FINANCIAL SCIENCES NAUKI O FINANSACH ISSN 2080-5993
Year 2021, vol. 26, no. 2 e-ISSN 2449-9811

LIQUIDITY RISK AND HEDGE FUND PERFORMANCE EVALUATION

Richard Van Horne
Poznan University of Economics and Business, Poznan, Poland
e-mail: richard.vanhorne@ue.poznan.pl
ORCID: 0000-0002-4648-9601

Quote as: Van Horne, R. (2021). Liquidity risk and hedge fund performance evaluation. *Financial Sciences*, *26*(2).

DOI: 10.15611/fins.2021.2.06
JEL Classification: G12, G23, C38

Abstract: In this article the author uses two models, a lagged-effects model and a serial correlation model, which identify potential liquidity risk in hedge fund portfolios. From the serial correlation model a liquidity risk factor was developed and added to a multi-factor equilibrium model in order to re-estimate Alpha across a universe of hedge funds. It was found that much of what passes for fund Alpha in a multi-factor risk model lacking a liquidity risk factor is actually a compensation for bearing liquidity risk in the context of a model that includes the innovative liquidity risk factor. This result has implications for both a pre-investment due diligence and a manager selection as well as the post-investment fund performance evaluation and risk management.

Keywords: liquidity risk, liquidity factor, alpha ratio, hedge fund performance.

1. Introduction

Jensen's Alpha (Jensen, 1968) is a prominent measure of reward-adjusted-for-risk used in the world of hedge funds. Alpha is typically defined as the estimated intercept in a regression-based equilibrium model. Multi-risk-factor equilibrium models enjoy widespread acceptance in the literature and in industry for fund performance evaluation, including the estimation of fund Alpha. In mutual fund evaluation, examples of models in common use are the Fama-French 3 or 5-factor (Fama & French, 1993, 2015) and the Carhart 4-factor (Carhart, 1997) models. Researchers in hedge funds often explore fund characteristics and estimate Alpha using a Fung and Hsieh 7-factor model (Fung & Hsieh, 2004), or a model related to it (Fung & Hsieh, 2007). All these widely-used models are similar in one respect: they do not take liquidity risk into account, and yet they should, especially after the Global Financial

Crisis. This crisis showed that sustaining liquidity is crucial for financial stability (Mishra, Parikh & Spahr, 2020), however it also demonstrated that timing liquidity is essential for explaining hedge fund returns (Cao, Chen, Liang, & Lo, 2013; Li, Li & Tee, 2020; Luo, Tee & Li, 2017).

In this study the author devised his own equilibrium model, based on Fung and Hsieh (2004), and a liquidity risk factor, with the aim of providing researchers and practitioners with an additional analytical tool that can be used to estimate the compensation for bearing liquidity risk. as well as to more accurately estimate fund Alpha. The base model is a 7-factor model, to which the author added the liquidity risk factor to form an 8-factor model. Alphas were then estimated for every fund in the universe of 542 hedge funds with monthly returns for the 2005 through 2016 period, using both the 7-factor model and the 8-factor model. It was found that a healthy portion of what appears to be "Alpha" for certain funds under a 7-factor equilibrium model that does not account for liquidity risk, may in fact be compensation for bearing liquidity risk when estimating Alpha using the more complete 8-factor model. The study also investigated other approaches to adjusting fund Alpha for liquidity risk. The author found that the liquidity risk factor provides deeper insights than the other approaches into the risk and performance characteristics in the universe of the hedge funds for the time period under study. Both the models proposed and the findings obtained in this study contribute to the literature and to the evaluation of fund performance.

The report on this research is organised as follows: Section 2 reviews the literature; Section 3 presents the data; Section 4 describes the methods, including the author's model and liquidity risk factor; Section 5 presents the findings; and Section 6 concludes, providing some ideas for future research.

2. Literature review

The hedge fund literature includes research on the problem of illiquidity, as well as smoothing (which may be related to illiquidity), in hedge fund portfolios.

Asness, Krail, and Liew (2001) address the title question "Do Hedge Funds Hedge?". They warn against reliance on contemporaneous monthly data, finding that a hedge fund's market exposure is better measured over a period of three or four months, utilizing a lagged effects model. They find heightened market exposure, and hence less evidence of hedging, in hedge fund strategies where latent effects are present. In particular, they point to over-the-counter securities or less frequently traded exchange-listed securities in hedge fund portfolios as the source of the "non-synchronous price reactions." Their method can detect the presence of stale prices, which can be a proxy for fund illiquidity. One could use their lagged effects approach as a method to identify potential fund illiquidity, and use their lagged Beta as a measure to proxy liquidity risk.

Lo (2002) focuses on both the numerator (i.e. returns) and the denominator (i.e. standard deviation) in pointing out the flaws in the Sharpe ratio. With regard to liquidity risk in particular, Lo (2002) argues that the standard deviation as a measure of risk is understated for funds with illiquid exposures. The study proposes a method for adjusting a fund's Sharpe ratios, based on the fund's exposure to illiquid investments, where the fund's correlation to its own one-month lagged returns proxies the liquidity risk.

Getmansky, Lo, and Makarov (2004) take this analysis further, proposing an AR(1) serial correlation model to measure a fund's liquidity risk. The theoretical underpinning is the idea that, in efficient markets, information spreads quickly and returns should be serially uncorrelated. In cases where the securities cannot be traded quickly, cannot be traded in suitable volume, or cannot be traded without large price impact, in other words, in illiquid or inefficient markets, returns may be serially autocorrelated. Hence, the presence of serial autocorrelation can be taken as a sign of smoothing and/or fund illiquidity, and as a proxy for liquidity risk. The authors also offer a methodology for modifying the Sharpe ratio to incorporate liquidity risk.

The presence of serial correlation and lags in hedge fund returns can be caused by various factors, as explained by Getmansky et al. (2004) and Asness et al. (2001), including: a) the fund investment strategy and nature of assets in the fund; b) the method of month-end pricing; and c) the deliberate 'smoothing' of returns by the fund manager.

One factor is the investment strategy and the nature of the assets. Large cap equity funds should have low levels of serial correlation. Large cap stocks are liquid; the price at month-end does not have much to do with the price at the end of the previous month. With small cap stocks, one should expect slightly higher serial correlation and lagged effects. Small cap stocks do not trade as actively as large cap stocks, so the stock's price at a month-end may be influenced by or related to the stock's price at the previous month-end. Hedge fund strategies such as distressed debt may have higher levels of serial correlation and lagged effects than strategies based on liquid equities. Distressed debt may not trade every day, so the freshest price discovery may not necessarily be at month-end, and the pricing can be even more 'sticky' than in the case of small cap stocks.

A second factor that can cause serial correlation and lagged effects in hedge fund returns is the method of pricing the portfolio at month-end (which is associated to some extent with the investment strategy and the nature of the assets mentioned in the preceding paragraph). Large cap stocks are easy to price – just take the last traded price from the stock exchange. In the case of pricing small cap stocks, one still takes the last traded price from the exchange, but the trading is less frequent, so the price may be a bit stale. The pricing may be sticky compared to the pricing of large cap stocks, so one may expect to see higher levels of serial correlation. In the case of distressed debt, month-end broker quotes may be based on modelling (e.g. spreads to Treasuries, or EV and EBITDA multiples) rather than on actual market transactions.

This will lead to a month-end price being somewhat related to the previous month-end price, and to a higher measure of serial correlation.

A third factor that can cause serial correlation and lagged effects is the deliberate smoothing of the returns, which one can think of as a form of manager dishonesty or fraud. A manager might be tempted to smooth the returns in order to turn a negative performance month into a positive performance month[1] or to reduce the fund's standard deviation, thereby increasing the fund's Sharpe ratio. Many hedge funds employ third party service providers for pricing, thus taking the month-end portfolio pricing exercise out of the hands of the manager.[2] In the case of SEC-registered mutual funds, the regulatory regime makes it much less likely that mutual fund management could engage in smoothing.

Therefore, the use of the serial correlation and lagged effects models can serve two purposes. First, as tools in manager evaluation and risk-reward measurement; one should get out of the habit of looking primarily at a fund's standard deviation as the measure of risk and at a fund's Sharpe ratio as a measure of fund performance, without also looking at the fund's serial correlation and lagged effects measures. Serial correlation indicates risk, for which investors should demand to be paid. In the presence of high serial correlation, the standard deviation is not a true or complete measure of risk or volatility (or potential volatility). Funds in strategies that tend to have high serial correlation – such as distressed debt, micro-cap stocks, PIPES, or fixed income arbitrage – have a greater risk of dislocation and of a large negative performance surprise. In short, for these types of funds, the standard deviation understates the actual risk, and the Sharpe ratio overstates the reward-for-risk tradeoff. Similarly, for these types of funds, the lagged effects model gives us a better understanding of the fund's real sensitivity to the market or benchmark. To the extent the real market exposure is higher, then the measure of manager value added (i.e. the intercept in the regression or the manager Alpha) must necessarily be lower, as will be the real diversification benefit derived from including the fund in the portfolio.

These models can also serve a second purpose, namely as tools in the liquidity risk measurement of the funds. The main factors giving rise to higher readings for

---

[1] This 'smoothing' of returns can lead to fund standard deviation being understated, as well as manipulation of metrics that treat negative returns differently than positive returns, such as up capture/down capture, asymmetry ratios, downside deviation, Sortino ratio, etc. Bollen and Pool (2009) create a histogram of monthly hedge fund returns for 1994 to 2005. They find a discontinuity in the distribution of monthly returns around the zero monthly return, as well as a curious excess of small positive returns and a dearth of small negative returns. The authors conclude that the phenomenon does not exist when using bimonthly returns, meaning the positive returns are reversed in the short term, and identify manager overstatement of returns as a possible cause of the discontinuity. This leads to risk metrics making hedge funds look less risky than they actually are.

[2] Getmansky et al. (2004) report that, among the several potential sources of serial correlation in hedge fund return streams, "the most likely explanation is illiquidity exposure and smoothed returns."

serial correlation and lagged effects (i.e. fund strategy, the nature of the assets, and the method of month-end pricing, taken as three conjoined factors) are essentially those that bear directly on the liquidity of the fund's underlying assets and therefore of the fund itself.

Khandani and Lo (2011) extend the analysis from hedge funds to mutual funds and artificially created portfolios of stocks, finding higher levels of autocorrelation of monthly returns among fund types and security types known to be less liquid. They create a risk factor for liquidity based on AR(1) serial correlation across a broad range of hedge funds, mutual funds, and artificially created equity portfolios.

Billio, Getmansky, and Pelizzon (2011) study periods of financial distress and the fact that some hedge funds perform particularly poorly at these times. They find that funding problems and asset illiquidity play a role in the rise of latent factors during times of financial stress.

In addition to the above-mentioned work in the area of fund or market specific liquidity risks, there is also research on systemic liquidity risks, namely aggregate market-wide liquidity risk as an undiversifiable risk factor. Brandon and Wang (2013) state that accounting for systemic liquidity risk explains a significant portion of fund Alpha for about a third of hedge funds. Sadka (2010) and Sadka (2012) find that illiquid funds perform well in non-crisis environments but suffer large losses during periods of global liquidity shocks. Their analysis is based on the application of liquidity risk factors derived from aggregate global market data, for instance, different from the risk factor developed in Khandani and Lo (2011), and from the risk factor presented in this article. Prior to Sadka (2010) and Sadka (2012), Pastor and Stambaugh (2003) developed a liquidity risk factor based on the formation of ranked and sorted portfolios of stocks on market microstructure measures such as bid/offer spread and trading volume, as proxies for systemic or aggregate liquidity. They found that their aggregate liquidity measure helped to explain the cross-section of stock returns.

3. Data

The hedge fund data here are taken from the Morningstar hedge fund database, formerly known as the Morningstar CISDM Database, the forerunner of which was the MAR Hedge database, one of the oldest in the hedge fund industry. The author was able to use this database for academic purposes at no cost due to the generosity of Morningstar, which is gratefully acknowledge.

The author started with the full database of several thousand hedge funds in 1995-2016; this time frame results from the data availability limitations. The funds were eliminated that stopped reporting prior to December 2016. In order to have a full twelve years of performance data, the author also eliminated funds that started reporting after January 2005, as well as funds that reported in currencies other than the US dollar and those with any missing data (no funds were eliminated from the universe based on small asset size, because a visual inspection of the AUM field revealed that the size data were either missing, likely wrong or out-of-date for many funds). Next the data were downloaded from the database into Excel for the monthly holding period returns for the 144 months of the 2005 through to 2016 period. In Excel, the author calculated the pair-wise correlations for funds with similar names, to eliminate from the universe duplicate funds (e.g. an off-shore fund that shares a portfolio or an investment strategy with an on-shore fund may have a very high pair-wise correlation with that on-shore fund; a correlation coefficient of 0.98 or 0.99 is indicative of a duplicate fund). After this procedure, one was left with a universe of 542 hedge funds for the 12-year period.[3] Similar procedures were also used to create a database of 1,101 hedge funds for the 6-year period, 2011 to 2016, referenced later.

The author also used the hedge fund indices maintained by EDHEC, the Ecole des Hautes Etudes Commerciales du Nord, a leading university in France. In particular, the EDHEC-Risk group at the EDHEC Business School in Nice focuses on financial research and maintains the EDHEC-Risk indices and databases.

4. Methods, including Model and Liquidity Risk Factor

One can think of the portfolio as an amalgam of exposures to various investment risk factors. The effort to evaluate and attribute the performance of mutual funds has paralleled the overall development of academic finance. In Markowitz (1952), the return of each asset was compared to the return of every other asset. Treynor (1965) and Sharpe (1963, 1964), among others, applied the Markowitz risk/return framework in the context of the market portfolio, i.e. rather than comparing each asset to all other assets in a pair-wise fashion, they found it more efficient to compare each asset to the aggregate of all other assets. Treynor (1965) focused his analysis on the plotting of the fund's periodic return against the stock market's periodic return, a line fitted to these data being what he called the "characteristic line". Treynor explained that the slope of the characteristic line tells the investor about the risk of the fund, and its sensitivity to fluctuations of the general stock market. For two funds with the same slope, the fund with the higher characteristic line is to be preferred – more return for the same risk. Sharpe (1966) referred to the slope of Treynor's characteristic line as β, the Beta of the fund. These are the first instances of evaluating mutual fund performance with reference to a risk factor, here namely the equity market risk factor.

Soon after that, Jensen (1968) employed the CAPM equation in the evaluation of mutual fund performance. Jensen introduced the framework as " a direct application of the theoretical results of the capital asset pricing models derived independently by Sharpe, Lintner, and Treynor" (Jensen, 1968, p. 390) of the following general form:

[3] Unfortunately, the database did not contain information on investment strategy or fund type.

$$E(R_i) - R_f = B_i * \left(E(R_m) - R_f\right) + \varepsilon_i \tag{1}$$

where $E(R_i)$ is the fund's expected return, R_f the risk-free rate, $E(R_m)$ the market's expected return, B_i the fund's Beta, and ε_i is the random error term. Jensen points out that this framework is sufficient to estimate the systematic risk of any individual security or any *unmanaged* portfolio, but then raises the case of a *managed* portfolio where "the manager is a superior forecaster. His portfolio will earn more than the 'normal' risk premium for its level of risk. Allowance for such forecasting ability can be made by simply not constraining the estimate to pass through the origin" (Jensen, 1968, p. 393). Thus, Jensen allowed the regression intercept to be non-zero. Hence what was born, was not the concept of manager added-value or Alpha, but rather that of measuring Alpha as the intercept in the regression in the context of the CAPM:

$$E(R_i) - R_f = \alpha_i + B_i * \left(E(R_m) - R_f\right) + \mu_i \tag{2}$$

where α_i is the fund's Alpha, and μ_i the new error term. This measure of manager skill or value added came to be known as Jensen's Alpha.

The hedge fund business is all about active management and manager skill. Manager skill is the all-important – and elusive – Alpha. Yet, to assess manager skill, one must measure Alpha in relation to an appropriate benchmark and in a useful model. This research deploys an equilibrium model for use in the context of hedge funds. This model is essentially a bridge between the widely accepted Fama-French (1993) and Carhart (1997) models from the US equity space and the hedge-fund specific Fung-Hsieh model (2004). Importantly, the Fung-Hsieh (2004) model includes interest rate and credit spread factors, but leaves out the value factor and momentum. It turns out that these are important risk exposures for many hedge funds that tend to exhibit equity risk exposure. Hence, the basic 7-Factor Model which the author created and employed here includes recognisable elements from the earlier models:

$$\begin{gathered} r_{it} - rf_t = \propto_{iT} + \beta_{1iT}(RMRF)_t + \beta_{2iT}(SMB)_t + \beta_{3iT}(AQRHML)_t + \\ \beta_{4iT}(MOM)_t + \beta_{5iT}(10yrUST)_t + \beta_{6iT}(10yrUST - Baa\ Bonds)_t + \\ \beta_{7iT}\left(EM\ Equity - R_f\right)_t + e_{it}, \\ t = 1, 2, \ldots, T \end{gathered} \tag{3}$$

The seven factors are: market risk, size, value (here using the AQR measure for value in preference to the Fama-French measure), momentum, interest rates, credit spreads, and emerging market equity risk. The study found that this model yields higher adjusted R-squares as well as lower estimates of fund Alpha in general, and a reduction in the number of funds in the overall universe that exhibit statistically significant positive Alpha compared to Alpha estimates using the other models. In other words, using this 7-Factor Model allows the analyst to avoid attributing to manager skill that part of the return which can be attributed to exposure to various identifiable investment risks.

Naturally, the developed 7-Factor Model suffers from the same deficiency as the earlier models: it does not account for liquidity risk. The author was not the first to incorporate a liquidity risk factor into a multi-factor model to evaluate hedge fund performance and to estimate hedge fund Alpha; earlier examples would include Brandon and Wang (2013) who incorporated the systemic liquidity risk factor of Pástor and Stambaugh (2003); Sadka (2010) who incorporated a systemic liquidity risk factor of his own devising; and Sadka (2012) who found that his systemic liquidity risk factor explains a substantial part of hedge fund returns.

Pástor and Stambaugh (2003) and Sadka (2006) report on a systematic component of liquidity, or the concept of market-wide liquidity as an undiversifiable risk factor. This literature builds up a system-wide liquidity time-series based on stock market microstructure data, and essentially quantifies the market-wide liquidity condition month by month, finding from the stock trading data that the markets suffer short liquidity crises every few years. Pástor and Stambaugh (2003) turned this into a traded liquidity factor, while Sadka (2006) created a non-traded liquidity factor based on price-impact factors from the US equity markets. The factor is correlated with negative shocks to market-wide liquidity, including the Russian bond default and the LTCM collapse in September 1998, the Lehman bankruptcy in September 2008, the advent of decimalization in pricing on the NYSE in January 2001, and the Quant Liquidity Crunch of August 2007. Sadka (2006) and (2010) applied a market-wide liquidity factor to hedge funds, finding that a wide variety of hedge fund investment strategies are sensitive to global liquidity shocks[4] and that a large portion of hedge fund Alpha is in fact compensation for bearing this market-wide liquidity risk. Brandon and Wang (2013), using the Pástor and Stambaugh systemic liquidity factor, found that accounting for systemic liquidity risk explains a significant portion of fund Alpha for about a third of hedge funds.

Whilst Sadka (2006, 2010) studied the sensitivity of hedge funds to global liquidity forces coming from sources outside the world of hedge fund, this study focused on examining the differences in liquidity (and liquidity risk) in and among the hedge funds themselves, namely more in what is going on inside the individual hedge funds and how the liquidity risk varies across the individual funds, and less with how hedge funds in general react to global or macro-level changes in financial liquidity. With the motivation of finding a way to estimate the portion of the individual fund's Alpha that is associated with the fund's liquidity risk, the author constructed

[4] Traders often say that "all correlations go to 1" and that "there is no place to hide" in market downdrafts characterised by poor liquidity, even for asset classes or investment strategies that are normally non or less-correlated. Thus, the research findings that hedge funds, like most other asset classes and individual securities, are sensitive to global market liquidity shocks make sense.

a liquidity risk factor specifically for use with funds pursuing hedge fund investment strategies.

This paper follows Getmansky et al. (2004) and Asness et. al. (2001) in looking to serial correlation and lagged effects as proxies for liquidity risk. Getmansky et al. (2004) used an AR(1) process as their serial correlation model:

$$r_{it} = \propto_{iT} + \beta_{iT} r_{it-1} + e_{it} \tag{4}$$

They identified the presence of serial correlation in funds that invest using various hedge fund investment strategies, and detect relatively higher measures of serial correlation among funds that follow certain investment strategies – some are more likely to exhibit higher levels of serial correlation than others.[5]

Asness et al. (2001) described a situation where standard regression results "may be misleading [since] many hedge funds hold [...] illiquid exchange-traded securities or difficult-to-price over-the-counter securities, which can lead to non-synchronous price reactions", furthermore noting that "the presence of stale prices [...] can artificially reduce estimates of volatility and correlation with traditional indexes" (Asness et al., 2001, p. 7). Their study also revived from previous literature[6] a lagged effects model measuring the power of an index (or market or benchmark) return to explain the return of the particular fund on a contemporaneous basis and also on the basis of time lags. In analysis of fund performance, this will typically be on monthly data with the time lags being for one, two, and three months as per their model:

$$r_{i,t} = \propto_i + \beta_{i,t}(SP500)_t + \beta_{i,t-1}(SP500)_{t-1} + \beta_{i,t-2}(SP500)_{t-2} + \beta_{i,t-3}(SP500)_{t-3} + e_{it}. \tag{5}$$ [7]

The Beta that is familiar from, e.g. the Capital Asset Pricing Model or the Fama-French 3-factor model, is the contemporaneous Beta, in the case of Equation (6), denoted as $B_{i,t}$.

$$r_{i,t} = \propto_i + \beta_{i,t}(SP500)_t + e_{it} \tag{6}$$

where $(SP500)_t$ represents the return on the SP500 index in period t.

Asness et al. (2001) found that funds that invest using various hedge fund investment strategies may exhibit attractively low Betas to the market return on a contemporaneous basis, but higher overall Betas when the contemporaneous reading is augmented with lagged readings. In this case, these lagged periods extend three months back, for a total of four explanatory variables, as in Equation (5). Obviously,

[5] Some individual funds may exhibit higher levels of serial correlation without reference to the investment strategy, on an individual fund or idiosyncratic basis.

[6] See (Dimson, 1979; Scholes & Williams, 1977).

[7] The Asness et al. (2001) model uses the SP500 index as the explanatory variable in Eq. (5); in practice, one could vary this as appropriate.

higher overall dependence on the market return for a fund implies less diversification benefit from that fund and less fund return attributable to alternative (non-market) sources of risk than as measured by a simpler, contemporaneous CAPM regression.

Significantly, the data requirements for the serial correlation and lagged effects models are very different from the data requirements for other popular methods of liquidity risk measurement used by the SEC and other researchers. These methods require information on fund flows, on the fund's portfolio holdings, and on the liquidity (trading volume and daily price changes) of the individual securities held in the portfolio. Such detailed, high quality data are available for US equity mutual funds, but not necessarily for other types of mutual funds, not to mention hedge funds. The data requirements for the lagged effects and serial correlation models are the monthly holding period returns for the funds. Such data are available for virtually any hedge fund or mutual fund, irrespective of investment strategy or type of asset held in the portfolio. The analyst can apply these models and assess liquidity risk at fund level across a wide variety of fund investment strategy categories.

In constructing the risk factor, the author followed the same methodology that is wide-spread and standard in the academic literature, namely, a zero-investment, factor-mimicking portfolio, in this case equal-weighted. In considering whether my liquidity risk factor is 'priced', the study used same tests and techniques as employed by others, for instance Pástor and Stambaugh (2003).

5. Results

As discussed previously, one of the useful proxies for liquidity in the hedge fund universe is the first order serial correlation coefficient, referred to as AR(1). Using a 12-year (2005-2016) universe of 542 hedge funds, the author calculated the AR(1) measure for each fund over the 36-month rolling window, January 2005 through to December 2007. The fund universe was sorted by AR(1) measure, and then grouped the funds into ten portfolios based on AR(1) decile. Next, the equal-weighted return was calculated for each decile portfolio for each month from January 2008 to December 2008 using the available historical performance data. To calculate the decile portfolio returns for the January 2009 to December 2009 calendar year, the author recalculated the 36-month rolling window AR(1) measure for each fund, moving the rolling window forward twelve months from January 2006 to December 2008. Repeating this process up to December 2016 resulted in 108 months (i.e. January 2008 to December 2016) of performance data for the ten AR(1) decile portfolios.

The composition of the decile portfolios would necessarily change somewhat in each succeeding calendar year as the years pass, depending on the relative AR(1) measure for each fund over the previous three year period. The decile portfolios are reconstituted once a year, and then held constant for the subsequent twelve months, during which periods the monthly weighted average performance of each of the ten decile portfolios were calculated.

The following table shows some characteristics of the ten decile portfolios formed by sorting on the AR(1) liquidity risk measure:

Table 1. Summary Characteristics of Liquidity Risk Sorted Decile Portfolios

Decile	Excess Return (% per annum)	t-stat	7-Factor Model Alpha (% per annum)	t-stat/*p*-value
1	6.86%	2.99	4.43%	3.79 / .0003
2	5.10%	2.09	2.42%	2.35 / .0206
3	6.06%	2.25	3.45%	2.10 / .0379
4	5.12%	1.84	2.51%	1.91 / .0587
5	5.26%	1.89	2.56%	2.18 / .0319
6	5.22%	2.05	2.85%	2.46 / .0158
7	3.65%	1.40	1.16%	0.96 / .3398
8	2.96%	1.21	0.84%	0.63 / .5270
9	2.69%	1.09	–0.25%	–0.16 / .8764
10	6.37%	2.91	3.51%	1.94 / .0545
decile 1 – HF Index	4.39%	4.38	3.84%	4.32 / .000

Source: author's calculations.

Typically, the returns for the ranked and sorted decile portfolios in these kinds of persistence or risk factor studies decline, not always monotonically, from the first to the tenth decile portfolios, and the no-capital-invested, factor-mimicking, long/short portfolio used in subsequent analysis is created by subtracting the return of the tenth decile portfolio from the return of the first decile portfolio. It was found that subtracting the tenth decile (or even the ninth decile) returns from the first decile returns, to form a risk factor data set suitable for use in an equilibrium model, gave results that made no intuitive sense. Why was this the case?

As shown in the above table, the returns for the liquidity risk sorted portfolios decline by decile (more or less) to the ninth decile, and then increase substantially in the tenth decile. The AR(1) measures are negative for the individual funds in the ninth and tenth deciles, as well as for most eighth decile funds in most years. There are interesting phenomena with negative serial correlation funds that need to be borne in mind. The AR(1) for the SP500 was .154 for the period 2008 through 2016; AR(1) measures that are similar to the AR(1) measure for the SP500 are considered to be reflective of little or no liquidity risk in general. Hence, if funds with AR(1) measures of serial correlation of around 0.10 to 0.15 can be characterized as little or no liquidity risk funds, then what to make of funds with AR(1) measures of zero or –0.10 or –0.25? Is there such a thing as less liquidity risk than no liquidity risk? The author thinks not. One can consider funds with negative, near-zero, or only very modest levels of positive serial correlation to be funds characterized by mean reverting returns. Funds with negative measures for AR(1) tend to be in areas such as managed futures, global macro trading, etc., with high turnover and high exposure to non-equity and non-bond securities such as FX, futures, and other derivatives.

The returns of the first decile portfolio sorted on liquidity risk are, by construction and by definition, reflective of returns to be earned by bearing the risk associated with: a) illiquidity; and b) various hedge fund exposures in general. In the typical persistence study framework, subtracting out the returns of the tenth AR(1) decile portfolio would neutralize the first AR(1) decile's general hedge fund exposure and accentuate the liquidity risk exposure. Due to the phenomena that liquidity risk does not decline once it reaches the level of little or no liquidity risk and that the negative AR(1) hedge funds are different by nature and composition than most other hedge funds, one cannot obtain sensible results by following the usual practice of subtracting out the tenth decile returns. Instead, the author formed the risk factor data set by subtracting out from the first decile returns the returns to the HFRI Hedge Fund Composite Index. This accomplishes the necessary step of neutralizing the return for general hedge fund risk while isolating in the risk factor data set the returns to illiquidity in the hedge fund space.

One can see from the graph below of price or index level that exposure to the no-capital-invested, factor-mimicking, long/short risk factor portfolio, produces positive returns over time.

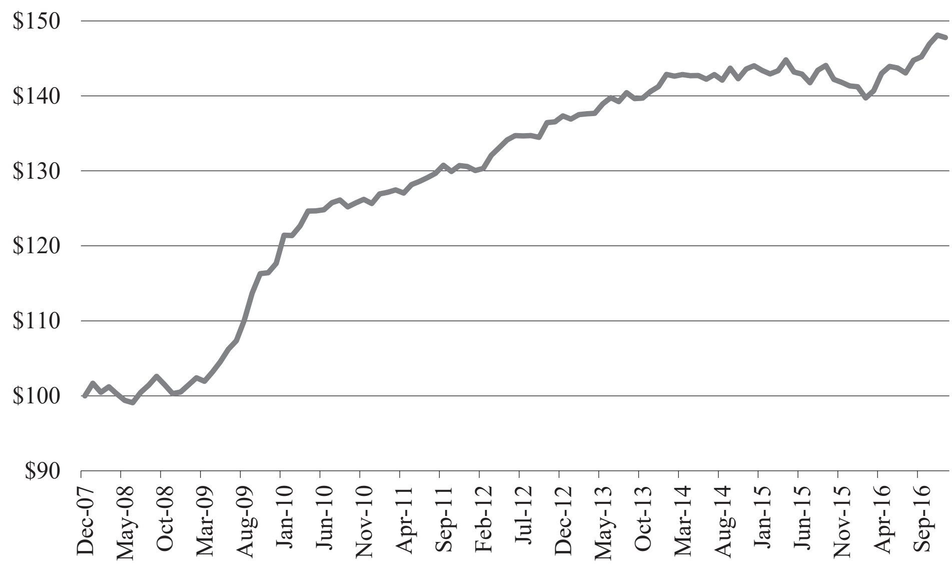

Fig. 1. Value of $100 Invested, Liquidity Risk Factor, 2008-2016

Source: author's calculations.

On a risk-adjusted basis, the return is also positive and statistically significant. The author used the 7-factor model to estimate the risk-adjusted return, or Alpha, equal to 3.84% on an annualised basis, with a t-stat of 4.32 and a *p*-value of 0.000:

Table 2. Multifactor Regression of Liquidity Risk Factor on Other Explanatory Variables, 2008-2016

Dependent Variable = **Liquidity Risk Factor**			Adjusted R^2
Independent Variable(s)	loading	*p*-value	.3473
1. Rm-Rf	–.0624	.028	
2. SMB	.0005	.988	
3. AQR-HML	.1314	.000	
4. MOM	.0274	.319	
5. BondMarket	.0847	.080	
6. CreditSpread	.2442	.000	
7. EM Risk	–.0548	.008	
Intercept	.3203	.000	
Intercept annualized	3.84%		

Source: author's calculations using STATA software.

Additionally, the liquidity risk factor, when added to the 7-factor model, is not competing with other factors to explain the variability in the independent variable, but acts complementarily, as demonstrated by the VIF results:

Table 3. VIF (variance inflation factor) Calculation for 7-Factor Model, with and without Liquidity Risk Factor, 2005-2016

Risk Factor	7-Factor Model	8-Factor Model, including the liquidity risk factor
RmRf	3.73	3.91
SMB	1.22	1.22
AQRHML	4.59	5.25
MOM	4.47	4.52
BondMarket	1.85	1.91
CreditSpread	3.16	3.84
Emerging Market Risk	4.27	4.58
Liquidity risk factor (decile 1 minus HRFI Index)		1.64
Average	3.33	3.36

Source: author's calculations using STATA software.

Based these, one can conclude that this time series is a useful risk factor and is priced, i.e. provides a return to investors a priori, earns Alpha (provides returns to investors on a risk-adjusted basis), and improves the predictive power of the model.

The simplest approach to gauging how much of the hedge fund Alpha is compensation for exposure to liquidity risk is to examine the differences in the Alphas, first using the 7-factor model and then the 8-factor model with the liquidity risk factor added to the model. This analysis was carried out in the context of the full range of hedge fund investment strategies using EDHEC subindices.

The liquidity risk factor loads positively and statistically significantly on six strategies that invest in securities known to be less liquid and/or harder to price and to mark-to-market, namely: convertible arb, distressed debt, emerging markets, event driven, fixed income arb, and relative value trading (shown in **bold** in Table 4). Among these six strategies, in the 7-factor model, three had positive and statistically significant Alphas at the 95% confidence level, and a fourth at the 90% confidence level, while the remaining two had Alphas that were not different than zero. Re-estimating Alpha in the 8-factor model to account for liquidity risk, it was found that three of the "has Alpha" strategies become "not-different than zero" Alpha strategies (namely, Distressed Securities, Event Driven, and Fixed Income Arbitrage) and fourth one (Relative Value) saw a decline in Alpha from 2.38% p.a. to 1.73% p.a. The other two strategies remained as "not-different than zero" Alpha strategies. Including the liquidity factor in the model identifies a significant risk factor affecting the performance of the funds in these investment strategies, provides a new lower estimate of Alpha (minus the compensation for liquidity risk), and allows to quantify the proportion of 7-factor Alpha that is due to bearing liquidity risk.

For strategies that focus in areas with more liquid securities, loadings on the liquidity risk factor with p-values above the 0.05 significance level suggest only limited or almost no exposure to illiquidity. These four areas include equity market neutral, long/short equity, merger arb, and short selling, all of which involve mostly large cap, easy-to-trade, listed equities (see Table 4). Here, the changes in Alpha are in the negative direction for market neutral, merger arb, and short selling, and "n.a." for long/short equity as that Alpha is not different than zero in either model.

Finally, as mentioned just above, strategies with significant or near-significant negative loadings on the liquidity risk factor (namely, CTA Global and Global Marco) are in areas such as managed futures, global macro trading, etc., with high turnover and high exposure to very-liquid non-equity and non-bond securities such as FX, futures, and other derivatives. The table shows n.a. (in bold) in the far-right column for these two strategies, since the author was not going to show an Alpha higher than the 7-factor model Alpha for these "no-liquidity-risk" strategies just because the loading is negative for the liquidity risk factor. The results shown above which included the liquidity risk factor (particularly the sign of the loadings, the statistical significance of the loadings, and the change in Alpha between the 7-factor model and the 8-factor model), accord with the intuition about the

Table 4. Alphas of Various Indices in Multi-Factor Model, with and without Liquidity Risk Factor, 2008-2016

January 2008 through to December 2016	8-Factor Alpha	p-value	8-Factor Adj. R^2	*	Liquidity Risk Factor Loading p-value	7-Factor Alpha	p-value	7-Factor Adj. R^2	Proportion of 7-Factor Alpha lost
CTA Global	Not-different than zero	0.115	0.1480	–	0.010	Not-different than zero	0.565	0.0973	**n.a.**
Convertible Arbitrage	Not-different than zero	0.383	0.8196	+	**0.001**	Not-different than zero	0.624	0.8005	n.a.
Distressed Securities	Not-different than zero	0.479	0.8234	+	**0.000**	3.05%	0.012	0.7849	100%
Emerging Markets	Not-different than zero	0.255	0.9248	+	**0.002**	Not-different than zero	0.928	0.9183	n.a.
Equity Market Neutral	1.98%	0.038	0.4815	+	*0.439*	2.27%	0.010	0.4836	13%
Event Driven	Not-different than zero	0.432	0.8509	+	**0.004**	1.95%	0.043	0.8394	100%
Fixed Income Arbitrage	Not-different than zero	0.707	0.7965	+	**0.000**	1.59%	0.089	0.7375	100%
Funds of Funds	–2.02%	0.038	0.7858	+	0.363	–1.68%	0.061	0.7862	–21%
Global Macro	2.70%	0.032	0.4227	–	0.064	Not-different than zero	0.126	0.4083	**n.a.**
Long/Short Equity	Not-different than zero	0.129	0.8891	–	*0.729*	Not-different than zero	0.130	0.8901	n.a.
Merger Arbitrage	2.29%	0.003	0.5789	+	*0.548*	2.46%	0.000	0.5816	7%
Relative Value	1.73%	0.011	0.8853	+	**0.016**	2.38%	0.000	0.8795	27%
Short Selling	Not-different than zero	0.120	0.8788	–	*0.510*	–3.17%	0.049	0.8795	100%
HFRI Composite HF Index	Not-different than zero	0.494	0.8967	+	0.952	Not- different than zero	0.438	0.8978	n.a.
* = Sign of loading for liquidity risk factor									

Source: author's calculations. Data from EDEHEC.

nature of the funds within the various strategy groups and the liquidity characteristics of the securities those funds invest in.[8]

Next, the liquidity risk factor at the level of the individual funds was applied. First, the author recalculated a 7-factor model fund Alpha for each of the 542 hedge funds for the period January 2008 through to December 2016. Second, the liquidity-risk-adjusted Alphas for each fund were calculated, having augmented the 7-factor model with the liquidity risk factor. The summary results are presented in the context of the "has positive Alpha" funds, that is, those funds with positive and statistically significant (p-value < 0.05) Alphas under the 7-factor model. These were categorised into "has positive Alpha" funds into three groups, as follows: a) load positively on the liquidity risk factor and still "has Alpha" under the 8-factor model that includes the liquidity risk factor (i.e. Alpha p-value < 0.05 in the 8-factor model); b) load positively on the liquidity risk factor but no longer "has Alpha" under the 8-factor model (Alpha p-value > 0.05 in the 8-factor model); and c) load negatively on the liquidity risk factor and still "has positive Alpha" under the 8-factor model.

Table 5. Effect of Liquidity Risk Factor on Fund Alphas, 2005-2016

Description	# of funds	Avg. 7-Factor Alpha	Avg. 7-Factor p-value	Avg. 8-Factor Alpha	Avg. 8-Factor p-value	% drop in Alpha
HF – positive loading; still "has Alpha"	31	8.25%	.004	7.17%	.013	–13%
HF – positive loading; no longer "has Alpha"	27	6.47%	.019	4.05%	.155	–37%
HF – negative loading; still "has Alpha"	32	8.66%	.013	no change	n.a.	0%

Source: authors' calculations.

For the period 2008 to 2016, there were 87 "has positive Alpha" hedge funds (16% of the 542 fund universe). One can see that the "has Alpha" hedge funds give up 13% to 37% of their Alpha to liquidity risk; about a third of the "has Alpha" hedge funds drop that status when accounting for liquidity risk. The proportion of hedge funds loading negatively on liquidity risk is about a third of the "has positive Alpha" funds.

[8] Different from the author's findings, Brandon and Wang (2013) found that the hedge strategy categories that exhibit the greatest liquidity risk are event driven, emerging market, long/short equity. Their findings are reasonable considering that their liquidity risk measure is a global systematic liquidity risk factor from Pástor and Stambaugh (2003) which measures overall market liquidity and is particularly sensitive to macro level global market liquidity turmoil.

In addition to the foregoing analysis using the formulated liquidity risk factor, the author also investigated the power of the Asness et. al. (2001) lagged effects model to adjust fund Alpha for liquidity risk, first in the context of the EDHEC hedge fund strategy categories, and then the entire 542 fund universe. To implement a lagged effects model in the 7-factor framework, three additional risk factors were added to address potential latent Beta in certain hedge fund strategies. Thus the author added to the base model's seven factors, and three additional factors, namely RMRF lagged by 1, 2, and 3 months. The regression's intercept should be smaller than the original 7-factor model intercept to the extent that the original intercept included compensation for a risk absent from the original model, namely, the fund's liquidity risk.

The author estimated the new regression for each fund, but this time with a particular focus on the individual funds where the original, 7-Factor Model Alpha is significant at the 95% confidence level. In the six-year hedge fund universe of 1,101 funds, there are 282 such funds (25.6% of all funds). Of these, 74% of the 282 non-zero Alpha funds have positive Alpha. Nonetheless, an examination of the averages across these subsets of funds shows again that the hedge funds have higher levels of likely liquidity risk.

Table 6. Effect on Alpha of using Lagged Effects in the Multi-Factor Model ("Has Alpha" and "No Alpha" Funds), 2011-2016

6-year period 2011 through to 2016	Hedge Funds
Funds with p-value < .05 for Multi-Factor Model Alpha	282/1,101
Funds Alpha > 0	209/282
Average Alpha in original 7-Factor Model	2.72% (282 funds)
Average Alpha in 10-factor lagged-effects model	0.94%
Change in average Alpha (difference between)	–1.77%
Change in average Alpha (% change)	–65.1%

Source: author's calculations.

In the lagged-effects Multi-Factor Model, the author re-estimated the Alphas, incorporating among the model independent variables the lagged equity risk factors to give effect to the risks of latent Beta and the concomitant increased market risk exposure. This has the effect of reducing the intercept by removing from it compensation for the risks added to the model. These added risks include some liquidity risk revealed by the lagged-effects. The drop in Alpha is from 2.72% per annum to 0.94% per annum, a reduction of 65%, testament to the hedge funds' exposure to liquidity risks.

Then the study delved further into fund Alpha. A principal tenet of finance theory is that investors should earn a return for bearing risk. The obverse of this tenet is that, markets being efficient in finance theory, investors should not earn a return in the absence of risk. Here one can investigate a possible connection between heightened liquidity risk, on the one hand, and the investor's compensation for bearing risk, on the other, in particular, looking at the power of fund returns, fund exposure to liquidity risk, and fund exposure to identifiable investment factor risks in general in explaining the level of fund Alpha.

This part restricts the universe of funds under study to those funds that show intercept p-values less than 0.05 in the 7-Factor Model regression (namely, the "has Alpha" and the "no Alpha" funds previously identified). By doing this, the author avoided mixing into the answering the question of "What drives fund Alpha?" those funds where it was not even certain that the Alphas are different than zero at the 95% confidence level.

A single-factor regression of the form was run:

$$\alpha_i = \alpha + \beta * (R_i - R_f) + \varepsilon_i \tag{7}$$

where α_i represents the 7-Factor Model Alpha of the i-th fund, $(R_i - R_f)$ represents the excess return of the i-th fund, and α and β represent the estimated intercept and slope coefficient of the regression. One is interested in the estimated "Beta" of the regression, showing the sensitivity of the funds' Alphas to the funds' annual returns, as well as the adjusted R^2 of the regression, showing how much of the variability of the Alpha can be explained by the variability of the returns. Using 12-year data, and the 10-factor Multi-Factor Model output for the 62 of the 542 hedge funds that are sensitive to the three Fung-Hsieh dynamic risk factors, the results are:

Table 7. Regression of Multi-Factor Model Alphas on Fund Return, 2005-2016

Dependent Variable = **Fund Multi-Factor Model Alphas**			Adjusted R^2
Independent Variable(s)	Loading	p-value	.7700
1. Fund Annual Returns	1.2475	.000	
Intercept	–4.6644	.000	

Source: author's calculations using STATA software.

These results make intuitive sense. The annual return is the non-risk-adjusted fund return, while the Alpha is the risk-adjusted annual return. For funds where the Alpha is statistically significantly different than zero, one should expect certain positive relations between return and risk-adjusted return across a large group of funds. Hence, funds with non-zero and negative Alpha probably have lower annual returns than funds with some moderate level of non-zero positive Alpha, which in turn probably have lower annual returns than funds with a high level of non-zero positive Alpha. The adjusted R^2 is 0.77, and the slope of the regression is 1.24 (with t-stat 18.95 and p-value 0.000). For every 1% increase in annual return, Alpha goes up by 1.25%.

As explained above, when adding the liquidity risk factor to the 7-Factor Model as an additional explanatory variable, the estimated Alpha declines, reflective of the fact that some of the previously estimated Alpha is actually compensation for exposure to liquidity risk. Therefore, does it follow that funds with greater exposure to liquidity risk provide investors with either higher returns or greater Alpha than funds with less liquidity risk exposure? Two single-factor regressions of the form were run:

$$\alpha_i = \alpha + \beta * (HLRloading_i) + \varepsilon_i \tag{8}$$

and:

$$annualreturn_i = \alpha + \beta * (HLRloading_i) + \varepsilon_i \tag{9}$$

where α_i represents the 7-Factor Model Alpha of the i-th fund, ($HLRloading_i$) represents the loading of the i-th fund returns on the high liquidity risk factor in a simple single-factor regression using nine years of monthly data for the i-th fund, $annualreturn_i$ represents the annual return for the i-th fund, and α and β represent the estimated intercept and slope coefficient of the regression. In doing so, to focus on the funds that have liquidity risk, the analysis was restricted to the 50 funds, out of the 108 total hedge funds with statistically significant Alphas, which load positively on the liquidity risk factor. The results are:

Table 8. Regression of Annual Return on Liquidity Risk Factor Loading ("Has Alpha" and Positive Loading Hedge Funds, 2005-2016)

Dependent Variable = **Fund Annual Returns**			Adjusted R^2
Independent Variable(s)	loading	p-value	.1828
1. Fund Liquidity Risk Factor Loadings	4.5647	.001	
Intercept	6.8573	.000	

Source: author's calculations using STATA software.

Table 9. Regression of Annual Alpha on Liquidity Risk Factor Loading ("Has Alpha" and Positive Loading Hedge Funds, 2005-2016)

Dependent Variable = **Fund 7-Factor Model Alphas**			Adjusted R^2
Independent Variable(s)	loading	p-value	.2111
1. Fund Liquidity Risk Factor Loadings	6.3668	.000	
Intercept	3.5081	.002	

Source: author's calculations using STATA software.

The adjusted R^2s are in the neighborhood of .20, the t-stats are highly significant; the liquidity risk factor loadings seem to explain about 20% of the variation in fund Alphas and in fund returns. Among the funds that have Alphas that are statistically significantly different than zero, a fund's exposure to liquidity reveals something about the fund's returns and its Alpha. A fund's liquidity risk exposure is positively related to the fund's return and Alpha. Though the concepts are mutually exclusive,[9] this finding is complementary to the previous finding that much of the 7-Factor Model Alpha is actually compensation for bearing liquidity risk.

6. Conclusions

In this research, the author focused on Alpha as the main measure of fund performance evaluation. The normal way that one sees Alpha estimated in the literature does not incorporate liquidity risk, either in its definition or among the controlled risk factors. The study proposed a method for incorporating liquidity risk in fund evaluation measures by re-estimating fund Alpha. The analyst can do this either by: a) including among the independent variables three lagged-effects market benchmark factors, to capture the liquidity risk of funds with latent Beta exposure, or b) using an innovative liquidity risk factor, specifically designed to identify and measure liquidity risk in hedge fund investment strategies, as an additional independent variable in a multi-risk-factor equilibrium model. This is a direct method for estimating the compensation for bearing liquidity risk in hedge fund investment strategies, borrowing from the literature the use of the serial correlation measure as a liquidity risk proxy and extending that to create a liquidity risk factor. It was found that much of what appears to fund Alpha estimated in a model that does not include liquidity risk as a measurable risk factor turns out to be compensation for bearing liquidity risk.

The use of the serial correlation and the lagged-effects models to identify potential liquidity risk is based on the phenomenon of 'sticky' mark-to-market pricing month to month. Where this phenomenon is obtained, one may infer that the fund's true risk is higher than the risk implied by the depressed or subdued month-to-month volatility of the monthly holding period returns as recorded in the fund's historical record through the actual monthly mark-to-market process. The lagged-effects model identifies aggregates and indices with elevated liquidity risk along the lines of those identified in the serial correlation model. However, the lagged-effects model relies on the SP500 for its explanatory variables; one finds that the model does not readily identify liquidity risk in fixed income-focused hedge fund strategies, such as fixed income arbitrage, where liquidity risk is known to reside, as such strategies do not load highly on equity indices in regression analysis. The

[9] What is meant here is that it could be possible for a cross-section of funds' liquidity risk exposure not to be explanatory of those funds' returns or Alpha, and yet still to find that a lot of those funds' 7-factor Alphas are derived from exposure to liquidity risk.

liquidity risk factor deployed in a multi-risk-factor setting seems to be more capable of identifying potential liquidity risk across the full spectrum of hedge fund strategies. These results confirm the usefulness of employing both models to identify liquidity risk across a diverse spectrum of trading strategies, acknowledging that the models give similar results in most cases.

This research contributes to the literature and to evaluation of fund performance. The author created a dynamic liquidity risk factor for use in an equilibrium model. Unlike other more general liquidity risk factors in the literature that are derived from market microstructure data for the purpose of gauging fund response to system-wide or global liquidity changes, this liquidity risk factor corresponds to that of the Khandani and Lo (2011) risk factor, based on the sensitivity of fund returns to changes in a fund level liquidity risk measure. Yet, differently from Khandani and Lo (2011), this risk factor is designed specifically to measure the liquidity risk factor exposure in hedge funds and similar funds. By adding the liquidity risk factor to a multi-factor model, the author estimated at a fund-by-fund level the portion of fund Alpha that is represented by compensation for bearing liquidity risk. Based on analysis using the author's own liquidity risk factor, the study found that about 50% of the funds in a subset of the highest returning hedge funds load positively on the liquidity risk factor, and that accounting for liquidity risk leads to over a 40% reduction in fund Alpha for these funds. The liquidity risk factor can be applied to fund due diligence and manager selection prior to investing as well as to ongoing fund performance evaluation and risk management after the investment.

The implications of this research for investors are multiple. In offering this as advice to the wealth management community, the author's suggestions would be to:

1. Pay attention to liquidity risk. Alpha as normally calculated ignores liquidity risk. For funds where the difference between 7-Factor Mode and 8-Factor Model Alpha is large, try to understand the reasons why. Add a liquidity risk factor designed for the specific analytic purpose to the multi-factor model; try to estimate the portion of Alpha attributable to bearing liquidity risk. Additionally, the serial correlation model is easy to implement and may give immediate insight into potential illiquidity in fund portfolio holdings just used by itself.

2. View liquidity risk as a priced risk factor, namely take liquidity risk when the compensation for the risk is appropriately high, and when the addition of liquidity risk will diversify the overall portfolio and enhance the reward-for-risk tradeoff.

3. The choice of model makes a difference. The goal is to remove from the estimated Alpha that portion of the return that is actually compensation for bearing investment risks. In the hedge fund space, this author's 7-Factor Model seems to do a better job of this than the Fung-Hsieh or the Carhart models.

This research suggests several possible directions for future research:

1. Portfolio Efficiency and Liquidity Risk. It would be interesting to investigate the extent to which hedge funds are efficient portfolio diversifiers due to their exposure to liquidity risk as opposed to their exposure to various other fresh risk factors that they bring to the investor's pre-existing portfolio.

2. Compensation for Bearing Liquidity Risk. It would be interesting to investigate the return to investors for bearing liquidity risk in a broader context. For instance, in the realm of hedge funds, one could create a liquidity risk factor with a longer history and based on a larger data set. This would allow for longer studies of the compensation for bearing liquidity risk, as well as of the proportion of Alpha or of return that is associated with liquidity risk. In particular, it would be useful to observe the development over time: are hedge fund Alphas shrinking? Is the portion of return attributable to liquidity risk increasing?

3. An Improved Sharpe Ratio. It would be interesting to investigate whether a return-for-risk ratio that takes liquidity into account, rather than relying on standard deviation as a measure of "total risk" as does the Sharpe Ratio, would be a better tool for analyst and investor use.

It is well-known in the hedge fund industry, and well-reported in the press and in the literature[10], that hedge fund performance (read, Alpha) has been at a lower level post the Global Financial Crisis than in the performance heyday of the hedge fund industry that came before the GFC. Several reasons are likely for this diminution in manager performance measured by risk-adjusted return, including: lower risk free rates; large institutional investors gravitating toward very large-sized hedge fund managers who provide the diversification and the low-volatility that investors desire, often at the expense of performance; too much money being allocated to the space; retail investors moving into index funds and away from their own activity in the markets, depriving hedge fund managers of a readily-available source of Alpha, to name just a few. Hence, other researchers have already found evidence of diminished performance by hedge funds over the past ten years, even as they may be overstating the fund Alphas due to the usual practice of estimating Alpha without accounting for liquidity risk, thereby including in fund Alpha the part of the return that is compensation for bearing liquidity risk.

References

Asness, C., Krail, R., & Liew, J. (2001). Do hedge funds hedge? Be cautious in analyzing monthly returns. *Journal of Portfolio Management*, *28*(1), 6-19. https://doi.org/10.3905/jpm.2001.319819

Billio, M., Getmansky, M., & Pelizzon, L. (2011). *Crises and hedge fund risk* (UMASS-Amherst Working Paper; Yale ICF Working Paper No. 07-14). https://doi.org/10.2139/ssrn.1130742

Bollen, N. P., & Pool, V. K. (2009). Do hedge fund managers misreport returns? Evidence from the pooled distribution. *The Journal of Finance*, *64*(5), 2257-2288.

Brandon, R. G., & Wang, S. (2013). Liquidity risk, return predictability, and hedge funds' performance: An empirical study. *Journal of Financial and Quantitative Analysis*, *48*(1), 219–244. https://doi.org/10.1017/S0022109012000634

Cao, C., Chen, Y., Liang, B., & Lo, A. W. (2013). Can hedge funds time market liquidity? *Journal of Financial Economics*, *109*(2), 493-516. https://doi.org/10.1016/j.jfineco.2013.03.009

[10] One recent example is (Sullivan, 2020).

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance*, *52*(1), 57-82. https://doi.org/10.1111/j.1540-6261.1997.tb03808.x

Dimson, E. (1979). Risk measurement when shares are subject to infrequent trading. *Journal of Financial Economics*, *7*(2), 197-226. https://doi.org/10.1016/0304-405X(79)90013-8

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3-56. https://doi.org/10.1016/0304-405X(93)90023-5

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, *116*(1), 1-22. https://doi.org/10.1016/j.jfineco.2014.10.010

Fung, W., & Hsieh, D. A. (2004). Hedge fund benchmarks: A risk-based approach. *Financial Analysts Journal*, *60* (5), 65-80. https://doi.org/10.2469/faj.v60.n5.2657

Fung, W., & Hsieh, D. A. (2007). Will hedge funds regress towards index-like products? *Journal of Investment Management*, *5*(2), 56-80. https://papers.ssrn.com/abstract=989612

Getmansky, M., Lo, A. W., & Makarov, I. (2004). An econometric model of serial correlation and illiquidity in hedge fund returns. *Journal of Financial Economics*, *74*(3), 529-609. https://econpapers.repec.org/RePEc:eee:jfinec:v:74:y:2004:i:3:p:529-609

Jensen, M. C. (1968). The performance of mutual funds in the period 1945-1964. *The Journal of Finance*, *23*(2), 389-416. https://doi.org/10.1111/j.1540-6261.1968.tb00815.x

Khandani, A. E., & Lo, A. W. (2011). Illiquidity premia in asset returns: An empirical analysis of hedge funds, mutual funds, and US equity portfolios. *Quarterly Journal of Finance*, *1*(2), 205-264. https://doi.org/10.1142/S2010139211000080

Li, C., Li, B., & Tee, K. H. (2020). Are hedge funds active market liquidity timers? *International Review of Financial Analysis*, *67*, 101415. https://doi.org/10.1016/j.irfa.2019.101415

Lo, A. W. (2002). The statistics of sharpe ratios. *Financial Analysts Journal*, *58*(4), 36-52. https://doi.org/10.2469/faj.v58.n4.2453

Luo, J., Tee, K. H., & Li, B. (2017). Timing liquidity in the foreign exchange market: Did hedge funds do it? *Journal of Multinational Financial Management*, *40*, 47-62. https://doi.org/10.1016/j.mulfin.2017.04.001

Markowitz, H. (1952). Portfolio selection. *The Journal of Finance*, *7*(1), 77-91. https://doi.org/10.2307/2975974

Mishra, A. K., Parikh, B., & Spahr, R. W. (2020). Stock market liquidity, funding liquidity, financial crises and quantitative easing. *International Review of Economics and Finance*, *70*, 456-478. https://doi.org/10.1016/j.iref.2020.08.013

Pástor, Ľ., & Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy*, *111*(3), 642-685. https://doi.org/10.1086/374184

Sadka, R. (2006). Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk. *Journal of Financial Economics*, *80*(2), 309-349. https://doi.org/10.1016/j.jfineco.2005.04.005

Sadka, R. (2010). Liquidity risk and the cross-section of hedge-fund returns. *Journal of Financial Economics*, *98*(1), 54-71. https://doi.org/10.1016/j.jfineco.2010.05.001

Sadka, R. (2012). Hedge-fund performance and liquidity risk. *Journal of Investment Management*, *10*, 60-72. https://papers.ssrn.com/abstract=2072774

Scholes, M., & Williams, J. (1977). Estimating betas from nonsynchronous data. *Journal of Financial Economics*, *5*(3), 309-327. https://doi.org/10.1016/0304-405X(77)90041-1

Sharpe, W. F. (1963). A simplified model for portfolio analysis. *Management Science*, *9*(2), 277-293. https://doi.org/10.1287/mnsc.9.2.277

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, *19*(3), 425-442. https://doi.org/10.1111/j.1540-6261.1964.tb02865.x

Sharpe, W. F. (1966). Mutual fund performance. *The Journal of Business*, *39*(S1), 119-138. https://doi.org/10.1086/294846

Sullivan, R. N. (2020). Hedge fund alpha: Cycle or sunset?, *The Journal of Alternative Investments*, *23*(3), 55-79.
Treynor, J. L. (1965). How to rate management of investment funds. *Harvard Business Review*, *43*(1), 63-75.

RYZYKO PŁYNNOŚCI I OCENA WYNIKÓW INWESTYCYJNYCH FUNDUSZY HEDGINGOWYCH

Streszczenie: W artykule wykorzystano dwa modele – opóźnionych efektów i autokorelacji – do identyfikacji potencjalnego ryzyka płynności w portfelach funduszy hedgingowych. Na podstawie modelu autokorelacji opracowano czynnik ryzyka płynności, który dodano do wieloczynnikowego modelu równowagi w celu ponownego oszacowania współczynnika alfa jako miary wyników inwestycyjnych dużego spektrum funduszy hedgingowych. Otrzymane wyniki wskazują, że duża część wypracowanej alfy z modelu wieloczynnikowego pozbawionego czynnika ryzyka płynności jest w rzeczywistości rekompensatą za to ryzyko. Wynik ten jest istotny zarówno dla przedinwestycyjnego badania *due diligence* dotyczącego wyboru menedżerów funduszy hedgingowych, jak i poinwestycyjnej oceny wyników tych funduszy oraz zarządzania ryzykiem.

Słowa kluczowe: ryzyko płynności, czynnik ryzyka płynności, współczynnik alfa, wyniki funduszy hedgingowych.