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Liquidity as an Investment Style

Roger G. Ibbotson, Zhiwu Chen, Daniel Y.-J. Kim, and Wendy Y. Hu

Liquidity should be given equal standing with size, value/growth, and momentum as an investment style. As measured by stock turnover, liquidity is an economically significant indicator of long-run returns. The returns of liquidity are sufficiently different from those of the other styles that it is not merely a substitute. Finally, a stock's liquidity is relatively stable over time, with changes in liquidity associated with changes in valuation.

William F. Sharpe suggested the idea of investment styles as early as 1978 in a general paper about investment (Sharpe 1978). He later refined the idea of style analysis (Sharpe 1988) and applied it to asset allocation (Sharpe 1992); in the latter study, Sharpe defined four criteria that characterize a benchmark style: (1) "identifiable before the fact," (2) "not easily beaten," (3) "a viable alternative," and (4) "low in cost."[1] The Morningstar Style Box popularized the size versus value categorizations during that same year.

In this article, we propose that equity liquidity is a missing investment style that should be given equal standing with the currently accepted styles of size (Banz 1981), value/growth (Basu 1977; Fama and French 1992, 1993), and momentum[2] (Jegadeesh and Titman 1993, 2001). When assembled into portfolios, these styles define a set of betas that can be beaten only if the portfolios provide a positive alpha.

The literature on the relationship between liquidity and valuation in the U.S. equity market has grown dramatically since Amihud and Mendelson (1986) used bid–ask spreads to show that less liquid stocks outperform more liquid stocks.[3] Using various measures of liquidity, other researchers have confirmed the impact of liquidity on stock returns. Despite this significant and multifaceted body of evidence, a recent survey of the last 25 years of literature on the determinants of expected stock returns found that liquidity is rarely included as a control (Subrahmanyam 2010).[4]

Roger G. Ibbotson is professor in the practice of finance at the Yale School of Management, New Haven, Connecticut, and chairman and CIO of Zebra Capital Management, LLC, Milford, Connecticut. Zhiwu Chen is professor of finance at the Yale School of Management, New Haven, Connecticut. Daniel Y.-J. Kim is research director at Zebra Capital Management, LLC, Milford, Connecticut. Wendy Y. Hu is senior quantitative researcher at Permal Asset Management, Inc., New York City.

In our study, we used stock turnover, which is a well-established measure of liquidity that is negatively correlated with long-term returns in the U.S. equity market. Haugen and Baker (1996) and Datar, Naik, and Radcliffe (1998) demonstrated that low-turnover stocks, on average, earn higher future returns than do high-turnover stocks. We examined stock-level liquidity in a top 3,500 market-capitalization universe of U.S. equities over 1971–2011 and subjected it to the four style tests of Sharpe (1992). Our empirical findings, which extend and amplify the existing literature, are that liquidity clearly meets all four criteria. In the sections that follow, we discuss each criterion in turn. Appendix A describes the datasets and stock universe that we used in our analysis.

Long-Term Return Comparisons

There are numerous ways to identify liquidity. Amihud and Mendelson (1986) used bid–ask spreads to explain a cross section of stock returns. Brennan and Subrahmanyam (1996) regressed the price impact of a unit trade size from microstructure trading data. Amihud (2002) developed a metric that uses the average price impact relative to the daily trading volume of each security. Pástor and Stambaugh (2003) demonstrated that stock returns vary with their sensitivity to marketwide liquidity.

We used stock turnover as our "before the fact" measure of liquidity. It is a characteristic, but it can also be expressed as a covariance factor. Another frequently used and readily measured liquidity metric is that of Amihud (2002), though Idzorek, Xiong, and Ibbotson (2012) showed that turnover exhibits greater explanatory power for U.S. mutual fund returns. A single "perfect" measure of liquidity is unlikely to exist: Brown, Crocker, and Foerster (2009) found that liquidity measures may encode momentum and information effects in large-cap stocks.

We do not claim that turnover is the "best" way to measure liquidity, but we argue that it is a simple measure that works well. The other styles can also be measured in various ways. Value versus growth can be measured by price-to-earnings ratios (Basu 1977), book-to-market ratios (Fama and French 1992, 1993), dividend-to-price ratios, or other fundamental ratios. Momentum can be measured over various horizons and weighting schemes. Even size can be measured over various capitalization ranges and universes. The goal of our study was not to compare the various liquidity metrics but, rather, to show that a simple liquidity measure can match the results of the other styles in such a way that liquidity deserves to have equal standing with the accepted styles of size, value, and momentum.

The methodology of our study consisted of a two-part algorithm for the selection (prior) year and the performance (current) year. For each selection year (1971–2010), we examined the top 3,500 U.S. stocks by year-end capitalization. From this universe, we recorded liquidity as measured by the annual share turnover (the sum of the 12 monthly volumes divided by each month's shares outstanding), value as measured by the trailing earnings-to-price ratio (with lagged earnings because of reporting delays) as of the year end, and momentum as measured by the annual return during the selection year (i.e., 12-month momentum). For each variable, we ranked the universe and sorted into quartiles so that each stock within the selection-year portfolio received quartile numbers for turnover, size, value, and momentum.

In each of the performance years (1972–2011), the portfolios selected were equally weighted at the beginning of each year and passively held. Delistings of any kind (e.g., liquidations, mergers) caused the position to be liquidated and held as cash for the remainder of the performance year. We recorded returns at the end of the performance year for each selection-year portfolio so that the portfolios were "identifiable before the fact."

Table 1 reports the long-term annualized geometric mean, arithmetic mean, and standard deviation of returns for each equal-weighted quartile portfolio with respect to liquidity, size, value, and momentum. The annualized geometric mean is the compound annual return realized by the portfolios over the period, which, unlike the arithmetic mean, is not diminished by the variability of the returns. Liquidity appears to differentiate the returns about as well as the other styles.

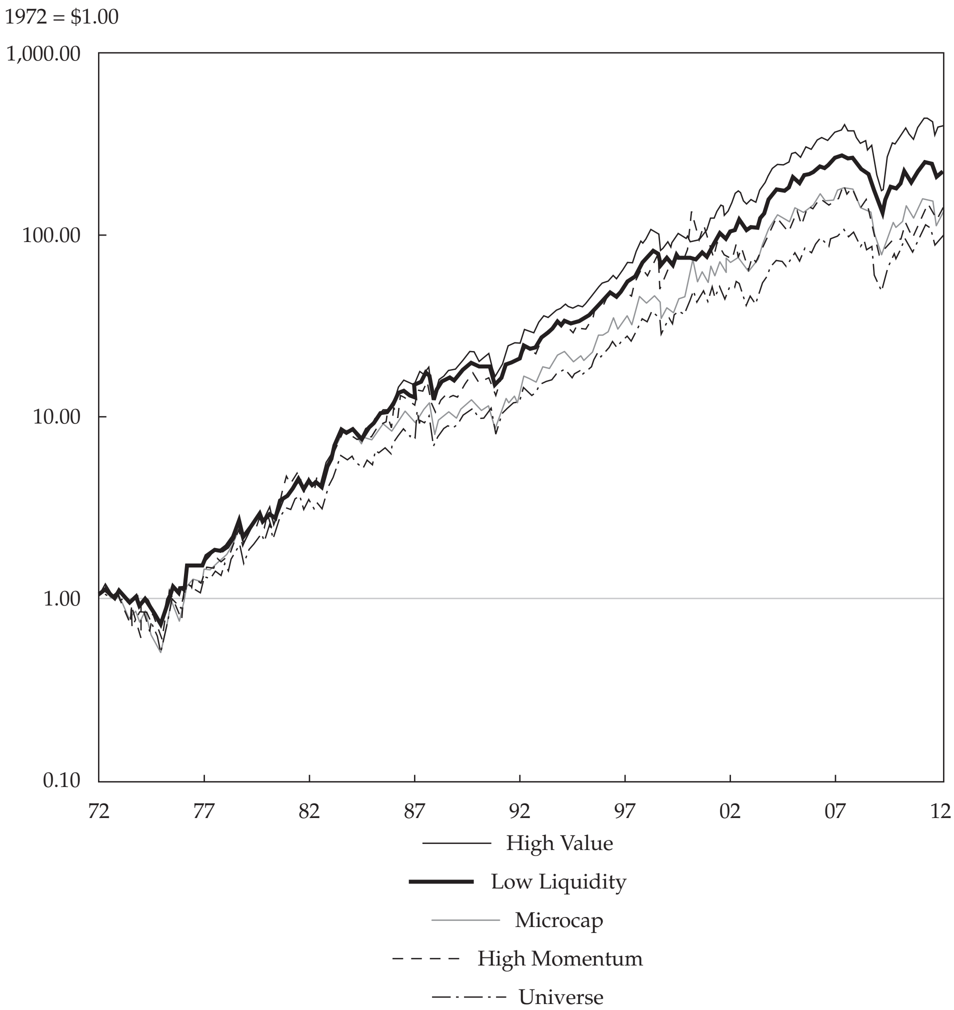
Figure 1 depicts the long-term cumulative returns of the Quartile 1 (Q1) portfolio for each style. The Q1 portfolios for value, liquidity, size, and momentum all outperform the equally weighted universe portfolio. The low-liquidity quartile portfolio

Table 1. Cross-Sectional Style Returns, 1972–2011

Cross Section	Result	Q1	Q2	Q3	Q4
Size					
(Q1 = micro; Q4 = large)	Geometric mean	13.04%	11.93%	11.95%	10.98%
	Arithmetic mean	16.42	14.69	14.14	12.61
	Standard deviation	27.29	24.60	21.82	18.35
Value					
(Q1 = value; Q4 = growth)	Geometric mean	16.13%	13.60%	10.10%	7.62%
	Arithmetic mean	18.59	15.42	12.29	11.56
	Standard deviation	23.31	20.17	21.46	29.42
Momentum					
(Q1 = winners; Q4 = losers)	Geometric mean	12.85%	14.25%	13.26%	7.18%
	Arithmetic mean	15.37	16.03	15.29	11.16
	Standard deviation	23.46	19.79	21.21	29.49
Liquidity					
(Q1 = low; Q4 = high)	Geometric mean	14.50%	13.97%	11.91%	7.24%
	Arithmetic mean	16.38	16.05	14.39	11.04
	Standard deviation	20.41	21.50	23.20	28.48
Universe aggregate	Geometric mean	12.15%			
	Arithmetic mean	14.46			
	Standard deviation	22.39			

Note: Each style quartile portfolio contains an average of 742 stocks a year, or one-fourth of the universe aggregate average of 2,969 stocks a year.

Figure 1. Comparison of Top Style Quartile Portfolios, 1972–2011



clearly outperforms both the microcap portfolio and the high-momentum portfolio, producing returns that are indeed "hard to beat." The strategies presented here are all passive, rebalanced once each year end. Thus, we can characterize all these style portfolios as beta portfolios.

Table 1 shows little evidence that styles are related to risk, at least as measured by standard deviation. For value and momentum, the Q1 portfolio is less risky than the Q4 portfolio. Only size has a clear risk dimension: The smaller the capitalization, the larger the standard deviation. For liquidity, there is an inverse relationship between the returns and risk, with the low-liquidity portfolio having the highest return but the lowest risk. We believe that less liquid portfolios have higher returns in equilibrium—not because they are more risky but, rather, because they have higher transaction costs.

Using differences in returns across the quartiles, we can construct risk factors from any style or characteristic—that is, styles can be presented as either metrics or risk factors. Lou and Sadka (2011) differentiated liquidity levels from liquidity risks. Li, Mooradian, and Zhang (2007) showed that commission costs can also be expressed as either a metric or a risk factor. But the fact that we can make risk factors does not mean there is a payoff for risk; rather, there is a payoff for a factor that fluctuates, which is associated with the underlying characteristic. Indeed, as we have seen, low-liquidity portfolios are not riskier than high-liquidity portfolios.

In equilibrium, a style gives a payoff for taking on a characteristic that the market considers undesirable. For some factors, like size, the payoff may be related to risk. But investors might not like small-size stocks for other reasons as well (e.g., the high trading costs of acquiring big positions). Investors may also dislike value because the companies may be in a distressed state. Growth stocks are more exciting and more in demand because the companies have more potential.

Of all the styles, liquidity has the most obvious connection to valuation. Investors want more liquidity and wish to avoid less liquidity. Less liquidity has a cost—namely, that stocks may take longer to trade and/or have higher transaction costs. In other words, all else being equal, investors will pay more for more liquid stocks and less for less liquid stocks. Fortunately, trading costs can be mitigated by those investors who have longer horizons and do less trading, which translates into higher returns for the less liquid stocks (before trading costs). Later in the article, we consider whether a less liquid stock portfolio can be managed at low cost.

The idea that investors are willing to pay for liquidity is not the same as saying that less liquidity has more risk. Indeed, Table 1 shows that less liquid portfolios have *lower* standard deviations. As we will show later, less liquid portfolios also have low market betas and long–short liquidity factors have negative market betas. It is, of course, possible to imagine less liquid portfolios as risky in a different sense. Such portfolios may involve tail risk or the risk of needing to quickly liquidate positions in a crisis. During the recent financial liquidity crises, however, stock liquidity increased. Furthermore, more passively held portfolios can largely mitigate this risk.

Liquidity vs. Size, Value, and Momentum

In our study, we sought to show that liquidity is "a viable alternative" to the other well-established styles. We focused on distinguishing turnover from size, value, and momentum by constructing double-quartile portfolios that combined liquidity with each of the other styles.

It is often assumed that investing in less liquid stocks is equivalent to investing in small-cap stocks. To determine whether liquidity is effectively a proxy for size, we constructed equally weighted double-sorted portfolios in capitalization and turnover quartiles.

Table 2 reports the annualized geometric mean (compound) return, arithmetic mean return, and standard deviation of returns, as well as the average number of stocks, for each intersection portfolio. Across the microcap quartile, the low-liquidity portfolio earned an annual geometric mean return of 15.36%, in contrast to the high-liquidity portfolio return of 1.32%. Across the large-cap quartile, the low- and high-liquidity portfolios returned 11.53% and 8.37%, respectively, producing a liquidity effect of 3.16 percentage points (pps). Within the two midsize portfolios, the liquidity return spread is also significant. Therefore, size does not capture liquidity (i.e., the liquidity premium holds regardless of size group). Conversely, the size effect does

Table 2. Size and Liquidity Quartile Portfolios, 1972–2011

Quartile	Low Liquidity	Mid-Low Liquidity	Mid-High Liquidity	High Liquidity
Microcap				
Geometric mean	15.36%	16.21%	9.94%	1.32%
Arithmetic mean	17.92%	20.00%	15.40%	6.78%
Standard deviation	23.77%	29.41%	35.34%	34.20%
Average no. of stocks	323	185	132	103
Small cap				
Geometric mean	15.30%	14.09%	11.80%	5.48%
Arithmetic mean	17.07%	16.82%	15.38%	9.89%
Standard deviation	20.15%	24.63%	28.22%	31.21%
Average no. of stocks	196	193	175	179
Midcap				
Geometric mean	13.61%	13.57%	12.24%	7.85%
Arithmetic mean	15.01%	15.34%	14.51%	11.66%
Standard deviation	17.91%	20.10%	22.41%	28.71%
Average no. of stocks	141	171	197	233
Large cap				
Geometric mean	11.53%	11.66%	11.19%	8.37%
Arithmetic mean	12.83%	12.86%	12.81%	11.58%
Standard deviation	16.68%	15.99%	18.34%	25.75%
Average no. of stocks	83	194	238	227

not hold across all liquidity quartiles, especially in the highest-turnover quartile. The liquidity effect, however, is strongest among microcap stocks and declines from micro- to small- to mid- to large-cap stocks. The microcap geometric mean row contains both the highest- and the lowest-return cells in the matrix.

Similarly, to address the question of how the liquidity style differs from value, we constructed equally weighted double-sorted portfolios on turnover and the earnings-to-price ratio (E/P), with the understanding that E/P is highly correlated with the dividend-to-price and book-to-price ratios. We also constructed a liquidity factor and compared it with the Fama–French book-to-market factor (discussed later in the article).

Table 3 reports the annual return results for the 16 value and liquidity portfolios. Among the high-growth stocks, the low-liquidity stock portfolio had an annualized geometric mean (compound) return of 9.99% whereas the high-liquidity stock portfolio had a return of 2.24%. Among the high-value stocks, low-liquidity stocks had an 18.43% return whereas high-turnover stocks had a return of 9.98%. Value and liquidity are distinctly different ways of picking stocks. The best return comes from combining high-value stocks with low-liquidity stocks; the worst return comes from combining high-growth stocks with high-turnover stocks.

Finally, **Table 4** shows the returns from equally weighted double-sorted portfolios for turnover and 12-month momentum quartiles. We ranked momentum stocks by the previous year's returns and placed the winners in Quartile 1 and the losers in Quartile 4. The highest annualized geometric mean (compound) return, 16.03%, was achieved by the high-momentum, low-liquidity stocks; the lowest return, 3.03%, came from the low-momentum, high-liquidity stocks. Again, momentum and liquidity are different stock-picking styles and not merely substitutes for one another.

Because the liquidity style differs from each of the established styles, one might expect to observe a synergistic effect when combining low liquidity with the other styles. This outcome proves to be the case, as illustrated in **Figure 2**, which shows cumulative long-term returns of selected quartile and double-quartile portfolios from Tables 1–4. In all three cases, it is clear that liquidity mixes well with the higher-performing portfolio and adds an incremental return.

Liquidity as a Factor

To further demonstrate that liquidity is "a viable alternative," we can also express liquidity as a factor (i.e., a series of dollar-neutral returns) and attempt to decompose it as a linear combination of the other style factors. Most researchers refer to

Table 3. Value/Growth and Liquidity Quartile Portfolios, 1972–2011

Quartile	Low Liquidity	Mid-Low Liquidity	Mid-High Liquidity	High Liquidity
High value (high E/P)				
Geometric mean	18.43%	16.69%	15.97%	9.98%
Arithmetic mean	20.47%	19.00%	18.72%	13.37%
Standard deviation	21.69%	22.88%	24.75%	26.46%
Average no. of stocks	232	182	172	156
Midvalue				
Geometric mean	14.75%	14.44%	12.67%	11.76%
Arithmetic mean	16.27%	16.07%	14.78%	14.67%
Standard deviation	18.60%	19.38%	21.65%	24.70%
Average no. of stocks	210	204	184	144
Midgrowth				
Geometric mean	12.53%	12.09%	9.96%	6.58%
Arithmetic mean	14.27%	13.93%	12.20%	10.40%
Standard deviation	19.69%	20.15%	21.37%	28.16%
Average no. of stocks	154	183	197	209
High growth (low E/P)				
Geometric mean	9.99%	12.32%	8.39%	2.24%
Arithmetic mean	13.12%	16.08%	12.41%	7.58%
Standard deviation	25.70%	29.00%	29.98%	34.13%
Average no. of stocks	146	173	189	234

Table 4. Momentum and Liquidity Quartile Portfolios, 1972–2011

Quartile	Low Liquidity	Mid-Low Liquidity	Mid-High Liquidity	High Liquidity
High momentum (winners)				
Geometric mean	16.03%	15.18%	12.97%	8.53%
Arithmetic mean	18.08%	17.43%	15.42%	12.41%
Standard deviation	21.08%	22.69%	23.01%	29.33%
Average no. of stocks	146	165	187	244
Mid-high momentum				
Geometric mean	16.02%	15.31%	13.43%	9.05%
Arithmetic mean	17.73%	16.99%	15.33%	12.15%
Standard deviation	19.53%	19.52%	20.39%	25.56%
Average no. of stocks	215	205	186	137
Mid-low momentum				
Geometric mean	14.61%	14.65%	12.85%	7.97%
Arithmetic mean	16.51%	16.50%	15.03%	11.45%
Standard deviation	20.84%	20.50%	22.07%	27.08%
Average no. of stocks	225	206	181	131
Low momentum (losers)				
Geometric mean	10.30%	9.62%	7.52%	3.03%
Arithmetic mean	13.24%	13.63%	11.87%	7.76%
Standard deviation	25.57%	30.07%	31.40%	32.18%
Average no. of stocks	156	166	189	230

these series as risk factors, although we regard the "risk" label as somewhat unsatisfactory because our results show that less liquid stock portfolios appear to be less risky than more liquid portfolios—when measured by either standard deviation or market beta. To some extent, this decoupling between factors and risk may also apply to some of the other style factors.[5] Nevertheless, it is mechanically possible to recast liquidity into a factor framework, which we did in our study in order to further our case for establishing liquidity as a fourth investment style.

We constructed monthly returns of a long–short portfolio in which the returns of the most liquid quartile were subtracted from the returns of the least liquid quartile. This series constituted a dollar-neutral liquidity factor, which we regressed on the (extended) framework of the capital asset pricing model (CAPM) by using dollar-neutral factors for market, size, value,[6] and momentum obtained from Kenneth R. French's website.[7]

In the CAPM framework, the liquidity long–short (dollar-neutral) factor is regressed on the excess returns of the market portfolio:

$$R_{it} = \alpha + \beta_{iM}\left(R_{Mt} - R_{ft}\right) + \varepsilon_{it}. \tag{1}$$

In the standard Fama–French three-factor model, the long–short liquidity factor is regressed on the long market portfolio and the long–short size and value portfolios:

$$\begin{aligned} R_{it} &= \alpha + \beta_{iM}\left(R_{Mt} - R_{ft}\right) + S_i\text{SMB} \\ &\quad + h_i\text{HML} + \varepsilon_{it}. \end{aligned} \tag{2}$$

Finally, we regressed on a four-factor model that also included the momentum factor:

$$\begin{aligned} R_{it} &= \alpha + \beta_{iM}\left(R_{Mt} - R_{ft}\right) + S_i\text{SMB} \\ &\quad + h_i\text{HML} + m_i\text{WML} + \varepsilon_{it}. \end{aligned} \tag{3}$$

We performed a similar analysis with the long-only portfolios by regressing the least liquid quartile portfolio less the risk-free rate from T-bills on the CAPM:

$$R_{it} - R_{ft} = \alpha + \beta_{iM}\left(R_{Mt} - R_{ft}\right) + \varepsilon_{it}. \tag{4}$$

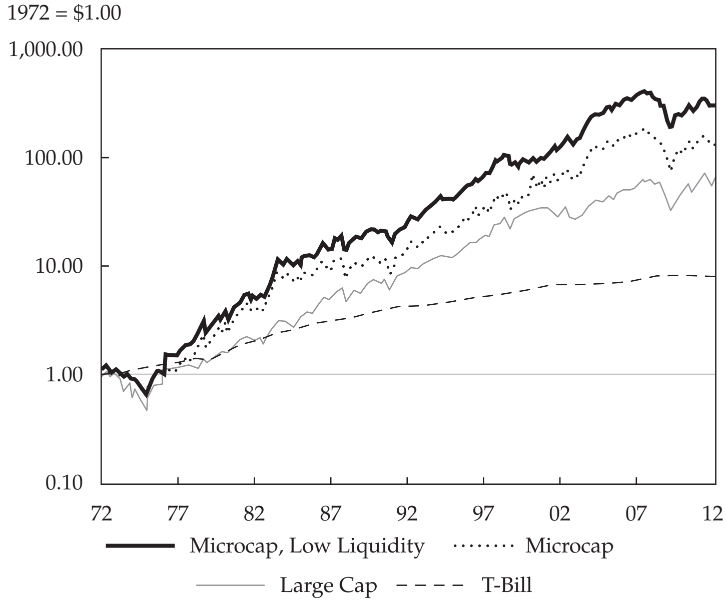
We conducted the Fama–French and four-factor regressions on the long-only portfolios less the risk-free rate similarly to Equation 2 and Equation 3. (Note that it is unnecessary to subtract the risk-free rate from the size, value, and momentum factors because they contain zero net positions.)

Table 5 reports the results. In the CAPM variant, the long–short liquidity factors are negatively associated with the market (beta = –0.66). The low-liquidity long portfolio has a low beta, 0.75. In both cases, the monthly alpha is very positive and significant.

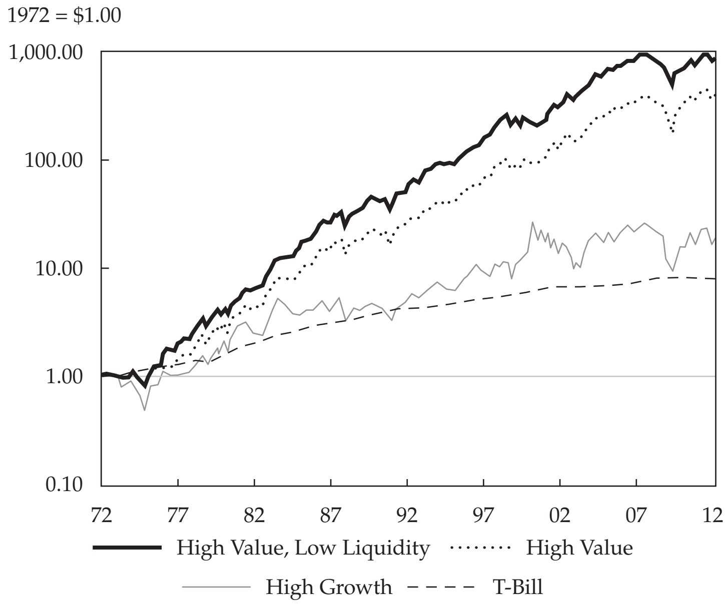
After including the size and value factors in the regression, we can see that the liquidity factor is negatively related to size but positively related to value. The liquidity factor is also positively related to momentum in the four-factor model. But after

Figure 2. Cumulative Investment Returns for Intersection Portfolios, 1972–2011

A. Liquidity- and Market-Cap-Related Portfolios



B. Liquidity- and Value/Growth-Related Portfolios



(continued)

adjusting for the market, size, and value factors in the Fama–French model or after adding momentum in the four-factor model, we can see that the less liquid alpha is still positive and significant.

Similarly, for the low-liquidity long portfolio, there is a positive and statistically significant alpha for the CAPM, Fama–French, and four-factor equations. This positive alpha exists even after adjusting for the market, size, value, and momentum factors.

We interpret the positive and significant monthly alphas for the long–short factor and the less liquid long portfolios as further evidence that less liquid portfolios are "not easily beaten." An efficient portfolio should not have a significant alpha intercept left over; therefore, the size, value, and momentum styles together cannot completely describe the set of betas needed to put together an efficient portfolio.

The links between the liquidity long–short factor and the market, size, value, and momentum factors are also seen in the cross-correlations shown in **Table 6**. The liquidity factor has the largest negative

Figure 2. Cumulative Investment Returns for Intersection Portfolios, 1972–2011 (continued)

C. Liquidity- and Momentum-Related Portfolios

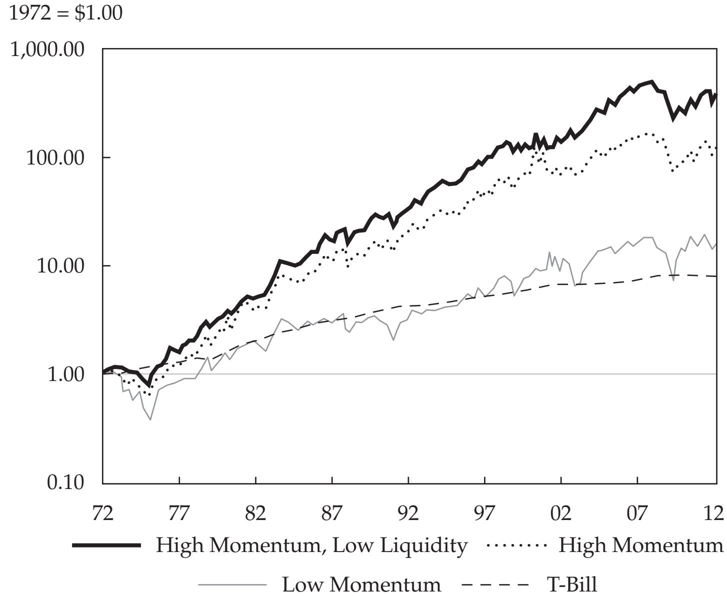


Table 5. Regression Analyses of Dollar-Neutral Liquidity Factor and Low-Liquidity Long Portfolios, 1972–2011
(*t*-statistics in parentheses)

	Monthly Alpha (%)	Market Beta	Size	Value	Momentum	Adjusted R^2 (%)	*N*
Liquidity factor							
CAPM	0.66	–0.66				48.0	480
	(4.52)	(–21.06)					
Fama–French	0.44	–0.47	–0.39	0.54		70.4	480
	(3.93)	(–18.55)	(–10.53)	(14.05)			
Four factor	0.31	–0.45	–0.39	0.58	0.14	72.2	480
	(2.80)	(–17.66)	(–10.87)	(15.33)	(5.54)		
Low-liquidity long							
CAPM	0.45	0.75				67.4	480
	(3.97)	(31.47)					
Fama–French	0.16	0.73	0.56	0.44		88.2	480
	(2.41)	(47.32)	(24.98)	(18.63)			
Four factor	0.16	0.74	0.56	0.44	0.00	88.2	480
	(2.30)	(46.40)	(24.95)	(18.24)	(0.25)		

Table 6. Pearson Correlations of Monthly Liquidity Factor Returns with Other Factors, 1972–2011

Variable	Liquidity Factor (all)	Market	Size	Value	Momentum
Liquidity factor	1	–0.694	–0.503	0.594	0.139
Market	–0.694	1	0.281	–0.316	–0.137
Size	–0.503	0.281	1	–0.233	–0.005
Value	0.594	–0.316	–0.233	1	–0.160
Momentum	0.139	–0.137	–0.005	–0.160	1

correlations with the market and size factors and a substantial positive correlation with value. Value and size are negatively correlated with each other. None of the other factors are as strongly negatively related to the market factor as is the liquidity factor.

Table 7 shows the results from regressing the combined-style long (net of the risk-free rate) portfolios (i.e., the northwest corner portfolios of Tables 2–4) on the CAPM, Fama–French, and four-factor models. These portfolios all correlate with the market but have low betas. Again, they are related to the size and value portfolios but are no longer positively related to the momentum factor—except, of course, for the high-momentum portfolio. In all but two borderline cases, the monthly alphas are significant at the 5% level.

We constructed a liquidity factor that the size, value, and momentum factors did not fully explain because there was a significant alpha left over in almost every regression. Previous studies have established that the liquidity premium is not captured by the four-factor model, but the results in Table 7 go a step further in showing that the four-factor model does not explain the returns from the three liquidity combined-style portfolios.

Much of the liquidity literature uses stock sensitivity to a liquidity factor instead of measuring the impact of the characteristic itself. We used the methodology of Daniel and Titman (1998) to examine whether the turnover of a stock (characteristic) or the sensitivity to the turnover factor (covariance) has a larger impact on a stock's performance.

Table 8 contrasts characteristic versus covariance liquidity metrics by using double-sorted portfolio returns. The characteristic cross section (table columns) is based on ranked turnover rates from the selection year, just as in Tables 2–4. To obtain the covariance cross section (table rows), we regressed the 12-month returns of each stock (less market universe returns) on a modified turnover factor that uses only selection-year returns. In this regression, we used a shorter-than-ideal 12-month return period in order to be consistent with the time period of the characteristic metric, annual share turnover. By independently

Table 7. Regression Analyses of Enhanced Liquidity Portfolios, 1972–2011 (*t*-statistics in parentheses)

	Monthly Alpha (%)	Market Beta	Size	Value	Momentum	Adjusted R^2 (%)	*N*
Microcap, low liquidity							
CAPM	0.54	0.75				51.0	480
	(3.41)	(22.34)					
Fama–French	0.21	0.70	0.78	0.47		78.2	480
	(2.00)	(28.85)	(22.57)	(12.99)			
Four factor	0.20	0.70	0.78	0.48	0.01	78.2	480
	(1.85)	(28.36)	(22.55)	(12.78)	(0.46)		
High value, low liquidity							
CAPM	0.75	0.71				56.5	480
	(5.66)	(24.94)					
Fama–French	0.41	0.72	0.56	0.57		81.3	480
	(4.59)	(35.73)	(19.63)	(18.87)			
Four factor	0.44	0.71	0.56	0.56	–0.04	81.4	480
	(4.88)	(34.77)	(19.68)	(18.09)	(–1.81)		
High momentum, low liquidity							
CAPM	0.55	0.84				61.2	480
	(3.85)	(27.53)					
Fama–French	0.36	0.74	0.74	0.21		81.5	480
	(3.60)	(32.44)	(22.74)	(6.02)			
Four factor	0.14	0.79	0.74	0.29	0.24	85.7	480
	(1.52)	(38.58)	(25.89)	(9.25)	(11.94)		

Table 8. Characteristic vs. Covariance Liquidity Metrics, 1972–2011

Quartile	Low Liquidity	Mid-Low Liquidity	Mid-High Liquidity	High Liquidity
High β_{LMH} (correlates with low liquidity)				
Geometric mean	13.44%	13.05%	12.21%	**6.43%**
Arithmetic mean	15.24%	14.91%	14.12%	**9.09%**
Standard deviation	20.28%	20.63%	20.77%	**23.54%**
Average no. of stocks	293	204	146	**99**
Mid-high β_{LMH}				
Geometric mean	15.18%	13.94%	12.71%	9.95%
Arithmetic mean	17.03%	15.61%	14.74%	12.62%
Standard deviation	20.29%	19.22%	21.13%	24.27%
Average no. of stocks	232	215	184	112
Mid-low β_{LMH}				
Geometric mean	15.12%	14.65%	12.39%	8.89%
Arithmetic mean	17.42%	16.95%	14.81%	12.06%
Standard deviation	22.07%	22.66%	22.82%	25.72%
Average no. of stocks	147	194	217	185
Low β_{LMH} (correlates with high liquidity)				
Geometric mean	**13.49%**	13.40%	9.30%	5.10%
Arithmetic mean	**16.98%**	17.58%	13.67%	10.52%
Standard deviation	**29.32%**	31.02%	31.23%	34.33%
Average no. of stocks	**70**	130	195	347

Notes: Our liquidity factor (LMH) is the dollar-neutral return series of the liquidity long–short portfolio (i.e., low-liquidity quartile minus high-liquidity quartile). The off-diagonal returns (in bold) reveal the relative importance of characteristics versus covariances.

assigning liquidity and liquidity-beta quartiles to each stock, we obtained the intersection portfolios shown in Table 8. The returns vary strongly and directionally across columns (characteristic) but vary weakly and nondependently across rows (covariance), thus supporting the hypothesis that liquidity characteristics have greater explanatory power for returns.

Because most high-turnover (low-turnover) stocks exhibit selection-year return patterns that correlate with those of the high-liquidity (low-liquidity) quartile, the stocks tend to cluster in the diagonal portfolios. However, as Daniel and Titman (1998) observed, the off-diagonal portfolios illustrate the relative importance of characteristics versus covariances. **Figure 3** shows longitudinal returns from the two extreme off-diagonal portfolios of Table 8. Low-turnover stocks that exhibit high-turnover return patterns during the selection year outperform high-turnover stocks that exhibit low-turnover return patterns.

In summary, we found that despite the success of our liquidity factor, the data support a liquidity-characteristic model of stock returns as opposed to a liquidity-covariance model. Our results concur with those of Daniel and Titman (1998), who showed similar results for the value/growth style.

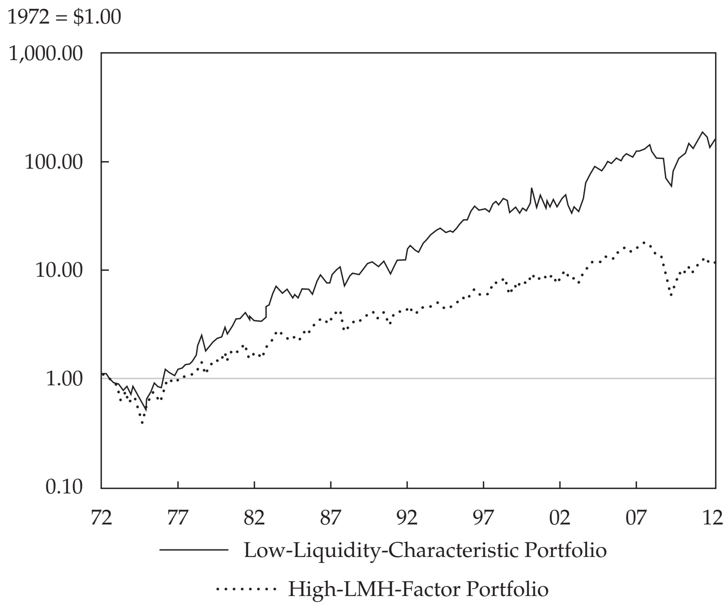
Liquidity Stability and Migration

The remaining investment style criterion is that the style be "low in cost." In our study, we sought to meet this criterion by showing that the liquidity portfolios can be managed relatively passively. Our previous double-sorted results suggested that our portfolios are stable; the rebalancing frequency is only once a year. We next examined directly the migration of stocks in the liquidity portfolios, which would also help explain why investing in less liquid stocks pays extra returns.

Panel A of **Table 9** shows how the stocks in each liquidity quartile (in the selection year) migrate to other liquidity quartiles (in the performance year). For the lowest-liquidity quartile, 77.28% remained in the quartile the following year and 22.72% migrated to higher-liquidity quartiles. Overall, 62.93% of the stocks remained in the same liquidity quartile from the selection year to the subsequent performance year.

Panels B, C, and D of Table 9 show the corresponding year-to-year migration of stocks among size, value, and momentum quartiles. The fractions of stocks in these quartile portfolios that remained in the same quartile for the subsequent year are 78.73% for size, 51.63% for value, and 29.03% for

Figure 3. Characteristics (Solid) vs. Covariances (Dotted), 1972–2011



Note: This figure depicts the historical returns of the southwest (solid) and northeast (dotted) portfolios of Table 8.

momentum. Therefore, liquidity is observed to be significantly more stable than 12-month momentum as a basis for portfolio formation and is comparably stable with respect to the well-accepted styles of size and value.

That liquidity is observed to be a relatively stable characteristic of stocks has two implications in the Sharpe style framework. First, it further reinforces the notion that a liquidity-based portfolio is "identifiable before the fact." Second, it implies that the transactions associated with maintaining a liquidity-based portfolio are "low in cost." Indeed, Idzorek, Xiong, and Ibbotson (2012) analyzed U.S. equity mutual fund holdings and confirmed that the liquidity premium remains economically and statistically significant net of trading and all other costs.

Table 10 reports the mean arithmetic returns from our stock universe by liquidity migration. The evidence shows that as less liquid stocks become more liquid, their returns increase dramatically. Conversely, as more liquid stocks become less liquid, their returns drop. Fama and French (2007) observed similarly striking effects for stocks that migrate in size and value. Because migration is not known *a priori*, separation of the return components listed in each row is also not possible *a priori*. Nevertheless, these results demonstrate that changes in liquidity strongly correlate with changes in valuation.

Conclusion

William F. Sharpe (1992) provided four criteria to identify an investment style. We believe that liquidity, as measured by stock turnover, meets these criteria.

First, the previous year's stock turnover is "identifiable before the fact." Other liquidity measures could have met that criterion as well, but we chose turnover because it is simple and easy to measure and has a significant impact on returns.

When we compared the Quartile 1 returns of the various styles, they all outperformed the equally weighted market portfolio. The returns of the low-liquidity quartile were comparable to those of the other styles, beating size and momentum but trailing value. We consider all four styles to be "not easily beaten."

We examined double-sorted portfolios, comparing liquidity with size, value, and momentum in four-by-four matrices. The impact of liquidity on returns was somewhat stronger than that of size and momentum and roughly comparable to that of value. It was also additive to each style. Thus, we determined that liquidity is "a viable alternative" to size, value, and momentum.

We also constructed a liquidity factor by subtracting the Quartile 4 return series from that of Quartile 1. This factor added significant alpha to all the Fama–French factors when expressed either as a factor or as a low-liquidity long portfolio. The existence of the significant positive alpha

Table 9. Migration of Stocks' Style Quartiles One Year after Portfolio Formation, 1972–2011

	Year $t+1$ Liquidity			
	1 (low)	2	3	4 (high)
A. Liquidity migration (62.93% stay in the same quartile)				
Year t Liquidity				
1 (low)	**77.28%**	18.06%	3.54%	1.11%
2	18.80	**53.11**	22.29	5.80
3	2.96	24.26	**49.99**	22.79
4 (high)	0.77	4.19	23.70	**71.33**
	Year $t+1$ Market Cap			
B. Size migration (78.73% stay in the same quartile)				
Year t Market Cap				
1 (micro)	**83.46%**	15.65%	0.87%	0.02%
2	19.85	**64.75**	15.19	0.21
3	1.20	13.89	**74.66**	10.25
4 (large)	0.07	0.22	7.67	**92.03**
	Year $t+1$ Value			
C. Value migration (51.63% stay in the same quartile)				
Year t Value				
1 (low)	**65.22%**	18.46%	7.55%	8.77%
2	21.01	**44.47**	23.85	10.68
3	9.92	23.07	**43.41**	23.61
4 (high)	12.73	10.75	23.09	**53.43**
	Year $t+1$ Momentum			
D. Momentum migration (29.03% stay in the same quartile)				
Year t Momentum				
1 (low)	**37.29%**	21.49%	19.63%	21.60%
2	23.97	**27.20**	28.01	20.82
3	22.35	27.86	**28.23**	21.56
4 (high)	30.73	23.50	22.36	**23.42**

Note: All rows sum (within rounding error) to 100%.

Table 10. Returns Associated with Migration in Liquidity Quartiles, 1972–2011

	Year $t+1$ Liquidity			
Year t Liquidity	1 (low)	2	3	4 (high)
1 (low)	**9.81%**	24.32%	60.98%	109.43%
2	2.55	**10.87**	23.17	65.36
3	–6.55	2.70	**12.18**	29.45
4 (high)	–5.89	–11.19	1.22	**14.41**

Note: This table reports the arithmetic mean annual returns by liquidity migration (as in Panel A of Table 9).

further confirmed that investors need to include liquidity with the other styles to form efficient portfolios.

Finally, we demonstrated that less liquid portfolios could be formed "at low cost." Our portfolios were formed only once a year, and 62.93% of the stocks stayed in the same quartile. The high-performing low-liquidity quartile had 77.28% of the stocks stay in that quartile. Thus, liquidity portfolios themselves exhibit low turnover, which can keep their costs low.

Liquidity has perhaps the most straightforward explanation as to why it deserves to be a style. Investors clearly want more liquidity and are willing to pay for it in all asset classes, including stocks. Less liquidity comes with costs: It takes longer to trade less liquid stocks, and the transaction costs tend to be higher. In equilibrium, these costs must be compensated by less liquid stocks earning higher gross returns. The liquidity style rewards the investor who has longer horizons and is willing to trade less frequently.

As with less liquidity, in equilibrium, investors may wish to avoid—and demand to be compensated for holding—small stocks, value stocks, and high-momentum stocks. But in many of these cases, the underlying rationale is less clear. Small stocks are more risky, but high-value stocks are not necessarily more risky than growth stocks. High-momentum stocks appear to be less risky than low-momentum stocks. These styles are often presented as risk premiums, but we are more convinced by the idea that the styles embody characteristics (other than or in addition to risk) that the market seeks to avoid.

Using the simple stock-level characteristic of turnover, we have shown that liquidity is "identifiable before the fact." Through both single- and double-style portfolio returns, we have shown that liquidity is "not easily beaten." Our regression and covariance results show that liquidity is "a viable alternative." Our results also show that liquidity may be managed "low in cost" by using a low-portfolio-turnover strategy. In conclusion, we have demonstrated that liquidity meets all four of Sharpe's criteria for a benchmark style.

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This article qualifies for 1 CE credit.

Appendix A. Data and Methodology

We measured U.S. stock returns over 1972–2011. We collected our sample—consisting of companies listed on the NYSE, Amex, and NASDAQ—from the CRSP and Capital IQ Compustat databases, accessed via Wharton Research Data Services. We formed portfolios at the end of December of each selection year (1971–2010) using the following filters: (1) We excluded all REITs, warrants, American Depositary Receipts, exchange-traded funds, Americus Trust components, and closed-end funds; (2) a stock had to have available information on trading volume, monthly total returns, earnings, number of shares outstanding, and stock price for all 12 months of the selection year; and (3) the year-end share price had to be at least $2, and the market capitalization had to rank within the largest 3,500 for the year *and* exceed $5 million.

To ensure a sufficient stock universe for our analyses, we chose to focus on the period January 1972–December 2011, which covers the oil crisis of 1973, the resulting bear market of the mid-1970s, the bull markets of the 1980s and 1990s, and the two recessions of the current century.

Table A1 reports summary statistics for our universe, including the number of stocks and the largest, average, median, and minimum market capitalizations for each year. The years listed in Table A1 lag the performance periods by one year because we based our portfolio selections on prior-year (selection-year) metrics.

We measured the annual turnover of each stock by summing the 12 monthly turnovers, defined as the trading volume divided by shares outstanding. For purposes of style comparisons, we measured the capitalization of each stock at year end. Earnings data were taken from the CRSP/Compustat merged database. We calculated earnings-to-price ratios for each company as the EPS divided by the year-end price. Specifically, we used the four most recent quarters (or the two most recent semiannual periods) of EPS, with the most recent quarter ending two months prior to the portfolio formation date. This approach avoids forward-looking bias because companies usually take several weeks to report their quarterly earnings after the end of the quarter. We measured momentum from the prior year's return. After constructing the portfolios from selection-year metrics, we measured returns in the subsequent performance year.

For NASDAQ stocks, we divided all reported trading volumes by a factor to counter the relative overreporting of volume on that exchange. This factor was our weighted average of the correction factors from Anderson and Dyl (2005), based on a comparison of trading volumes of companies that switched from NASDAQ to the NYSE. We applied this correction factor for NASDAQ volume data throughout the period covered by this analysis because Anderson and Dyl (2007) found no evidence that the relative overreporting of NASDAQ volumes lessened in 2003–2005 relative to 1990–1996, despite the regulatory and technological changes that took place at NASDAQ in the early 2000s.

We created a liquidity factor by selecting our lowest-liquidity quartile returns and then subtracting our highest-liquidity quartile returns. We compared our liquidity long–short factor with the factors on Kenneth R. French's website. Those factors include a market return that is the CRSP capitalization-weighted average return of NYSE, Amex, and NASDAQ stocks; a risk-free rate that is the Ibbotson Associates one-month U.S. Treasury bill rate; and the three Fama–French long–short zero net exposure size, value/growth, and momentum portfolios.

Table A1. Summary Statistics of Stock Universe by Year

		Market Capitalization ($ millions)			
Selection Year	No. of Stocks	Mean	Median	Maximum	Minimum
1971	1,733	385	70	38,696	5.0
1972	1,875	432	70	46,701	5.0
1973	1,761	374	53	35,832	5.0
1974	1,611	289	47	24,979	5.0
1975	1,816	350	54	33,289	5.0
1976	1,770	443	78	41,999	5.0
1977	1,906	387	74	40,333	5.0
1978	1,894	404	82	43,524	5.0
1979	1,894	471	107	37,569	5.0
1980	1,867	610	135	39,626	5.0
1981	1,834	574	132	47,888	5.1
1982	1,848	655	146	57,982	5.2
1983	3,478	472	80	74,508	5.0
1984	3,500	444	75	75,437	5.8
1985	3,500	566	88	95,607	5.9
1986	3,500	632	83	72,711	5.3
1987	3,500	626	72	69,815	5.2
1988	3,500	687	85	72,165	6.6
1989	3,447	850	94	62,582	5.0
1990	3,105	856	95	64,529	5.0
1991	3,398	1,046	121	75,653	5.0
1992	3,500	1,119	146	75,884	12.1
1993	3,500	1,262	204	89,452	26.8
1994	3,500	1,271	230	87,193	44.3
1995	3,500	1,709	305	120,260	62.9
1996	3,500	2,080	383	162,790	77.4
1997	3,500	2,734	478	240,136	101.6
1998	3,500	3,405	427	342,558	81.0
1999	3,500	4,169	451	602,433	76.6
2000	3,500	3,920	401	475,003	48.2
2001	3,500	3,465	435	398,105	55.5
2002	3,500	2,720	323	276,631	35.7
2003	3,500	3,615	516	311,066	64.3
2004	3,500	3,965	614	385,883	66.4
2005	3,500	4,144	623	370,344	66.3
2006	3,500	4,566	669	446,944	76.3
2007	3,500	4,616	552	511,887	45.4
2008	3,228	3,013	375	406,067	5.0
2009	3,418	3,631	449	322,668	5.5
2010	3,386	4,212	564	368,712	5.2
Whole sample	118,769	2,004	223	602,433	5.0

Notes

1. We quote Sharpe's original language for the criteria but reorder them here. In conversations, Sharpe does not claim to have invented the concept of style because others were using the same terminology during the 1980s.
2. We do not take a position here as to whether momentum is truly a style in the Sharpe framework. However, given that it is often included as a control in studies of the cross section of returns, we treated momentum as a style in our study in order to more thoroughly test liquidity as an independent style.
3. For a review of the liquidity literature, see Amihud, Mendelson, and Pedersen (2005).

4. According to Subrahmanyam (2010, p. 37), "In general, most studies use size, book/market, and momentum as controls, but it is quite rare for liquidity controls to be used."
5. An examination of the Fama–French value and momentum decile portfolios over 1972–2011 reveals that the risk profile of both factors is U-shaped; middle portfolios exhibit the least risk and extreme portfolios are higher risk. Only size has a clear risk dimension, with small-cap stocks being riskier than large-cap stocks.
6. The Fama–French value factor is based on the book-to-market ratio instead of the earnings-to-price ratio that we used earlier in the article. Although we take no position as to which method is better for forming value/growth portfolios, here we use the more commonly used Fama–French factors.
7. We used Kenneth French's labels for the following factors: SMB (small minus big) for size, HML (high minus low book-to-market ratio) for value, and WML (winners minus losers) for momentum; see http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

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