# Liquidity Commonality and Pricing in UK Equities

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**Abstract**
We investigate the pricing of systematic liquidity risk in UK equities using a large sample of daily data. Employing four alternative measures of liquidity we first find strong evidence of commonality in liquidity across stocks. We apply asymptotic principal component analysis (PCA) on the sample of stocks to extract market or systematic liquidity factors. Previous research on systematic liquidity risk, estimated using PCA, is focused on the US, which has very different market structures to the UK. Our pricing results indicate that systematic liquidity risk is positively priced in the cross-section of stocks, specifically for the quoted spread liquidity measure. These findings around the pricing of systematic liquidity risk are not affected by the level of individual stock liquidity as a risk characteristic. However, counter-intuitively, we find that the latter is negatively priced in the cross-section of stocks, confirming earlier research.

Keywords: Liquidity pricing, liquidity risk, commonality.

JEL Classification: G11, G12, C14, C15.

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## 1. Introduction

One of the most significant trends in global financial markets over the last twenty years has been the growth in aggregate stock market trading volume. For UK investors this increase in trading volume has been accompanied by a move from a traditional quote driven trading system to an order book system on the London Stock Exchange (LSE). This changing market structure has led to falling trading costs, and narrower spreads, for the most liquid stocks. For anyone operating during this period the relationship between changes in systematic liquidity and stock returns is particularly relevant. In this paper we investigate commonality in stock liquidity and the pricing of systematic liquidity risk in the UK equity market.

Unlike the US where trading is fragmented, in the UK all trading takes place on a single exchange. Both regions historically operated very different market structures. In the US, trading on Nasdaq has evolved from a quotation driven structure to a hybrid model including an order book system while the NYSE has a hybrid system where specialists have an obligation to stabilize their assigned stocks. On the LSE trading is a mix of a pure order book (the Stock Exchange Electronic Trading Service (SETS)) and a hybrid quote/order book driven system (SETSmm) and a quote driven SEAQ system for more thinly traded stocks. SETS was introduced in 1997 for constituents of the FTSE100 index, representing the most liquid stocks on the exchange. In September 1999, 47 mid cap stocks from the FTSE 250 were also added to SETS and in 2003 the remaining FTSE250 stocks were added to a hybrid SETSmm system where dealers still have an obligation to provide quotes in their registered stocks but investors have the option of using the electronic order book.

The differing market structure of the UK and US exchanges leads to large differences in liquidity characteristics (Huang and Stoll, 2001). By providing evidence on the pricing of systematic liquidity in the UK market we are able to assess whether these differences in market structure and liquidity characteristics affect conclusions on the relation between systematic liquidity and stock returns as documented in the predominantly US literature.

Using daily data between January 1991 and December 2013 we make two key contributions to the literature. First, we test for commonality in liquidity across stocks in the UK using a range of stock liquidity measures, demonstrating that shocks to the liquidity of an individual stock are correlated with shocks to the liquidity of the rest of the market. Second, we examine whether systematic liquidity risk in stocks is priced in the cross-section of returns. Previous studies have found that liquidity risk exhibits a common component across US stocks (Korajczyk and Sadka, 2008) and has a significant asset pricing effect (Cotter, O'Sullivan and Rossi, 2014).

Microstructure liquidity literature focusses on idiosyncratic determinants of a stock's liquidity. Theories put forward to explain cross sectional differences in liquidity include inventory cost models (Stoll, 1978) and information based models (Kyle, 1985). Chordia, Roll and Subrahmanyam (2000) find that liquidity shows systematic patterns with changes in an individual stock's liquidity exhibiting contemporaneous correlation with changes in market liquidity. This study was followed by a number of papers investigating commonality in liquidity across longer time periods, different trading mechanisms (Brockman and Chung, 2002; Galariotis and Giouvris, 2007) and different countries (Brockman et al., 2009). Commonality implies a risk to investors of adverse changes in market liquidity which may not be fully diversifiable and may constitute a priced risk factor. Examples of periods where liquidity largely disappeared include the October crash of 1987, the Long Term Capital Management crisis of 1998 and the recent financial crisis period. In such events investors who may wish to liquidate their positions find themselves severely hindered in doing so.

The literature contains many alternative measures of liquidity, such as quoted bid-ask spreads (Amihud and Mendelson, 1986), effective bid-ask spreads, turnover, the ratio of absolute stock returns to trading volume (Amihud, 2002) or propensity for return reversals (Pastor and Stambaugh, 2003). Each of these measures may have systematic and asset specific components while there may also be correlation in the systematic components of liquidity across measures (Korajczyk and Sadka, 2008).

Liquidity may be priced in two ways. Liquidity as a priced characteristic considers the level of liquidity as a determinant of assets returns. 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, for example wider bid-offer spreads. Liquidity as a risk factor refers to systematic liquidity risk, i.e., sensitivity of stock returns to changes in market liquidity that may not be diversifiable. Such high liquidity risk stocks should command a higher required return to induce investors to hold them.

While studies of commonality in liquidity now cover a large number of countries, studies in the pricing of systematic liquidity risk concentrate on the US. An exception is Stahel (2005) who investigates the US, the UK and Japan, albeit using a smaller sample of stocks than considered here. Lu and Hwang (2007) study the pricing of liquidity as a characteristic in the UK and find that illiquid stocks earn lower returns than more liquid stocks. We add to this sparse literature on liquidity pricing in the UK stock market by using asymptotic principal component analysis to examine the pricing of systematic liquidity risk using a long period of daily data for the first time.

The paper is organised as follows: section 2 describes the dataset and liquidity measures. Section 3 describes the testing methodologies and results of tests for commonality in liquidity. Section 4 presents the methodology and results of liquidity risk pricing tests while section 5 concludes.

## 2. Data and Liquidity Measures

The dataset is taken from Datastream. Our initial sample size is 1,274 stocks in 1991 rising to a peak of 2,240 stocks in 2006. We have daily price, return, turnover, bid price, ask price, shares outstanding and daily market value for the period 1st January 1991 to 31st December 2013. Both surviving and non-surviving stocks are included to control for survivorship bias. We construct four liquidity measures for each stock for each month. We require stocks to have at least 15 daily observations in the month for inclusion. We now briefly describe the liquidity measures.

### 2.1 Quoted Spread

A mainstay of the literature, the (proportional) quoted spread is the difference between the daily closing bid and ask prices expressed as a percentage of the midpoint of the prices. We calculate the daily average each month. For stock *s* in month *m* it is given by

$$Q_{s,m} = \frac{1}{n_{s,m}} * \sum_{t=1}^{n_{s,m}} \frac{P_{s,t}^{A} - P_{s,t}^{B}}{m_{s,t}} \quad (1)$$

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

### 2.2 Amihud Trade Impact

Amihud (2002) develops a measure of liquidity that seeks to capture the tendency for the price of illiquid assets to be more sensitive to trades, similar to Kyle's λ (Kyle, 1985). For month *m*, the Amihud measure is given by

$$Amihud_{s,m} = \frac{1}{n_{s,m}} * \sum_{t=1}^{n_{s,m}} \frac{|r_{s,t}|}{dvol_{s,t}} \quad (2)$$

where $dvol_{s,t}$ is the dollar volume on day *t*, $r_{s,t}$ is the return on day *t* and $n_{s,m}$ is the number of daily observations in the month *m*. For this study $dvol_{s,d}$ is replaced by number of shares traded $(vol_{s,t})$ to mitigate size effects. Similar to Lu and Hwang (2007), we take the natural log of this measure because of severe skewness in its distribution. The adjusted measure is given by

$$\ln Amihud_{s,m} = \frac{1}{n_{s,m}} * \sum_{t=1}^{n_{s,m}} \ln\left(\frac{|r_{s,t}|}{vol_{s,t}}\right) \quad (3)$$

Higher levels of the Amihud measure are associated with lower levels of liquidity.

**2.3 Turnover**

In several studies turnover is used as a measure of liquidity. This has a strong basis in the inventory based models of liquidity such as Stoll (1978) and the trading pattern models of Foster and Viswanathan (1990) in which liquidity is expected to increase in periods of concentrated trading with narrower spreads. Alternative views suggest that turnover may not be indicative of liquidity. Subrahmanyam (2005) argues that turnover may instead be related to momentum where it is found that high turnover for stocks with high recent performance predicts better future returns and the opposite is the case for stocks with poor recent performance. This has implications that stock turnover may be more related to sentiment than liquidity. Similarly, Lee and Swaminathan (2000) posit that trading volume may act as a bridge between intermediate horizon under-reaction and long term over-reaction effects. The relevance of turnover to liquidity studies is therefore still an open question. However, for comparison with past studies we include it as one of our measures here. Turnover is defined as the number of shares traded divided by the shares outstanding. The measure is given by

$$\mathrm{Turn}_{s,m} = \frac{1}{n_{s,m}} * \sum_{t=1}^{n_{s,m}} \frac{\mathrm{Vol}_{s,t}}{\mathrm{SO}_{s,t}} \qquad (4)$$

where $\mathrm{Vol}_{s,t}$ is the number of shares traded on day *t*, $\mathrm{SO}_{s,t}$ is the number of shares outstanding and $n_{s,m}$ is the number of daily observations in month *m*. Higher levels of turnover are associated with higher levels of liquidity.

**2.4 Effective Spread (Roll, 1984)**

Empirical evidence suggests that the price at which most trades take place is often inside the quoted spread (Blume and Goldstein, 1992). This inner spread is known as the effective spread. Roll (1984) develops a simple model to facilitate estimation of the effective spread. The market is assumed to be efficient in gross terms (pre-transactions costs, where the bid/ask spread is the only source of cost) so serial covariance in returns is due only to the "bid-ask bounce" caused by the shifting of price from the bid to the ask prices.

The estimate of the effective spread, for stock *s*, is given by

$$C_s = 200 * \sqrt{-\mathrm{Cov}(r_{t,s}, r_{t-1,s})} \qquad \left(C_s \notin R\right) \rightarrow (C_s = 0) \qquad (5)$$

A problem with this approach is that it requires negative covariance in returns, which is found to only hold approximately half of the time. Hasbrouck (2005) performs a study comparing daily data and tick data based measures of liquidity. The study finds that simply replacing non-real estimates of daily effective spread with zero leads to the measure being highly correlated with the high frequency trade and quote (TAQ) based measure of effective spread. As a result, in this study if the general method of moments estimate is complex then it is simply replaced by zero. Higher levels of effective spread are associated with lower levels of liquidity.

*Descriptive Statistics of the Liquidity Measures.*

Table 1 and Figure 1 present summary statistics for the various liquidity measures[1]. For example, from Table 1 the time series and cross-sectional average quoted spread is a large 7.85%. Figure 1 plots the time series of the monthly cross-sectional value weighted average (normalised) liquidity level for each liquidity measure. (In Figure 1, for ease of comparison all liquidity measures are first signed to represent liquidity, rather than illiquidity). The patterns suggest that market liquidity was lower in the 1990's before increasing towards the end of the sample period.

**Table 1 about here**

**Figure 1 about here**

## 3. Testing for Commonality

[1] The number of stocks used for each measure varies due to varying data availability across the inputs required to calculate each measure. E.g., volume, bid-ask spreads etc.

The literature contains a number of tests of commonality in liquidity. Chordia et al. (2000) test a simple and intuitive market model of liquidity. Huberman and Halka (2001) test the correlation in liquidity between two mutually exclusive portfolios of stocks after controlling for other factors and find that they are significantly correlated. Hasbrouck and Seppi (2001) use canonical correlations and principal component analysis for the Dow 30 and only find weak evidence of commonality. In this study we examine commonality using the market model approach of Chordia et al. (2000) and the asymptotic principal component (APC) approach of Korajczyk and Sadka (2008).

### 3.1 Market Model of Liquidity

For a given liquidity measure *i*, Chordia et al. (2000) measure market liquidity by each month calculating the cross-sectional mean of all stocks' liquidity measures. A regression for each stock *s* and liquidity measure *i* is then estimated as follows

$$DL^{i}_{s,t} = \alpha_s + \beta_s * DL^{i}_{Ms,t} + \gamma_s * C_{s,t} + \varepsilon_{s,t} \qquad (6)$$

where $DL^{i}_{s,t}$ is the change in liquidity measure *i* for stock *s* in month *t* from month *t-1*. $DL^{i}_{Ms,t}$ is the equal weighted average change across all stocks except stock *s*. $C_{s,t}$ is the vector of control variables for time *t*. The control variables are individual volatility (taken as volatility of daily returns during the month) and individual return[2]. If there is commonality in liquidity, changes in individual stock's liquidity will be significantly related to changes in market liquidity and we expect $\beta_s > 0$.

[2] Lead and lag market liquidity are not included here, results not reported indicate that they are not statistically significant.

The results of these regressions are presented in Table 2. There is strong evidence of commonality where the cross-sectional average value of $\hat{\beta}_s$ is positive and highly statistically significant for all liquidity measures. The percentage of significantly positive coefficients ranges from 23% to 60%, much larger than the test size of 5%. The percentage of stocks with statistically significant negative estimates of $\beta_s$ (at 5% significance) is extremely small. In the final row of Table 2 we report the percentage of stock regressions which exhibit non-normal residuals. As this non-normality issue is quite prevalent, we also calculate nonparametric bootstrap p-values of $\beta_s$ (Cuthbertson et al., 2008). However, these paint a qualitatively similar picture indicating a high degree of commonality among the stocks.

**Table 2 about here**

In results not shown, we repeat the analysis in Table 2 for decile portfolios of stocks sorted by size (market value) to test if commonality is related to a link between liquidity and size. However, we find that all size sorted portfolios exhibit significant commonality. This indicates that commonality in liquidity across stocks is not a size related phenomenon.

### 3.2 Asymptotic Principal Components Approach

In a procedure similar to that of Korajczyk and Sadka (2008) we use asymptotic principal component analysis to construct market liquidity factors which capture systematic variation or commonality in liquidity across stocks. For each liquidity measure we have a (T x n) matrix of liquidity observations where T = number of months and n = number of stocks.

From this matrix we extract the first three principal components which by design capture common variation in liquidity across stocks. We refer to these as ‘within-measure’ market liquidity factors. In addition to estimating market liquidity factors for each individual liquidity measure, we also construct liquidity factors across all four liquidity measures taken together which also capture common variation across liquidity measures. Here, we first stack the (T x n) matrices above to form a (T x 4n) matrix from which we again extract the first three principal components. We refer to these as our ‘across-measure’ market liquidity factors.

It is necessary to first normalize the liquidity measures to avoid one liquidity measure driving the extracted factors because of its relative magnitude. If $L^i$ is a (T x n) matrix of the stock liquidity levels of measure *i*, $NL^i$ is the standardised liquidity measure

$$NL^i_{s,t} = \frac{L^i_{s,t} - \hat{\mu}^i_{s,t}}{\hat{\sigma}^i_{s,t}} \tag{7}$$

where $\hat{\mu}^i_{s,t}$ 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 measure *i* for stock *s* up to time *t-1*.. The extracted factors are signed to represent liquidity[3]. These factors are then pre-whitened using an AR (2) process so as to represent shocks to market liquidity.

[3] The sign of the extracted factors is ambiguous so to represent liquidity they are signed to be negatively (positively) correlated with the time series of the cross sectional average of the relevant measure if it represents illiquidity (liquidity). In the case of the across measure factor the sign is chosen so that the factor is negatively correlated with the time series of the cross sectional average of all the measures where turnover is first multiplied by -1 before averaging.

In Figure 2 we plot the pre-whitened extracted liquidity factors (first extracted principal component) for each liquidity measure and for the across measure. The most extreme shock to market liquidity is evident very early in the sample period, most likely reflecting recession in the UK economy for most of the 1991-1993 period. The period from 1997 to around 2001 also exhibits shocks to market liquidity reflecting a number of events impacting financial markets including the Asian currency crisis, the failure of Long Term Capital Management, Russian debt default, tech-stock bubble crash and 9/11.The Roll measure in particular shows the market liquidity shocks around the more recent financial crisis period. The other measures, e.g., the across measure, indicate market shocks during the 2007-2010 period also but not of the magnitude of some of the earlier shocks perhaps reflecting an overall increase in market liquidity over time, consistent with the rising trend in liquidity over time exhibited in Figure 1 previously[4].

**Figure 2 About here**

With the (pre-whitened) factors acting as proxies for market liquidity shocks, we estimate a market liquidity model similar to the Chordia et al (2000) model in (6) but with average market liquidity replaced by the (pre-whitened) first extracted principal component within and across liquidity measures as follows

[4] This is a feature of the rolling individual normalization process. In unreported results using future information to normalize at time t, the extracted factors still show greater magnitude of shocks in the early 1990’s and early 2000s compared to the latest financial crisis, the magnitude difference, however, is substantially reduced.

$$NL^{i}_{s,t} = \alpha_s + \beta^{i,in}_s * F^{i,in}_t + \beta^{acr}_s * F^{acr}_t + \gamma * C_{s,t} + \varepsilon^{i}_{s,t} \qquad (8)$$

where $F^{i,in}$ and $F^{acr}$ represent the within measure and across measure factors respectively and are orthogonalised. $C_{s,t}$ is the control variable vector of individual volatility and individual return as in (6).

Table 3 presents the results of the stock regressions. Since the extracted factors represent liquidity evidence for commonality is provided by significant negative coefficients on the market liquidity shock variables. (Turnover is multiplied by -1 for ease of comparison). We report the percentage of stocks which reject the null hypothesis of no commonality, including by bootstrap p-value as before. The average coefficients are not reported as they are not economically meaningful. The results in Table 3 indicate commonality among stocks where, for example, according to the ln Amihud across measure factor in the case of 39% of stocks, changes in stock liquidity are related to market liquidity shocks. The percentage of stocks exhibiting commonality in liquidity is slightly smaller but qualitatively similar to the commonality results in Table 2[5].

**Table 3 About Here**

## 4. The Pricing of Liquidity Risk: Characteristic and Systematic Risk

[5] In results not shown, we again repeat the analysis in Table 3 for decile portfolios of stocks sorted by size (market value) to test if commonality is related to a link between liquidity and size. However, again we find that all size sorted portfolios exhibit significant commonality, indicating that commonality in liquidity across stocks is not a size related phenomenon.

We now turn our attention to liquidity and asset pricing. Liquidity may be priced either as a characteristic or as a systematic risk factor. First, liquidity may be priced as a characteristic to compensate investors for the higher costs associated with an individual stock's illiquidity (Amihud and Mendelson, 1986). Lu and Hwang (2007) examine the pricing of liquidity as a characteristic for the UK and report a counter-intuitive finding that illiquid stocks underperform liquid stocks. Second, the strong degree of commonality in liquidity among UK stocks over the period established in section 3 points to systematic liquidity risk. This prompts the question as to whether systematic liquidity risk is priced in the cross-section of stocks where such stocks should offer investors a higher expected return as a risk compensation to induce investors to hold them.

Here, we examine the pricing of liquidity both as a characteristic and as a systematic risk factor. Firstly, we want to re-examine the counter-intuitive finding of Lu and Hwang (2007) and second we want to control for liquidity as a risk characteristic in our tests of liquidity as a systematic risk factor. We begin by looking at a stock's liquidity level as a risk characteristic. For each liquidity measure, each month we rank stocks by their level of liquidity over some past ranking period $r$, $r$ = 1,6 or 11. We then sort stocks into equal weighted decile portfolios and hold the portfolios for some forward looking holding period $h$, $h$ = 1 or 6. The portfolios are reformed at the end of the holding period. A liquidity characteristic mimicking portfolio is formed by taking a long position in the illiquid portfolio and a short position in the liquid portfolio. We refer to this as the 'IML', or illiquid minus liquid, portfolio. The time series of the IML portfolio is then regressed on CAPM, Fama and French (1996) three factor and Carhart (1997) four factor models and a performance alpha is estimated. As a second test, we estimate the alpha of each portfolio decile above as well as each decile's cross-sectional and time series average liquidity. A simple cross-sectional (across deciles) regression of decile alphas on decile average liquidity is then estimated.

Our results are presented in Table 4. Panel A shows the liquidity characteristic mimicking portfolio (long position in the illiquid portfolio and a short position in the liquid portfolio) performance alphas for the alternative ranking and holding periods described above. The evidence clearly indicates that illiquid stocks severely underperformed liquid stocks. This is the case for all liquidity measures and almost all models and ranking/holding period combinations. The observed premia are large, particularly for the CAPM alphas with the quoted spread mimicking portfolio showing an alpha of -2.45% per month ($r$ = 1, $h$ = 1). The consistency in findings across liquidity measures is interesting and suggests that either they do not measure different aspects of liquidity or that the different aspects of liquidity are similarly priced. In Panel B, the cross-sectional regressions of decile alpha on decile average liquidity indicate that the findings in Panel A are not just due to the performance of extreme decile portfolios (though this finding is less robust in the case of turnover as a measure of liquidity). In short, the unexpected results of Lu and Hwang (2007) are wholly confirmed here.

**Table 4 about here**

We now turn to examining the pricing of systematic liquidity risk among stocks. We first construct a systematic liquidity risk mimicking portfolio. For each market liquidity factor, i.e., for each within-measure factor and the across-measure factor (first extracted principal components, 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.[6] We estimate this regression over the previous 36 months (minimum 24 month requirement for stock inclusion). Stocks are then sorted into fractile portfolios (we examine vigintiles, deciles, quintiles and terciles) according to their liquidity risk, i.e., their estimated beta relative to the market liquidity factor as follows

$$r_{i,t} = \theta_i + \beta_i * F_t^L + \gamma_i * F_t^O + \varepsilon_{i,t} \qquad (9)$$

where $F_t^L$ is the relevant (pre-whitened) market liquidity factor, L = 1, 2…5. $F_t^O$ 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 20 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, e.g., 20-1. The time series of returns for each of these liquidity

[6] The market factor is the monthly excess return of the FTSE All Share index. The size factor is calculated by creating portfolios from the sample of stocks by ranking them on market value and forming deciles. The size risk mimicking portfolio is formed by going long the smallest decile and taking a short position in the largest decile and reforming monthly. The value factor is calculated by creating portfolios from the sample of stocks by ranking them according to book to market (BTM) value and forming deciles. The value factor mimicking portfolio is formed by going long the high BTM decile and taking a short position in the low BTM decile and reforming monthly. The momentum factor is constructed by sorting stocks into portfolios based on returns over the previous 11 months and holding for 1 month. The MOM factor is the holding period difference in returns between the top 30% and the bottom 30% of stocks.

risk mimicking portfolios is then regressed on CAPM, Fama and French (1996) and Carhart (1997) models to estimate the post liquidity risk ranking alphas.

The results of our systematic liquidity pricing tests are presented in Table 5. Panel A presents the performance alphas for the 20-1, 10-1, 5-1 and 3-1 liquidity risk mimicking portfolios. In the case of the quoted spread measure there is strong evidence that systematic liquidity risk is positively priced in the cross-section of stocks. This finding is statistically significant at the 1% significance level for all fractile portfolios and models. However, in the case of the other liquidity measures the results generally indicate that systematic liquidity risk is not priced (with a few exceptions). These differences in findings between measures may indicate that the liquidity measures capture different aspects of systematic liquidity risk. Overall, the across measure liquidity factor, which captures commonality both across stocks and across liquidity measures, indicates strongly that systematic liquidity risk is significantly positively priced in stock returns independent of market, size, value and momentum risk. The across measure is clearly influenced by the strength of the finding around the quoted spread measure.

**Table 5 about here**

In order to control for liquidity as a risk characteristic in our tests of systematic liquidity risk pricing, Table 5 Panel B presents the performance alphas of the same portfolios as in Panel A but with each performance model augmented with the liquidity characteristic mimicking portfolio, IML. (Specifically, we use an 11 month ranking and 1 month holding period IML portfolio). The results in Panel B are qualitatively very similar to those in Panel A. (In the case of the ln Amihud measure there is slightly stronger evidence of systematic liquidity risk pricing compared to Panel A). This indicates that characteristic liquidity risk does not alter our findings around the pricing of systematic liquidity risk and indeed these two types of liquidity risk represent distinct effects on stock returns.

In results not shown, we repeated the pricing tests reported in Table 4 and Table 5 over a shorter sample period ending in December 2007, i.e., excluding the recent financial crisis period, to examine whether the crisis period altered our findings. In the shorter period the key findings are confirmed where characteristic liquidity risk is negatively priced while systematic liquidity risk is positively priced in the cross-section of stocks. There is some evidence that the systematic liquidity risk premium is partly explained by a momentum risk factor indicating a link between momentum and liquidity risk. This finding does not persist when the recent financial crisis period is included in the analysis. Overall, however, our findings are qualitatively very similar between the two sub-periods.

Overall, our results on liquidity risk pricing provide evidence that systematic liquidity risk is positively priced in the cross-section of stock returns specifically in the case of the quoted spread measure. On characteristic liquidity risk, the findings of Lu and Hwang (2007) that the level of stock liquidity as a stock characteristic is negatively priced is strongly confirmed in our results. This is a counter-intuitive result and is not explained away by other risk factors such as size or momentum risk. Most liquid stocks on the LSE trade on the SETS order book system, whereas the less liquid stocks trade on a quote driven system. It is plausible that these differences in market structure, as well as multiple stock exchanges in the US, contribute to the contrasting findings around the pricing of characteristic liquidity risk between the UK and US markets. Also, Sadka and Scherbina (2007) report that US stocks which have a high level of analyst disagreement, which are often illiquid, tend to be overpriced and subsequently underperform other stocks. We leave a deeper examination of these questions to future research.

## 5. Conclusion

In this study, using daily data we analyze the role of systematic liquidity risk in UK equity pricing. We use asymptotic principal component analysis to construct systematic or market liquidity factors. We find strong evidence of commonality in liquidity where shocks to the liquidity of an individual stock are correlated with shocks to the liquidity of the rest of the market. Capturing liquidity commonality both across stocks and across liquidity measures, we find evidence that systematic liquidity risk is positively priced in the cross-section of stock returns. Controlling for the level of stock liquidity as characteristic risk does not affect these findings. However, we find that illiquid stocks underperform liquid stocks and the former provide a negative abnormal return not explained away by other commonly priced risk factors. This is a curious finding and requires further exploration in future research.

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**Table 1: Descriptive Statistics for Cross-section of Liquidity Measures**

The average of the time series of liquidity observations is calculated for each individual stock. 'Mean' is the cross-sectional average of the time series averages. 'Average Standard Dev' is the cross-sectional standard deviation of the time series means of each measure. The ln Amihud measure is the natural log of the adjusted trade impact measure developed by Amihud (2002), calculated as the monthly average of the natural log of the ratio of absolute daily return and daily volume. Quoted Spread is the average daily closing spread for a given month divided by the midpoint of the closing bid and ask prices. The Roll (1984) measure of effective spread for a given month is the square root of the negative of the serial covariance of returns, multiplied by 200, complex estimates are set to zero. Turnover is the monthly average of the ratio of daily volume to shares outstanding for a given stock.

| | **ln Amihud** | **Turnover** | **Quoted Spread** | **Roll Measure** |
|---|---|---|---|---|
| **Mean** | -8.32 | 0.29 | 7.85 | 1.05 |
| **Average Standard Dev** | 1.87 | 0.30 | 6.75 | 0.76 |
| **Average Skewness** | -0.53 | 3.90 | 1.36 | 2.44 |
| **Average Kurtosis** | 3.17 | 28.24 | 4.78 | 13.92 |
| **Max** | -3.66 | 3.54 | 41.07 | 7.43 |
| **Min** | -14.87 | 0.00 | 0.07 | 0.00 |
| **Number of Stocks** | 3231 | 3835 | 4234 | 4021 |

**Table 2: Estimation Results of the Market Model of Liquidity.**

For each stock liquidity measure the time series of changes in liquidity is regressed on the equal weighted average of the changes in all other stocks' liquidity levels and other control variables. 'Average Beta' is the cross-sectional average of the estimated coefficients on the market liquidity variable. The t-statistic tests the null hypothesis of the cross-sectional average beta being equal to zero. '% Positive' is the percentage of all estimated coefficients for a given liquidity measure that are positive. '% Significantly Positive' is the percentage of estimated coefficients for a given liquidity measure that are significantly positive for a 5% two tailed t-test. t-statistics are Newey-West adjusted for 2 lags. '% Bootstrap Significantly Positive' is the percentage of estimated coefficients for a given liquidity measure that are significantly positive at 5% significance using a bootstrapped probability distribution. The definitions of '% Significantly Negative' and % Bootstrap Significantly Negative' are defined similarly. '% Non Normal' indicates the percentage of stocks for which a Jarque-Bera test of normally distributed regression residuals is rejected at 5% significance. The Amihud measure is the natural log of the adjusted trade impact measure developed by Amihud (2002), calculated as the monthly average of the natural log of the ratio of absolute daily return and daily volume. Quoted Spread is the average daily closing spread for a given month divided by the midpoint of the closing bid and ask prices. The Roll (1984) measure of effective spread for a given month is the square root of the negative of the serial covariance of returns, multiplied by 200, complex estimates are set to zero. Turnover is the monthly average of the ratio of daily volume to shares outstanding for a given stock.

| | **Ln Amihud Measure** | **Turnover** | **Quoted Spread** | **Roll Measure** |
|---|---|---|---|---|
| **Average Beta** | 0.89*** | 0.70*** | 0.73*** | 0.80*** |
| **t-stat** | 23.02 | 24.24 | 29.58 | 27.02 |
| **% Positive** | 92.89 | 74.74 | 85.46 | 79.07 |
| **% Significantly Positive** | 59.63 | 23.36 | 28.66 | 29.19 |
| **% Bootstrap Significantly Positive** | 55.28 | 20.91 | 22.33 | 21.23 |
| **% Significantly Negative** | 0.15 | 0.39 | 0.67 | 1.33 |
| **% Bootstrap Significantly Negative** | 0.08 | 0.26 | 0.27 | 0.72 |
| **Average $R^2$** | 0.15 | 0.10 | 0.14 | 0.12 |
| **Average Adjusted $R^2$** | 0.10 | 0.06 | 0.10 | 0.07 |
| **Number of Estimates** | 1308 | 2324 | 3273 | 1658 |
| **% Non Normal** | 45.95 | 89.50 | 75.13 | 24.97 |

**Table 3: Commonality Results: Asymptotic Principal Components Approach.**
For each stock the time series of normalised liquidity is regressed on the extracted, prewhitened (by AR (2) process), orthogonalised liquidity factors and other control variables. '% Negative' is the percentage of all estimated coefficients for a given liquidity measure that are negative. '% Significantly Negative' and '% Bootstrap Significantly Negative' are the percentage of estimated coefficients for a given liquidity measure that are significantly negative by t-test and by a bootstrapped probability distribution respectively. t-statistics are Newey-West adjusted for 2 lags. '% Significantly Positive' and '% Bootstrap Significantly Positive' are defined similarly. The ln Amihud measure is the natural log of the adjusted Amihud (2002) measure, calculated as the monthly average of the natural log of the ratio of absolute daily return and daily volume. Quoted Spread is the average daily closing spread for a given month divided by the midpoint of the closing bid and ask prices. The Roll (1984) measure of effective spread for a given month is the square root of the negative of the serial covariance of returns, multiplied by 200, complex estimates are set to zero. Turnover is the monthly average of the ratio of daily volume to shares outstanding for a given stock.

| | **Ln Amihud Measure** | | **Turnover** | | **Quoted Spread** | | **Roll Measure** | |
|---|---|---|---|---|---|---|---|---|
| | **Across** | **Within** | **Across** | **Within** | **Across** | **Within** | **Across** | **Within** |
| **% Negative** | 83.17 | 75.85 | 71.75 | 65.86 | 59.83 | 64.56 | 48.32 | 72.09 |
| **%Significantly Negative** | 39.06 | 23.15 | 20.68 | 14.92 | 11.62 | 12.34 | 3.75 | 22.65 |
| **% Bootstrap Significantly Negative** | 33.27 | 17.90 | 15.78 | 12.85 | 7.80 | 9.24 | 2.02 | 18.09 |
| | | | | | | | | |
| **% Significantly Positive** | 1.53 | 1.06 | 1.68 | 2.67 | 2.38 | 2.60 | 6.16 | 2.33 |
| **% Bootstrap Significantly Positive** | 0.93 | 0.60 | 1.07 | 1.46 | 1.28 | 1.19 | 3.49 | 0.86 |
| | | | | | | | | |
| **% F-test Significant** | 65.60 | | 54.94 | | 65.31 | | 45.87 | |
| **Average $R^2$** | 0.19 | | 0.15 | | 0.18 | | 0.14 | |
| **No. Stocks estimated** | 1503 | | 2326 | | 3194 | | 2322 | |

**Table 4: Pricing of Liquidity as a Characteristic.**

Each month stocks are ranked according to their average liquidity level over the previous 1,6 or 11 months. Stocks are then sorted into equal weighted decile portfolios that are held for 1 or 6 months before reforming. This is done for each liquidity measure. Panel A shows the performance results of the characteristic mimicking portfolios formed by taking a long position in the most illiquid portfolio and a short position in the most liquid portfolio. The portfolios are tested against the CAPM, Fama and French and Carhart models and performance alphas are estimated. t-statistics are Newey West adjusted for 2 lags. In Panel B, the time series average liquidity of each decile is first calculated. A cross-sectional regression (across deciles) of alpha on average liquidity is estimated. Slope coefficient estimates are multiplied by 1,000 for ease of presentation as indicated. 'Rank' is the length of the backward looking ranking period, 'Hold' is the length of the forward looking holding period. *** Indicates Significance at 1%, ** Significance at 5% and * Significance at 10%.

| **Panel A** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Rank = 1, Hold = 1** | | | **Rank = 6, Hold = 6** | | | **Rank = 11, Hold = 1** | | |
| | **CAPM** | **F&F** | **Carhart** | **CAPM** | **F&F** | **Carhart** | **CAPM** | **F&F** | **Carhart** |
| **ln Amihud** | -1.57*** | -0.87*** | -0.73* | -1.58*** | -0.82*** | -0.53* | -1.74*** | -0.98*** | -0.70*** |
| **t-stat** | -4.46 | -3.45 | -1.73 | -4.97 | -3.65 | -1.84 | -5.44 | -4.28 | -2.22 |
| **Share Turnover** | -1.82*** | -1.65*** | -1.47*** | -1.30*** | -1.10*** | -1.02*** | -1.34*** | -1.13*** | -1.03*** |
| **t-stat** | -7.68 | -6.61 | -5.61 | -6.11 | -5.77 | -3.69 | -6.01 | -5.61 | -3.67 |
| **Quoted Spread** | -2.45*** | -1.32*** | -0.96*** | -2.14*** | -1.11*** | -1.21*** | -2.11*** | -1.10*** | -1.20*** |
| **t-stat** | -7.81 | -7.66 | -5.28 | -7.31 | -6.78 | -6.34 | -7.32 | -6.61 | -6.20 |
| **Roll Measure** | -1.01*** | -0.59*** | -0.23 | -1.08*** | -0.72*** | -0.37*** | -1.37*** | -1.01*** | -0.65*** |
| **t-stat** | -5.07 | -3.61 | -1.00 | -6.88 | -5.05 | -2.04 | -8.19 | -7.14 | -3.44 |
| **Panel B** | | | | | | | | | |
| | **Rank = 1, Hold = 1** | | | **Rank = 6, Hold = 6** | | | **Rank = 11, Hold = 1** | | |
| | **CAPM** | **F&F** | **Carhart** | **CAPM** | **F&F** | **Carhart** | **CAPM** | **F&F** | **Carhart** |
| **(ln Amihud)* 1000** | -1.99*** | -0.82** | -0.56 | -2.04*** | -0.84** | -0.49 | -2.12*** | -0.97** | -0.67 |
| **t-stat** | -7.00 | -2.45 | -1.36 | -8.65 | -2.85 | -1.42 | -7.20 | -2.67 | -1.72 |
| **Share Turnover** | -1.37** | -1.24** | -1.00* | -0.75 | -0.53 | -0.46 | -0.72 | -0.54 | -0.43 |
| **t-stat** | -2.39 | -2.90 | -2.21 | -1.36 | -1.16 | -0.97 | -1.37 | -1.23 | -0.91 |
| **Quoted Spread** | -0.12*** | -0.08*** | -0.07*** | -0.11*** | -0.07*** | -0.07*** | -0.10*** | -0.07*** | -0.07*** |
| **t-stat** | -7.02 | -6.38 | -6.09 | -9.49 | -8.87 | -8.66 | -8.17 | -7.86 | -9.06 |
| **Roll Measure** | -0.02*** | -0.01*** | -0.01*** | -0.02*** | -0.01*** | -0.01*** | -0.02*** | -0.01*** | -0.01*** |
| **t-stat** | -5.98 | -5.55 | -3.77 | -9.60 | -10.21 | -4.32 | -12.57 | -11.50 | -5.14 |

**Table 5: The Pricing of Systematic Liquidity Risk**

Each month we regress each stock's return on the market liquidity factor (first extracted principal component, pre-whitened) over the previous 36 months. Stocks are ranked and placed into fractiles according to factor sensitivity (market liquidity beta) and reformed monthly. Liquidity risk mimicking portfolio are formed by calculating the difference in returns between the high and low liquidity risk fractiles. The liquidity risk mimicking portfolios are regressed against CAPM, Fama and French and Carhart models. In Panel A we report alpha and its (Newey-West adjusted) t-statistic for the various liquidity measure factors as well as for the across measure factor. In Panel B we present results of the same tests as in Panel A but where the performance models are augmented by a liquidity characteristic mimicking portfolio (IML). This is formed by each month ranking stocks by their average liquidity level over the previous 11 months, sorting stocks into decile portfolios and holding these portfolios for 1 month. IML is the return on the illiquid minus liquid portfolio. Portfolio are reformed monthly. *** Indicates Significance at 1%, ** Significance at 5% and * Significance at 10%.

| **Panel A** | **CAPM** | | | | **Fama & French** | | | | **Carhart** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Liquidity Measure** | **20** | **10** | **5** | **3** | **20** | **10** | **5** | **3** | **20** | **10** | **5** | **3** |
| **Across Measure** | 0.99*** | 0.68*** | 0.26** | 0.16 | 1.01*** | 0.78*** | 0.40** | 0.30** | 1.05*** | 0.80** | 0.43 | 0.33* |
| **t-stat** | 4.40 | 3.64 | 1.97 | 1.58 | 3.50 | 3.18 | 2.09 | 2.25 | 2.79 | 2.41 | 1.63 | 1.79 |
| **Ln Amihud** | 0.15 | 0.10 | -0.01 | -0.01 | 0.35 | 0.30 | 0.21 | 0.20 | 0.68 | 0.48 | 0.39 | 0.36* |
| **t-stat** | 0.53 | 0.46 | -0.06 | -0.06 | 1.04 | 1.13 | 1.18 | 1.48 | 1.42 | 1.21 | 1.53 | 1.87 |
| **Turnover** | 0.05 | -0.38** | -0.18 | -0.12 | -0.01 | -0.46*** | -0.21 | -0.12 | 0.18 | -0.25 | -0.18 | -0.09 |
| **t-stat** | 0.19 | -2.12 | -1.40 | -1.21 | -0.05 | -2.59 | -1.51 | -1.12 | 0.57 | -1.12 | -1.08 | -0.65 |
| **Quoted Spread** | 1.26*** | 0.97*** | 0.54*** | 0.43*** | 1.38*** | 1.09*** | 0.69*** | 0.59*** | 1.25*** | 0.96*** | 0.58*** | 0.51*** |
| **t-stat** | 4.91 | 4.85 | 3.86 | 4.30 | 4.63 | 4.53 | 4.20 | 4.91 | 3.43 | 2.97 | 2.88 | 3.75 |
| **Roll Measure** | -0.16 | -0.05 | -0.09 | -0.05 | -0.13 | 0.06 | 0.03 | 0.06 | 0.13 | 0.23 | 0.24 | 0.27** |
| **t-stat** | -0.63 | -0.25 | -0.61 | -0.47 | -0.52 | 0.30 | 0.20 | 0.51 | 0.44 | 1.02 | 1.47 | 1.96 |

| **Panel B** | **CAPM+IML** | | | | **Fama & French +IML** | | | | **Carhart+IML** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Liquidity Measure** | **20** | **10** | **5** | **3** | **20** | **10** | **5** | **3** | **20** | **10** | **5** | **3** |
| **Across Measure** | 0.97*** | 0.77*** | 0.41** | 0.44*** | 1.12*** | 0.89*** | 0.51** | 0.50*** | 1.09*** | 0.84*** | 0.48** | 0.51*** |
| **t-stat** | 3.39 | 3.10 | 2.09 | 2.87 | 3.78 | 3.55 | 2.60 | 3.22 | 3.06 | 2.77 | 1.97 | 2.62 |
| **Ln Amihud** | 0.29 | 0.31 | 0.30 | 0.31* | 0.34 | 0.33 | 0.39* | 0.37** | 0.53 | 0.50 | 0.51* | 0.45** |
| **t-stat** | 0.77 | 1.07 | 1.38 | 1.89 | 0.89 | 1.12 | 1.77 | 2.18 | 1.16 | 1.37 | 1.85 | 2.16 |
| **Turnover** | 0.08 | -0.32* | -0.10 | -0.02 | 0.15 | -0.19 | -0.03 | 0.01 | 0.27 | -0.10 | -0.03 | 0.01 |
| **t-stat** | 0.27 | -1.65 | -0.73 | -0.15 | 0.50 | -0.93 | -0.19 | 0.05 | 0.84 | -0.44 | -0.22 | 0.05 |
| **Quoted Spread** | 1.52*** | 1.12*** | 0.73*** | 0.63*** | 1.62*** | 1.14*** | 0.80*** | 0.68*** | 1.51*** | 1.08*** | 0.74*** | 0.63*** |
| **t-stat** | 4.29 | 4.92 | 4.33 | 4.81 | 4.41 | 4.77 | 4.77 | 5.26 | 3.22 | 3.61 | 3.57 | 3.84 |
| **Roll Measure** | -0.26 | -0.06 | 0.05 | 0.04 | -0.22 | 0.04 | 0.11 | 0.10 | 0.01 | 0.22 | 0.25 | 0.25* |
| **t-stat** | -0.89 | -0.27 | 0.28 | 0.30 | -0.76 | 0.19 | 0.67 | 0.72 | 0.04 | 1.01 | 1.40 | 1.74 |

**Figure 1: Time Series Plots of Monthly Cross-sectional Value Weighted Average Liquidity.**
ln Amihud is the natural log of the adjusted Amihud (2002) measure, calculated as the monthly average of the natural log of the ratio of absolute daily return and daily volume. Quoted Spread is the average daily closing spread for a given month divided by the midpoint of the closing bid and ask prices. The Roll (1984) measure of effective spread for a given month is the square root of the negative of the serial covariance of returns, multiplied by 200, complex estimates are set to zero. Turnover is the monthly average of the ratio of daily volume to shares outstanding for a given stock. The figure plots the time series of the monthly cross-sectional value weighted average (normalised) liquidity level for each liquidity measure.

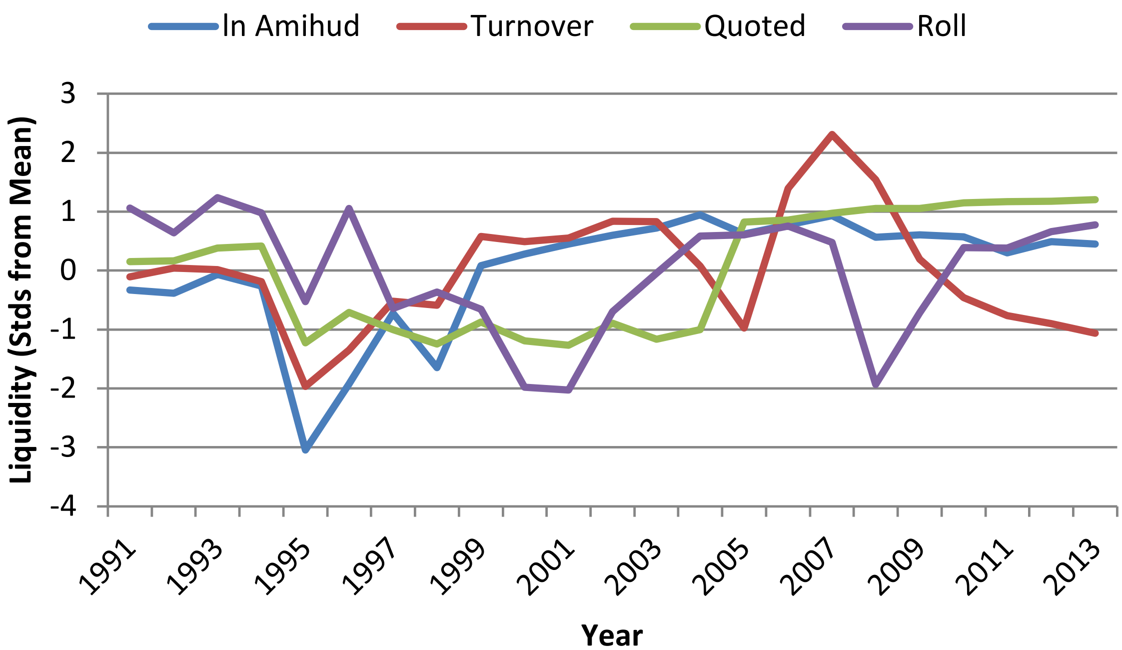

**Figure 2: Market Liquidity Shocks**

Using asymptotic principal component analysis common factors are extracted within each liquidity measure and across all four liquidity measures together. We denote these as market liquidity factors. The factors are then pre-whitened by an AR(2) process to capture shocks to market liquidity. The time series of the shocks are plotted for each measure and across all measures for the time period June 1991 to December 2013.