

# LIQUIDITY AND PORTFOLIO MANAGEMENT: AN INTRA-DAY ANALYSIS

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## Abstract

A recent area of interest among both financial economists and market practitioners has been the measurement of liquidity and its impact on asset prices. Broadly speaking, *liquidity* is the ease with which a financial asset can be traded. *Liquidity risk*, on the other hand, can be defined in terms of the uncertainty associated with the measure of liquidity. Using the ILLIQ measure first proposed by Amihud (2002) as the basis, we provide empirical evidence in support of a more-refined version of this liquidity measure based on intra-day data. Our results strongly validate the notion that liquidity affects financial market performance, and, as a consequence, have implications for both portfolio construction and risk management. Our approach permits us to identify different liquidity regimes in financial markets by measuring the relation between aggregate market liquidity and the market's *pricing* of liquidity risk. It hence has the potential to displace

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other traditional indirect proxies of liquidity in standard asset pricing tests. Finally, by using the liquidity measures developed here, and market instruments with relatively low transaction and liquidity costs, we derive the rationale for, and present the results of, an easily-implementable and profitable liquidity-driven trading strategy.

## 1. Introduction

Liquidity has long been an area of concern among market practitioners, who have often been constrained by its effects on portfolio management. However, academic interest in the measurement of liquidity, and its impact on asset prices, is much more recent, dating back less than three decades. Broadly speaking, liquidity is the ease with which a financial asset can be traded.<sup>2</sup> Liquidity risk, on the other hand, can be defined as the uncertainty associated with the liquidity in the market.

The financial press is replete with articles on liquidity and its effects, especially during the Long Term Capital Management (LTCM) crisis of August 1998, the “quant-driven” crisis of August 2007, and, most prominently, the more recent global financial crisis involving credit markets and financial institutions, which commenced in 2007. As an example of this interest, the Federal Reserve Chairman, Ben Bernanke, remarked on May 15, 2008 that “Another crucial lesson from recent events is that financial institutions must understand their liquidity needs at an enterprise-wide level, and be prepared for the possibility that market liquidity may erode quickly and unexpectedly.”<sup>3</sup>

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<sup>2</sup> The term liquidity is often used in a variety of contexts, ranging from the ease of funding at the macro-level to access and cost of trading in markets. Our focus here is on the cost and ease of trading a financial asset.

<sup>3</sup> See Federal Reserve Bank of Chicago's Annual Conference on Bank Structure and Competition, Chicago, Illinois, May 15, 2008. Available at:

Academic interest in liquidity issues can be traced back to the classic paper by Amihud and Mendelson (1986), which demonstrates that, for investors with a short horizon, transaction costs are important, and liquid assets are likely to be the better investment, despite being priced higher than their illiquid counterparts. However, for investors with longer holding periods, transaction costs are less important, since they are amortized over a longer period, and the illiquid asset may be the better investment since it has a lower price, *ceteris paribus*. As a consequence, short-term investors would invest in the most liquid securities, while long-term investors, such as pension funds and insurance companies, can potentially use illiquid instruments to fund long-term liabilities and earn the extra liquidity premium. This would lead to an equilibrium in which investors are sorted into liquidity clienteles, based on their investment horizons. This concept has been elaborated on in a number of papers in the literature, as documented in Amihud, Mendelson and Pedersen (2005). We briefly discuss below a selected list of papers in the literature that are directly related to our own research.<sup>4</sup>

In a paper on illiquidity, Amihud (2002) proposes a measure of price impact that is intuitive and simple to implement. It is based on the  $\lambda$  measure of Kyle (1985), which measures the marginal impact of price with respect to a unit of trading volume. More

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<http://www.federalreserve.gov/newsevents/speech/bernanke20080515a.htm>

<sup>4</sup> We do not attempt to survey the whole literature on the effects of liquidity on asset prices here. Please see Amihud, Mendelson and Pedersen (2005) for a more comprehensive survey.

specifically, the Amihud measure, *ILLIQ*, is the average ratio of the absolute return in a stock to its dollar trading volume in any given period, i.e.,  $\frac{1}{T} \sum_{t=1}^T \frac{|r_t|}{V_t}$  where  $r_t$  is the daily stock's return,  $V_t$  is the trading volume in dollars during that day, and  $T$  is the number of trading days during the time period.

In an equilibrium context with liquidity risk, Acharya and Pedersen (2005) derive a liquidity-adjusted capital asset pricing model, in which the security's equilibrium rate of return depends on its expected liquidity as measured by the *ILLIQ* measure, as well as the liquidity risks measured by the covariances of its returns with that of the market's return and liquidity costs. In addition, their model yields the result that investors are more attracted to liquid securities when the market return is low. This result is broadly consistent with the empirical findings of Hameed, Kang and Viswanathan (2007) who document that negative market returns decrease stock liquidity for high volatility stocks, especially during times of tightness in the funding market.

In the context of portfolio optimization, Lo, Petrov, and Wierzbicki (2003) explicitly model liquidity into the portfolio construction process. Using mean-variance optimized portfolios adjusted for liquidity in three distinct ways, Lo et al. find that portfolios "close to each other" on the traditional mean-variance efficient frontier can differ substantially in their liquidity characteristics. Their analysis also reveals that simple forms of liquidity optimization can yield significant benefits in reducing a portfolio's liquidity-risk exposure, without sacrificing a great deal of expected return per unit of risk.

In our paper, we define, develop, and empirically test some measures of liquidity and liquidity risk, both at the stock- and market-levels. Using the well-accepted ILLIQ measure of liquidity, as defined first by Kyle (1985) and then operationalized by Amihud (2002), as the basis, we provide empirical evidence that a more-refined version of this liquidity measure, which uses intra-day data, strongly validates the notion that liquidity affects financial market performance. As a consequence, it has direct implications for both optimal portfolio construction and risk management.

This paper's major contributions are manifold. First, to our knowledge, it is the first paper to analyze intraday price returns and trading volume data for US stocks in order to estimate financial market liquidity, both in terms of its level and its risk. Second, we propose and employ a liquidity normalization factor, which substantially improves the time-series characteristics of the liquidity measures. Our measure permits the identification of different market liquidity regimes by using new transactions-based, market-wide metrics of illiquidity. It measures the interaction between aggregate market liquidity and the market's pricing of liquidity risk. Third, the liquidity risk factor that results from our analysis has the ability to displace other traditional indirect proxies of liquidity, such as the Fama-French size factor (SMB), in standard asset pricing tests. Last, but not least, by using the liquidity measures developed herein, we derive the rationale for a profitable and implementable liquidity-driven trading strategy.

The paper is organized as follows. In Section 2, we develop the basic empirical model of liquidity and liquidity risk that we use in our empirical analysis. We next formulate a

market-wide metric of illiquidity in Section 3 to represent fluctuations in aggregate market liquidity. We test this metric in Section 4 to determine whether the illiquidity measures developed have incremental explanatory power for equity returns relative to the Fama and French three-factor model. Section 5 builds on the results of the previous section to develop the rationale for a simple liquidity-based trading strategy, while Section 6 concludes.

## **2. An Empirical Model of Liquidity Risk**

### *2.1. The Illiquidity Measure*

The first question one can ask in the context of liquidity and portfolio management is the concept and measurement of liquidity. Although there are many aspects of liquidity, the two most common types of measures used in practice are:

1. Funding Effect: This is the ease with which or availability to finance positions over a short period (for example, as reflected in repo and reverse repo markets);
2. Transaction Effect: This is the ease with which positions can be created or liquidated.

While the first effect reflects the broader market environment, the second directly relates to an investor's ability to create or liquidate positions without significantly affecting prices: i.e., being able to buy or sell a security close to the prevailing market value. The second measure is the one most commonly used by financial economists and market participants, and the one we adopt in this paper.

Strictly speaking, Kyle's notion on which Amihud's measure is based, has to be interpreted over a very short time interval, as it measures the price impact of individual trades. Furthermore, from a trader's perspective, liquidity is a short-term phenomenon, and hence needs to be addressed over a short time interval. We therefore deliberately model the liquidity factor, as well as the liquidity attributes of individual securities, in the intra-day context.

The modeling of liquidity in the current paper follows a two-step process. In the first step, we estimate the ease with which positions can be liquidated. This is the magnitude of price movements resulting from a given order size, and is based on the Amihud (2002) measure of illiquidity described above. We restrict our universe to U.S. domiciled common stocks. In our model, each trading day is divided into 10 equal trading time intervals, with each time interval being equal to 39 minutes. (The normal trading hours for U.S. equity markets are between 9.30 am and 4 pm, a total of 390 minutes.) For each security  $i$ , for a given time interval  $t$  ( $= 1 - 10$ , for each trading day in that particular month), and month  $m$  (January 1993 through December 2009) we first compute the trade volume weighted price as  $p_{t,m}^i$ . The return for the trading interval is then given as  $r_{t,m}^i = (p_{t,m}^i - p_{t-1,m}^i) / p_{t-1,m}^i$ , where  $p_{t-1,m}^i$  is the trade volume weighted price for the prior trading interval within the same trading day. (The return is not defined for the first trading interval within the day.) Hence, for each trading day, with 10 trading intervals, 9 (i.e., 2 - 10) return observations are computed. Defining  $V_{t,m}^i$  as the dollar volume (in millions),

we compute Amihud's measure for each of the 9 trading intervals for stock  $i$  in time interval  $t$  and month  $m$  as:

$$ILLIQ_{t,m}^{i*} = \frac{|r_{t,m}^i|}{V_{t,m}^i}; \quad i = 1,2,\dots,I; \quad t = 1,2,\dots,10,\dots,T; \quad m = 1,2,\dots,M; \quad (1)$$

where  $i$  is the index of the security,  $t$  is the trading day in month  $m$ , and  $m$  is the running counter of the calendar month. There are  $I$  securities,  $T$  trading days and  $M$  months, in our sample. Note that the asterisk in the notation of Equation (1) is to differentiate this measure from the equivalent normalized illiquidity measure defined below in section 2.4.

We define illiquidity cost as the market impact cost of trading a USD 1 Million order in a given trading interval (i.e., USD 10 Million per trading day over 10 trading intervals). Denoting this as  $ILLIQ\_COST^*$  for each trading interval, we have

$$ILLIQ\_COST_{t,m}^{i*} = 1,000,000 \times * ILLIQ_{t,m}^{i*} \quad (2)$$

## 2.2. *The Portfolio Universe*

The intra-day trading data used in our analysis are obtained from the NYSE TAQ database. We construct portfolios based on the equities of U.S. domiciled companies, and rebalance them monthly, for the period January 1993 through December 2009, as described below. We employ intraday trading data and calculate the  $ILLIQ^*$  measure, for every stock, for every month in our sample period, using Equation (1). Observations with very high illiquidity cost (i.e., > 99.99 percentile) or very low illiquidity cost (i.e., < 0.01

percentile) are dropped. At the end of each month, we sort stocks (for which ILLIQ\* data are available) by average market capitalization for the month, and then construct an equally-weighted portfolio of the largest 3,000 stocks. We maintain this portfolio constant for the following month, and repeat the process at the end of each month. This monthly-rebalanced, equally-weighted portfolio is used for the empirical analysis in this paper.

Table 1 provides a summary of the excess return characteristics of this portfolio universe, and compares it with the return characteristics of the Fama-French market excess return factor (market return minus the risk-free interest rate).<sup>5</sup> In order to make an unbiased comparison with the Fama-French market factors, the *value-weighted* return characteristics of the portfolio universe are calculated. This table reports that the monthly return correlation between our sample and that of Fama-French is over 99%, indicating that our portfolio sample is a good representation of the U.S. equity market. Nevertheless, there are differences in the excess returns and Sharpe ratios between the two. This is due to the fact that the Fama-French market factor portfolio is an *annually* rebalanced, value-weighted portfolio, whereas the value-weighted portfolio universe constructed here is based on *monthly* rebalancing.

<Insert Table 1 Here>

### 2.3. *Descriptive Statistics*

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<sup>5</sup> See Fama and French (1992) and (1993).

We next present descriptive statistics of ILLIQ\* formed portfolios using the universe described above. We form five portfolios, 1 through 5, sorted using the monthly average of ILLIQ\*. Portfolio 1 is the most liquid (i.e., lowest ILLIQ\*), while Portfolio 5 is the most illiquid (i.e., highest ILLIQ\*). Table 2 indicates that the monthly illiquidity premium for U.S. equities is 19 basis points. The illiquidity premium is defined as the difference between the return to illiquid stocks (Portfolio 5) and the return to liquid stocks (Portfolio 1). The corresponding liquidity cost differential is 413 basis points, as measured by ILLIQ\_COST\*, indicating that the average holding period necessary to realize the positive illiquid premium is around 22 months.

Table 2 also compares ILLIQ\* with other proxies for illiquidity, such as the dollar trading volume and market capitalization for each of the five portfolios based on monthly rebalancing. The dollar trading volume and market capitalization of illiquid stocks (Portfolio 5) is 1/90th and 1/34th of liquid stocks (Portfolio 1), respectively. Table 2 also indicates that liquid stocks have lower market, size and valuation betas as compared to illiquid stocks. The betas are computed using contemporaneous regressions of portfolio excess returns of the monthly Fama-French factors as the exogenous variables. Portfolio 1 has a low beta to the size factor, which is a commonly used proxy for liquidity. Moreover, it has an insignificant beta against the valuation factor. The results are similar to, but somewhat stronger than, those obtained using yearly rebalancing by Fama and French (1992).

<Insert Table 2 here>

#### 2.4. Unbiased estimate of illiquidity

A problem with the ILLIQ\* metric defined above is that it is a biased measure, since it has an intrinsic time trend associated with it: the denominator is given as the dollar trading volume (i.e., Price Per Share times Trading Volume). Both Price Per Share and Trading Volume generally increase with the passage of time due to effects independent of market liquidity, such as economic growth, inflation and stock splits or dividends. Therefore, ILLIQ\* generally has a downward trend over time.

In order to convert the measure into an unbiased time series estimate, and to allow for comparisons across time, we apply a simple statistical adjustment or normalization. This adjustment is the ratio of the US CPI Index (All Urban Consumers) as of the end of the prior month ( $CPI_{m-1}$ ) and the US CPI Index as of the end of December 1979 ( $CPI_0$ ). We define this normalized value as ILLIQ.<sup>6</sup> The choice of CPI as the normalization variable is driven by two factors: firstly, its simplicity as a de-trending measure, and secondly, its lack of correlation with market specific variables such as market capitalization.

The adjusted measure, ILLIQ, is defined as:

$$ILLIQ_{t,m}^i = \frac{|r_{t,m}^i|}{V_{t,m}^i} \times \frac{CPI_{m-1}}{CPI_0}; \quad i = 1,2,\dots,l; \quad t = 1,2,\dots,10,\dots,T; \quad m = 1,2,\dots,M; \quad (3)$$

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<sup>6</sup> To distinguish between the normalized and non-normalized values of ILLIQ, we drop the asterisk for the former definition.

where  $i$ ,  $t$  and  $m$  and  $I$ ,  $T$  and  $M$  have the same interpretation as in equation (1). As in equation 2, we define the illiquidity cost for each trading interval as:

$$ILLIQ\_COST_{t,m}^i = 1,000,000 \times ILLIQ_{t,m}^i \quad (4)$$

We calculate various statistics for ILLIQ as well as its log transformation. The value of each statistic is first computed for each security for the entire period, and then averaged across the portfolio universe. The skewness and kurtosis of the ILLIQ measure are reduced substantially by the log transformation - skewness decreases by a factor of 3, while kurtosis decreases by a factor of 10. Hence, we use logarithmic transformations for the subsequent analysis in this paper.

## 2.5. The Time Series Model

We next model the time series of the ILLIQ measure, following Amihud (2002), as an AR(1) equation. The regression is performed every month  $m$  for every stock  $i$  and is given as

$$\log(ILLIQ_{t,m}^i) - \theta_m^i = \rho_m^i [\log(ILLIQ_{t-1,m}^i) - \theta_m^i] + \sigma_m^i \varepsilon_{t,m}^i \quad (5)$$

where  $\varepsilon_{t,m}^i \sim N(0,1)$  is the i.i.d. shock,  $\theta_m^i$  is the unconditional mean,  $\rho_m^i$  is the autoregressive component, and  $\sigma_m^i$  is the conditional variance.

We define the unconditional distribution of the AR(1) process as

$$\log(ILLIQ_{t,m}^i) \sim N\left(\theta_m^i, \frac{\sigma_m^{2i}}{1 - \rho_m^{2i}}\right) \quad (6)$$

Hence, the estimate of the monthly illiquidity level for stock  $i$  in month  $m$ , denoted by  $IlliquidityLevel_m^i$ , and is given as the mean of the unconditional distribution, i.e.,

$$IlliquidityLevel_m^i = \theta_m^i \quad (7)$$

Similarly, the estimate for monthly liquidity risk for stock  $i$  in month  $m$  is given by the standard deviation of the distribution, i.e.,

$$LiquidityRisk_m^i = \sqrt{\frac{\sigma_m^{2^i}}{1 - \rho_m^{2^i}}} \quad (8)$$

### 3. Market-wide Liquidity Metrics and the Corresponding Liquidity Regimes

#### 3.1 Market Illiquidity Level (MIL)

We next define a transaction-based, market-wide metric of liquidity, measured from intra-day trading, to represent fluctuations in aggregate equity market liquidity. To the best of our knowledge, such a *transactions-based* metric does not exist today, particularly at the intra-day level. Most market participants currently use other proxies for liquidity, such as the difference between the 3 month LIBOR and the 3 Month T-Bill (also known as the Treasury-Eurodollar or TED spread), the spread between on-the-run and off-the-run government debt, or the VIX (Chicago Board Options Exchange’s Market Implied Volatility Index) as proxies for market liquidity. Unfortunately, many of these metrics, be they *funding-based* or *risk-based*, are not direct measures of equity market liquidity, albeit reasonable proxies.

In this section, we define our transaction-based, market-wide illiquidity metric, which we refer to as *Market Illiquidity Level (MIL)*. MIL represents the average liquidation cost of

a basket of U.S. equities at a given point in time. To derive this, let  $MIL_m$  represent MIL for month  $m$ . The first step in computing  $MIL_m$  is to compute aggregate stock illiquidity.

This is defined as

$$IlliquidityLevel_m = \frac{1}{3000} \sum_{i=0}^{3000} IlliquidityLevel_m^i \quad (9)$$

where  $IlliquidityLevel_m^i$  is the illiquidity for stock  $i$  in month  $m$ , as defined in equation 7. The market illiquidity level,  $IlliquidityLevel_m$ , is averaged over the 3,000 largest US stocks by market capitalization, which comprises our stock universe.

As in Equation (4), we define  $MIL_m$  as the average cost of trading USD 1 million per trading interval or an USD 10 Million position in a day for month  $m$ . Hence, it is given as:

$$MIL_m = 1,000,000 e^{IlliquidityLevel_m} \quad (10).$$

Figure 1 shows MIL as a time series from January 1993 through December 2009. An increase in this level indicates deteriorating market liquidity conditions. This is evident in the illiquidity spikes seen during the LTCM crisis of 1998 and the global financial crisis of 2007-2008. MIL jumped by 114 basis points between March and October of 1998 during the LTCM crisis. It jumped by 146 basis points between June 2007 and November 2008 during the global financial crisis, indicating that the latter was more pronounced in both magnitude and length.

It should be noted that following the liquidity crisis of 2007-2008, central banks worldwide unleashed a concerted effort to pump unprecedented funding liquidity into global markets. This effort, which commenced after the collapse of Lehman Brothers in

September 2008, had a substantial impact in improving market liquidity conditions, as measured by transaction liquidity during the following year. This is evident in the decline in MIL by 78 basis points from September 2008 through December 2009. However, as of December 2009, liquidity conditions were still significantly worse compared to pre-crisis levels in 2007.

< Insert Figure 1 here >

Table 3 reports the coefficients of correlation between MIL and other commonly-used proxies for illiquidity and the Fama-French risk factors. The liquidity proxies used are the VIX and the TED spread. As observed in the table, the degree of correlation between MIL and the other liquidity proxies, including the SMB factor, is small. One of the reasons why MIL is weakly correlated to the SMB factor may be because the pricing of illiquidity often lags the actual state of illiquidity in the market. Additionally, the SMB factor, while capturing the size premium, does not capture the true illiquidity premium, which may also exist for some stocks with large market capitalization, albeit to a lesser extent as compared to smaller stocks. Furthermore, as discussed in Section 3.3 below, during periods of extreme market illiquidity, liquid stocks may actually underperform illiquid stocks, as the former are easier to offload in order to meet de-leveraging targets and broker margin calls.

In summary, Table 3 suggests that MIL measures an entirely different aspect of liquidity in the market as a whole.

< Insert Table 3 here >

### 3.2 *Market Illiquidity Factor (MIF)*

We next introduce an index to measure how illiquidity is priced by market participants, which we call the *Market Illiquidity Factor (MIF)*. It is computed on a monthly basis as follows. At the beginning of each month, the largest 3000 U.S. equities (as defined in Section 2.2) are sorted by the prior month's illiquidity as defined in Equation 7. An equally-weighted portfolio is formed by going long the 600 most illiquid stocks (i.e., the top quintile) and going short the 600 least illiquid stocks (i.e., the bottom quintile). The constituents of the portfolio are held constant for the remainder of the month, while the portfolio is rebalanced at the beginning of each month. The monthly return of this portfolio, which is the Market Illiquidity Factor (MIF), is shown in Figure 2. It measures the cumulative return of illiquid securities relative to liquid securities, and can be thought of as the market price of illiquidity measured as a return premium. The MIF for U.S. equities is based on an initial value of 100 registered on February 1, 1993.

< Insert Figure 2 here >

Table 4 reports the monthly correlations between the MIF and the Fama-French risk factors – namely market, size and valuation. The correlations are performed using monthly data for the period February 1993 - December 2009.

< Insert Table 4 here >

**Discuss this more clearly.** In Table 5, we report factor regressions of the six Fama-French portfolios based on size and value. The regressions are performed using monthly data for the period 1994 - 2009. The portfolios, which are constructed at the end of June each year, are the intersection of two portfolios formed on size (market value of equity, ME) and three portfolios formed on the ratio of book value of equity to market value of equity (BE/ME). The size breakpoint for year  $t$  is the NYSE median market value of equity at the end of June of year  $t$ . The BE/ME ratio of year  $t$  is the book value of equity for the previous fiscal year end in  $t-1$  divided by the market value of equity at the end of December of year  $t-1$ . The BE/ME break-points are the NYSE's 30th and 70th percentiles. The portfolio returns are based on equally-weighted constituents. The explanatory variables are the Fama-French risk factors (Market:  $R_m\_minus\_R_f$ ; Size: SMB ; and Valuation: HML) and the Market Illiquidity Factor (MIF).

It is interesting to note from Table 5 that MIF is a significant factor in the presence of the commonly-used factors in asset pricing tests. In the absence of any explicit market illiquidity factor such as MIF, the SMB factor is a commonly-used proxy for liquidity in various asset pricing regressions. In the presence of MIF, the SMB factor is rendered insignificant for large capitalization (Big ME) portfolios. As expected, MIF loadings for large capitalization portfolios are smaller than the loadings for small capitalization portfolios.

### 3.3 *Determining Market Liquidity Regimes using MIL and MIF*

The state of liquidity in a market has two dimensions – the level of illiquidity, as measured by MIL, and the pricing of illiquidity by market participants, as measured by MIF. Hence, our approach to modeling liquidity herein is rich enough to allow us to describe four distinct states of market liquidity, or liquidity regimes.

1. ***Benign Liquidity Regime:*** This state is defined as an improvement in liquidity conditions (negative change in the MIL) accompanied by an out-performance of illiquid securities (positive change in the MIF). As an example, the year 2009 witnessed a sharp improvement in liquidity conditions as a consequence of the concerted effort by central banks to flush markets with liquidity. Markets responded by pricing illiquidity favorably, leading to an increase in the MIF.

< Insert Table 5 here >

2. ***Liquidity Crisis Regime:*** This state is defined as the deterioration in liquidity conditions (positive change in the MIL) accompanied by underperformance of illiquid securities (negative change in the MIF). The LTCM liquidity crisis of 1998 is a case in point.
3. ***De-Leveraging Regime:*** This state is defined as the deterioration in liquidity conditions (positive change in the MIL) accompanied by out-performance of illiquid securities (positive change in the MIF). This pattern typically lasts for short periods of time. It occurs during periods of extreme market stress such as in June 2008 through September 2008, when market participants were forced to shed positions quickly to raise capital. As the most liquid securities are easiest to liquidate, they bear the brunt of the selling pressure, and hence the most deterioration in price relative to illiquid securities, thereby pushing up the MIF.

4. *Liquidity Correction Regime*: This state is defined as an improvement in liquidity conditions (negative change in the MIL) accompanied by an underperformance of illiquid securities (negative change in the MIF). This pattern also lasts for short periods of time. It typically occurs after a de-leveraging regime, when market participants correct for the dislocation in security markets by dumping illiquid securities, which were difficult to sell during the prior period of severe market stress.

< Insert Figure 3 here >

#### **4. Illiquidity and Asset Pricing**

Traditional equilibrium asset pricing models are based on the assumption of standard, perfectly competitive, Walrasian markets that are frictionless. However, in reality, markets are plagued by various forms of frictions such as illiquidity and transaction costs. Hence, prices are not always at fundamental value, and are affected by trading activity. As a consequence, asset pricing models should incorporate liquidity as an endogenous factor, as argued by Amihud (2002). However, one should first establish that this factor is indeed priced in the cross-section of asset returns.

Our goal in this section is to test whether the illiquidity measures derived in Section 2, have incremental explanatory power for the cross-section of asset returns relative to the Fama-French 3-factor model. First, for each month, we sort our universe of 3,000 stocks by the stock Illiquidity Level as defined in Section 2.5, in ascending order, and split them into 100 portfolios with 30 stocks in each portfolio. We obtain rolling estimates of Fama

and French factor loadings for each portfolio  $p$  and each month  $m$ , by using a regression of the past 60 months of excess return data. The regression equation is given as

$$Ret_m^p - Rf_m = \beta_{MKT_m}^p MKT_m + \beta_{SMB_m}^p SMB_m + \beta_{HML_m}^p HML_m + \xi_m^p \quad (11)$$

Where  $Ret_m^p$  is the portfolio return computed as an equally-weighted average return of the constituents, and  $Rf_m$  is the risk free rate,  $\beta_{MKT_m}^p$ ,  $\beta_{SMB_m}^p$  and  $\beta_{HML_m}^p$  are the factor loadings for the Fama and French factors  $MKT_m$  (Market),  $SMB_m$  (Size) and  $HML_m$  (Valuation) respectively and  $\xi_m^p$  is the error term.

Next, we seek to explain the next period's excess return with the exogenous variables given as the Fama-French factor loadings computed as above, along with the illiquidity level, liquidity risk and change in illiquidity level for the portfolio. The illiquidity level and liquidity risk of the portfolio are computed as equally-weighted averages of the constituents. We denote them by  $IlliquidityLevel_m^p$  and  $LiquidityRisk_m^p$  respectively for portfolio  $p$  in month  $m$ .

The change in the illiquidity level of portfolio  $p$  between month  $m-1$  and  $m$  is given as

$$\Delta IlliquidityLevel_m^p = IlliquidityLevel_m^p - IlliquidityLevel_{m-1}^p \quad (12)$$

The fixed-effects regression equation can then be formulated as

$$\begin{aligned} Ret_{m+1}^p - Rf_{m+1}^p = & \alpha + u^p + c^{MKT} \beta_{MKT_m}^p + c^{SMB} \beta_{SMB_m}^p + c^{HML} \beta_{HML_m}^p + \\ & c^{IlliquidityLevel} IlliquidityLevel_m^p + c^{\Delta IlliquidityLevel} \Delta IlliquidityLevel_m^p + \\ & c^{LiquidityRisk} LiquidityRisk_m^p + e_m^p \end{aligned} \quad (13)$$

where  $(\alpha + u^p)$  represents the time invariant intercept for every portfolio  $p$  and  $c^{MKT}$ ,  $c^{SMB}$ ,  $c^{HML}$ ,  $c^{IlliquidityLevel}$ ,  $c^{\Delta IlliquidityLevel}$  and  $c^{LiquidityRisk}$  are the regression coefficients.<sup>7</sup> Under the null hypothesis,  $(Ret_{m+1}^p - Rf_{m+1}^p)$  should only depend on  $c^{MKT}$ ,  $c^{SMB}$ , and  $c^{HML}$ . As a consequence, the loadings for Illiquidity, i.e.,  $c^{IlliquidityLevel}$ ,  $c^{\Delta IlliquidityLevel}$  and  $c^{LiquidityRisk}$  should be 0, under the null hypothesis that only the Fama-French factors are priced.

Table 6, however, demonstrates that all three coefficients of the liquidity factors are statistically significant. Hence, we can reject the null hypothesis and establish that the level of illiquidity, the change in the illiquidity from the prior period, and liquidity risk are important in explaining future asset returns. The positive loading for the illiquidity level is to be expected as market participants need to be compensated for the higher transaction cost of owning illiquid securities.

However, the negative loadings for changes in the illiquidity level and liquidity risk (which both measure the volatility in liquidity) contradict traditional wisdom. A negative correlation is also observed in Chordia, Subrahmanyam and Anshuman (2001), O'Hara (2002), Chollete (2004), and Fu (2008). Chen (2008) explains this phenomenon as the volatility of liquidity being driven by the idiosyncratic risk of the stock that cannot be

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<sup>7</sup> We are not directly interested in the estimation of the fixed effects, i.e.  $u^p$ . The fixed effects are removed by time de-meaning each variable (the so called within estimator), i.e.  $Ret_{m+1}^p - \overline{Ret}^p$ ,  $\beta_{MKT_m}^p - \overline{\beta_{MKT}^p}$  etc.

diversified away.. Conventional wisdom indicates that if investors are not able to fully diversify risk, then they will demand a premium for holding stocks with high idiosyncratic risk. Merton (1987) suggests a rationale for this phenomenon in an information-segmented market, in which firms with larger firm-specific variances require higher returns to compensate investors for holding imperfectly diversified portfolios. Therefore, the negative premium observed in this study and other papers in the literature may be related to as the idiosyncratic risk premium puzzle.

< Insert Table 6 here >

## **5. A Simple Liquidity-based Trading Strategy**

### *5.1 Does liquidity in the prior period influences the returns in the subsequent period?*

If illiquidity is indeed being awarded a return premium, it would be interesting to examine whether an investment trading strategy can be established to exploit the illiquidity premium by trading illiquid assets against their liquid counterparts, after adjusting for risk. To analyze this, we first examine whether a liquidity trading strategy, which sorts equally-weighted portfolios of the largest 3,000 stocks by illiquidity quintiles using ILLIQ\* (see Section 2.2), can produce excess returns. This is similar in spirit to other trading strategies reported in the academic literature involving portfolio quintiles or deciles.

We next study this issue from a practical perspective by examining whether a similar liquidity trading strategy involving actively traded stock market indices, which differ

substantially in terms of the liquidity of their component stocks, can also produce significant returns.

For the trading strategy using illiquid and liquid securities, we define the benchmark portfolio as being long the most illiquid quintile portfolio and short the most liquid quintile portfolio, over the entire sample period. We maintain this *static* benchmark portfolio throughout the trading period. Similarly for the trading strategy based on stock market indices, we define the benchmark as being long the Russell 2000 index (a stock index proxy for illiquid securities) and short the Dow Jones Industrial Average (a stock index proxy for liquid securities).

For the purpose of calculating the trailing liquidity change for month  $m$ , we examine  $MIL_{m-1}$  against  $MIL_{m-2}$ , which measures the liquidity change in month  $m$  over the prior 2 months. Trailing liquidity is improving for month  $m$ , if  $MIL_{m-1} < MIL_{m-2}$ . Similarly, liquidity is deteriorating for month  $m$ , if  $MIL_{m-1} > MIL_{m-2}$ .

## *5.2. Trading Strategy Involving Liquidity-Quintile Portfolios*

Table 7 shows that equity portfolios sorted by illiquidity quintiles using ILLIQ\* exhibit superior performance when the prior liquidity improves as compared to the case when the prior liquidity deteriorates. More specifically, we construct two liquidity-sorted portfolios based on the prior month's ILLIQ score - a low liquidity portfolio consisting of the top ILLIQ quintile stocks, and a high liquidity portfolio consisting of the bottom ILLIQ quintile stocks.

For example, when liquidity deteriorates, the most liquid portfolio almost always has a higher return on average than the most illiquid portfolio. This outcome generally reverses when market liquidity conditions improve. Furthermore, both the most liquid and most illiquid portfolios have higher volatility in markets with deteriorating liquidity, as compared to their respective volatility when liquidity is improving.

< Insert Table 7 here >

The empirical evidence here demonstrates that illiquid stocks, on average, outperform liquid stocks when liquidity improves, and vice versa. This would suggest a trading strategy involving buying the illiquid stocks (or index) when liquidity conditions are improving. Similarly when liquidity conditions are deteriorating, it calls for buying the liquid stocks (or index). This central finding governs the implementation of our trading strategy as described in the section below. We do this by using the most liquid and illiquid portfolios, by quintiles, for both monthly and weekly rebalancing, albeit by using the same monthly change in liquidity in both cases, i.e., by comparing  $MIL_{m-1}$  against  $MIL_{m-2}$ .

As discussed above, we first implement a naïve investment trading strategy that takes a long position in the most illiquid quintile portfolio when prior liquidity is improving. Conversely, the strategy takes a long position in the most liquid quintile portfolio when prior liquidity is deteriorating. The most liquid and most illiquid portfolios are constructed based on the liquidity quintiles approach described heretofore. This strategy does not take into account transaction costs, and is rebalanced on a monthly as well as weekly basis.

Our liquidity model is based on a partial equilibrium model of intraday trading, where the liquidity signal changes rapidly as new price and volume information arrive and get incorporated on a high frequency basis. The more frequent the revision in the trading strategy in response to a signal, the smaller the time-decay in the trading signal's efficacy. As a consequence, we conducted the trading strategy over two different rebalancing cycles, mainly weekly and monthly.

While the empirical analysis and tests in the paper have been based on monthly rebalancing up until now, we introduce weekly rebalancing in this trading strategy section, purely to take advantage of the illiquidity signal's changing strength as new information is incorporated into the signal's parameters. Weekly rebalancing would also take into account the realities of active portfolio trading, which would require more frequent revisions of the portfolio, due to corresponding revisions in the signal.

Figures 4a and 4b demonstrate that the dynamic liquidity-sorted portfolio trading strategy for the trading period March 1993 through December 2009 strongly outperforms a naïve benchmark. As defined above, the static benchmark is long the most illiquid quintile portfolio and short the most liquid quintile portfolio, held over the entire sample period.

< Insert Figure 4a here >

< Insert Figure 4b here >

The dark colored line in each graph represents the performance of the static benchmark portfolio, while the light colored line represents the performance of the dynamic liquidity-sorted portfolio strategy. As is evident, the dynamic strategy clearly

outperforms the static benchmark strategy. The extent of the outperformance is greater for the weekly rebalancing (in Figure 4b) than for the monthly rebalancing (in Figure 4a), demonstrating the importance of a timely response to the signal. The trading strategy performance is quite robust across various liquidity cycles.

We next conduct a factor regression of the liquidity-based trading strategies for both monthly and weekly rebalancing frequencies. Table 9 provides the results of the contemporaneous regression of monthly returns of liquidity based on monthly and weekly rebalanced long/short trading strategies. The exogenous variables are the Fama-French risk factors for market, size (SMB) and valuation (HML). The regression is estimated based on the two liquidity-sorted portfolios. The strategies take a long position in the low liquidity portfolio and a short position in the high liquidity portfolio when prior liquidity is improving. Conversely, the strategies take a short position in the low liquidity portfolio and a long position in the high liquidity portfolio when prior liquidity is deteriorating. Liquidity is improving when the Market Illiquidity Level (MIL) decreases over the prior 2 months, and irrespective of the rebalancing frequency. Liquidity is deteriorating when the MIL increases over the prior 2 months, again irrespective of the rebalancing frequency.

As Table 8 indicates, the Sharpe ratio for the liquidity-based trading strategy is much stronger when the portfolio is rebalanced on a weekly basis versus when it is rebalanced on a monthly basis. The liquidity-based trading strategy yields an annualized Sharpe ratio and alpha of 0.72 and 9.63%, respectively, for the weekly rebalanced liquidity-based portfolio strategy, versus 0.29 and 4.18% for the monthly rebalanced one.

< Insert Table 8 here >

We observe from the above table that a weekly rebalanced liquidity-based portfolio has much better risk-adjusted performance as compared to the monthly rebalanced one, as also seen in Figures 4a and 4b.

The above discussion also reflects a common phenomenon in quantitatively-driven portfolio trading strategies, where the portfolio backtests are carried out on a monthly frequency and over a much longer data test period, whereas the strategy itself is deployed as a live portfolio with more active rebalancing so as to mitigate the signal's time decay effect. The implicit assumption made herein is that the model of equilibrium presented is invariant to the rebalancing frequency, which would be a function of signal turnover, transaction costs, data availability, and so on.

### *5.3. Trading Strategy Involving Index Portfolios*

Since an argument can be made that it would be too costly to transact the liquidity-based trading strategy based on illiquidity quintiles, we provide here a simple index-level trading strategy, which would have much lower transaction costs. For this index-level liquidity trading strategy, we analyze the return distribution of U.S. equity indices when the trailing liquidity, as measured by the Market Illiquidity Level (*MIL*), is improving versus when the trailing liquidity is deteriorating. For the purpose of implementing an investment trading strategy with relatively low transaction costs, we consider two different U.S. equity indices with component stocks exhibiting different liquidity characteristics. Both the indices exist as very liquid Exchange Traded Funds (ETFs), or as futures contracts, and hence can be traded as a basket with minimal transaction costs.

The Russell 2000 Index is chosen as a proxy for illiquid stocks as it is a portfolio of smaller capitalization stocks, which are typically less liquid, while the Dow Jones Industrial Average Index (DJIA) is chosen as a proxy for liquid stocks as it is a portfolio of large capitalization and blue chip stocks, which are typically very liquid. Indeed, in Table 9, we demonstrate that the Russell 2000 Index has significantly more liquidity risk than the DJIA, as indicated by various liquidity measures such as daily dollar trading volume, market capitalization, bid-ask spread and ILLIQ cost. The table reports liquidity statistics for calendar year 2009, using the index constituents as of December 31, 2008. It is interesting to note that the ILLIQ cost differential between the Russell 2000 and DJIA is far higher compared to the bid-ask spread differential. (The bid-ask spread is defined as a percentage of the mid-point closing price.) This is to be expected, however, as the bid-ask spread is typically the cost for smaller-sized transactions, whereas liquidity cost is associated with larger, institutional-sized trades.

< Insert Table 9 Here >

Although the Russell 2000 Index and DJIA are not exact proxies for the most illiquid and the most liquid portfolios of US equities, respectively, they have the advantage of being easy to implement.

Table 10 demonstrates that the Russell 2000 Index, our proxy for illiquid stocks, exhibits superior performance and improved risk characteristics when prior liquidity improves. This is in contrast to the case when the prior period liquidity deteriorates. For example, when liquidity is improving, the Russell 2000 has a higher return on average than the

DJIA, which is our proxy for liquid stocks. This outcome reverses during deteriorating conditions of market liquidity. Furthermore, both the DJIA and Russell 2000 have lower volatility in markets with improving liquidity, as compared to their respective volatility when liquidity is deteriorating.

< Insert Table 10 here >

As we did in the previous section using liquidity-sorted portfolios, we next implement a naïve index-level trading strategy that takes a long position in the Russell 2000 Index and a short position in the DJIA when prior liquidity is improving. Conversely, the strategy takes a short position in the Russell 2000 and a long position in the DJIA when prior liquidity is deteriorating. Again, the strategy does not take into account transaction costs. However, the analysis is once again conducted and reported on both a monthly and weekly rebalancing basis.

Figures 5a and 5b demonstrate that the equity index strategy for the trading period March 1993 through December 2009 strongly outperforms a naïve static benchmark that is long the Russell 2000 Index and short the DJIA throughout the period, for both the monthly and weekly rebalanced portfolios. The performance of this trading strategy is also robust across various liquidity cycles.

< Insert Figure 5a here >

< Insert Figure 5b here >

We next conduct a factor regression of the index-based trading strategies for both monthly and weekly rebalancing frequencies. Table 11 provides the results of

contemporaneous regressions of monthly returns of liquidity based on monthly and weekly rebalanced long/short trading strategies. The exogenous variables are the Fama-French risk factors for market, size (SMB) and valuation (HML). The regression is estimated based on the Dow Jones Industrial Average (DJIA) and Russell 2000 Index. The strategy takes a long position in the Russell 2000 Index and a short position in the DJIA portfolio when prior liquidity is improving. Conversely, the strategy takes a short position in the Russell 2000 and a long position in the DJIA when prior liquidity is deteriorating. Liquidity is improving when the Market Illiquidity Level (MIL) decreases over the prior 2 months, and irrespective of the rebalancing frequency. Liquidity is deteriorating when the MIL increases over the prior 2 months.

As Table 11 indicates, the Sharpe ratio for the equity index trading strategy is much stronger when the portfolio is rebalanced on a weekly basis versus when it is on a monthly basis. The Russell 2000 Index / DJIA equity index trading strategy yields an annualized Sharpe ratio and alpha of 0.67 and 10.02%, respectively, for the weekly rebalanced trading strategy, versus 0.21 and 3.96% for the monthly rebalanced strategy.

These results are encouraging as, from the practical perspective, it goes to show that the liquidity-based trading strategy described in this paper is viable and implementable as a portfolio trading strategy, with minimal transaction costs.

< Insert Table 11 here >

## **6. Conclusion**

This paper defined, developed, and empirically tested some transactions-based measures of liquidity and liquidity risk, both at the stock- and market-levels, that are easy to implement. By using intraday, transactions-level data to estimate the level and uncertainty of liquidity, we provide strong empirical evidence that validates the notion that liquidity affects financial market performance, and as a consequence, has implications for both portfolio construction and risk management. For example, illiquid equities ranked by our Stock Illiquidity Level indicator underperformed liquid equities by 15.8% during the 2007-2008 illiquidity build-up during the global financial crisis, and by 18.4% during the 1998 LTCM crisis.

By using new transactions-based, market-wide metrics of illiquidity, which measure the interaction between aggregate market liquidity and the market's pricing of liquidity risk, we identify four different market regimes for liquidity. We also demonstrate that in the presence of the liquidity variables introduced in this paper, commonly-used proxies for liquidity, such as size and turnover, are rendered insignificant in explaining cross-sectional asset returns.

Finally, as an illustration of the efficacy of our approach to understanding and exploiting liquidity changes, two simple trading strategies were developed using the Market Illiquidity Level indicator to generate profitable long/short investment trading strategies.

We first conducted a similar liquidity-based trading strategy that takes a long (short) position in the lowest quintile liquidity portfolio and a short (long) position in the highest quintile liquidity portfolio when prior liquidity is improving (deteriorating). The second strategy calls for a long (short) position in the Russell 2000 Index and a short (long) position in the Dow Jones Industrial Average Index when prior liquidity is improving (deteriorating). The Russell 2000 Index serves as a proxy for illiquid equities, while the Dow Jones Industrial Average Index serves as a proxy for liquid equities.

The results are fairly strong: the quintile-based, weekly rebalanced portfolio-level trading strategy yielded an annualized return of 9.63% and a Sharpe ratio of 0.72 for the period March 1993 through December 2009, while the corresponding index-level trading strategy yielded an annualized return of 10.02% and a Sharpe Ratio of 0.67.

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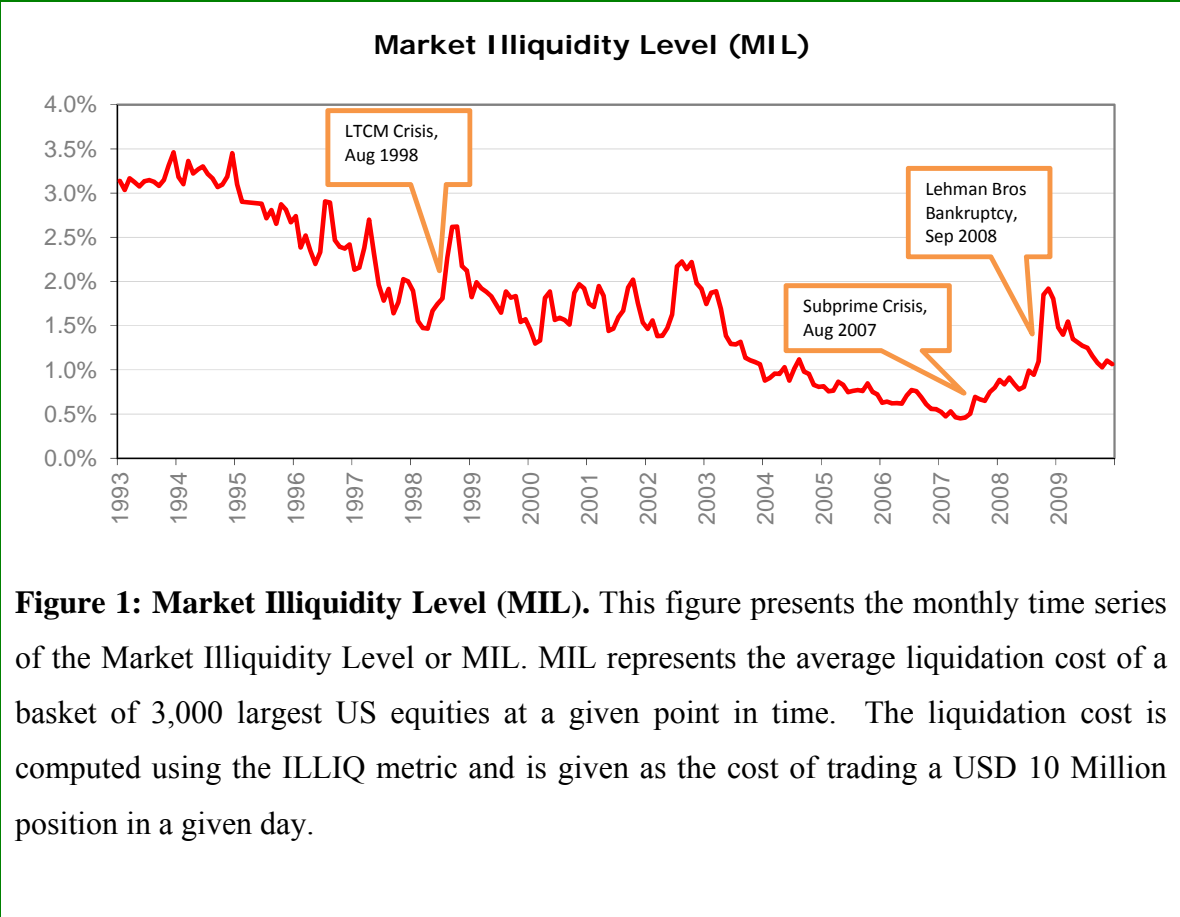
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| <i>Sample Portfolio</i> |                 |                     | <i>Fama- French Market Factor</i> |                 |                     | <i>Correlation</i> |
|-------------------------|-----------------|---------------------|-----------------------------------|-----------------|---------------------|--------------------|
| <i>Excess Ret</i>       | <i>Std Dev.</i> | <i>Sharpe Ratio</i> | <i>Excess Return</i>              | <i>Std Dev.</i> | <i>Sharpe Ratio</i> |                    |
| 7.16%                   | 15.55%          | 0.46                | 5.50%                             | 15.75%          | 0.35                | 0.99               |

**Table 1: Monthly excess return characteristics of the portfolio universe in the sample.** This table reports value-weighted return characteristics of the portfolio used in this study. The portfolio constituents are constructed at the end of every month by picking the 3,000 largest US stocks, by average market capitalization, for the month. The constituents are held constant for the next month. Excess return is computed as the monthly return of the portfolio ( $R_m$ ) minus the 1-month T-Bill return ( $R_f$ ). The table also reports return characteristics of the monthly Fama-French excess market return ( $R_m$  minus  $R_f$ ). The correlation between the excess returns of the two series (the present sample versus the Fama-French market portfolio) is also reported. All values are reported as annualized numbers for the period January 1993 through December 2009.

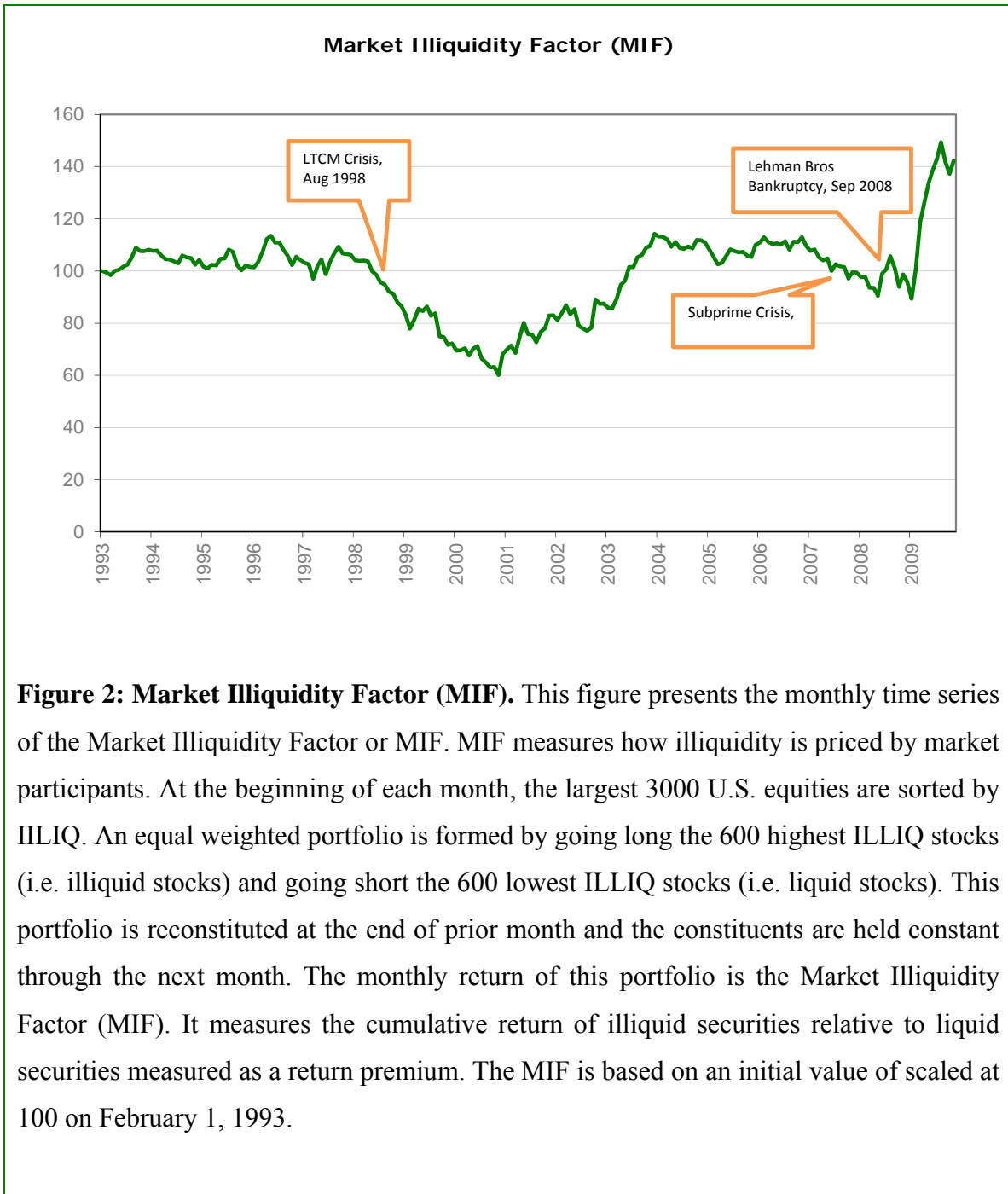
| <i>Illiquidity Portfolio</i> | <i>Next month ret</i> | <i>Log dollar trade volume</i> | <i>Log market cap</i> | <i>Log Illiq*</i><br><i>Cost</i> | <i>Market Beta</i> | <i>Size Beta</i>   | <i>Valuation Beta</i> |
|------------------------------|-----------------------|--------------------------------|-----------------------|----------------------------------|--------------------|--------------------|-----------------------|
| 1                            | 0.96%<br>(5.22%)      | 20.75***<br>(0.70)             | 22.64***<br>(0.38)    | -7.52***<br>(0.79)               | 1.03***<br>(0.022) | 0.18***<br>(0.029) | -0.06<br>(0.031)      |
| 2                            | 0.95%<br>(6.12%)      | 19.15***<br>(0.63)             | 20.97***<br>(0.34)    | -5.70***<br>(0.87)               | 1.15***<br>(0.027) | 0.58***<br>(0.035) | 0.04<br>(0.037)       |
| 3                            | 1.06%<br>(6.65%)      | 18.17***<br>(0.58)             | 20.16***<br>(0.34)    | -4.60***<br>(0.79)               | 1.19***<br>(0.026) | 0.83***<br>(0.034) | 0.12***<br>(0.036)    |
| 4                            | 1.14%<br>(6.97%)      | 17.23***<br>(0.53)             | 19.55***<br>(0.34)    | -3.79***<br>(0.57)               | 1.26***<br>(0.033) | 0.86***<br>(0.043) | 0.23***<br>(0.046)    |
| 5                            | 1.15%<br>(6.97%)      | 16.25***<br>(0.31)             | 19.11***<br>(0.39)    | -3.17***<br>(0.35)               | 1.27***<br>(0.049) | 0.79***<br>(0.064) | 0.42***<br>(0.067)    |

**Table 2: Properties of Illiquidity Portfolios.** This table reports the properties of 5 portfolios sorted using ILLIQ\*, based on the Amihud measure of illiquidity. Portfolio 1 has the lowest illiquidity and Portfolio 5 has the highest illiquidity. The portfolios are formed at the end of each month from a universe of 3,000 largest US stocks by average market capitalization for the month. The Market, HML and SMB betas are computed using contemporaneous monthly regressions of excess portfolio returns with Fama-French factors for the Market ( $R_{m\_minus\_R_f}$ ), Size (SMB) and Valuation (HML). All values are reported as monthly averages for the period January 1993 through December 2009. The standard errors are shown in parenthesis. The asterisk next to the coefficient estimates denotes the level of statistical significance. Single asterisk, double asterisks and triple asterisks denote significance levels of 0.05, 0.02 and 0.01 respectively.



|           | <i>MIL</i> | <i>VIX</i> | <i>TED<br/>Spread</i> | <i>Market</i> | <i>Size</i> | <i>Valuation</i> |
|-----------|------------|------------|-----------------------|---------------|-------------|------------------|
| MIL       | 1.00       |            |                       |               |             |                  |
| VIX       | -0.05      | 1.00       |                       |               |             |                  |
| TED       | -0.12      | 0.55       | 1.00                  |               |             |                  |
| Market    | 0.00       | -0.24      | -0.19                 | 1.00          |             |                  |
| Size      | -0.09      | -0.07      | -0.07                 | 0.22          | 1.00        |                  |
| Valuation | -0.02      | -0.14      | -0.17                 | -0.30         | -0.35       | 1.00             |

**Table 3: Correlation between market illiquidity measures.** This table shows the cross-correlations between the Market Illiquidity Level (MIL), the Chicago Board Options Exchange Market Volatility Index (VIX), the difference between the interest rates on 3 month LIBOR and 3 Month T-Bill (TED Spread), and the Fama-French risk factors for Market ( $R_{m\_minus\_R_f}$ ), Size (SMB) and Valuation (HML). The correlations are based on monthly data for the period January 1993 through December 2009.



**Figure 2: Market Illiquidity Factor (MIF).** This figure presents the monthly time series of the Market Illiquidity Factor or MIF. MIF measures how illiquidity is priced by market participants. At the beginning of each month, the largest 3000 U.S. equities are sorted by ILLIQ. An equal weighted portfolio is formed by going long the 600 highest ILLIQ stocks (i.e. illiquid stocks) and going short the 600 lowest ILLIQ stocks (i.e. liquid stocks). This portfolio is reconstituted at the end of prior month and the constituents are held constant through the next month. The monthly return of this portfolio is the Market Illiquidity Factor (MIF). It measures the cumulative return of illiquid securities relative to liquid securities measured as a return premium. The MIF is based on an initial value of scaled at 100 on February 1, 1993.

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|           | <i>Market</i> | <i>Size</i> | <i>Valuation</i> | <i>MIF</i> |
|-----------|---------------|-------------|------------------|------------|
| Market    | 1.00          |             |                  |            |
| Size      | 0.22          | 1.00        |                  |            |
| Valuation | -0.28         | -0.39       | 1.00             |            |
| MIF       | 0.24          | 0.50        | 0.14             | 1.00       |

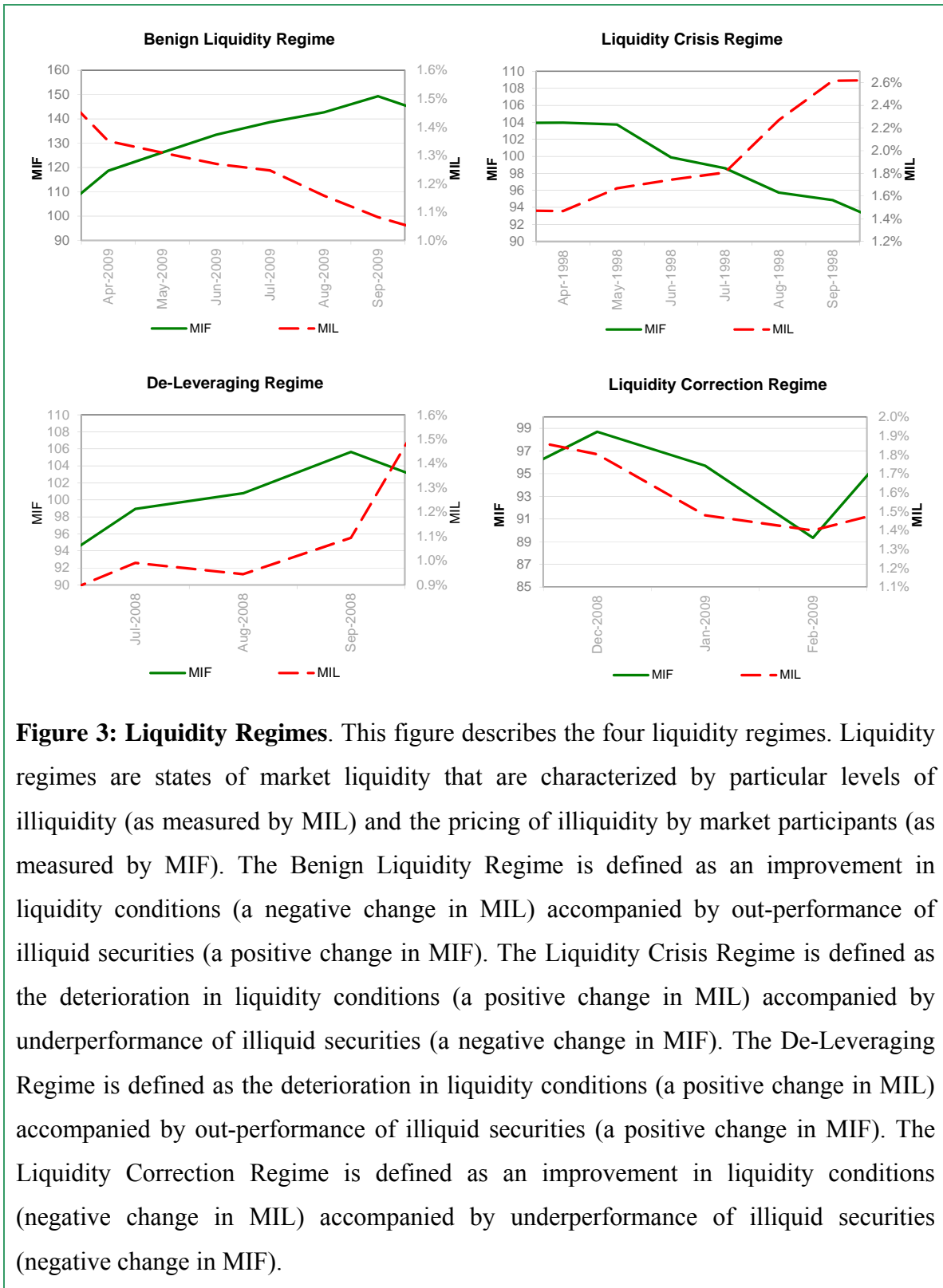
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**Table 4: Correlation between the MIF and Fama-French Factors.** This table shows the monthly correlations between the Market Illiquidity Factor (MIF) and the Fama-French risk factors for Market ( $R_m$  minus  $R_f$ ), Size (SMB) and Valuation (HML). MIF measures how illiquidity is priced by market participants. At the beginning of each month, the largest 3000 U.S. equities are sorted by ILLIQ. An equal weighted portfolio is formed by going long the 600 highest ILLIQ stocks (i.e. illiquid stocks) and going short the 600 lowest ILLIQ stocks (i.e. liquid stocks). This portfolio is reconstituted at the end of prior month and the constituents are held constant through the next month. The monthly return of this portfolio is the Market Illiquidity Factor (MIF). The correlations are based on monthly data for the period January 1993 through December 2009.

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|           | <i>Small ME</i>      |                         |                       | <i>Big ME</i>        |                         |                       |
|-----------|----------------------|-------------------------|-----------------------|----------------------|-------------------------|-----------------------|
|           | <i>Low<br/>BE/ME</i> | <i>Medium<br/>BE/ME</i> | <i>High<br/>BE/ME</i> | <i>Low<br/>BE/ME</i> | <i>Medium<br/>BE/ME</i> | <i>High<br/>BE/ME</i> |
| Constant  | 0.00<br>(-0.89)      | 0.01***<br>(5.62)       | 0.01***<br>(5.24)     | 0.00***<br>(2.85)    | 0.00***<br>(2.59)       | 0.00*<br>(2.25)       |
| Market    | 1.04***<br>(21.08)   | 0.86***<br>(32.73)      | 0.86***<br>(23.46)    | 1.10***<br>(39.6)    | 1.08***<br>(37.54)      | 1.04***<br>(40.56)    |
| Size      | 0.56***<br>(7.33)    | 0.49***<br>(12.08)      | 0.58***<br>(10.06)    | 0.04<br>(0.87)       | 0.02<br>(0.51)          | 0.02<br>(0.46)        |
| Valuation | -0.62***<br>(-8.35)  | 0.13***<br>(3.23)       | 0.34***<br>(6.17)     | -0.27***<br>(-6.5)   | 0.51***<br>(11.83)      | 0.73***<br>(18.87)    |
| MIF       | 0.70***<br>(9.53)    | 0.42***<br>(10.95)      | 0.37***<br>(6.82)     | 0.16***<br>(3.94)    | 0.09*<br>(2.02)         | 0.17***<br>(4.48)     |
| Adjusted  | 0.88                 | 0.92                    | 0.86                  | 0.92                 | 0.89                    | 0.91                  |

**Table 5: Factor Regressions.** This table shows the results of contemporaneous regressions of the returns on the six Fama-French portfolios on various risk factors. The Fama-French portfolios are the intersections of two portfolios formed on size (market value of equity or ME) and three portfolios formed on valuation (the ratio of book value of equity to market value of equity, or BE/ME). The portfolio constituents are equally weighted. The explanatory variables are the Fama-French risk factors for Market (Rm\_minus\_Rf), Size (SMB) and Valuation (HML) and the Market Illiquidity Factor (MIF). MIF measures the return of illiquid securities relative to liquid securities, and can be thought of as the market price of illiquidity measured as a return premium. The regressions are based on monthly data for the period January 1993 through December 2009. *t*-stats are shown in parenthesis. The asterisk denotes the level of significance. Single asterisk, double asterisks and triple asterisks denote significance level of 0.05, 0.02 and 0.01, respectively.

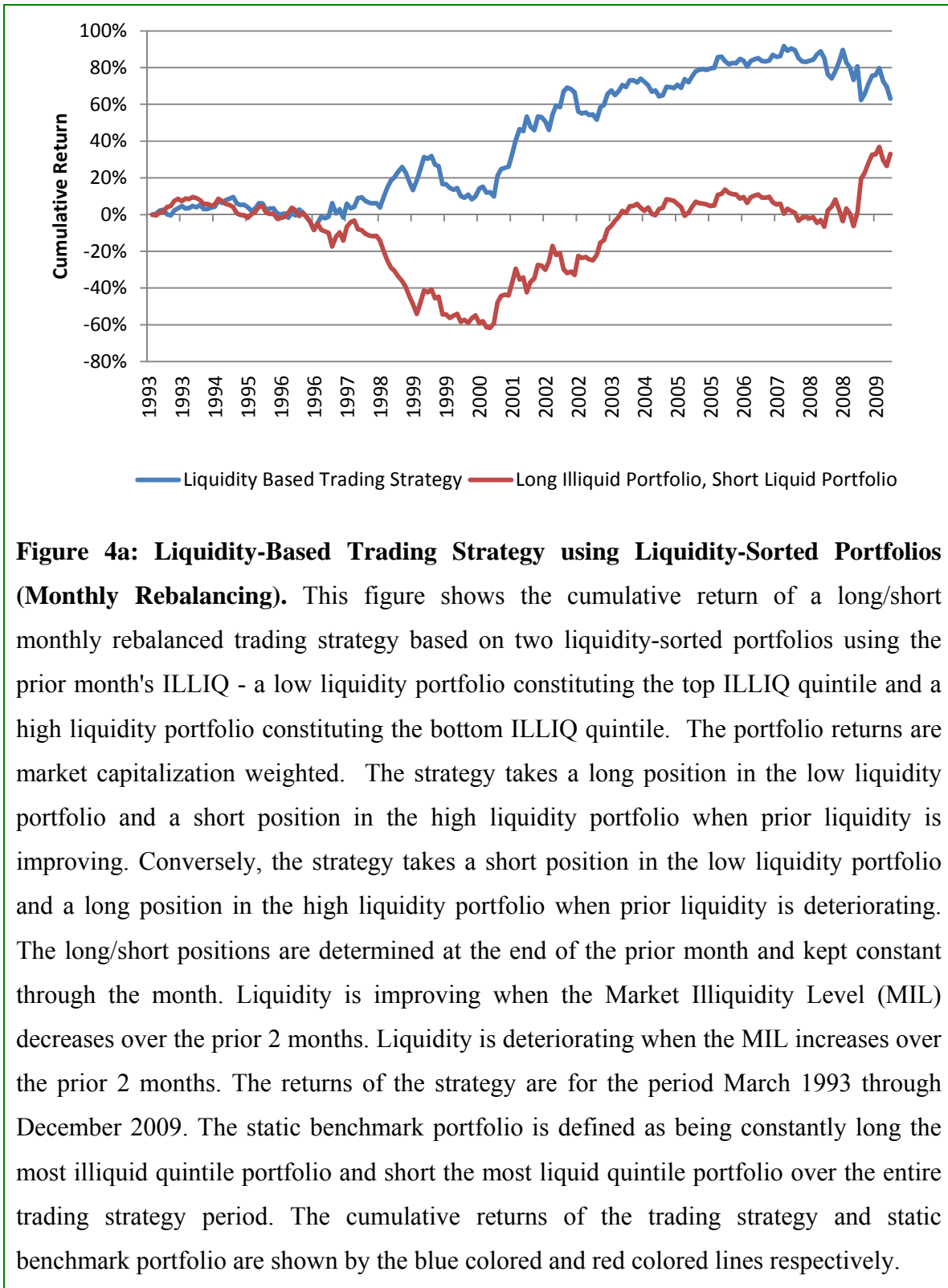


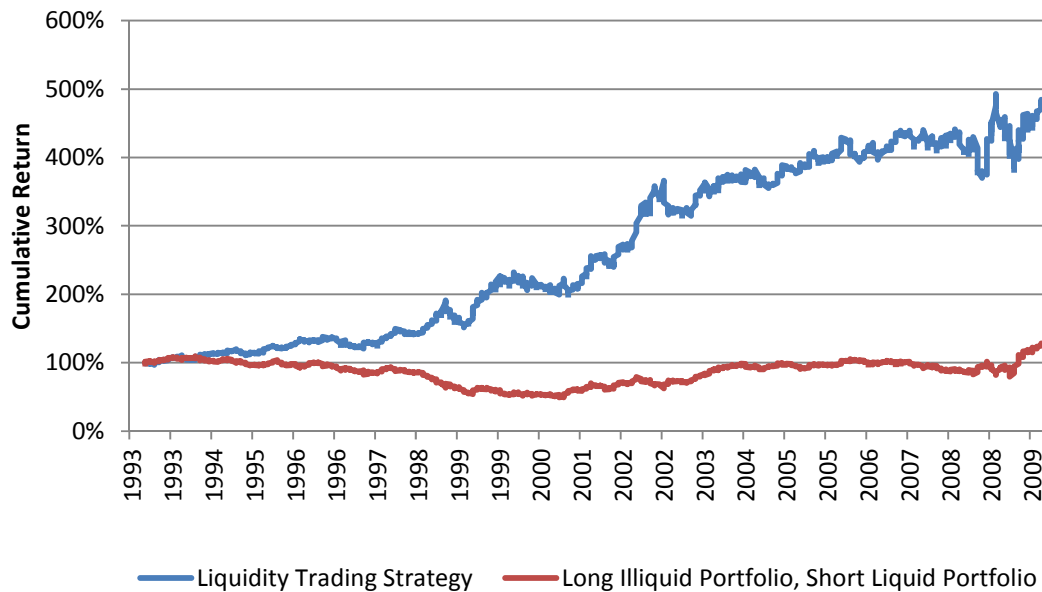
|                         | <i>Intercept</i> | $\beta_{MKT}$     | $\beta_{SMB}$     | $\beta_{HML}$       | <i>Illiquidity Level</i> | <i>Change in Illiquidity Level</i> | <i>Liquidity Risk</i> |
|-------------------------|------------------|-------------------|-------------------|---------------------|--------------------------|------------------------------------|-----------------------|
| Estimate                | 0.00<br>(0.00)   | 0.05***<br>(8.83) | 0.01***<br>(3.66) | -0.02***<br>(-7.16) | 0.02***<br>(16.02)       | -0.05***<br>(-10.56)               | -0.10***<br>(-11.84)  |
| Adjusted R <sup>2</sup> | 0.03             |                   |                   |                     |                          |                                    |                       |

**Table 6: Fixed Effects Regression of Fama-French Betas and Liquidity Metrics.** This table presents the regression results of the next month's excess returns against exogenous variables defined as Fama-French factor loadings for MKT, SMB and HML along with various liquidity metrics. The liquidity metrics used are the illiquidity level, the change in the illiquidity level, and liquidity risk. The regressions are performed as fixed effects on 100 portfolios sorted on liquidity level, for the period January 1993 through December 2009. The portfolio variables are computed as equally-weighted averages. The t-stats are shown in parenthesis. Single asterisk, double asterisks and triple asterisks denote significance level of 0.05, 0.02 and 0.01, respectively.

| <i>Prior Liquidity</i> | <i># of months</i> | <i>Illiquid Portfolio Return</i> | <i>Liquid Portfolio Return</i> | <i>Illiquid Portfolio Std Dev</i> | <i>Liquid Portfolio Std Dev</i> |
|------------------------|--------------------|----------------------------------|--------------------------------|-----------------------------------|---------------------------------|
| Deteriorating          | 89                 | 6.5%                             | 8.5%                           | 24.5%                             | 16.8%                           |
| Improving              | 112                | 17.4%                            | 12.2%                          | 18.5%                             | 14.1%                           |

**Table 7: Liquidity-sorted Portfolio Returns.** This table shows the performance of the Illiquid and Liquid portfolio returns when the prior liquidity is improving, as well as for case when the prior liquidity is deteriorating. The portfolios are sorted using prior month's ILLIQ, from a universe of 3000 largest US stocks by average market capitalization for the month. The constituents of the illiquid portfolio comprise the top quintile ILLIQ values, while the constituents of the liquid portfolio comprise the bottom quintile ILLIQ values. The portfolios are reconstituted at the beginning of each month and held constant for the remainder of the month. The portfolio returns are weighted by market capitalization as of the prior month. Liquidity is improving when the Market Illiquidity Indicator (MIL) in the prior month is lower than the month before. Liquidity is deteriorating when MIL in the prior month is higher than the month before. The returns and standard deviation of returns are based on monthly data for the period March 1993 through December 2009, and are expressed as annualized values.





**Figure 4b: Liquidity-Based Trading Strategy using Liquidity-Sorted Portfolios (Weekly Rebalancing).** This figure shows the cumulative return of a long/short weekly rebalanced trading strategy based on two liquidity-sorted portfolios using the prior month's ILLIQ - a low liquidity portfolio constituting the top ILLIQ quintile and a high liquidity portfolio constituting the bottom ILLIQ quintile. The portfolio returns are market capitalization weighted. The strategy takes a long position in the low liquidity portfolio and a short position in the high liquidity portfolio when prior liquidity is improving. Conversely, the strategy takes a short position in the low liquidity portfolio and a long position in the high liquidity portfolio when prior liquidity is deteriorating. The long/short positions are determined at the end of the prior week and kept constant through the week. Liquidity is improving when the Market Illiquidity Level (MIL) decreases over the prior 2 months. Liquidity is deteriorating when the MIL increases over the prior 2 months. The returns of the strategy are for the period March 1993 through December 2009. . The static benchmark portfolio is defined as being constantly long the most illiquid quintile portfolio and short the most liquid quintile portfolio over the entire trading strategy period. The cumulative returns of the trading strategy and static benchmark portfolio are shown by the light colored and dark colored lines respectively.

| <i>Long Short<br/>Trading<br/>Strategy</i>    | <i>Alpha<br/>per<br/>Period</i> | <i>Market</i>         | <i>SMB</i>         | <i>HML</i>         | <i>Annu-<br/>alized<br/>Return</i> | <i>Annu-<br/>alized<br/>Std Dev</i> | <i>Annu-<br/>alized<br/>Alpha</i> | <i>Sharpe<br/>Ratio</i> |
|-----------------------------------------------|---------------------------------|-----------------------|--------------------|--------------------|------------------------------------|-------------------------------------|-----------------------------------|-------------------------|
| <u>Monthly<br/>Rebalancing</u>                |                                 |                       |                    |                    |                                    |                                     |                                   |                         |
| Illiquid<br>Portfolio,<br>Liquid<br>Portfolio | 0.003<br>(1.308)                | -0.140***<br>(-2.324) | 0.079<br>(1.008)   | 0.039<br>(0.469)   | 3.77%                              | 12.98%                              | 4.18%                             | 0.29                    |
| <u>Weekly<br/>Rebalancing</u>                 |                                 |                       |                    |                    |                                    |                                     |                                   |                         |
| Illiquid<br>Portfolio,<br>Liquid<br>Portfolio | 0.002***<br>(3.011)             | -0.003<br>(-0.118)    | -0.057<br>(-1.262) | -0.033<br>(-0.765) | 9.41%                              | 13.05%                              | 9.63%                             | 0.72                    |

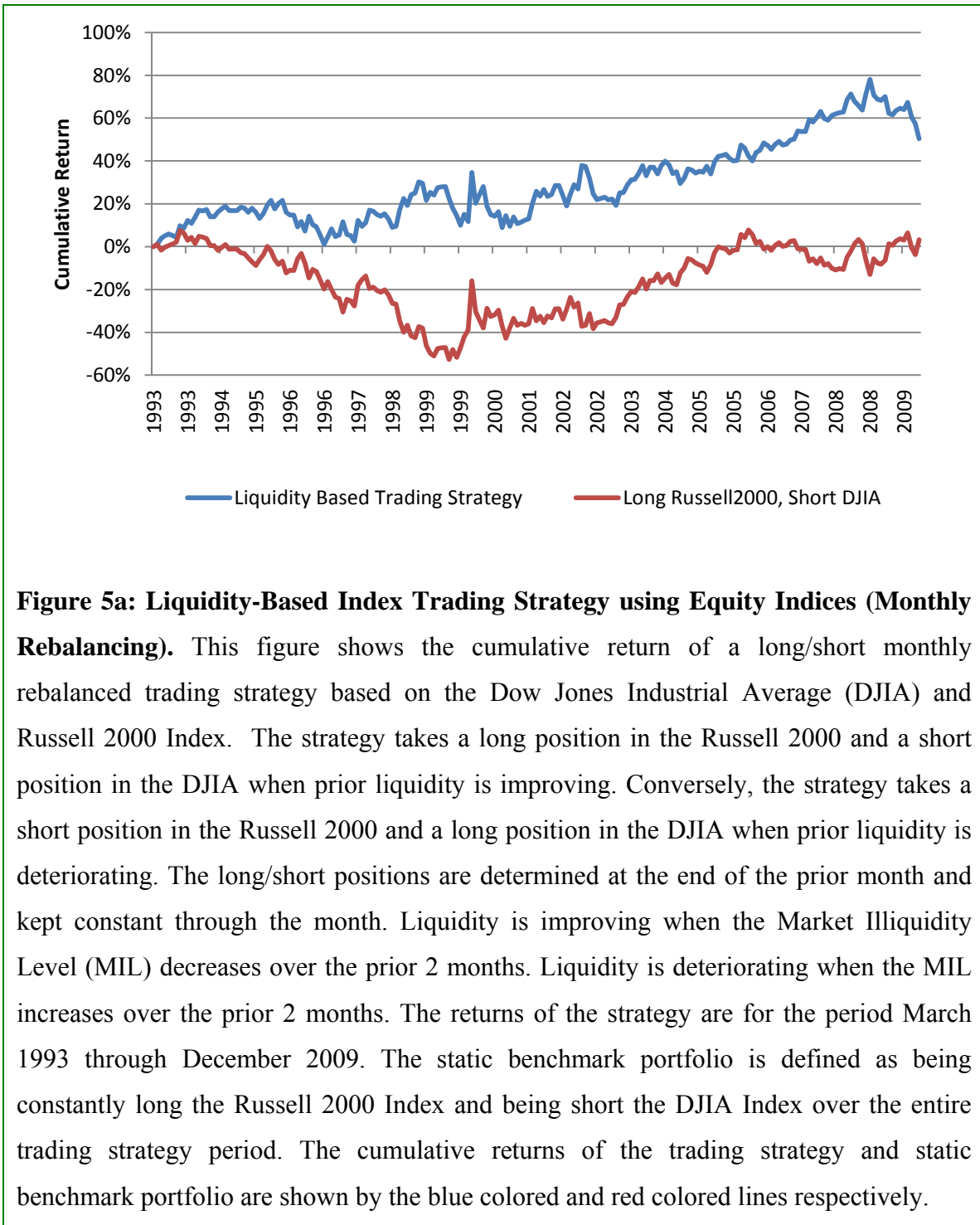
**Table 8: Factor Regression of Liquidity-sorted Trading Strategies.** This table shows the results of the contemporaneous regression of weekly and monthly returns of the liquidity-based long/short trading strategy using the two liquidity-sorted portfolios. The exogenous variables are the Fama-French risk factors for market, size (SMB) and valuation (HML). The regression is formed using the two liquidity-sorted portfolios based on prior month's ILLIQ - a low liquidity portfolio constituting the top ILLIQ quintile and a high liquidity portfolio constituting the bottom ILLIQ quintile. The portfolio returns are expressed as market cap weighted. The strategy takes a long position in the low liquidity portfolio and a short position in the high liquidity portfolio when prior liquidity is improving. Conversely, the strategy takes a short position in the low liquidity portfolio and a long position in the high liquidity portfolio when prior liquidity is deteriorating. Liquidity is improving when the Market Illiquidity Level (MIL) decreases over the prior 2 months. Liquidity is deteriorating when the MIL increases over the prior 2 months. The returns of the strategy are for the period March 1993 through December 2009. The t-stats are shown in parenthesis. The asterisk next to the coefficient estimates denotes the level of significance. Single asterisk, double asterisks and triple asterisks denote significance level of 0.05, 0.02 and 0.01 respectively.

| <i>Index</i> | <i>Dollar Trading Volume</i> | <i>Market Cap</i> | <i>Bid-Ask Spread %</i> | <i>Illiquidity Cost</i> |
|--------------|------------------------------|-------------------|-------------------------|-------------------------|
| DJIA         | 846,356,180                  | 95,376,693        | 0.05%                   | 0.01%                   |
| Russell 2000 | 6,008,233                    | 344,102           | 0.22%                   | 3.87%                   |

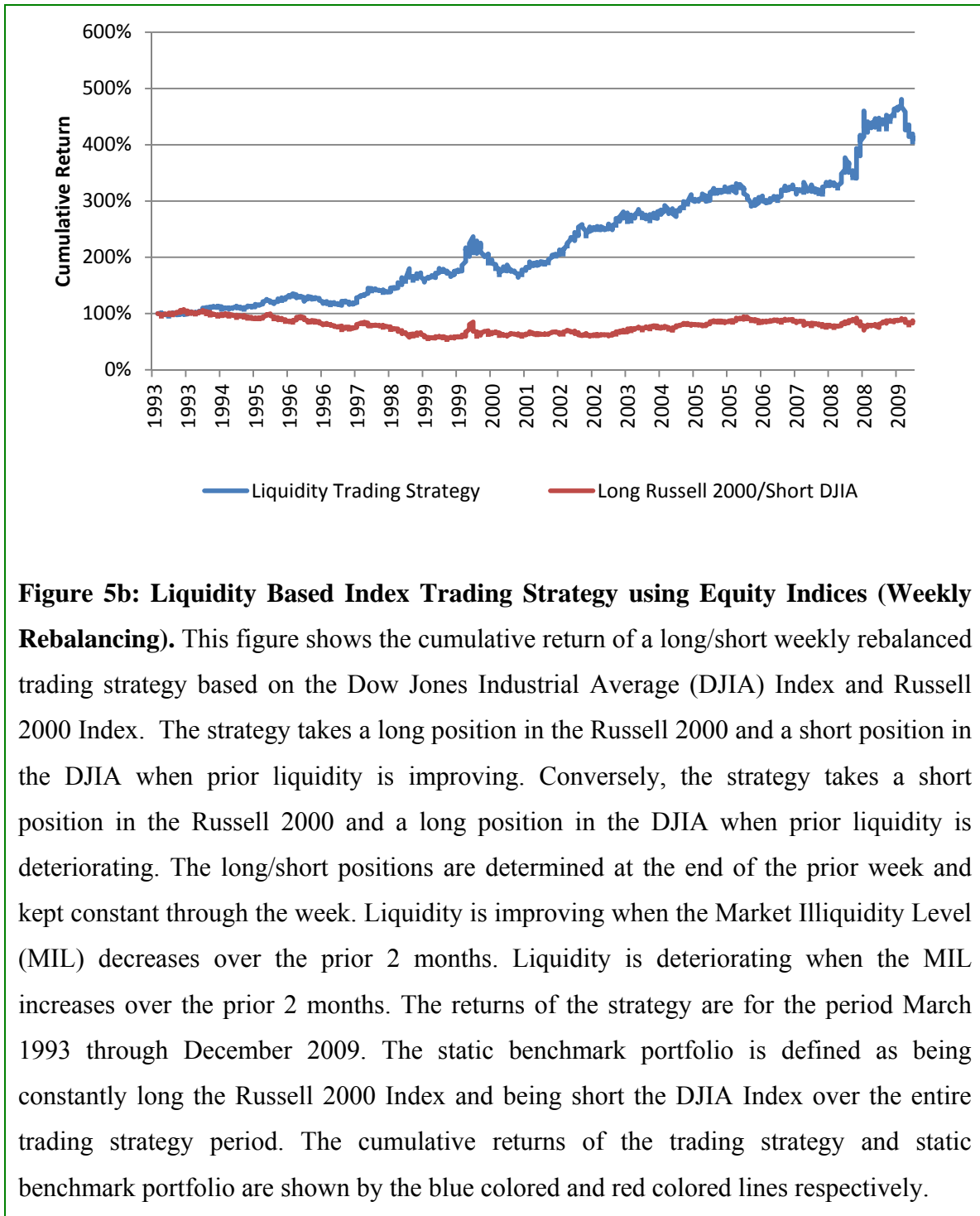
**Table 9: Liquidity properties of the Dow Jones Industrial Average (DJIA) and Russell 2000 Indices.** This table reports dollar trading volume, market capitalization, bid-ask spread% and illiquidity cost of the Dow Jones Industrial Average (DJIA) and Russell 2000 Indices, for the calendar year 2009, using constituents as of the end of 2008. The median liquidity property estimate is computed each day for each index. The average value for calendar year 2009 is reported in the table. Bid-Ask Spread% is calculated as [(ask price - bid price)/closing price], using daily close values. Illiquidity Cost is the market impact cost of trading USD 10 million in a trading day and is estimated using intraday data.

| <i>Prior Liquidity</i> | <i># of months</i> | <i>Russell 2000 Return</i> | <i>DJIA Return</i> | <i>Russell 2000 Std Dev</i> | <i>DJIA Std Dev</i> |
|------------------------|--------------------|----------------------------|--------------------|-----------------------------|---------------------|
| Deteriorating          | 89                 | 4.0%                       | 7.1%               | 22.6%                       | 16.1%               |
| Improving              | 112                | 12.3%                      | 9.4%               | 16.6%                       | 14.2%               |

**Table 10: Prior Liquidity Influences U.S. Equity Index Returns.** This table shows the performance of the Dow Jones Industrial Average (DJIA) and Russell 2000 Index returns when the prior liquidity is improving as well as for period when the prior liquidity is deteriorating. Liquidity is improving when the Market Illiquidity Indicator (MIL) in the prior month is lower than the month before. Liquidity is deteriorating when MIL in the prior month is higher than the month before. The returns and standard deviation of returns are based on monthly data for the period January 1993 through December 2009, and are expressed as annualized values.



**Figure 5a: Liquidity-Based Index Trading Strategy using Equity Indices (Monthly Rebalancing).** This figure shows the cumulative return of a long/short monthly rebalanced trading strategy based on the Dow Jones Industrial Average (DJIA) and Russell 2000 Index. The strategy takes a long position in the Russell 2000 and a short position in the DJIA when prior liquidity is improving. Conversely, the strategy takes a short position in the Russell 2000 and a long position in the DJIA when prior liquidity is deteriorating. The long/short positions are determined at the end of the prior month and kept constant through the month. Liquidity is improving when the Market Illiquidity Level (MIL) decreases over the prior 2 months. Liquidity is deteriorating when the MIL increases over the prior 2 months. The returns of the strategy are for the period March 1993 through December 2009. The static benchmark portfolio is defined as being constantly long the Russell 2000 Index and being short the DJIA Index over the entire trading strategy period. The cumulative returns of the trading strategy and static benchmark portfolio are shown by the blue colored and red colored lines respectively.



| <i>Long Short Trading Strategy</i> | <i>Alpha per Period</i> | <i>Market</i>         | <i>SMB</i>          | <i>HML</i>         | <i>Annualized Return</i> | <i>Annualized Std Dev</i> | <i>Annualized Alpha</i> | <i>Sharpe Ratio</i> |
|------------------------------------|-------------------------|-----------------------|---------------------|--------------------|--------------------------|---------------------------|-------------------------|---------------------|
| <u>Monthly Rebalancing</u>         |                         |                       |                     |                    |                          |                           |                         |                     |
| Russell 2000, DJIA                 | 0.003<br>(1.172)        | -0.210***<br>(-3.283) | 0.218***<br>(2.638) | -0.119<br>(-1.346) | 2.95%                    | 14.11%                    | 3.96%                   | 0.21                |
| <u>Weekly Rebalancing</u>          |                         |                       |                     |                    |                          |                           |                         |                     |
| Russell 2000, DJIA                 | 0.002***<br>(2.988)     | -0.088***<br>(-3.389) | -0.083<br>(-1.750)  | -0.017<br>(-0.388) | 9.30%                    | 13.80%                    | 10.02%                  | 0.67                |

**Table 11: Factor Regression of Liquidity Based, Index Trading Strategies.** This table shows the results of the contemporaneous regression of monthly returns of the liquidity-based long/short trading strategy based on monthly rebalancing. The exogenous variables are the Fama-French risk factors for market, size (SMB) and valuation (HML). The regression is formed based on the Dow Jones Industrial Average (DJIA) and the Russell 2000 Index. The strategy takes a long position in the Russell 2000 and a short position in the DJIA when prior liquidity is improving. Conversely, the strategy takes a short position in the Russell 2000 and a long position in the DJIA when prior liquidity is deteriorating. Liquidity is improving when the Market Illiquidity Level (MIL) decreases over the prior 2 months. Liquidity is deteriorating when the MIL increases over the prior 2 months. The returns of the strategy are for the period March 1993 through December 2009. The t-stats are shown in parenthesis. The asterisk next to the coefficient estimates denotes the level of significance. Single asterisk, double asterisks and triple asterisks denote significance level of 0.05, 0.02 and 0.01 respectively.