refers to the case when the market return suddenly turns to be negative. Case III, which is reported in the right-most five column in the tables, shows the results for quintile extreme liquidity beta-sorted portfolios during periods without liquidity dry-ups and those with liquidity dry-ups. Here liquidity dry-ups includes months when the average liquidity is at least two standard deviations below its means measured by Pástor and Stambaugh (2003) liquidity innovations or the average illiquidity is at least two standard deviations above its means evaluated by Acharya and Pedersen (2005).

Table 7
Extreme Liquidity Loading-sorted Portfolio Returns: NYSE&AMEX only and NASDAQ only

	NYSE &AMEX Only				NASDAQ Only			
Extreme Liquidity Loading	5–1	*t-stat.*	10–1	*t-stat.*	5–1	*t-stat.*	10–1	*t-stat.*
Panel A: Annual Rebalance								
Value-weighted								
Mean	0.52	*2.81*	0.58	*2.50*	0.71	*3.15*	1.07	*3.66*
Alpha: FF	0.50	*2.65*	0.53	*2.26*	0.78	*3.42*	1.17	*3.97*
Alpha: FF + Mom	0.41	*2.17*	0.46	*1.92*	0.72	*3.13*	1.17	*3.88*
Alpha: FF + Mom + PS-Liquidity	0.43	*2.25*	0.47	*1.92*	0.72	*3.1*	1.19	*3.91*
Alpha: FF + Mom + PS-Liquidity + K-Tail	0.47	*2.43*	0.52	*2.15*	0.60	*2.69*	1.09	*3.62*
Alpha: AP-CAPM	0.67	*3.65*	0.75	*3.28*	0.83	*3.65*	1.19	*4.08*
Alpha: AP-CAPM + FF + Mom	0.59	*3.18*	0.7	*2.96*	0.71	*3.04*	1.16	*3.84*
Equal-weighted								
Mean	0.46	*3.59*	0.52	*3.17*	0.58	*3.23*	0.78	*3.52*
Alpha: FF	0.56	*4.42*	0.63	*3.87*	0.61	*3.62*	0.77	*3.65*
Alpha: FF + Mom	0.47	*3.73*	0.51	*3.13*	0.48	*2.83*	0.65	*3.04*
Alpha: FF + Mom + PS-Liquidity	0.47	*3.63*	0.50	*3.06*	0.52	*3.02*	0.69	*3.19*
Alpha: FF + Mom + PS-Liquidity + K-Tail	0.42	*3.35*	0.45	*2.78*	0.46	*2.72*	0.62	*2.91*
Alpha: AP-CAPM	0.54	*4.35*	0.62	*3.89*	0.76	*4.30*	0.96	*4.38*
Alpha: AP-CAPM + FF + Mom	0.49	*3.85*	0.52	*3.21*	0.48	*2.81*	0.65	*3.04*
Panel B: Monthly Rebalance								
Value-weighted								
Mean	0.45	*2.15*	0.38	*1.49*	0.52	*1.98*	0.83	*2.39*
Alpha: FF	0.64	*3.15*	0.61	*2.47*	0.58	*2.23*	0.93	*2.69*
Alpha: FF + Mom	0.58	*2.81*	0.57	*2.26*	0.60	*2.25*	1.07	*3.04*
Alpha: FF + Mom + PS-Liquidity	0.59	*2.82*	0.57	*2.26*	0.60	*2.23*	1.08	*3.04*
Alpha: FF + Mom + PS-Liquidity + K-Tail	0.51	*2.47*	0.45	*1.84*	0.44	*1.75*	0.89	*2.62*
Alpha: AP-CAPM	0.61	*3.01*	0.54	*2.21*	0.67	*2.55*	0.98	*2.80*
Alpha: AP-CAPM + FF + Mom	0.58	*2.79*	0.56	*2.25*	0.56	*2.08*	1.02	*2.89*
Equal-weighted								
Mean	0.44	*2.91*	0.53	*2.75*	0.45	*2.01*	0.66	*2.45*
Alpha: FF	0.57	*3.93*	0.68	*3.64*	0.46	*2.30*	0.64	*2.61*
Alpha: FF + Mom	0.51	*3.45*	0.61	*3.21*	0.45	*2.17*	0.64	*2.58*
Alpha: FF + Mom + PS-Liquidity	0.50	*3.35*	0.60	*3.12*	0.48	*2.31*	0.67	*2.66*
Alpha: FF + Mom + PS-Liquidity + K-Tail	0.44	*3.01*	0.51	*2.76*	0.38	*1.91*	0.55	*2.26*
Alpha: AP-CAPM	0.54	*3.74*	0.65	*3.48*	0.65	*2.95*	0.87	*3.28*
Alpha: AP-CAPM + FF + Mom	0.52	*3.52*	0.62	*3.27*	0.42	*2.05*	0.62	*2.50*

Table 7, continued

The table shows the statistics for two groups of the extreme liquidity beta-sorted portfolios, in which one is based on NYSE&AMEX stocks only and the other is based on NASDAQ stocks only. At each year end between 1972 and 2010, I estimate extreme liquidity risk sensitivities of individual stocks with respect to extreme liquidity risk by the form

$$E_t\, [r_{i,t+1}\,] = \mu_i + \beta_i\, ELR_t$$

Here the regression uses only data available at that time. And eligible stocks are defined as ordinary common shares traded on the NYSE, AMEX, or NASDAQ with at least four years of non-missing monthly returns out of five years and with stock prices between \$5 and \$1,000. Stocks are then sorted into quintile portfolios and decile portfolios based on their extreme liquidity risk loadings. Panel A reports monthly portfolio returns when portfolios are rebalanced annually and Panel B reports monthly returns when portfolios are rebalanced monthly. The table also reports portfolio alphas from regressions of portfolio returns using the Fama-French three-factor model as well as its extended four-, five- and six-factor models considering the momentum factor, the Pástor and Stambaugh (2003) traded liquidity factor (“PS-Liquidity” in the table), and Kelly’s (2011) tail risk factor (“K-Tail” in the table) as additional controls. In addition, the table shows portfolio alphas from regressions of portfolio returns using Acharya and Pedersen’s (2005) liquidity-adjusted CAPM (“AP-CAPM” in the table) as well as its extended model controlling the size, value and momentum factors. The first four columns report results on the group of NYSE&AMEX stocks for two high-minus-low zero net investment portfolios, one that longs quintile 5 and shorts quintile 1 and the other longs decile 10 and shorts decile 1, as well as *t*-statistics for the hedge portfolios' average returns and factor model alphas. The next four columns report results on the group of NASDAQ stocks for two high-minus-low zero net investment portfolios, one that longs quintile 5 and shorts quintile 1 and the other longs decile 10 and shorts decile 1, as well as *t*-statistics for the hedge portfolios' average returns and factor model alphas.

Table 8
Properties and Returns of Extreme Liquidity Loading-sorted Portfolios Based on Roll Impact: 1973-2011

Extreme Liquidity Loading	Low				High				
	1	2	3	4	5	**5–1**	*t-stat.*	**10–1**	*t-stat.*
Panel A: Properties									
Value-weighted									
Market cap	26.82	39.92	36.07	29.64	20.42	**-6.40**	*-3.53*	**-7.53**	*-4.08*
(Il)liquidity	0.05	0.04	0.04	0.06	0.13	**0.08**	*5.67*	**0.13**	*4.94*
MKT beta	0.98	0.97	0.96	1.03	1.05	**0.07**	*1.63*	**0.09**	*1.80*
SMB beta	-0.02	-0.12	-0.13	-0.02	0.27	**0.29**	*5.09*	**0.33**	*4.77*
HML beta	0.10	0.14	0.06	-0.01	-0.16	**-0.26**	*-4.18*	**-0.03**	*-0.42*
MOM beta	0.02	-0.03	-0.01	-0.04	0.03	**0.01**	*0.33*	**0.12**	*2.48*
PS-Liquidity beta	-0.04	-0.06	0.04	0.01	0.07	**0.11**	*2.38*	**0.08**	*1.36*
K-Tail beta	0.11	0.03	-0.03	-0.03	0.08	**-0.03**	*-0.63*	**0.00**	*0.09*
Equal-weighted									
Market cap	1.57	2.72	2.44	2.11	1.34	**-0.23**	*-2.78*	**-0.07**	*-1.54*
(Il)liquidity	1.05	1.22	1.37	1.24	1.35	**0.30**	*4.72*	**0.37**	*4.39*
MKT beta	0.96	0.89	0.87	0.89	0.97	**0.01**	*0.36*	**0.02**	*0.57*
SMB beta	0.64	0.45	0.44	0.51	0.74	**0.10**	*2.70*	**0.11**	*2.40*
HML beta	0.15	0.34	0.35	0.36	0.26	**0.10**	*2.61*	**0.20**	*4.20*
MOM beta	-0.11	-0.08	-0.07	-0.05	-0.03	**0.08**	*3.04*	**0.10**	*3.30*
PS-Liquidity beta	-0.04	-0.03	-0.01	0.00	0.01	**0.05**	*1.59*	**0.06**	*1.56*
K-Tail beta	0.05	0.03	0.01	0.03	0.08	**0.02**	*0.88*	**0.06**	*1.96*
Panel B: Returns									
Value-weighted									
Mean	0.97	0.88	0.90	0.99	1.22	**0.25**	*1.36*	**0.64**	*2.92*
Alpha: FF	0.00	-0.06	0.01	0.06	0.24	**0.24**	*1.36*	**0.53**	*2.47*
Alpha: FF + Mom	0.01	-0.03	0.02	0.08	0.23	**0.22**	*1.24*	**0.43**	*1.96*
Alpha: FF + Mom + PS-Liquidity	0.03	0.01	-0.01	0.08	0.19	**0.16**	*0.90*	**0.38**	*1.74*
Alpha: FF + Mom + PS-Liquidity + K-Tail	-0.02	-0.01	0.01	0.09	0.15	**0.17**	*0.96*	**0.38**	*1.73*
Alpha: AP-CAPM	0.05	0.00	0.03	0.07	0.22	**0.17**	*0.95*	**0.56**	*2.59*
Alpha: AP-CAPM + FF + Mom	0.02	-0.01	0.03	0.10	0.24	**0.22**	*1.23*	**0.42**	*1.94*
Equal-weighted									
Mean	1.00	1.18	1.26	1.30	1.36	**0.36**	*3.23*	**0.45**	*3.31*
Alpha: FF	-0.19	0.03	0.12	0.13	0.11	**0.30**	*2.65*	**0.34**	*2.51*
Alpha: FF + Mom	-0.08	0.10	0.18	0.18	0.16	**0.24**	*2.07*	**0.27**	*1.94*
Alpha: FF + Mom + PS-Liquidity	-0.06	0.12	0.19	0.18	0.16	**0.21**	*1.82*	**0.24**	*1.69*
Alpha: FF + Mom + PS-Liquidity + K-Tail	-0.08	0.11	0.18	0.17	0.12	**0.20**	*1.73*	**0.21**	*1.50*
Alpha: AP-CAPM	0.00	0.26	0.35	0.38	0.35	**0.35**	*3.08*	**0.43**	*3.13*
Alpha: AP-CAPM + FF + Mom	-0.10	0.07	0.15	0.15	0.13	**0.23**	*1.98*	**0.26**	*1.84*

Table 8, continued

The table shows the properties and returns for the extreme liquidity beta-sorted portfolios, in which the measure of extreme liquidity index is based on alternative proxy of the price impact, Roll Impact (Goyenko, Holden and Trzcinka, 2009). At each year end between 1972 and 2010, I estimate extreme liquidity risk sensitivities of individual stocks with respect to extreme liquidity risk by the form

$$E_t\,[r_{i,t+1}\,] = \mu_i + \beta_i\,ELR_t$$

Here the regression uses only data available at that time. And eligible stocks are defined as ordinary common shares traded on the NYSE, AMEX, or NASDAQ with at least four years of non-missing monthly returns out of five years and with stock prices between \$5 and \$1,000. Stocks are then sorted into quintile portfolios and decile portfolios based on their extreme liquidity risk loadings. The post-formation returns on these portfolios during the next 12 months are linked across years to form a single return series for each quintile portfolio and decile portfolio covering the period from July 1973 to December 2011. Panel A reports the time-series averages of the quintile portfolios' market capitalization and liquidity, obtained as the average of the corresponding measures across the stocks within each quintile. Market capitalization is reported in billions of dollars. A stock's liquidity in any given month is the Amihud (2002) illiquidity measure. Also reported are post-ranking betas with respect to the three Fama-French factors, a momentum factor, the Pástor and Stambaugh (2003) traded liquidity factor ("PS-Liquidity" in the table) and Kelly's (2011) tail risk factor ("K-Tail" in the table). The four right-most columns report results for two high-minus-low zero net investment portfolio, one that longs quintile 5 and shorts quintile 1 and the other longs decile 10 and shorts decile 1, as well as *t*-statistics for the hedge portfolios' corresponding measures. Panel B shows the monthly mean return for the extreme liquidity beta-sorted portfolios. The panel also reports portfolio alphas from regressions of portfolio returns using the Fama-French three-factor model as well as its extended four-, five- and six-factor models considering the momentum factor, the Pástor and Stambaugh (2003) traded liquidity factor ("PS-Liquidity" in the table), and Kelly's (2011) tail risk factor ("K-Tail" in the table) as additional controls. In addition, the table shows portfolio alphas from regressions of portfolio returns using the Acharya and Pedersen (2005)'s liquidity-adjusted CAPM ("AP-CAPM" in the table) as well as its extended model controlling the size, value and momentum factors. The four right-most columns report results for two high-minus-low zero net investment portfolios, one that longs quintile 5 and shorts quintile 1 and the other longs decile 10 and shorts decile 1, as well as *t*-statistics for the hedge portfolios' average returns and factor model alphas.

Figure 1
Number of Stocks for the Estimation of Extreme Liquidity Risk: 1950-2011

This figure plots the number of stocks each month used for the estimation of market-wide extreme liquidity risk from 1950 to 2011. Daily returns and volumes are taken from the CRSP daily stock file. I exclude NASDAQ in constructing the aggregate extreme liquidity measure because NASDAQ return and volume data are available from CRSP for only part of this period (beginning in 1982). Also, reported volume on NASDAQ includes interdealer trades, unlike the volumes reported on the NYSE and the AMEX. To exclude NASDAQ, I omit stocks with exchange codes of 3 or 33 as of the end of the previous year. Also, the CRSP sample covers all size groups, and indeed very small, microcap stocks produce challenging results (Fama and French, 2008), especially those with strong idiosyncratic liquidity shocks. Incorporating them into the estimation of market-wide extreme liquidity risk will make my estimate much noisy. I therefore control for the potential influence of microcap stocks by excluding AMEX stocks. I use only stocks classified as ordinary common shares (CRSP share codes 10 and 11), excluding American depository receipts, shares of beneficial interest, certificates, units, real estate investment trusts, closed-end funds, companies incorporated outside the United States, and Americus trust companies.

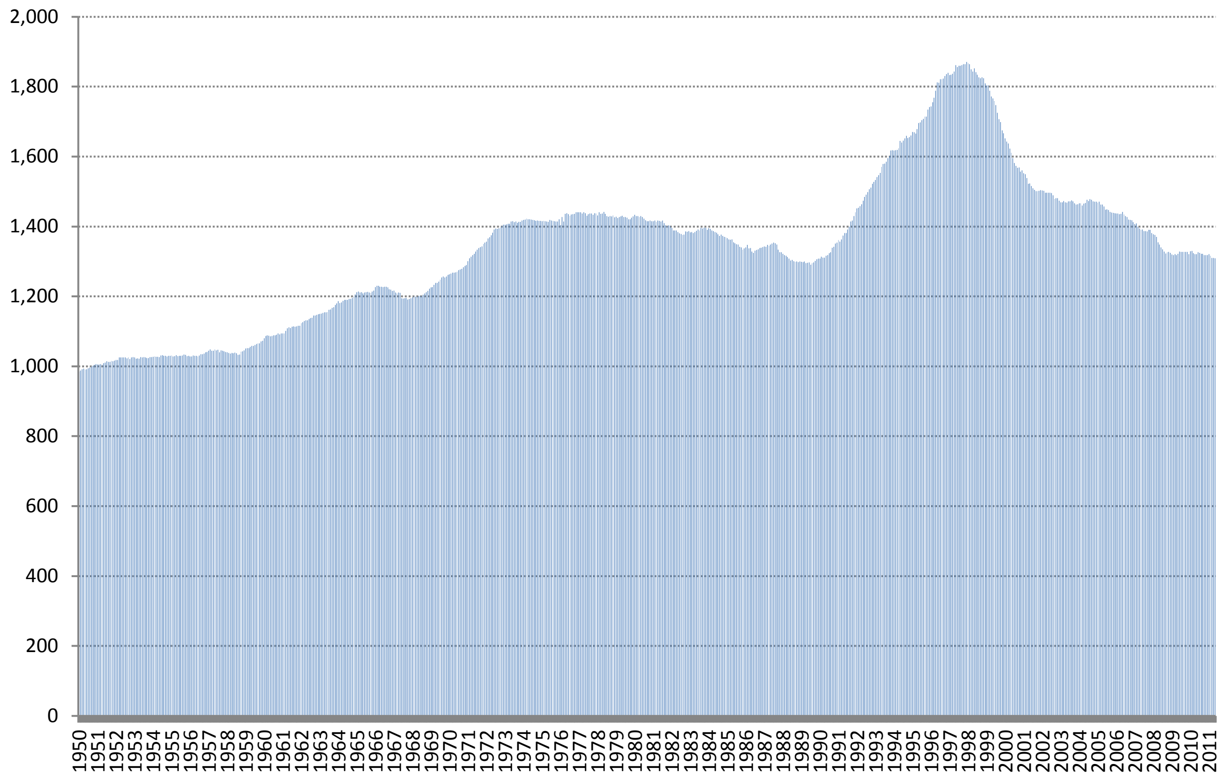
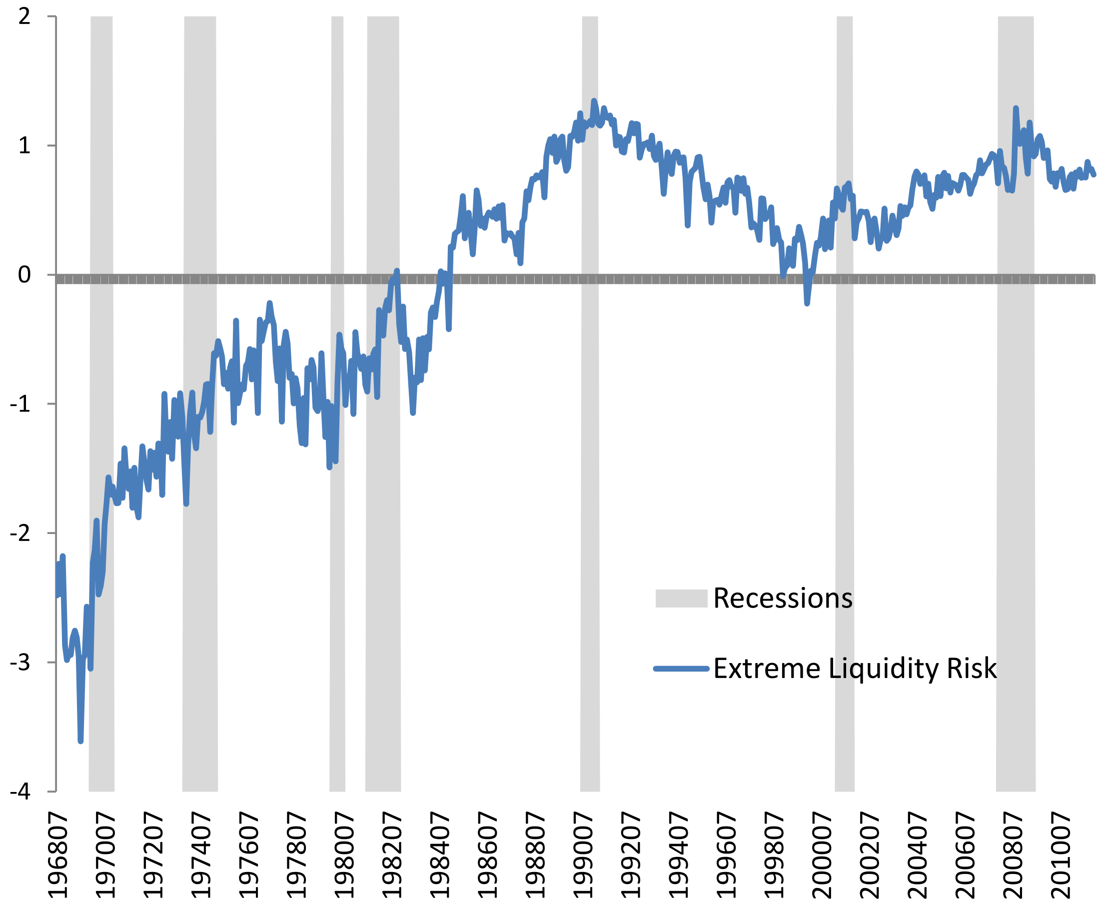


Figure 2
Extreme Liquidity Risk Estimates: 1968-2011
This figure plots the monthly estimated extreme liquidity risk time series. The extreme liquidity risk estimates are calculated month-by-month by pooling all daily Amihud (2002) illiquidity observations for the NYSE stocks. The tail series has been scaled to have mean zero and variance one. Shaded areas denote NBER recessions.



Appendix I
Correlations of Extreme Liquidity Index with Other Related Variables: 1973 – 2011

		I	II	III	IV	V	VI	VII
Panel A: Liquidity Variables								
I	Extreme Liquidity	1						
II	PS-Liquidity Innovation	0.12	1					
III	AP-Illiquidity Innovation	-0.07	-0.23	1				
IV	HPW-Noise Measure	0.15	-0.17	0.05	1			
V	S-Transitory Factor	0.03	0.08	-0.17	-0.10	1		
VI	S-Permanent Factor	0.01	0.21	-0.28	-0.15	0.16	1	
VII	Commonality in Liquidity	0.48	-0.15	-0.06	0.48	-0.11	-0.19	1
Panel B: Demand-side Factors								
I	Extreme Liquidity	1						
II	Commonality in Turnover	0.40	1					
III	Sentiment Index	0.20	-0.03	1				
IV	ETFs Volume	0.63	0.60	-0.15	1			
V	Global Country Fund Discount	-0.43	-0.01	0.44	-0.11	1		
VI	U.S. Local Country Fund Discount	-0.20	-0.20	-0.12	-0.06	0.21	1	
Panel C: Supply-side Factors								
I	Extreme Liquidity	1						
II	Term Spread	0.41	1					
III	Default Spread	-0.22	0.11	1				
IV	Commercial Paper Spread	0.03	-0.39	0.06	1			
V	TED Spread	-0.01	-0.16	0.36	0.76	1		
VI	Margin Debt Outstanding	0.50	0.12	-0.17	0.35	-0.03	1	
VII	Local Bank Returns	-0.05	-0.04	-0.18	-0.11	-0.15	-0.18	1
Panel D: Other Macro Variables								
I	Extreme Liquidity	1						
II	Dividend-Price Ratio	-0.52	1					
III	Unemployment	-0.14	0.52	1				
IV	Inflation	-0.48	0.39	-0.02	1			
V	CFNAI	-0.17	-0.05	-0.10	0.05	1		
VI	Market Volatility	0.06	-0.17	-0.01	-0.21	-0.38	1	

Appendix I, continued

Panel A of this table reports correlations between extreme liquidity risk estimates and a variety of aggregate (il)liquidity measures. They are considered as follow; Pástor and Stambaugh (2003) monthly aggregate liquidity measure ("PS-Liquidity Innovation" in the table) captures a dimension of liquidity associated with the strength of volume-related return reversals. It is an average of individual-stock measures estimated with daily data and relies on the principle that order flow induces greater return reversals when liquidity is lower. Acharya and Pedersen (2005) monthly liquidity measure ("AP-Illiquidity Innovation" in the table) captures the innovation in equally-weighted illiquidity cost for the market portfolio. As suggested in Acharya and Pedersen (2005), I form market portfolio for each month based on NYSE/AMEX stocks with beginning-of-month price between \$5 and \$1,000, and with at least 15 days of return and volume data in that month. For each stock in the market portfolio, I estimate its Amihud (2002) illiquidity cost for each month and normalize it to make it stationary and to put it on a scale corresponding to the cost of a single trade. Then I run a regression using equation (22) in Acharya and Pedersen (2005), to predict market illiquidity, and the residual of the regression is interpreted as the market illiquidity innovation. Hu, Pan, and Wang (2012) propose a market-wide liquidity measure ("HPW-Noise Measure" in the table) by exploiting the connection between the amount of arbitrage capital in the market and observed price deviations in U.S. treasury bonds. Data is from Prof. Jun Pan's website. Sadka's (2006) liquidity factors are based on the transitory-fixed ("S-Transitory Factor" in the table) and permanent-variable components ("S-Permanent Factor" in the table) of price impact, as measured from intraday data. The data is from CRSP database. Karolyi, Lee, and van Dijk (2012) construct monthly measures of commonality in liquidity ("Commonality in Liquidity" in the table) and the data is from Journal of Financial Economics website. Panels B and C of the table consider a set of both supply-side and demand-side sources of the commonality in liquidity. Proxies of demand-side forces include the average commonality in turnover, a comprehensive measure of the degree of correlated trading, which is denoted as "Commonality in Turnover" in the table, the U.S. investor sentiment index of Baker and Wurgler (2006) ("Sentiment Index" in the table), ETF volume in Karolyi, Lee, and van Dijk (2012), which is defined as dollar trading volume in exchange traded country funds for 28 countries traded on U.S. markets, Global country fund discount in Karolyi, Lee, and van Dijk (2012) and U.S. local country fund discount in Karolyi, Lee, and van Dijk (2012). Proxies of supply-side forces include term spread (the difference between yields on long and short term government bonds), default spread (the difference in yields on BAA and AAA corporate bonds), commercial paper spread (difference between the percentage 90-Day AA nonfinancial commercial paper interest rate and the three-month T-bill rate), TED spread (difference between the three-month EuroDollar LIBOR rate on the three-month U.S. Treasuries rate, the data is from Bloomberg), the amount of NYSE margin debt outstanding ("Margin Debt Outstanding" in the table), local bank returns in Karolyi, Lee, and van Dijk (2012). Panel D of the table reports correlations between extreme liquidity risk estimates and other macroeconomic variables. Macroeconomic variables include the S&P 500 log dividend-price ratio, the unemployment rate, inflation rate, the Chicago Fed National Activity Index (CFNAI), and market volatility. Sample horizon depends on availability of each variable.

Appendix II

Double-Sorted Portfolio Returns on Size and Extreme Liquidity Loading: 1973-2011

Extreme Liquidity Loading		Low				High		
		1	2	3	4	5	**5–1**	*t-stat.*
Panel A: Value-Weighted								
Mean								
All		0.74	0.84	0.94	1.12	1.29	**0.55**	*2.73*
Small	1	1.18	1.27	1.34	1.38	1.55	**0.37**	*2.49*
	2	0.94	1.19	1.40	1.46	1.57	**0.62**	*3.53*
	3	0.82	1.06	1.30	1.42	1.44	**0.61**	*3.43*
	4	0.77	1.12	1.14	1.30	1.48	**0.72**	*3.63*
Big	5	0.70	0.76	0.88	1.06	1.16	**0.46**	*2.00*
Alpha: FF + Mom								
All		-0.19	-0.10	-0.01	0.19	0.37	**0.56**	*2.84*
Small	1	-0.12	-0.02	0.11	0.14	0.28	**0.41**	*2.81*
	2	-0.28	-0.04	0.19	0.22	0.30	**0.58**	*3.52*
	3	-0.35	-0.13	0.13	0.28	0.28	**0.62**	*3.52*
	4	-0.30	0.02	0.03	0.26	0.41	**0.71**	*3.71*
Big	5	-0.14	-0.13	-0.03	0.18	0.35	**0.50**	*2.16*
Alpha: FF + Mom + PS-Liquidity + K-Tail								
All		-0.20	-0.08	-0.03	0.18	0.36	**0.55**	*2.81*
Small	1	-0.14	-0.01	0.11	0.13	0.27	**0.41**	*2.87*
	2	-0.28	-0.05	0.19	0.22	0.29	**0.58**	*3.50*
	3	-0.34	-0.14	0.10	0.26	0.25	**0.58**	*3.32*
	4	-0.26	0.03	0.02	0.22	0.36	**0.63**	*3.38*
Big	5	-0.14	-0.10	-0.05	0.17	0.34	**0.49**	*2.10*
Alpha: AP-CAPM								
All		-0.29	-0.09	0.07	0.25	0.37	**0.66**	3.39
Small	1	0.05	0.24	0.34	0.40	0.52	**0.47**	3.28
	2	-0.14	0.23	0.48	0.55	0.58	**0.72**	4.24
	3	-0.24	0.11	0.40	0.52	0.46	**0.69**	3.94
	4	-0.30	0.18	0.24	0.39	0.52	**0.82**	4.23
Big	5	-0.30	-0.16	0.01	0.19	0.27	**0.57**	2.52

Appendix II, continue

Extreme Liquidity Loading		Low				High		
		1	2	3	4	5	**5–1**	*t-stat.*
Panel B: Equal-Weighted								
Mean								
All		0.97	1.13	1.24	1.33	1.43	**0.46**	*3.15*
Small	1	1.10	1.20	1.29	1.38	1.44	**0.34**	*2.53*
	2	0.91	1.22	1.40	1.43	1.49	**0.58**	*3.49*
	3	0.82	1.11	1.28	1.39	1.42	**0.59**	*3.29*
	4	0.82	1.12	1.14	1.24	1.46	**0.64**	*3.15*
Big	5	0.91	0.90	0.99	1.11	1.21	**0.30**	*1.41*
Alpha: FF + Mom								
All		-0.14	0.01	0.14	0.25	0.31	**0.45**	*3.31*
Small	1	-0.09	0.03	0.16	0.25	0.25	**0.34**	*2.74*
	2	-0.23	0.02	0.21	0.23	0.29	**0.52**	*3.33*
	3	-0.29	-0.04	0.14	0.29	0.32	**0.61**	*3.41*
	4	-0.18	0.05	0.08	0.22	0.42	**0.60**	*3.01*
Big	5	0.00	-0.01	0.02	0.20	0.35	**0.35**	*1.66*
Alpha: FF + Mom + PS-Liquidity + K-Tail								
All		-0.16	0.01	0.12	0.24	0.29	**0.45**	*3.28*
Small	1	-0.12	0.04	0.14	0.23	0.22	**0.35**	*2.75*
	2	-0.25	0.01	0.20	0.22	0.28	**0.53**	*3.36*
	3	-0.27	-0.05	0.12	0.27	0.29	**0.57**	*3.20*
	4	-0.14	0.04	0.07	0.19	0.37	**0.52**	*2.68*
Big	5	0.00	0.01	-0.01	0.18	0.33	**0.33**	*1.58*
Alpha: AP-CAPM								
All		-0.15	0.13	0.29	0.39	0.42	**0.58**	*4.12*
Small	1	-0.07	0.13	0.25	0.35	0.38	**0.45**	3.50
	2	-0.17	0.26	0.48	0.53	0.52	**0.68**	4.22
	3	-0.25	0.17	0.38	0.49	0.44	**0.68**	3.86
	4	-0.24	0.19	0.25	0.33	0.49	**0.74**	3.70
Big	5	-0.14	-0.01	0.11	0.23	0.29	**0.43**	2.06

Appendix II, continued

This table reports average returns for double-sorted portfolios that are formed on the basis of extreme liquidity risk loading and size. At the end of each year, stocks are independently sorted by size and the preceding extreme liquidity loading. Portfolios are rebalanced annually. The size breakpoints come from Prof. Kenneth R. French data library. The breakpoints use all NYSE stocks with available market equity. Here eligible stocks are defined as ordinary common shares traded on the NYSE, AMEX, or NASDAQ with at least four years of non-missing monthly returns out of five years and with stock prices between \$5 and \$1,000. Panel A reports value-weighted portfolio returns and Panel B reports equal-weighted returns. In each panel, it also reports alphas from regressions of portfolio returns using the Carhart (1997)'s four-factor model, the extended six-factor model controlling the Pástor and Stambaugh (2003) traded liquidity factor ("PS-Liquidity" in the table) and Kelly's (2011) tail risk factor ("K-Tail" in the table), and Acharya and Pedersen's (2005) liquidity-adjusted CAPM ("AP-CAPM" in the table). The four right-most columns report results for two high-minus-low zero net investment portfolios, one that longs quintile 5 and shorts quintile 1 and the other longs decile 10 and shorts decile 1, as well as *t*-statistics for the hedge portfolios' average returns and factor model alphas.

Appendix III

Triple-Sorted Portfolio Returns on Size, liquidity and Extreme Liquidity Loading, 1973-2011

Extreme Liquidity Loading		Low				High		
Size	Amihud Illiquidity	1	2	3	4	5	**5–1**	*t-stat.*
Panel A: Value-Weighted								
Mean								
Small	Low	0.11	0.41	0.39	0.53	0.81	**0.70**	*3.03*
Small	2	0.33	0.47	0.43	0.74	0.90	**0.57**	*2.24*
Small	3	0.22	0.44	0.56	0.67	0.87	**0.65**	*2.65*
Small	High	0.32	0.59	0.57	0.69	0.88	**0.56**	*2.12*
2	Low	0.44	0.56	0.52	0.93	0.92	**0.48**	*1.57*
2	2	0.34	0.32	0.52	0.75	0.61	**0.27**	*0.87*
2	3	0.53	0.51	0.47	0.50	0.55	**0.03**	*0.09*
2	High	0.27	0.36	0.45	1.07	1.05	**0.79**	*2.46*
3	Low	0.43	0.67	0.51	0.73	1.05	**0.63**	*1.80*
3	2	0.34	0.51	0.68	1.18	1.13	**0.79**	*2.46*
3	3	0.66	0.61	0.50	0.71	0.98	**0.32**	*0.96*
3	High	0.32	0.64	0.11	1.39	0.75	**0.43**	*1.42*
Large	Low	0.46	0.57	0.67	0.70	0.94	**0.48**	*1.44*
Large	2	0.62	0.33	0.72	0.76	1.17	**0.55**	*1.62*
Large	3	0.35	0.57	0.34	0.92	0.82	**0.46**	*1.49*
Large	High	0.25	0.69	0.51	0.85	1.20	**0.95**	*2.38*
AVERAGE		0.37	0.52	0.50	0.82	0.92	**0.54**	*2.63*
Alpha								
Small	Low	-0.57	-0.06	-0.15	0.01	0.35	**0.92**	*3.93*
Small	2	-0.23	0.01	-0.12	0.35	0.46	**0.70**	*2.74*
Small	3	-0.17	-0.05	0.04	0.18	0.40	**0.57**	*2.33*
Small	High	-0.23	0.08	0.04	0.24	0.42	**0.65**	*2.41*
2	Low	-0.20	0.14	0.01	0.51	0.47	**0.67**	*2.14*
2	2	-0.15	-0.20	0.03	0.21	0.20	**0.34**	*1.08*
2	3	-0.14	0.05	-0.01	0.00	0.06	**0.19**	*0.63*
2	High	-0.23	-0.08	-0.03	0.71	0.72	**0.94**	*2.91*
3	Low	0.02	0.08	-0.09	0.27	0.46	**0.44**	*1.27*
3	2	-0.12	-0.03	0.26	0.84	0.68	**0.79**	*2.43*
3	3	0.11	0.09	-0.05	0.24	0.53	**0.41**	*1.21*
3	High	-0.33	0.23	-0.33	0.90	0.24	**0.57**	*1.84*
Large	Low	-0.10	0.12	0.22	0.17	0.36	**0.46**	*1.37*
Large	2	0.02	-0.14	0.34	0.25	0.68	**0.66**	*1.89*
Large	3	-0.16	0.07	-0.04	0.50	0.40	**0.56**	*1.82*
Large	High	-0.14	0.30	-0.04	0.40	0.89	**1.02**	*2.50*
AVERAGE		-0.16	0.04	0.01	0.36	0.46	**0.62**	*3.09*

Appendix III, continued

Extreme Liquidity Loading		Low				High		
Size	Amihud Illiquidity	1	2	3	4	5	**5–1**	*t-stat.*
Panel B: Equal-Weighted								
Mean								
Small	Low	0.65	0.74	0.85	0.92	0.90	**0.25**	*1.53*
Small	2	0.52	0.74	0.66	0.85	0.92	**0.40**	*2.49*
Small	3	0.56	0.76	0.86	0.81	1.09	**0.52**	*3.15*
Small	High	0.74	0.67	0.73	0.92	0.99	**0.25**	*1.54*
2	Low	0.67	0.85	0.82	0.93	0.94	**0.27**	*1.25*
2	2	0.41	0.61	0.74	0.92	0.86	**0.45**	*2.56*
2	3	0.54	0.84	0.85	0.84	1.07	**0.52**	*2.77*
2	High	0.72	0.78	0.74	1.00	0.95	**0.23**	*1.15*
3	Low	0.66	0.88	0.76	0.90	1.02	**0.36**	*1.77*
3	2	0.59	0.63	0.69	0.93	1.07	**0.48**	*2.27*
3	3	0.45	0.76	0.85	1.04	0.89	**0.44**	*1.78*
3	High	0.57	0.87	0.72	0.97	0.96	**0.39**	*1.92*
Large	Low	0.57	0.93	0.81	0.87	1.03	**0.46**	*2.02*
Large	2	0.53	0.78	0.80	0.84	0.93	**0.40**	*1.77*
Large	3	0.58	0.65	0.69	0.95	0.90	**0.32**	*1.46*
Large	High	0.62	0.75	0.91	1.04	0.95	**0.33**	*1.47*
AVERAGE		0.59	0.77	0.78	0.92	0.97	**0.38**	*2.57*
Alpha								
Small	Low	-0.05	0.05	0.15	0.24	0.25	**0.30**	*1.91*
Small	2	-0.18	0.05	0.01	0.26	0.25	**0.42**	*2.60*
Small	3	-0.13	0.11	0.19	0.21	0.43	**0.56**	*3.43*
Small	High	0.01	0.01	0.08	0.27	0.30	**0.30**	*1.83*
2	Low	0.02	0.20	0.22	0.31	0.31	**0.30**	*1.38*
2	2	-0.23	-0.06	0.12	0.33	0.20	**0.42**	*2.34*
2	3	-0.17	0.22	0.29	0.19	0.40	**0.57**	*2.98*
2	High	0.09	0.14	0.12	0.43	0.31	**0.22**	*1.12*
3	Low	0.07	0.24	0.13	0.32	0.39	**0.32**	*1.52*
3	2	-0.04	0.01	0.08	0.34	0.51	**0.56**	*2.64*
3	3	-0.28	0.09	0.24	0.45	0.25	**0.53**	*2.16*
3	High	-0.08	0.25	0.14	0.37	0.29	**0.37**	*1.83*
Large	Low	-0.12	0.31	0.25	0.31	0.36	**0.47**	*2.10*
Large	2	-0.13	0.13	0.22	0.26	0.40	**0.53**	*2.33*
Large	3	0.00	0.04	0.09	0.34	0.21	**0.21**	*0.93*
Large	High	-0.03	0.11	0.29	0.44	0.30	**0.33**	*1.45*
AVERAGE		-0.08	0.12	0.16	0.32	0.32	**0.40**	*2.82*

Appendix III, continued

This table reports average returns for the 80 ($4 \times 4 \times 5$) triple-sorted portfolios. Sorts are performed sequentially, first sorting on size and then again, within each group, on the basis of the Amihud (2002) illiquidity cost. Finally each of sixteen sub-groups is subdivided into five portfolios according to their estimated extreme liquidity loadings. Portfolios are rebalanced annually. The size breakpoints come from Prof. Kenneth R. French data library. The breakpoints use all NYSE stocks with available market equity. Here eligible stocks are defined as ordinary common shares traded on the NYSE, AMEX, or NASDAQ with at least four years of non-missing monthly returns out of five years and with stock prices between $5 and $1,000. Panel A reports value-weighted portfolio returns and Panel B reports equal-weighted returns. In each panel, it also reports portfolio alphas from regressions of portfolio returns using the extended six-factor model, which considers Kelly's (2011) tail risk factor as a sixth control beyond the Carhart (1997) four factors and the Pástor and Stambaugh (2003) traded liquidity factor. The two right-most columns report results for the high-minus-low zero net investment portfolio that longs quintile 5 and shorts quintile 1, as well as *t*-statistics for the hedge portfolios' average returns and factor model alphas.

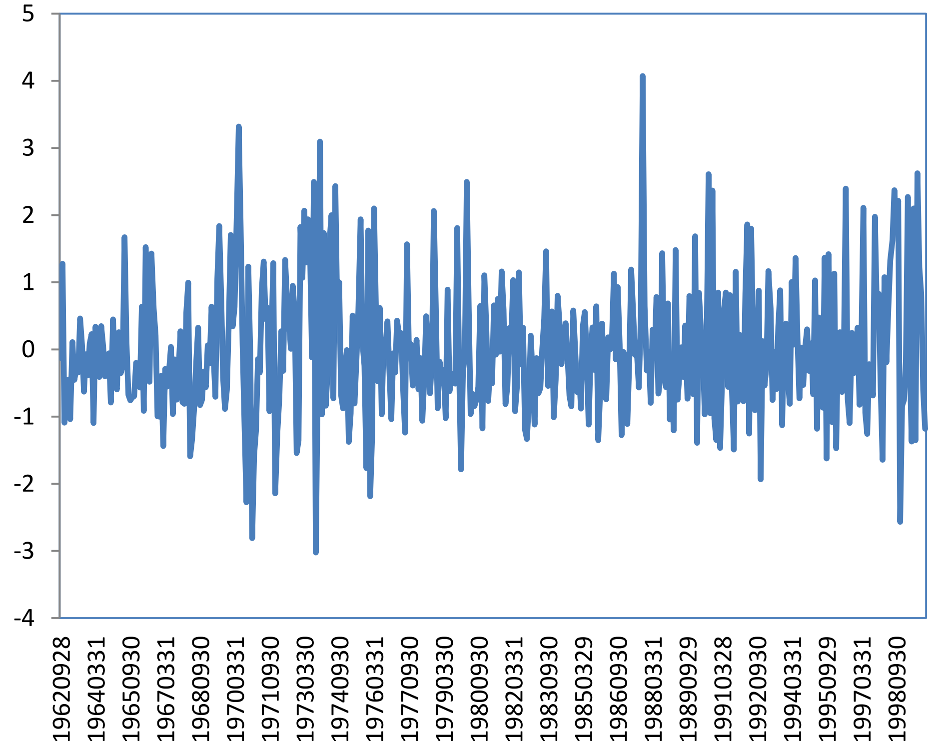
Appendix IV
Correlation of Extreme Liquidity Traded Factor with Other Priced Factors: 1973-2011

	MKT	SMB	HML	MOM	PS-Liquidity	K-Tail	**Extreme Liquidity**
MKT	1	0.28	-0.32	-0.13	-0.03	0.42	**-0.26**
SMB		1	-0.23	0.01	-0.03	0.31	**-0.20**
HML			1	-0.16	0.05	-0.16	**0.10**
MOM				1	-0.03	-0.33	**0.19**
PS-Liquidity					1	-0.04	**-0.07**
K-Tail						1	**-0.03**
Extreme Liquidity							**1**

This table reports the monthly correlations between extreme liquidity traded factor and other priced factors, including the Fama and French three factors ("MKT", "SMB", "HML" in the table), the momentum factor ("MOM" in the table), the Pástor and Stambaugh (2003) traded liquidity factor ("PS-Liquidity" in the table), and Kelly's (2011) tail risk factor ("K-Tail" in the table).

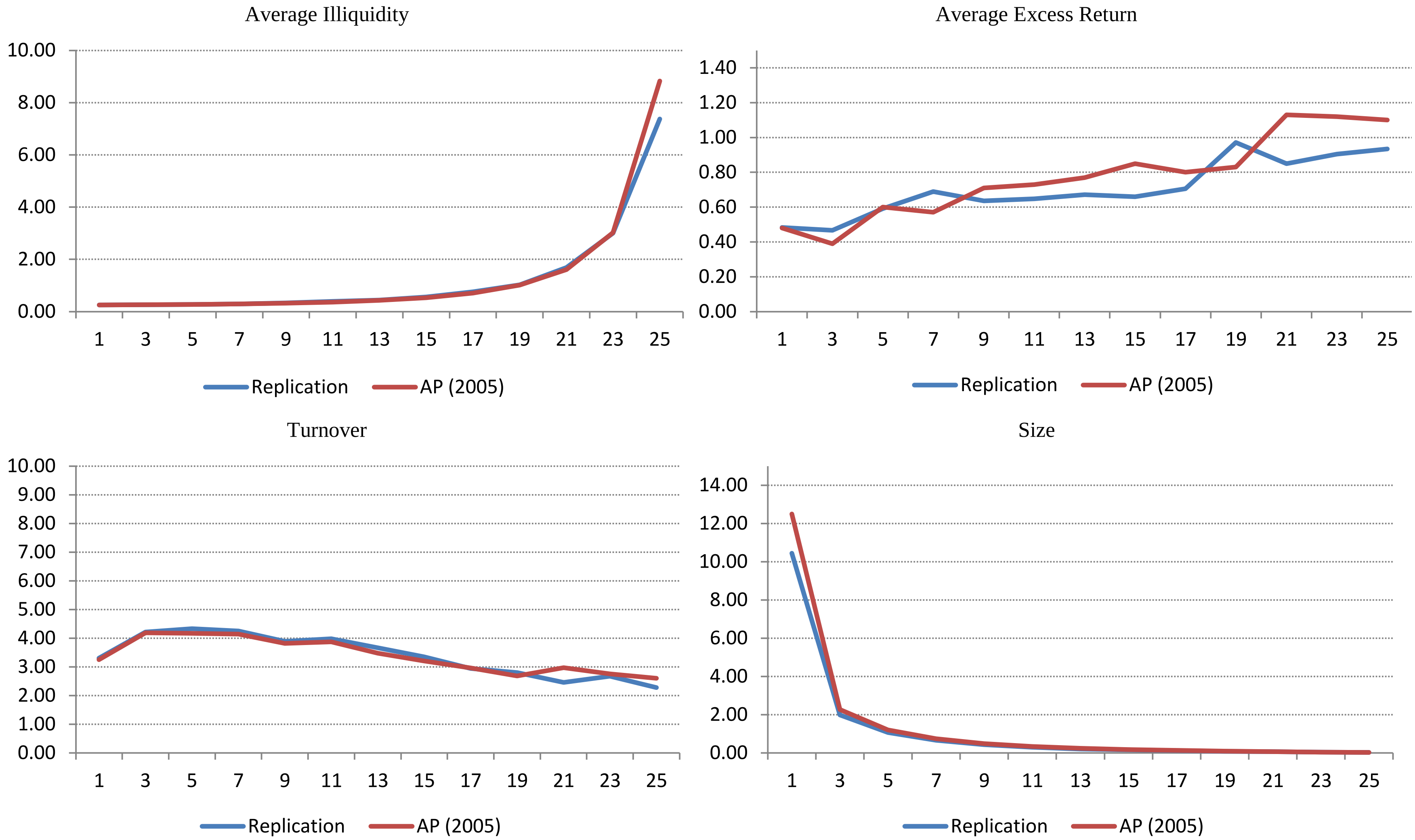
Appendix V

Replication Report for Acharya and Pedersen (2005, Journal of Financial Economics)



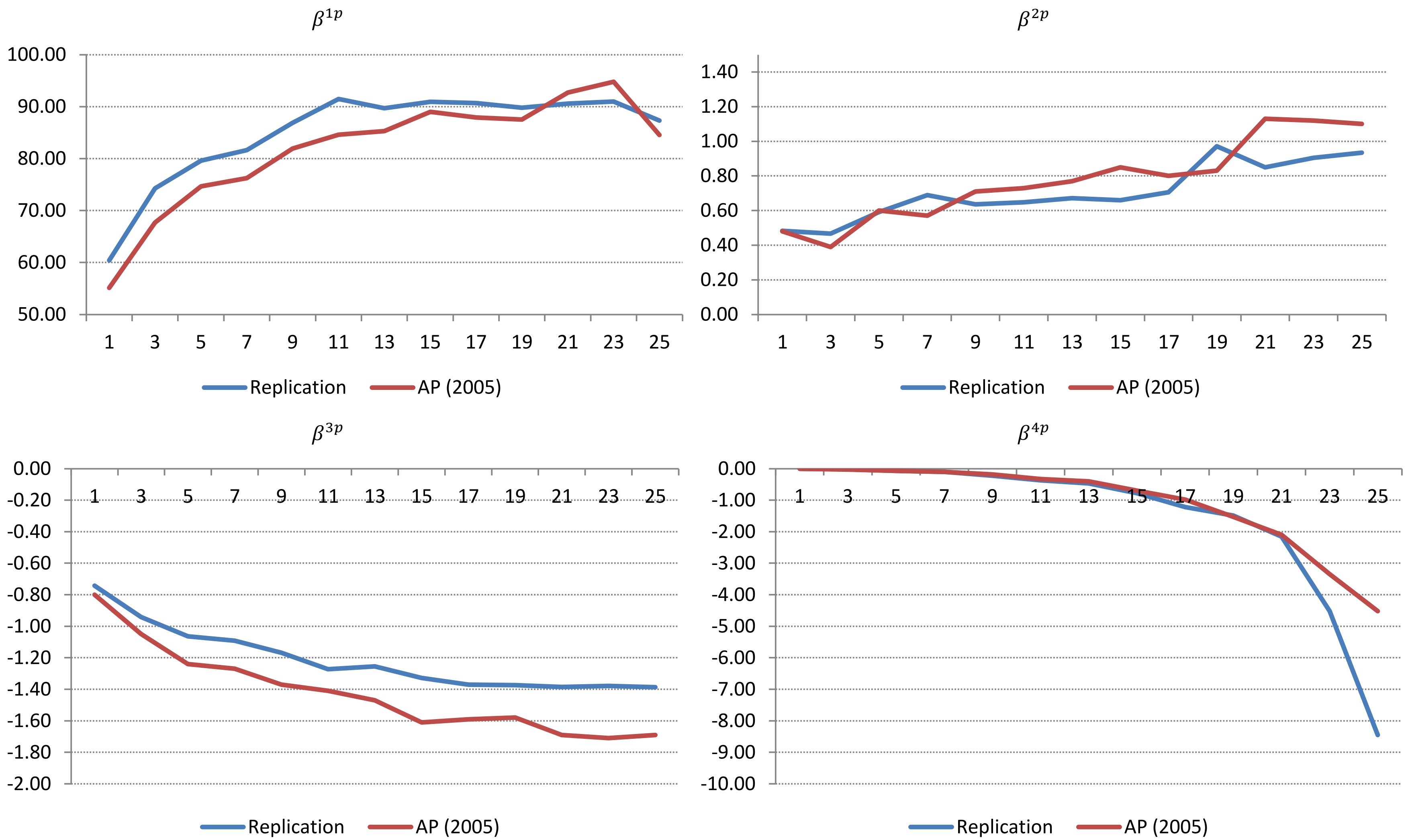
Appendix V Figure 1 Standardized innovations in market illiquidity (similar to Figure 1 in AP, 2005)

Appendix V, continued



Appendix V Figure 2 Properties of illiquidity portfolios (similar to Table 1 in AP, 2005)

Appendix V, continued



Appendix V Figure 2 (continued) Properties of illiquidity portfolios (similar to Table 1 in AP, 2005)

Appendix V, continued

Appendix V Table 1 Summary statistics of the innovations in market illiquidity

	R^2	Standard Deviation	Autocorrelation
AP (2005)	78%	0.17%	-0.03
Replication	77%	0.13%	-0.00

Appendix V Table 2 Properties of illiquidity portfolios (similar to Table 1 in AP, 2005)

Portfolio	β^{1p} (*100)	β^{2p} (*100)	β^{3p} (*100)	β^{4p} (*100)	$E(c^p)$ (%)	$\sigma(\Delta c^p)$ (%)	$E(r^{e,p})$ (%)	trn (%)	Size (bl$)
AP (2005)									
1	55.10	0.00	-0.80	0.00	0.25	0.00	0.48	3.25	12.50
3	67.70	0.00	-1.05	-0.03	0.26	0.00	0.39	4.19	2.26
5	74.67	0.00	-1.24	-0.07	0.27	0.01	0.6	4.17	1.20
7	76.25	0.00	-1.27	-0.10	0.29	0.01	0.57	4.14	0.74
9	81.93	0.01	-1.37	-0.18	0.32	0.02	0.71	3.82	0.48
11	84.59	0.01	-1.41	-0.33	0.36	0.04	0.73	3.87	0.33
13	85.29	0.01	-1.47	-0.40	0.43	0.05	0.77	3.47	0.24
15	88.99	0.02	-1.61	-0.70	0.53	0.08	0.85	3.20	0.17
17	87.89	0.04	-1.59	-0.98	0.71	0.13	0.8	2.96	0.13
19	87.50	0.05	-1.58	-1.53	1.01	0.21	0.83	2.68	0.09
21	92.73	0.09	-1.69	-2.10	1.61	0.34	1.13	2.97	0.06
23	94.76	0.19	-1.71	-3.35	3.02	0.62	1.12	2.75	0.04
25	84.54	0.42	-1.69	-4.52	8.83	1.46	1.1	2.60	0.02
Replication									
1	60.41	0.00	-0.74	0.00	0.25	0.00	0.48	3.30	10.44
3	74.24	0.00	-0.94	-0.02	0.26	0.01	0.47	4.21	1.98
5	79.62	0.00	-1.06	-0.07	0.27	0.01	0.59	4.33	1.06
7	81.65	0.00	-1.09	-0.10	0.29	0.01	0.69	4.25	0.66
9	86.85	0.01	-1.17	-0.22	0.33	0.02	0.64	3.89	0.43
11	91.47	0.01	-1.27	-0.37	0.39	0.10	0.65	3.98	0.29
13	89.67	0.01	-1.26	-0.47	0.44	0.05	0.67	3.66	0.20
15	90.94	0.02	-1.33	-0.78	0.56	0.10	0.66	3.35	0.16
17	90.70	0.04	-1.37	-1.22	0.76	0.14	0.70	2.95	0.11
19	89.77	0.05	-1.37	-1.49	1.03	0.18	0.97	2.80	0.08
21	90.59	0.08	-1.39	-2.16	1.69	0.35	0.85	2.46	0.06
23	90.99	0.14	-1.38	-4.52	3.00	0.70	0.90	2.67	0.04
25	87.31	0.32	-1.39	-8.45	7.38	1.54	0.93	2.28	0.02

Appendix V, continued

This table reports the replication results for Acharya and Pedersen (AP, 2005) and the comparison between my replication results and major empirical results in AP (2005). Appendix Figure 1 corresponds to Figure 1 in AP (2005), and Appendix Figure 2 compares key variables in Table 1 of AP (2005), including the average illiquidity, the average excess return, the turnover and the market capitalization, together with the market beta(β^{1p})and the liquidity beta ($\beta^{2p}, \beta^{3p}, and\ \beta^{4p}$). Appendix Table 1 shows the summary statistics of the innovation in market illiquidity, which is employed in this study. And Appendix Table 2 reports the properties of illiquidity portfolios, corresponding to Table 1 in AP (2005).