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Liquidity Risk and the Performance of UK Mutual Funds

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Abstract
We examine the role of liquidity risk, both as a stock characteristic as well as systematic liquidity risk, in UK mutual fund performance for the first time. We find that on average UK mutual funds are tilted towards liquid stocks (except for small stock funds as might be expected) but that, counter-intuitively, liquidity rather than illiquidity, as a stock characteristic is positively priced in the cross-section of fund performance. We find that systematic liquidity risk is positively priced in the cross-section of fund performance although controlling for momentum effects weakens the robustness of this finding somewhat. Overall, our results reveal a strong role for stock liquidity level and systematic liquidity risk in fund performance evaluation models.

JEL Classification: C15, G11.

Keywords: Mutual fund performance, liquidity risk, liquidity characteristics.

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1. Introduction

During the recent financial crisis fund managers witnessed a severe drop in liquidity across global financial markets. This led to a large increase in trading costs and greater price impact and has heightened awareness of the importance of liquidity risk. We examine the role of liquidity risk in mutual fund performance in the UK. The pricing of liquidity risk has attracted some attention in US studies but almost no work has been done on the UK market. The US and UK operate under different market structures. Unlike the US where trading is fragmented, in the UK all trading takes place on a single exchange. In the US, trading on Nasdaq is order book driven while the NYSE has a hybrid system whereas in the UK, London Stock Exchange (LSE) trading is a mix of order book driven (the Stock Exchange Electronic Trading Service (SETS)) and a hybrid quote/order book driven system (SETSmm).

The differing market structure of UK and US exchanges leads to large differences in liquidity characteristics (Huang and Stoll, 2001). Liquidity may be priced in two ways. Liquidity as a priced characteristic considers a stock's own liquidity as a determinant of its return. Amihud and Mendelson (1986) argue that illiquid stocks should earn a premium over liquid stocks to compensate investors for the trading costs incurred which reduce realisable returns, e.g., wider bid-offer spreads. Liquidity as a risk factor refers to systematic liquidity risk, i.e., the sensitivity of returns to changes in market liquidity that may not be diversifiable. A number of papers demonstrate commonality in liquidity across stocks, (Chordia, Roll and Subrahmanyam (2000), Hasbrouck and Seppi (2001)) while Pastor and

Stambaugh (2003), Acharya and Pedersen (2005), Chen (2005), Korajczyk and Sadka (2008) and Sadka (2006) provide evidence of a premium for this systematic liquidity risk. There is also strong evidence indicating that liquidity plays a role in asset pricing in UK equities. Lu and Hwang (2007) report counter-intuitive findings around the pricing of liquidity as a stock characteristic in the UK where liquid stocks are found to outperform illiquid stocks, Foran et al. (2014b) confirm this result. Foran et al. (2014a) report evidence of a premium for systematic liquidity risk in the UK equity market.

We examine the role of liquidity risk in UK mutual fund performance. To our knowledge, in the case of the UK mutual fund industry there have been no past studies of performance which control for stocks' liquidity characteristics and systematic liquidity risk in performance. We address this gap in the literature. Using a high frequency tick data set, which covers much of the financial crisis period, we first construct several measures of stock liquidity, some of which are not possible with lower frequency daily data. We construct risk mimicking factor portfolios for both liquidity as a stock characteristic and systematic liquidity risk. We then examine the exposure of UK mutual funds to these liquidity risks as well as their pricing in the cross-section of fund performance. In particular, for the first time in the UK mutual fund industry, we examine the impact on performance alphas of the inclusion of both these liquidity factors.

Studies of UK mutual fund performance typically evaluate either *ex-post* risk adjusted performance or *ex-ante* performance persistence (Cuthbertson et al., 2012, 2008; Otten and Reijnders, 2012; Quigley and Sinquefield, 1999; Fletcher, 1997) Risk adjusted fund performance is typically taken as the estimated alpha from a multi-factor model which attempts to control for return attributable to various risk factors. Perhaps the most well established models here are the Fama and French (1996) and Carhart (1997) models which control for market, size, value and momentum risk factors. Cuthbertson et al. (2010) provide a comprehensive survey of both the theory and empirical findings around mutual fund performance globally. Cuthbertson et al. (2008) specifically examine UK mutual fund performance, distinguishing skill from luck in performance using a nonparametric bootstrap procedure to construct a distribution of random sampling variation in performance or luck against which a sample of actual funds' performance is compared. The paper concludes that less than 2% of funds achieve a level performance beyond that which could be attributed to chance. Cuthbertson et al. (2012) apply a false discovery rate (FDR) procedure to UK mutual funds. This method determines the proportion of significant fund alphas that are not just type 1 errors or 'false discoveries'. The authors find a false discovery rate of around 30% among funds.

However, the literature on mutual funds seldom accounts for liquidity in estimating risk adjusted performance. Given the theoretical and empirical findings around the pricing of stock liquidity characteristics and systematic liquidity risk, our objective here is to examine the role of both these risks in UK mutual fund performance for the first time.

The paper is organised as follows: section 2 describes our tick data set of trades on the London Stock Exchange (LSE) as well as our mutual fund data set. Section 3 outlines our testing methodology while in section 4 we describe our results.

2. Data

We use two large data sets in our analysis. We obtain tick data and best price data from the London Stock Exchange (LSE) information products division[1]. Our mutual fund dataset is obtained from Morningstar. The sample covers the period January 1997 to February 2009.

The tick file contains all trades of which the LSE has a record. The data for each trade includes the trade time, publication time, price at which the trade occurs, the number of shares, the currency, the tradable instrument code (TIC) and SEDOL of the stock, the market segment and sector through which the trade was routed as well as the trade type. The tick data files contain 792,995,147 trades.

The best price files contain the best bid and ask prices available on the LSE for all stocks for the same time period; this includes the tradable instrument code

[1] This dataset is the same as that used in Foran et al. (2014a) which provides further data discussion.

(TIC), SEDOL, country of register, currency of trade and time stamp of best price. The files contain 1,956,681,874 best prices.

In cleaning the dataset some trades are excluded as follows: Trades outside the Mandatory Quote Period (SEAQ)/continuous auction (SETS) are removed (i.e., only trades between 08:00:00 and 16:30:00 are included). Cancelled trades are excluded. We also exclude opening auctions as their liquidity dynamics may differ from that of continuous auction trades. We exclude trades not in sterling. Best prices that only fill one side of the order book (e.g., where there is a best bid but no corresponding ask price) are removed. We also remove a small number of trades with unrealistically large quoted spreads: for stocks with a price greater than £50, spreads >10% are removed while for stocks with prices less than £50, spreads >25% are removed. Only ordinary, automatic and block trades are used in this study. Following these filters, 673,421,155 trades and 594,647,452 best bid and ask prices remain.

We conduct our analysis on the historic constituents of the FTSE All Share index, i.e., we cross-reference with the London Share Price Database (LSPD) Archive file which records the constituents of the FTSE All Share index historically. We cross-reference the LSE and LSPD data sets by comparing SEDOL numbers[2]. This leaves us with a comprehensive universe of stocks that UK equity mutual funds realistically choose from.

[2] To control for the fact that the SEDOL numbers of certain stocks have changed multiple times over the sample period we use the LSPD's SEDOL Master File.

Our mutual fund data set is obtained from Morningstar and contains monthly returns on 1,141 actively managed UK equity unit trusts and Open Ended Investment Companies. 'UK Equity' funds (by definition) have at least 80% of the fund invested in UK equity. By restricting our analysis to funds investing in UK equities, more accurate performance benchmarks may be used. This data set represents almost the entire set of UK equity funds which have existed at any point during the period January 1997 – June 2009, including 672 nonsurviving funds. Funds are also categorised by investment objectives: 'Equity income' funds (221 funds), which aim to achieve a dividend yield greater than 110% of the market, 'General Equity' funds (779), which invest in a broad range of equity and small company funds (141), which are invested in stocks which form the lowest 10% of the market by market capitalization. Fund returns are measured before taxes on dividends and capital gains but net of management fees.

Table 1 reports summary statistics of the mutual fund sample. Panel A presents the number of funds in the sample by year which ranges from 447 in 2000 (total across all investment styles) to 792 in 2005. The table also provides a yearly breakdown of the numbers of new funds entering the industry along with the numbers of nonsurvivors exiting which includes funds either closing down or merging. We see a particularly large number of funds exiting the industry around 1999 around the Asian and Russian financial crisis periods and again in 2007/8 following the more recent financial crisis period. In Panel B, we present statistics describing the distribution of returns in the cross-section of funds over time, which we breakdown by fund investment style. Equity income funds yield the highest average monthly return of 0.74% and the lowest standard deviation of 0.61% while at 0.44% small company funds yield the lowest return but the highest standard deviation of 0.89% where, in results not shown, returns range from 6.69% to -5.14%. All fund styles exhibit sufficient variation in returns which is helpful in identifying the potential impact of the various risk factors including liquidity. We return to discuss the normality characteristics of the fund returns later and the need to calculate nonparametric bootstrap p values in tests of statistical significance.

3. Methodology

In this section we develop factor models against which we evaluate mutual fund performance. Our baseline models are the Fama and French (1996) three factor model and the Carhart (1997) four factor model with market, size, value and momentum risk factors. We augment these models with a liquidity factor mimicking portfolio - firstly with an illiquidity characteristic risk mimicking portfolio and secondly with a systematic liquidity risk mimicking portfolio. In each case, we measure liquidity by four alternative measures. We employ several alternative liquidity measures as the different measures may capture different facets of liquidity. We employ quoted spread and effective spread as well the temporary fixed price impact measure and permanent fixed price impact measures of Sadka (2006). We choose these liquidity measures as these are the measures found to have the strongest asset pricing effects in previous research on liquidity risk in UK equities, Foran et al. (2014a). We begin in this section by briefly describing our four liquidity measures.[3]

3.1 Liquidity Measures

3.1.1. Quoted Spread

The (average) quoted spread for stock *s* in month *m* is given as

$$Q_{s,m} = \frac{1}{qu_{s,m}} * \sum_{t=1}^{qu_{s,m}} \frac{P_{s,t}^{A} - P_{s,t}^{B}}{m_{s,t}} \tag{1}$$

where $P_{s,t}^{A}$ is the ask price of quote *t* for stock *s*, $P_{s,t}^{B}$ is the bid price of quote *t* for stock *s*, $qu_{s,m}$ is the number of quotes in month *m* for stock *s*. $m_{s,t} = (P_{s,t}^{A} + P_{s,t}^{B})/2$ is the midpoint of the bid/ask prices. Higher levels of quoted spread are associated with lower levels of liquidity.

3.1.2. Effective Spread

We calculate the effective spread by comparing the price at which a trade occurs with the midpoint of the latest best bid/ask price that was in place at least five seconds previously. We express this as a percentage of the midpoint and as an average across all trades for stock *s* in month *m* as follows:

[3] As the liquidity measures have been previously presented in the literature (Foran et al., 2014a; Korajczyk and Sadka, 2008; Sadka, 2006) we provide only a brief description here.

$$E_{s,m} = \frac{1}{tr_{s,m}} * \sum_{t=1}^{tr_{s,m}} \frac{P_{s,t}^{tr} - m_{s,t-5}}{m_{s,t-5}} \qquad (2)$$

$$m_{s,t-5} = (P_{s,t-5}^{A} + P_{s,t-5}^{B}) / 2$$

where $P_{s,t-5}^{A}$ and $P_{s,t-5}^{B}$ are the ask and bid prices in place five seconds before trade *t* for stock *s*, $tr_{s,m}$ is the number of trades in month *m* for stock *s*. $P_{s,t}^{tr}$ is the price at which a trade occurs. Higher levels of effective spread are associated with lower levels of liquidity.

3.1.3. Price Impact Mode - Sadka (2006.)

Sadka (2006) suggests that trades affect prices in four ways – through permanent informational effects and temporary inventory effects where in turn each of these effects are also modelled as fixed (independent of trade size) and variable (dependent on trade size). The model is given by

$$\Delta p_t = \Psi \varepsilon_{\psi,t} + \lambda \varepsilon_{\lambda,t} + \bar{\Psi} \Delta D_t + \bar{\lambda} \Delta (DV_t) + y_t \qquad (3)$$

where Δp_t is the change in price between trade *t* and trade *t-1*. D_t is an indicator variable equal to +1 (-1) for a buyer (seller) initiated trade. ΔD_t is the change in order direction for trade *t*. ΔDV_t is the change in total signed order size in trade *t*. $\varepsilon_{\psi,t}$ is the unexpected trade direction, $\varepsilon_{\lambda,t}$ is the unexpected signed order flow.

$\Psi_{s,t}$, $\lambda_{s,t}$, $\bar{\Psi}_{s,t}$, and $\bar{\lambda}_{s,t}$ are the permanent fixed, permanent variable, temporary fixed and temporary variable price impact measures respectively for stock *s* in month *t*. All price impact measures are scaled by price to allow the coefficient to be interpreted as the percentage impact on price rather than the absolute impact. In this study we use the temporary fixed and permanent fixed price impact measures. Our liquidity measures are winsorised at 1% and 99% percentiles to reduce the effect of outliers (Korajczyk and Sadka, 2008)[4].

3.2. Constructing Liquidity Factors

3.2.1. Illiquidity Characteristic Mimicking Portfolio

Several studies such as Amihud and Mendelsen (1986) and Lu and Hwang (2007) argue that stock's illiquidity level is priced as a characteristic. In order to test this in the performance of mutual funds, we begin by constructing an illiquidity characteristic mimicking portfolio for each liquidity measure as follows: each month all stocks are sorted into decile portfolios based on their liquidity where decile 1 represents high liquidity stocks while decile 10 represents low liquidity stocks. Equal weighted decile portfolio returns are calculated over the following one month holding period and the process is repeated over a one month rolling window. The illiquidity characteristic mimicking portfolio is the difference between the returns of the top decile (decile 10) and bottom decile (decile 1) portfolios, or illiquid minus liquid stocks.

[4] We refer the reader to Sadka (2006) and Korajczyk and Sadka (2008) for fuller discussion of the price impact model.

3.2.2. Systematic Liquidity Risk Mimicking Portfolio

Korajczyk and Sadka (2008), Sadka (2006) and Foran et al. (2014a) all provide evidence of a premium for systematic liquidity risk. In order to test this in mutual fund performance we need to construct a systematic liquidity risk mimicking portfolio. For each liquidity measure we have a (T x n) matrix of liquidity observations where T = number of months and n = number of stocks. In a procedure similar to Korajczyk and Sadka (2008), from this matrix we extract the first principal component, which captures systematic variation or commonality in liquidity across stocks. We refer to this as a systematic liquidity risk factor. We first normalise all liquidity measures before extracting the principal components as follows[5]: $NL^{i}_{s,t} = \frac{L^{i}_{s,t} - \hat{\mu}^{i}_{s,t}}{\hat{\sigma}^{i}_{s,t}}$ where $L^{i}_{s,t}$ is the liquidity observation of liquidity measure *i* for stock *s* at time *t*, $\hat{\mu}^{i}_{s,t}$ is the estimated mean of liquidity measure *i* for stock *s* up to time *t-1*, $\hat{\sigma}^{i}_{s,t}$ is the estimated standard deviation of liquidity measure *i* for stock *s* up to time *t-1* and $NL^{i}_{s,t}$ is the normalised liquidity observation. Our liquidity measures are measures of illiquidity. In keeping with approaches in the literature, we sign all extracted factors so as to represent liquidity. Here, factors are signed to be negatively correlated with the time series of the monthly cross-sectional average of the relevant measure. In order to examine the risk around market liquidity shocks rather than anticipated changes in market liquidity, in the case of each liquidity factor we use the residuals of an AR(2) process applied to the factor.

[5] This is to avoid issues of scale in the different liquidity measures affecting the extracted factors.

In order to capture systematic liquidity risk in a mimicking portfolio, we do the following: for each market liquidity factor, i.e., first extracted principal component, pre-whitened to measure market liquidity shocks, each month individual stock (excess) returns are regressed on the market liquidity factor as well as factors for market, size, value and momentum risk. We estimate this regression over the previous 36 months (minimum 24 month requirement for stock inclusion). Stocks are then sorted into deciles according to their liquidity risk, i.e., their estimated beta (sensitivity) relative to the market liquidity factor as follows:

$$r_{i,t} = \theta_i + \beta_i * F_t^L + \gamma_i * F_t^O + \varepsilon_{i,t} \qquad (4)$$

where F_t^L is the relevant (pre-whitened) market liquidity factor, L = 1, 2…4. F_t^O is a matrix of the other risk factors, $r_{i,t}$ is the excess return on stock *i* and time *t*. Stocks are assigned to a portfolio based on $\hat{\beta}_i$, which measures sensitivity to market liquidity shocks, in ascending order, e.g., portfolio 1 contains low liquidity risk (low beta) stocks while portfolio 10 contains high liquidity risk (high beta) stocks. Each portfolio return is the equal weighted average return of its constituent stocks for the following month. Portfolios are reformed monthly. The liquidity risk mimicking portfolio is taken to be the difference between the high minus low portfolios, i.e., 10-1.

Figure 1 shows time series charts of both the illiquidity characteristic risk mimicking portfolio (factor) and the systematic liquidity risk mimicking portfolio (factor) for each liquidity measure. Consistent with the findings of Lu and Hwang (2007), the chart reveals that for most of the period the illiquidity characteristic risk factor (returns on illiquid stocks minus returns on liquid stocks) is negative indicating that illiquid stocks underperformed liquid stocks. We investigate its pricing in mutual fund performance below. The systematic liquidity risk factor is generally positive, more pronounced in the early part of the sample period, indicating that market liquidity sensitive stocks offered a premium.

Figure 1 here

3.3 Mutual Fund Performance

Having constructed risk mimicking portfolios for characteristic illiquidity risk and systematic liquidity risk, we first examine the exposure of UK mutual funds to these liquidity risks and then estimate the liquidity risk adjusted performance, alpha, of the UK mutual fund industry. In particular, for the first time in the UK mutual fund industry, we compare the Fama and French three factor and Carhart four factor alpha with alpha that controls for characteristic and systematic liquidity risk. Our mutual fund performance evaluation model is of the form

$$r_{i,t} = \alpha_i + \beta_M * r_{m,t} + \beta_S * SMB_t + \beta_V * HML_t + \beta_{MOM} * MOM_t + \beta_L * LIQ_t + \varepsilon_t \quad (5)$$

where $r_{i,t}$ is the excess return of fund *i* in month *t*, $r_{m,t}$ is the excess FTSE All Share return in month *t*, SMB_t, HML_t, MOM_t are the size, value and momentum risk mimicking portfolios or benchmark factors in month *t*. LIQ_t is either the illiquidity characteristic risk or systematic liquidity risk mimicking portfolio (or both may be specified in some model estimations). FTSE All Share returns are used to represent market returns. The size risk factor, small minus big (SMB), is calculated from the sample by each month forming a portfolio that is long the decile of smallest stocks and short the decile of biggest stocks based on market capitalisation and holding for one month before reforming. The value factor, high book to market minus low book to market stocks (HML), is the return on the Morgan Stanley Capital International (MSCI) UK Value Index minus the return on the MSCI UK growth index. The momentum factor (MOM) is formed by ranking stocks each month based on performance over the previous 11 months. A factor mimicking portfolio is formed by going long the top performing 1/3 of stocks and taking a short position in the worst performing 1/3 of stocks over the following month. All portfolios are equal weighted. The risk free rate is the yield on 3 month sterling denominated gilts.

In addition to the above unconditional model, several conditional models have also appeared in the mutual fund performance literature that allow for time varying factor loadings based on public information (Ferson and Schadt, 1996; Christopherson et al., 1998). We also tested conditional models here but they were found to have no additional explanatory power and were consistently strongly rejected by the Schwarz Bayesian Information Criterion in favour of the more parsimonious unconditional model[6]. This was also a robust finding in Cuthbertson et al. (2008).

We estimate various forms of [5] and examine the pricing of our two liquidity factors as well as their impact on alpha in the cross-section of fund performance. We conduct separate analyses for alternative fund investment styles including income funds, general equity funds and small stock funds. We find that the majority of funds exhibit non-normally distributed residuals in the estimation of [5]. Cuthbertson et al. (2008) find that this non-normality significantly alters the interpretation of performance findings for many funds, particularly those in the tails of the cross-sectional performance distribution. To allow for this, we calculate and report bootstrap p-values of alpha.

4. Empirical Results

We begin our analysis by examining the performance of the UK mutual fund industry in a portfolio of funds approach. We construct a time series of the monthly cross-sectional (equally weighted) average fund return and estimate various forms of [5]. Results are presented in Table 2. We begin with a baseline model, i.e., either the CAPM, Fama and French (1996), denoted 'FF', or Carhart (1997) model. We then augment this baseline model with the illiquidity characteristic risk mimicking factor (henceforth 'illiquidity level' factor) or the systematic liquidity risk mimicking

[6] To conserve space we do not present these results in the paper.

factor (henceforth ‘liquidity risk’ factor) or both. Results in Table 2 are based on the effective spread liquidity measure [7].

Table 2 here

Consistent with previous findings in the literature, our baseline model results (first column) indicate a statistically significant role (by the bootstrap p-values) for market, size and momentum risk in explaining mutual fund returns but an insignificant role for value risk, (Cuthbertson et al., 2008). The last row denoted “Non-Normality” presents the percentage of funds where the null hypothesis of normally distributed residuals is rejected at 5% significance – the high percentages motivate our use of bootstrap p-values. On average the industry yields a negative and statistically significant alpha by the Carhart four factor model. In column 2 when we augment the baseline models with the illiquidity level factor (illiquid stock returns minus liquid stock returns) we see that it has a negative loading in the augmented Fama and French model - statistically significant at the 1% significance level - indicating that on average mutual funds are tilted towards liquid stocks. From Figure 1 previously, counter-intuitively, liquid stocks outperform illiquid stocks, or liquidity level as a stock characteristic is positively priced over time. There is evidence of a possible interaction between illiquidity level and momentum where, again in column 2, when a momentum factor is specified in the Carhart model the illiquidity level factor becomes statistically insignificant. A similar pattern can be

[7] In Table 2 in order to conserve space we present only the results for the effective spread measure of liquidity. The same tests for our other liquidity measures yield qualitatively similar results, available on request.

seen in column 4 where the illiquidity level factor and liquidity risk factor are both added to the baseline models. We return to this later.

When we augment the baseline models with the liquidity risk factor, (column 3), the initial results indicate that systematic liquidity risk does not explain mutual fund returns where the liquidity risk loadings in all augmented models are not statistically significant. However, this result conceals positive and negative loadings on the liquidity risk factor across individual funds which cancel out in this portfolio of funds approach. In results not shown, the number of funds with positive and negative loadings on the liquidity risk factor is approximately equal. This is a consistent finding across all our liquidity measures and prompts us to carry out further cross-sectional tests of liquidity risk pricing below. These findings around the illiquidity level factor and the liquidity risk factor are unchanged when we augment the baseline model with both liquidity factors at the same time, (denoted 'Illiquidity Level + Risk' in column 4), indicating that illiquidity as a stock characteristic and systematic liquidity risk measure distinct effects.

The role of an illiquidity level factor as well as a liquidity risk factor in mutual fund performance models is further supported by the results presented in Table 3. Here, we report the average Schwartz Information Criterion (SIC) model selection metric for our baseline CAPM, Fama and French and Carhart models as well as for each baseline model augmented by the illiquidity level factor, liquidity risk factor and both factors specified together. We present these results for liquidity factors derived from all four liquidity measures. In the case of all four liquidity measures the (lowest) SIC indicates that a Fama and French three factor model augmented by the illiquidity level factor and/or the liquidity risk factor is a better fit than a Carhart four factor model augmented by the liquidity factors. The Fama and French three factor model augmented by the illiquidity level and liquidity risk factors is generally the most parsimonious best fit model of all.

Table 3 here

To further investigate the role of liquidity exposure both as a stock characteristic and as a systematic risk factor in fund performance, we conduct cross-sectional pricing tests. For each fund, returns are regressed on the (i) Fama and French (1996) three factors and (ii) Carhart (1997) four factors and performance alphas are estimated in each case. These two models are then augmented with the illiquidity level factor or the liquidity risk factor and the two liquidity factor loadings are estimated in each model. This is done separately for all four liquidity measures. Table 4 presents the slope coefficients and their p-values from cross-sectional (across funds) regressions of the estimated Fama and French three factor alpha and the Carhart four factor alpha on (i) the estimated illiquidity level factor loading and (ii) the estimated liquidity risk factor loading. We report results for all funds taken together as well as for income funds, general equity funds and small stock funds separately. If the liquidity factors are not priced independently of the Fama and

French and Carhart factors there should be no relation between alpha and the liquidity loadings.

Table 4 here

In the case of the illiquidity level factor (returns on illiquid stocks minus returns on liquid stocks) we find a significant negative relation between the Fama and French three factor alpha and the illiquidity level loading. This is a consistent finding across all four liquidity measures indicating, counter-intuitively, that holding more liquid stocks is positively priced in the cross-section of fund performance. This finding is robust across all fund investment styles when examined separately except in the case the temporary fixed priced impact measure for small stock funds. (It is significant at the 10% significance level by the effective spread liquidity measure in the case of income funds). One possible explanation for this counter-intuitive finding is a possible overlap between momentum (winning) stocks and liquid stocks. Hence the positive pricing of liquidity may reflect momentum risk. Returning to Table 2 there is evidence of an interaction between illiquidity level and momentum where when a momentum factor is specified in the Carhart model the illiquidity level factor becomes statistically insignificant. However, our results in Table 4 for 'All Funds' indicate that this positive pricing of illiquidity level is in fact robust to controlling for momentum where we find a significant relation between the Carhart four factor alpha and the illiquidity level loading across all four liquidity measures. On the whole then, illiquidity level and momentum are distinct effects. When we look across investment styles, however, we see that this is only the case for general equity funds, whose large numbers dominate the sample, but that in the case of income funds and small stock funds the positive pricing of the illiquidity level factor in the three factor model is explained by momentum in a four factor model.

From Table 2 previously initial results indicated that systematic liquidity risk does not explain mutual fund returns where the liquidity risk loadings were not statistically significant but this concealed positive and negative loadings across individual funds which cancelled out in the portfolio of funds approach. In Table 4, our cross-sectional tests again examine this further. In the case of the liquidity risk factor for all funds we find a significant positive relation between the Fama and French three factor alpha and the liquidity risk loading, with the exception of the quoted spread liquidity measure where the relation is insignificant. This finding is consistent across all investment styles and indicates that systematic liquidity risk is positively priced. Funds which are tilted towards high (low) liquidity risk stocks have higher (lower) Fama and French three factor alphas. On controlling for momentum in the cross-sectional regressions of the Carhart four factor alpha on the liquidity risk loadings, the results are somewhat more mixed but generally continue to support the positive pricing of liquidity risk particularly in the case of the effective spread and permanent fixed price impact liquidity measures though not in the case of the temporary fixed price impact measure and less so in the case of quoted spread.

In order to test the robustness of our findings in Table 4, we repeat the analysis for all funds while varying the lengths of the backward looking ranking time window and forward looking holding period window. From section 3.2.1 when constructing the illiquidity level mimicking portfolio we rebalance the portfolio monthly. In robustness tests here we rebalance it annually. Also, from section 3.2.2 when constructing the systematic liquidity risk mimicking portfolio, each month individual stock (excess) returns are regressed on the market liquidity factor as well as factors for market, size, value and momentum risk. We estimate this regression over the previous 36 months. In robustness tests here, we also examine (i) a backward looking window of 24 months (instead of 36 months) and (ii) a holding period of 12 months (instead of 1 month). While we do not tabulate these voluminous results, we can report that none of these robustness tests change the overall conclusions presented in Table 4. These results are available on request.

Our results provide evidence that both liquidity (rather than illiquidity) as a stock characteristic and systematic liquidity risk are positively priced in the cross-section of fund performance. We examine the impact on mutual fund performance alphas of adjusting for liquidity exposure both as a stock characteristic and as a systematic risk factor. Table 5 reports fund alpha at various points in the cross-sectional distribution pre and post adjusting for our illiquidity level factor and liquidity risk factor. Notwithstanding a possible interaction between illiquidity level and momentum for income funds and small stock funds, the Schwartz Information Criterion values in Table 3 consistently point to the Fama and French three factors augmented with the illiquidity level and liquidity risk factors as the most parsimonious best fit model. Hence these are the models we focus on here in Table 5.

Table 5 first shows the baseline three factor alpha and its (Newey-West) adjusted t-statistic at various points in the cross-sectional distribution, e.g., ‘Max’ denotes the highest alpha, ‘max 99%’ is the alpha at the 99^{th} percentile etc. Owing to a significant degree of non-normality in the fund regression residuals we also report nonparametric bootstrap p-values to test the statistical significance of alpha. The table then shows the alpha, t-statistic of alpha and bootstrap p-value of the corresponding fund from the same baseline model augmented with the illiquidity level factor, liquidity risk factor and both factors as indicated. Panels A, B, C and D present results for the quoted spread, effective spread, temporary fixed price impact and permanent fixed price impact liquidity measures respectively. For example, by the quoted spread measure of liquidity in Panel A, the median Fama and French three factor alpha is -0.07 percent per month but falls to -0.14 percent per month after adjusting for the illiquidity level factor. Scanning the data in Table 5 generally indicates that adjusting for illiquidity level causes an increase in alpha at both the extreme high and low ends of the distribution while in the middle of the distribution, performance disimproves (around the median and “Min 25% areas). Adjusting for liquidity risk generally points to no notable change in alpha. More formally, however, we also report the Kolmogorov-Smirnov statistic in each case to test the significance of the difference between the distributions of alpha from the baseline three factor model and the liquidity factors augmented models. The null hypothesis that the cross-sectional distributions of alpha pre and post liquidity factor adjustment are from the same population distribution is firmly rejected in the case of illiquidity level for all four liquidity measures. However, in the case of the liquidity risk factor we fail to reject this hypothesis at 5% significance in the case of all liquidity measures, except the effective spread measure (Panel B)[8].

Table 5 here

While the Schwartz Information Criterion values in Table 3 indicate that the Fama and French three factors augmented with the illiquidity level and liquidity risk factors is the most parsimonious best fit model, in order to test the robustness of our findings in Table 5, we repeat the analysis presented therein for the Carhart four factor alpha instead of the Fama and French three factor alpha. The result (not shown) is that the Kolmogorov-Smirnov statistics in Table 3 prove strongly robust: adjusting the Carhart model for the illiquidity level factor leads to a statistically significant shift in the cross-sectional distribution of alpha (for the group of all funds) for all liquidity measures though, as in Table 5, this is not the case for the systematic liquidity risk factor.

Figure 2 presents graphical illustrations of the impact on the cross-sectional distribution of Fama and French three factor alphas of adjusting for the illiquidity

[8] Again, this is likely to be because the positive and negative loadings on liquidity risk across funds causes alpha to decrease and increase respectively but in aggregate the distribution is unchanged from that of the Fama and French three factor alpha according to the Kolmogorov-Smirnoff test.

level and liquidity risk factors. We present Kernel density estimates of the cross-sectional distributions of alpha pre and post liquidity factor adjustment. To conserve space Figure 2 presents results for the effective spread liquidity measure, which are representative of all measures (other results are available on request). Panels A, B and C relate to income funds, general equity funds and small company funds respectively. In each panel the upper graph shows the change in the three factor alpha after adjusting for both the illiquidity level and liquidity risk factors together, the lower left graph shows the change in alpha after adjusting for the illiquidity level factor while the lower right graph shows the change in alpha after adjusting for the liquidity risk factor. In the case of income funds and general equity funds, after adjusting for (i) the illiquidity level factor and (ii) the illiquidity level and liquidity risk factors together, the cross-sectional distribution of alpha clearly shifts to the left while in the case of small stock funds the distribution clearly shift to the right. In results not shown, Kolmogorov-Smirnov tests conducted separately for each fund style indicate that these shifts are statistically significant. These results are consistent with income and general equity funds having a negative loading on the illiquidity level factor, i.e., are tilted towards liquid stocks while small stock funds have a positive loading on the illiquidity level factor, i.e., are tilted towards illiquid stocks. Graphically, by eye the impact of adjusting for the liquidity risk factor, lower right graph in Panels A, B and C, shows a slight shift to the right in the case of general equity funds and small stock funds while in the case of income funds the right tail shifts slightly leftward. However, these shifts are not as pronounced as in the case of adjusting for the illiquidity level factor and by the Kolmogorov-Smirnov statistic the shift is only significant for general equity funds at 5% significance.

Overall, our results reveal a strong role for liquidity as a stock characteristic in UK mutual fund performance evaluation. Unexpectedly, we find that exposure to liquid stocks is positively priced in the cross-section of fund performance. While, *a priori*, a possible interaction between liquidity and momentum in stocks may explain why liquidity, rather than illiquidity, is positively priced in fund performance, our cross-sectional tests show that for the fund sample as a whole liquidity and momentum represent distinct effects. However, in the smaller number of income funds and small stock funds examined separately the positive pricing of the illiquidity level factor in the three factor model is explained away by momentum in a four factor model. Overall, the Schwartz Information Criterion robustly points to a Fama and French three factor model augmented by the illiquidity level factor and the liquidity risk factor as the most parsimonious model of best fit. Exposure to the systematic liquidity risk factor varies from positive to negative across funds. However, the cross-sectional tests generally find that systematic liquidity risk is positively priced the cross-section of fund performance although the robustness of this finding is weakened somewhat on controlling for momentum.

Amihud and Mendelson (1986) argue that illiquid stocks should earn a premium over liquid stocks to compensate investors for the costs incurred by illiquidity. Our findings are at variance with this expectation where liquidity, rather than illiquidity, as a stock characteristic earns a premium for UK equity mutual funds. This unusual finding in the UK market is consistent with past findings, Lu and Hwang (2007) and Foran et al. (2014b). An obvious question is what risk factors are responsible for this liquidity premium? Lu and Hwang (2007) ask whether there is any connection between liquidity and (market) beta. They report that the beta of the most liquid (illiquid) decile portfolio is 1.36 (0.90) and the Wald test highly rejects the equality of these two betas. However, Foran et al (2014b) find that while cross-sectional differences in returns exist across portfolios sorted by liquidity level, these are strongly robust to market, size, value and momentum risks. Our findings here also indicate that the liquidity premium earned by most general equity mutual funds is also robust to these risk factors but for income funds and small stock funds momentum appears to explain the liquidity premium. Lu and Hwang (2007) ask whether liquidity is a systematic risk and (by inference) whether this might explain the observed premium. Foran et al. (2014a) find strong commonality in liquidity and report a premium to stocks which exhibit high systematic liquidity risk but also report that controlling for liquidity level as a stock characteristic does not alter that conclusion. Our results here support this finding where our discussion around the results in Table 2 indicate that illiquidity as a stock characteristic and systematic liquidity risk measure distinct effects. In short, the unexpected finding that liquidity, rather than illiquidity, offers a return premium is consistent with past research on the equity UK market, is robust to other commonly tested risk factors and is distinct from systematic liquidity risk. It remains a puzzle which warrants further investigation. One possible avenue of investigation is that of Dong, Feng and Sadka (2013). Although examining systematic liquidity risk, rather than liquidity as a stock characteristic, the authors show that fund liquidity-risk exposures provide valuable information about future performance. However, the authors then show that only a small portion of the liquidity-risk-exposure premium is explained by the liquidity-beta premium of funds' underlying assets. The remainder is most likely explained by fund manager's ability to generate abnormal performance. We leave a similar analysis of the UK market to future research.

5. Conclusion

We find that in the UK mutual fund industry income funds and general equity funds are tilted towards liquid stocks while small stock funds are tilted towards illiquid stocks. However, counter-intuitively, liquidity, rather than illiquidity, as a stock characteristic is positively priced in the cross-section of fund performance. On controlling for stock holdings' liquidity, there is a statistically significant shift leftward (reduction) in the cross-sectional distribution of Fama and French three factor alphas. This is a robust finding across all fund investment styles examined and is also robust across alternative liquidity measures. This finding is also robust to a momentum factor for the majority of our sample of funds (general equity funds) but for the smaller set of income funds and small stock funds, there is evidence that momentum largely explains the pricing of this liquidity risk. Exposure to systematic liquidity risk varies from positive to negative across funds. However, the cross-sectional tests generally find that systematic liquidity risk is positively priced in the cross-section of fund performance, although the robustness of this finding is weakened somewhat on controlling for momentum effects. Schwartz

Information criteria indicate that a Fama and French (1996) three factor performance model augmented by factors for illiquidity as a stock characteristic (illiquidity level) and systematic liquidity risk is the most parsimonious best fit model. Overall, our results reveal a strong role for liquidity as a stock characteristic and systematic liquidity risk in fund performance evaluation models.

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Table 1: Descriptive Statistics of the Mutual Fund Sample

Panel A: The number of funds that exist at the start of each year is reported for the three investment styles. The second column under each investment objective reports the numbers of funds that enter and exit the sample during each year.

	Equity Income Funds		General Equity Funds		Small Company Funds	
Year	**Start of Year**	**Entered/Exit**	**Start of Year**	**Entered/Exit**	**Start of Year**	**Entered/Exit**
1997	117	5/0	343	18/0	88	2/0
1998	122	1/0	361	38/0	90	5/0
1999	123	17/60	399	36/126	95	5/42
2000	80	9/0	309	39/0	58	11/0
2001	89	16/0	348	62/0	69	9/0
2002	105	19/0	410	54/0	78	7/0
2003	124	14/2	464	59/3	85	5/0
2004	136	5/0	520	37/0	90	4/0
2005	141	5/10	557	38/46	94	2/6
2006	136	9/7	549	34/27	90	2/3
2007	138	5/22	556	19/72	89	0/22
2008	121	0/38	503	3/182	67	1/3
2009	83	0/0	324	0/0	65	0/0

Panel B: Statistics describing the entire distribution of returns across funds are reported by investment objective. The total number of funds examined in the sample under each objective I also reported.

	Equity Income	General Equity	Small Company
Mean	0.74	0.55	0.44
Standard Dev.	0.61	0.67	0.89
Skewness	-0.23	-1.35	0.80
Kurtosis	3.24	12.06	28.95
Max.	2.22	3.31	6.69
75th	1.01	0.94	0.63
Median	0.70	0.52	0.46
25th	0.44	0.23	0.21
Min.	-1.48	-4.35	-5.14
Number	221	779	141

Table 2. UK Mutual Fund Industry Performance: Liquidity Factor Augmented Models.
Each month fund returns are averaged across funds and the resultant time series is regressed on the CAPM, Fama and French (1996) and Carhart (1997) models. Each model is then augmented with the illiquidity characteristic (level) mimicking portfolio and/or the liquidity risk mimicking portfolio. The illiquidity level mimicking factor is formed by each month ranking stocks based on average effective spread over the previous 11 months and calculating the return on a long position in the most illiquid decile of stocks and a short position in the most liquid decile. The liquidity risk factor is formed each month by measuring the sensitivity of stock returns to an extracted market liquidity factor over the previous 36 months, sorting stocks into deciles based on sensitivity and calculating the return on a long position in the most sensitive decile and a short position in the least sensitive decile. Table 2 reports model alphas and loadings as well as bootstrap p values. 'Illiquidity Level + Risk' denotes both liquidity factors specified simultaneously. * indicates significance at 10%, ** indicates significance at 5% and *** indicates significance at 1%. The last row denoted "normality" presents the percentage of funds where we reject the null hypothesis of normally distributed residuals at 5% significance.

	Baseline			**Illiquidity Level**			**Liquidity Risk**			**Illiquidity Level + Risk**		
	CAPM	**FF**	**Carhart**	**CAPM**	**FF**	**Carhart**	**CAPM**	**FF**	**Carhart**	**CAPM**	**FF**	**Carhart**
A	0.04	-0.06	-0.14**	0.18**	-0.12**	-0.16***	0.06	-0.06	-0.14**	0.17*	-0.12**	-0.16***
p-val	0.64	0.20	0.02	0.04	0.02	0.01	0.62	0.25	0.01	0.07	0.03	0.00
Illiquidity Level				0.09***	-0.03***	-0.02				0.10***	-0.04**	-0.02
p-val				0.00	0.01	0.16				0.00	0.02	0.11
Liquidity Risk							-0.01	0.00	-0.02	0.01	-0.01	-0.02
p-val							0.71	0.86	0.20	0.69	0.47	0.14
Market	0.97***	0.94***	0.96***	0.93***	0.95***	0.96***	0.96***	0.94***	0.96***	0.94***	0.95***	0.96***
p-val	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Size		0.34***	0.36***		0.37***	0.37***		0.34***	0.36***		0.37***	0.38***
p-val		0.00	0.00		0.00	0.00		0.00	0.00		0.00	0.00
Value		-0.02	-0.01		-0.01	-0.01		-0.02	0.00		-0.01	0.00
p-val		0.32	0.62		0.54	0.16		0.35	0.92		0.70	0.91
Momentum			0.03**			0.02			0.04**			0.03**
p-val			0.03			0.16			0.01			0.05
Non-Normality	0.94	0.92	0.92	0.72	0.68	0.65	0.69	0.65	0.62	0.71	0.64	0.62

Table 3. Liquidity Factor Augmented Models - Schwarz Bayesian Information Criterion.
For each fund, returns are regressed on the CAPM, Fama and French (1996) and Carhart (1997) models. Each model then is augmented with the illiquidity characteristic (level) mimicking portfolio and/or the liquidity risk mimicking portfolio. This is done for each liquidity measure separately. The illiquidity level mimicking factor is formed by each month ranking stocks based on average liquidity over the previous 11 months and calculating the return on a long position in the most illiquid decile of stocks and a short position in the most liquid decile. The liquidity risk factor is formed each month by measuring the sensitivity of stock returns to an extracted market liquidity factor over the previous 36 months, sorting stocks into deciles based on sensitivity and calculating the return on a long position in the most sensitive decile and a short position in the least sensitive decile. Table 3 reports the Schwarz Information Criterion, averaged across fund regressions. Lowest values in each group are bolded and underlined.

Quoted Spread	**Baseline**	**Illiquidity Level**	**Liquidity Risk**	**Level and Risk**
CAPM	1.266	1.238	1.296	2.863
FF	1.022	**<u>1.010</u>**	1.052	1.016
Carhart	1.018	1.018	1.053	1.052
Effective Spread				
CAPM	1.266	1.217	1.282	2.814
FF	1.022	1.018	1.037	**<u>1.002</u>**
Carhart	1.018	1.024	1.036	1.041
Temporary Fixed				
CAPM	1.266	1.218	1.291	2.824
FF	1.022	1.013	1.042	**<u>1.005</u>**
Carhart	1.018	1.019	1.042	1.044
Permanent Fixed				
CAPM	1.266	1.217	1.293	2.828
FF	1.022	1.007	1.045	**<u>1.002</u>**
Carhart	1.018	1.014	1.043	1.038

Table 4. Cross-sectional Regressions of alpha on Liquidity Factor Loadings

For each fund, returns are regressed on the (i) Fama and French (1996) three factors and (ii) Carhart (1997) four factors and performance alphas are estimated in each case. These two models are then augmented with the illiquidity characteristic (level) mimicking portfolio or the liquidity risk mimicking portfolio and the two liquidity factor loadings are estimated. The illiquidity level mimicking factor is formed by each month ranking stocks based on average liquidity over the previous 11 months and calculating the return on a long position in the most illiquid decile of stocks and a short position in the most liquid decile. The liquidity risk factor is formed each month by measuring the sensitivity of stock returns to a market liquidity factor over the previous 36 months, sorting stocks into deciles based on sensitivity and calculating the return on a long position in the most sensitive decile and a short position in the least sensitive decile. This is done for each liquidity measure separately. Table 4 presents results of cross-sectional (across funds) regressions of (i) the estimated three factor alpha and (ii) the estimated four factor alpha on the estimated illiquidity level loading and liquidity risk loading. Specifically, we report the coefficients and their p-values (in parentheses) on the illiquidity level loading and liquidity risk loading. We report results for all funds taken together as well by investment style.

	Quoted Spread		**Effective Spread**		**Temporary Fixed**		**Permanent Fixed**	
	Illiquidity Level	Liquidity Risk	Illiquidity Level	Liquidity Risk	Illiquidity Level	Liquidity Risk	Illiquidity Level	Liquidity Risk
All Funds								
3FF	-0.82 (0.00)	0.01 (0.93)	-0.56 (0.00)	1.15 (0.00)	-0.56 (0.00)	0.69 (0.00)	-0.76 (0.00)	1.07 (0.00)
4F	-0.22 (0.02)	-0.14 (0.36)	-0.21 (0.02)	0.66 (0.00)	-0.18 (0.05)	-0.08 (0.55)	-0.20 (0.03)	0.94 (0.00)
Income								
3FF	-0.89 (0.00)	-0.68 (0.08)	-0.53 (0.09)	0.86 (0.04)	-1.31 (0.00)	-1.02 (0.01)	-0.78 (0.00)	1.22 (0.00)
4F	-0.35 (0.20)	-0.65 (0.09)	-0.19 (0.50)	0.81 (0.04)	-0.45 (0.14)	-0.72 (0.10)	-0.07 (0.79)	1.73 (0.00)
General Equity								
3FF	-0.64 (0.00)	0.09 (0.56)	-0.38 (0.00)	0.93 (0.00)	-0.36 (0.00)	0.59 (0.00)	-0.54 (0.00)	0.95 (0.00)
4F	-0.31 (0.01)	-0.09 (0.62)	-0.36 (0.00)	0.62 (0.00)	-0.27 (0.03)	-0.14 (0.36)	-0.31 (0.01)	0.78 (0.00)
Small Stock								
3FF	-1.16 0.00	-0.15 0.78	-0.74 0.01	1.73 0.00	-0.48 0.12	1.72 0.00	-1.02 0.00	1.04 0.02
4F	-0.16 (0.54)	-0.85 (0.09)	-0.14 (0.63)	0.38 (0.37)	0.04 (0.89)	0.54 (0.22)	-0.07 (0.80)	0.76 (0.06)

Table 5. The Cross-sectional Distribution of Mutual Fund Alpha pre and post Liquidity Factor Adjustment

For each fund, returns are regressed on the Fama and French (1996) three factors. This model is then augmented with the illiquidity characteristic (level) mimicking portfolio and/or the liquidity risk mimicking portfolio. The illiquidity level mimicking factor is formed by each month ranking stocks based on average liquidity over the previous 11 months and calculating the return on a long position in the most illiquid decile of stocks and a short position in the most liquid decile. The liquidity risk factor is formed each month by measuring the sensitivity of stock returns to a market liquidity factor over the previous 36 months, sorting stocks into deciles based on sensitivity and calculating the return on a long position in the most sensitive decile and a short position in the least sensitive decile. Table 5 presents alpha, its t-statistic and the bootstrap p-value of alpha at various points in the cross-sectional distribution. (t-stats are Newey-West adjusted for lag order 2). Panels A to D present results for the alternative liquidity measures as indicated. The Kolmogorov-Smirnov statistic tests the significance of the difference between the distributions of alpha from the baseline three factor model and the liquidity augmented models.

Panel A: Quoted Spread											
3 Factor	**Max**	**max 99%**	**max 95%**	**max 90%**	**Max 75%**	**Median**	**Min 25%**	**Min 10%**	**Min 5%**	**Min 1%**	**Min**
Alpha	0.97	0.72	0.46	0.29	0.09	-0.07	-0.23	-0.36	-0.45	-0.81	-2.36
t-stat	2.29	2.17	1.31	1.66	0.58	-0.76	-1.54	-1.50	-4.08	-1.98	-4.41
Bootstrap p-value	0.04	0.10	0.28	0.12	0.60	0.50	0.15	0.20	0.00	0.05	0.00
3 Factor + Illiquidity Level	Kolmogorov-Smirnov p-value: 0.00										
Alpha	1.27	0.79	0.40	0.28	0.06	-0.14	-0.27	-0.40	-0.49	-0.75	-1.63
t-stat	2.07	1.32	1.66	0.74	0.27	-0.88	-2.58	-1.08	-4.32	-4.75	-3.18
Bootstrap p-value	0.12	0.30	0.12	0.49	0.84	0.44	0.02	0.27	0.00	0.00	0.00
3 Factor + Liquidity Risk	Kolmogorov-Smirnov p-value: 1.00										
Alpha	0.96	0.72	0.46	0.28	0.09	-0.07	-0.22	-0.36	-0.47	-0.78	-1.80
t-stat	1.91	2.31	1.33	2.20	0.33	-0.37	-1.21	-2.70	-1.90	-4.76	-3.62
Bootstrap p-value	0.08	0.05	0.32	0.05	0.75	0.67	0.25	0.01	0.07	0.00	0.00
3 Factor + Illiquidity Level + Liquidity Risk	Kolmogorov-Smirnov p-value: 0.00										
Alpha	1.28	0.81	0.40	0.28	0.07	-0.12	-0.27	-0.41	-0.50	-0.74	-1.34
t-stat	2.12	1.31	1.68	2.33	0.52	-0.56	-2.97	-2.42	-3.57	-4.29	-2.75
Bootstrap p-value	0.12	0.32	0.11	0.01	0.60	0.58	0.01	0.02	0.00	0.00	0.02

Panel B: Effective Spread											
3 Factor	**Max**	**max 99%**	**max 95%**	**max 90%**	**Max 75%**	**Median**	**Min 25%**	**Min 10%**	**Min 5%**	**Min 1%**	**Min**
Alpha	0.97	0.72	0.46	0.29	0.09	-0.07	-0.23	-0.36	-0.45	-0.81	-2.36
t-stat	2.29	2.17	1.31	1.66	0.58	-0.76	-1.54	-1.50	-4.08	-1.98	-4.41
Bootstrap p-value	0.04	0.10	0.28	0.12	0.60	0.50	0.15	0.20	0.00	0.05	0.00
3 Factor + Illiquidity Level	Kolmogorov-Smirnov p-value: 0.00										
Alpha	1.45	0.87	0.43	0.29	0.06	-0.12	-0.26	-0.39	-0.50	-0.79	-1.92
t-stat	2.40	2.20	1.06	0.99	0.33	-1.48	-7.75	-0.92	-3.25	-4.78	-3.35
Bootstrap p-value	0.09	0.08	0.28	0.37	0.73	0.20	0.00	0.37	0.00	0.00	0.01
3 Factor + Liquidity Risk	Kolmogorov-Smirnov p-value: 0.02										
Alpha	0.87	0.71	0.44	0.28	0.10	-0.04	-0.18	-0.31	-0.41	-0.71	-1.30
t-stat	5.53	2.35	1.18	1.55	0.82	-0.26	-0.84	-1.84	-2.58	-1.82	-3.82
Bootstrap p-value	0.00	0.07	0.33	0.13	0.44	0.80	0.37	0.06	0.03	0.08	0.00
3 Factor + Illiquidity Level + Liquidity Risk	Kolmogorov-Smirnov p-value: 0.02										
Alpha	1.54	0.85	0.43	0.30	0.08	-0.10	-0.24	-0.37	-0.45	-0.76	-1.01
t-stat	2.09	2.80	1.09	0.44	0.51	-0.47	-1.16	-3.23	-4.01	-2.08	-2.28
Bootstrap p-value	0.04	0.01	0.30	0.69	0.62	0.65	0.33	0.00	0.00	0.10	0.06

Panel C: Temporary Fixed Price Impact											
3 Factor	**Max**	**max 99%**	**max 95%**	**max 90%**	**Max 75%**	**Median**	**Min 25%**	**Min 10%**	**Min 5%**	**Min 1%**	**Min**
Alpha	0.97	0.72	0.46	0.29	0.09	-0.07	-0.23	-0.36	-0.45	-0.81	-2.36
t-stat	2.29	2.17	1.31	1.66	0.58	-0.76	-1.54	-1.50	-4.08	-1.98	-4.41
Bootstrap p-value	0.04	0.10	0.28	0.12	0.60	0.50	0.15	0.20	0.00	0.05	0.00
3 Factor + Illiquidity Level	Kolmogorov-Smirnov p-value: 0.00										
Alpha	1.54	0.86	0.42	0.26	0.03	-0.16	-0.31	-0.43	-0.52	-0.83	-2.06
t-stat	2.41	2.47	1.58	2.09	0.13	-0.69	-1.37	-1.98	-3.07	-2.27	-3.37
Bootstrap p-value	0.08	0.03	0.11	0.04	0.89	0.57	0.18	0.07	0.00	0.01	0.00
3 Factor + Liquidity Risk	Kolmogorov-Smirnov p-value: 0.23										
Alpha	0.92	0.70	0.46	0.28	0.10	-0.05	-0.19	-0.31	-0.43	-0.71	-1.50
t-stat	2.86	1.44	2.14	0.62	0.76	-0.51	-1.71	-1.86	-2.78	-2.43	-3.33
Bootstrap p-value	0.01	0.25	0.03	0.57	0.43	0.66	0.14	0.07	0.02	0.00	0.01
3 Factor + Illiquidity Level + Liquidity Risk	Kolmogorov-Smirnov p-value: 0.00										
Alpha	1.60	0.87	0.42	0.27	0.05	-0.13	-0.29	-0.43	-0.51	-0.79	-1.29
t-stat	2.00	2.53	1.76	0.68	0.29	-1.53	-2.64	-3.70	-2.65	-5.00	-2.44
Bootstrap p-value	0.05	0.05	0.13	0.54	0.83	0.19	0.02	0.00	0.02	0.00	0.04

Panel D: Permanent Fixed Price Impact											
3 Factor	**Max**	**max 99%**	**max 95%**	**max 90%**	**Max 75%**	**Median**	**Min 25%**	**Min 10%**	**Min 5%**	**Min 1%**	**Min**
Alpha	0.97	0.72	0.46	0.29	0.09	-0.07	-0.23	-0.36	-0.45	-0.81	-2.36
t-stat	2.29	2.17	1.31	1.66	0.58	-0.76	-1.54	-1.50	-4.08	-1.98	-4.41
Bootstrap p-value	0.04	0.10	0.28	0.12	0.60	0.50	0.15	0.20	0.00	0.05	0.00
3 Factor + Illiquidity Level	Kolmogorov-Smirnov p-value: 0.00										
Alpha	1.40	0.82	0.39	0.27	0.06	-0.12	-0.27	-0.40	-0.49	-0.78	-1.48
t-stat	1.84	2.11	0.96	0.73	0.44	-0.96	-2.31	-3.72	-2.35	-5.07	-2.74
Bootstrap p-value	0.09	0.07	0.47	0.51	0.73	0.40	0.02	0.00	0.02	0.00	0.02
3 Factor + Liquidity Risk	Kolmogorov-Smirnov p-value: 0.34										
Alpha	0.87	0.73	0.44	0.25	0.09	-0.05	-0.20	-0.32	-0.43	-0.75	-1.46
t-stat	5.58	1.42	2.66	1.54	0.62	-0.40	-1.49	-2.27	-2.53	-4.49	-3.35
Bootstrap p-value	0.00	0.26	0.01	0.16	0.58	0.70	0.13	0.03	0.03	0.00	0.00
3 Factor + Illiquidity Level + Liquidity Risk	Kolmogorov-Smirnov p-value: 0.00										
Alpha	1.60	0.79	0.39	0.27	0.06	-0.12	-0.27	-0.39	-0.49	-0.78	-1.22
t-stat	2.16	2.57	1.61	2.16	0.35	-1.12	-2.44	-2.02	-3.10	-5.12	-2.82
Bootstrap p-value	0.04	0.02	0.12	0.05	0.75	0.31	0.02	0.04	0.01	0.00	0.03

Figure 1: Liquidity Mimicking Factor Portfolios
Time series plots of the illiquidity level factor and the liquidity risk factor by liquidity measure as indicated.

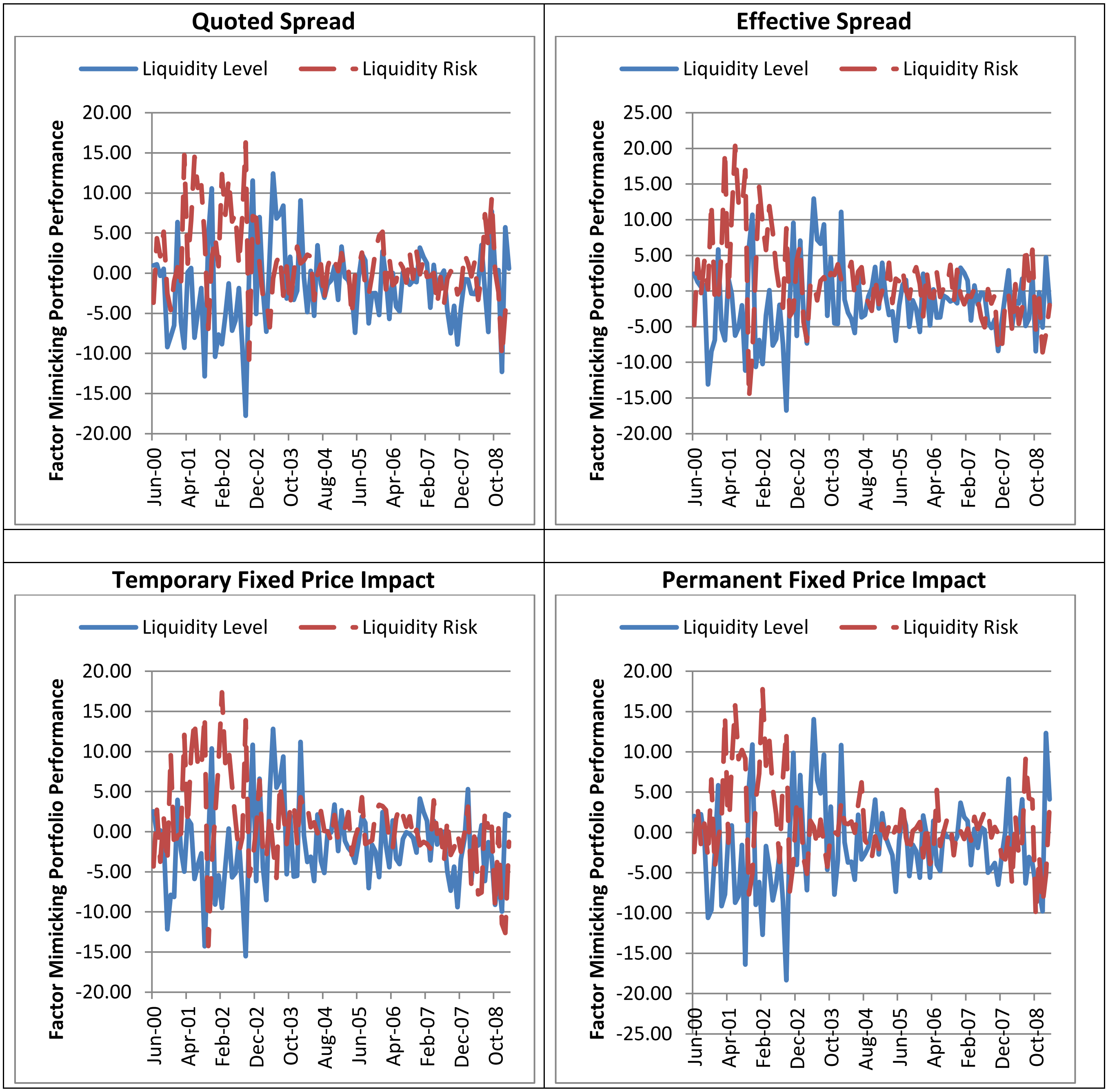
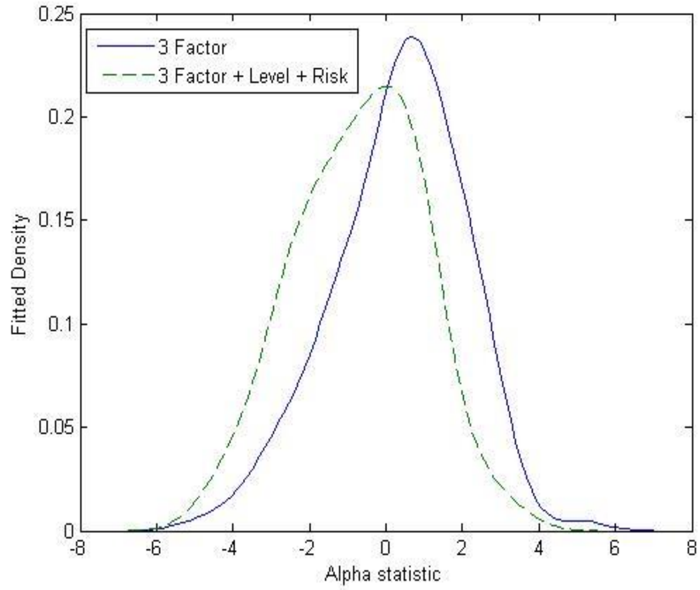
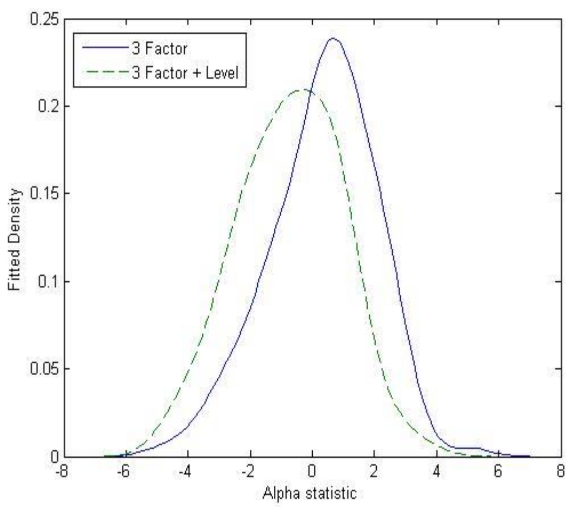


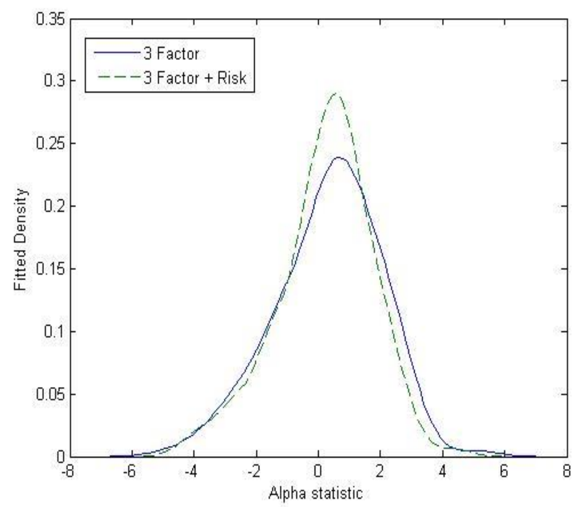
Figure 2. Kernel Density Estimate of Fund alphas

For each fund, returns are regressed on the Fama and French (1996) factors and alpha is estimated. This model is then augmented with the illiquidity characteristic (level) mimicking portfolio and /or the liquidity risk mimicking portfolio and alpha in the liquidity augmented model is estimated. Figure 1 plots Kernel density estimates of the cross-sectional distributions of alphas from the three factor versus the augmented models as indicated. The charts relate to the effective spread liquidity measure. Panels A, B and C show results for equity income, general equity and small stock funds respectively. Effective spread is used here, additional liquidity measures available on request

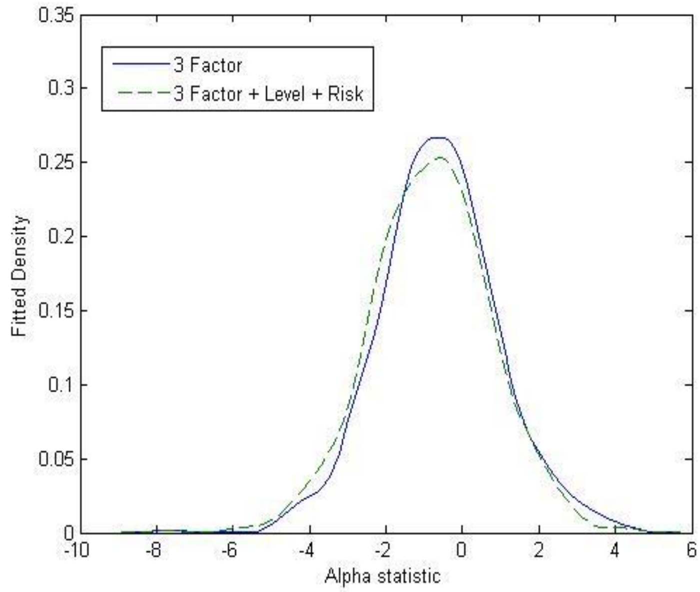
Panel A: Equity Income Funds

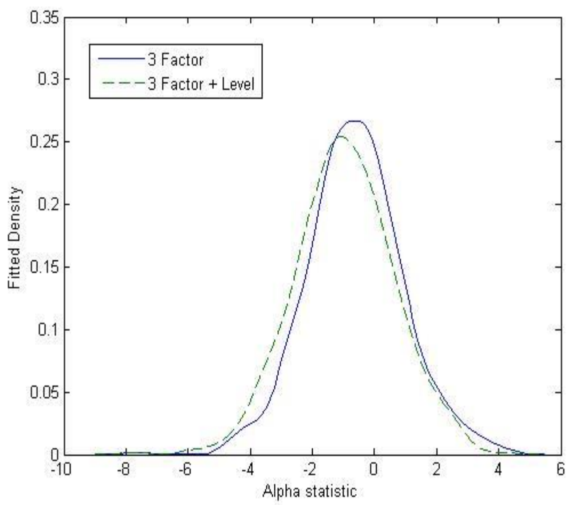


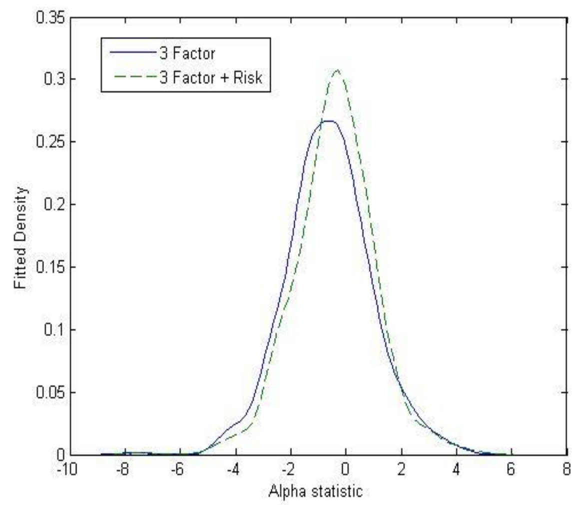




Panel B: General Equity Funds







Panel C: Small Company Funds