The Asset Pricing Effects of UK Market Liquidity Shocks: Evidence from Tick Data

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Abstract
Using tick data covering a 12 year period including much of the recent financial crisis we provide an unprecedented examination of the relationship between liquidity and stock returns in the UK market. Previous research on liquidity using high frequency data omits the recent financial crisis and is focused on the US, which has a different market structure to the UK. We first construct several microstructure liquidity measures for FTSE All Share stocks, demonstrating that tick data reveal patterns in intra-day liquidity not observable with lower frequency daily data. Our asymptotic principal component analysis captures commonality in liquidity across stocks to construct systematic market liquidity factors. We find that cross-sectional differences in returns exist across portfolios sorted by liquidity risk. These are strongly robust to market, size and value risk. The inclusion of a momentum factor partially explains some of the liquidity premia but they remain statistically significant. However, during the crisis period a long liquidity risk strategy experiences significantly negative alphas.

Keywords: Liquidity risk, liquidity measures, asset pricing.

JEL Classifications: G11, G12.

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1. Introduction

One of the striking features of the recent financial crisis was the abrupt drop in aggregate liquidity across global financial markets. This drop in liquidity is a market failure that led to a large increase in trading costs through wider spreads and greater price impact. The financial crisis has heightened awareness amongst investors of the importance of considering liquidity (Brunnermeier (2008) and Longstaff (2010)). In this paper we make three key contributions to the literature on liquidity and stock returns. We are the first paper to examine the pricing of liquidity risk in stock returns in the UK market. Second, we employ a high frequency intra-day dataset unprecedented in depth for a UK study. Finally, as we specify a sample period which incorporates this crisis incidence of market illiquidity, our paper provides much needed additional evidence on the role of liquidity in asset pricing.

Trading on the UK stock market is quite different to the US, where prior research on high frequency data has focused. In the UK all trading takes place on the London Stock Exchange (LSE) whereas in the US stocks trade primarily on two main exchanges, the Nasdaq and NYSE. On the LSE trading is a mix of order book driven (SETS) and a hybrid quote/order book driven system (SETSmm), whereas in the US trading on Nasdaq is order book driven and the NYSE has a hybrid system. The differing market structure of UK and US exchanges leads to differences in liquidity characteristics (Huang and Stoll (2001)). By providing evidence on the pricing of 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 liquidity and stock returns as documented in the predominantly US literature.

Using an extensive data set of over 1.2 billion tick and best price observations covering the period January 1997 to February 2009 we are able to construct several microstructure stock liquidity measures for the UK for the first time. Our tick data enable the calculation of liquidity measures, some of which cannot be calculated using lower frequency, even daily, data. Others can be estimated with daily data but we find such estimates risk biasing results[1]. We construct time series of seven liquidity measures for each of the FTSE All Share constituent stocks over our sample period. We examine a large number of measures as different aspects of liquidity risk may not all be captured by one measure. For each liquidity measure we use asymptotic principal component analysis to capture commonality in liquidity across stocks in order to develop a systematic market liquidity factor. We also develop a systematic market liquidity factor across all seven measures combined which draws on the commonality in liquidity across assets as well as the commonality across liquidity measures. We construct liquidity risk mimicking portfolios based on stocks' sensitivity to shocks to our systematic market liquidity factors. We examine several related questions: Is there a return premium for UK market or systematic liquidity risk? If so, is this return premium compensation specifically for the stock's systematic liquidity risk or the liquidity characteristics of the stock generally? What is the degree of commonality across liquidity measures among UK stocks? Are liquidity shocks persistent?

Briefly, we find that liquidity risk confers a significant premium in normal market conditions. There is evidence that the liquidity risk premium is related to momentum, consistent with Sadka (2006), but is unrelated to market, size and value risk. However, our new evidence around the recent financial crisis indicates that liquidity risk sensitive portfolios suffered significant abnormal negative returns during the period, highlighting the skewed nature of the pricing of liquidity risk.

The paper is organised as follows: Section 2 provides a brief discussion of the theory and empirical methods of the surrounding literature. Section 3 describes the extensive data set used. Section 4 outlines the methodology for estimating the liquidity measures from the data while section 5 presents the methodology and results of tests for the cross sectional pricing of liquidity risk. Section 6 concludes.

[1] For example, taking the quoted spread liquidity measure which can be calculated using high frequency tick data or lower frequency daily closing prices, we demonstrate that the quoted spread varies considerably throughout the day, falling steadily over the course of the morning and flattening out in the afternoon. Calculating this measure using daily closing prices could give a false impression of liquidity.

2. Theory and Empirical Methods

The traditional domain of market microstructure research is the individual security with liquidity studied as an idiosyncratic phenomenon. Models of this type include the inventory based models of Stoll (1978) and the information based models of Kyle (1985). US based studies indicate that liquidity exhibits systematic variations (Chordia et al. (2000), Huberman and Halka (2001), Korajczyk and Sadka (2008)). However, commonality in liquidity across stocks is not peculiar to the NYSE's idiosyncratic market structure, it has also been detected in order only markets. For example, Brockman and Chung (2002) analyse commonality in liquidity on the Hong Kong stock exchange which has no central market makers and find evidence of commonality. It has also been found across multiple markets (Brockman et al. (2009), Zhang et al (2009)). Karolyi et al. (2012) suggest that commonality is driven by demand side factors more than funding liquidity drivers. Specifically, the authors find that global market liquidity is not primarily driven by financiers increasing margin requirement in times of crisis but rather investors themselves influencing liquidity based on sentiment, information acquisition incentives and correlated trading activity.

A separate vein of microstructure research indicates that static illiquidity, namely the property of a stock being persistently more or less liquid over time, is cross sectionally priced as a characteristic (Amihud and Mendelsen (1986)). Certain theoretical models question this hypothesis. Constantinides (1986) argues that investors will adjust their trading frequency to offset any trading costs over multiple periods. Single period models which study the pricing of liquidity as a characteristic fail to take account of the empirically observed time variation in liquidity. Acharya and Pedersen (2005) develop an overlapping generations (OLG) model of liquidity risk and argue that liquidity risk may be split up into (i) sensitivity of individual asset's return to market liquidity, (ii) sensitivity of individual asset's liquidity to market liquidity and (iii) sensitivity of individual asset's liquidity to market return.

Also using tick data for the US, Korajczyck and Sadka (2008) is a comprehensive analysis of liquidity and liquidity pricing. The authors construct several liquidity measures and examine the commonality in liquidity across assets as well as the commonality across liquidity measures. The paper uses asymptotic principal component analysis to incorporate the commonality across assets into a systematic market liquidity factor for each liquidity measure while also developing a systematic market liquidity factor based on all liquidity measures jointly. The study finds in particular that systematic market liquidity based on this joint measure is priced as a factor and that high minus low liquidity risk portfolios generate a statistically significant positive alpha by CAPM and Fama-French (1996) specifications.

To our knowledge there is little research on systematic liquidity in the UK stock market. Galariotis and Giouvris (2007) report strong commonality among FTSE 100 stocks. Lu and Hwang (2007) study the pricing of illiquidity as a characteristic and report the surprising finding that illiquid stocks significantly underperform liquid stocks. Our paper adds to this literature by examining the pricing of systematic market liquidity risk employing a large and long intra-day data set, examining several new measures of liquidity and including much of the financial crisis period.

3. Data

The UK tick data and best price data analysed here were purchased from the LSE information products division and cover the period from 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 of the trade, 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. In total, the files contain 792,995,147 trades prior to any filtering. 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 TIC, SEDOL, country of register, currency of the trade and time stamp of best price. The files contain 1,956,681,874 best prices prior to any filtering.

We apply a number of filters to the data prior to our analysis. All trades and quotes that occur 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).[2] Opening auctions are removed as their liquidity dynamics may be different from continuous auction trades. Cancelled trades are removed. We estimate liquidity in a given month only if the stock was a constituent of the FTSE All Share that month[3]. The data are cross-referenced with the London Share Price Database (LSPD) Archive file, SEDOL master file and returns file used in the construction of benchmark portfolios in our multi-factor performance models. The LSPD Archive file records when a given stock was a constituent of the FTSE All Share. We cross reference the data sets by comparing SEDOL numbers[4]. Best prices that only fill one side of the order book (i.e., where there is a best bid but no corresponding ask price) are removed. Trades that occur in any currency other than GBP are removed. A small number of unrealistically large quoted spreads are removed on data quality grounds: 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. The result of

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[2] The data file covers trades of all the LSE's systems. The Stock Exchange Automated Quotation (SEAQ) system is a dealer centred system with dealers registered in a number of stocks. Dealers have an obligation to post firm bid and offer prices throughout the Mandatory Quotation Period (MQP) from 08:00:00 to 16:30:00. These bid and offer prices have to be honoured for at least the Normal Market Size (NMS) of a stock, defined as 2.5% of the average daily volume. The Stock Exchange Electronic Trading Service (SETS) system was set up in 1997 for the most liquid stocks on the exchange, namely FTSE100 stocks. This system is an order driven system where market participants have the choice between the traditional SEAQ style trade with dealers and an electronic order book that matches off setting orders. The inclusion of a stock in SETS removed the obligation of dealers to provide quotes and trades with dealers had to be negotiated. In September 1999, 47 mid cap stocks that were included in the FTSE 250 were transferred to SETS. In 2003 more stocks were added to a hybrid SETSmm where dealers still have an obligation to provide firm quotes in their registered stocks but investors have the option of using the electronic order book.

[3] The FTSE All Share Index is the aggregation of the FTSE 100, FTSE 250 and FTSE Small Cap indices comprising between 600 and 1,000 stocks on the LSE historically. We are satisfied this is sufficiently broad based and includes stocks most relevant to investors.

[4] 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.

applying these filters is that 673,421,155 trades and 594,647,452 best bid and ask prices remain.

As a preliminary analysis of intra-day liquidity we calculate the quoted spread for each 15 minute period within the trading day for each stock and average across all stock-days. The quoted spread is the bid/ask spread as a percentage of the midpoint of the bid/ask prices. Figure 1 (upper panel) plots the average (across stocks) quoted spread throughout the day. The spread is at its largest at the beginning of the day at 68 basis points before declining rapidly to below 40 bps by around 10.00. The average spread reaches its minimum around 13.30 at 35 bps before increasing marginally during early US trading. This pattern is consistent with that found in Admati and Pfleiderer (1988) as private information can accrue over the previous night impacting on morning trading. Tick data highlight the varying nature of liquidity throughout the day, a feature not captured by lower frequency daily data. We also estimate intra-day volatility by the same algorithm as Abhyankar et al. (1997), 1 minute returns are calculated from changes in the midpoints of quotes to avoid any bid-ask bounce. The absolute value of the returns are then aggregated up into 15 minute intervals which is then taken as a proxy for volatility. The graph of average intra-day volatility is shown in Figure 1 (lower panel). Volatility is quite high at the beginning of the trading day and remains elevated for the first hour or so before falling away for the remainder of the morning. There is a spike in volatility around closing.

[Figure 1]

In our multifactor pricing models the risk factor benchmark portfolios to proxy market, size, value and momentum risks are as follows: FTSE All Share returns are used to represent the market portfolio (source: LSPD). The size factor benchmark portfolio, small minus big (SMB), is calculated from the sample by each month forming a portfolio that is long the smallest decile of stocks and short the largest decile of stocks based on market value and holding for one month before reforming. Market value data are taken from the London Share Price Database (LSPD). The value factor benchmark portfolio, high book to market minus low book to market stocks (HML), is the return on the Morgan Stanley

Capital International (MSCI) Value Index minus the return on the MSCI Growth Index (Cuthbertson et al. (2008)). The Momentum factor benchmark portfolio (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 (Carhart (1997), Cuthbertson et al. (2008)). Return data are taken from the LSPD. All portfolios are equal weighted. The risk free rate is the yield on 3 month sterling denominated gilt (source: Bank of England).

4. Liquidity Measures

We estimate seven liquidity measures from the microstructure literature, each measure is estimated for each stock each month.

A. 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.

B. 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

$$E_{s,m} = \frac{1}{tr_{s,m}} * \sum_{t=1}^{tr_{s,m}} \frac{P^{tr}_{s,t} - m_{s,t-5}}{m_{s,t-5}} \tag{2}$$

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

where $P^{A}_{s,t-5}$ and $P^{B}_{s,t-5}$ 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*. $P^{tr}_{s,t}$ is the price at which a trade occurs. Higher levels of effective spread are associated with lower levels of liquidity.

C. Order Imbalance

We calculate order imbalance as the excess of buy volume over sell volume as a percentage of the month's total volume. Our raw data do not contain trade direction. A number of algorithms exist that attempt to sign trades such as the tick rule where if price increases (decreases) the trade is considered a buy (sell). We use the method of Ellis et al. (2000) where all trades executed at or above the ask quote are categorized as buys, all trades executed at or below the bid quote are categorized as sells. All other trades are categorized by the tick rule. Buyer-initiated trades are signed as +1 and seller-initiated trades are signed as -1. Trades that do not cause an increase or decrease in price are given the same sign as the previous trade. Order imbalance for stock *s* in month *m* is given as

$$OIB_{s,m} = \frac{100}{\sum_{t=1}^{tr_{s,m}} V_t} * \sum_{t=1}^{tr_{s,m}} D_t V_t \tag{3}$$

where V_t is the unsigned volume of each trade *t*, D_t is the sign of each trade *t*, $tr_{s,m}$ is the number of trades in month *m* for stock *s*. Higher levels of order imbalance are associated with higher levels of liquidity.

D. Price Impact Model (Sadka (2006))

We implement the Sadka (2006) price impact model on UK data for the first time. The model posits that trades affect prices in four ways – through permanent informational effects and transitory 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 where we adopt similar notation to Sadka (2006).[5]

$$\Delta p_t = \Psi \varepsilon_{\psi,t} + \lambda \varepsilon_{\lambda,t} + \bar{\Psi} \Delta D_t + \bar{\lambda} \Delta (DV_t) + y_t \tag{4}$$

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 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. As traders are known to break large orders up into smaller orders to reduce price impact effects order flow can be predictable. Sadka (2006) proposes using the residual from an estimated AR(5) process as a measure of unexpected order flow as follows:

$$DV_t = n_0 + \sum_{`j=1}^{5} n_j DV_{t-j} + \varepsilon_{\lambda,t} \tag{5}$$

The unexpected order sign is estimated by imposing normality on the error term. Expected direction becomes $E_{t-1}[D_t] = 1 - 2\varphi(-E_{t-1}[DV_t] / \sigma_\varepsilon)$ where σ_ε is the autocorrelation corrected standard deviation of the error term and $\phi(.)$ is the cumulative normal density function. (See Sadka (2006) for full details). Eq (4) is estimated by OLS each month. $\Psi_{s,t}$ is the permanent fixed price impact measure for stock *s* in month *t*.

[5] Korajczyk and Sadka (2008) also provide a summary of the estimation procedure.

$\lambda_{s,t}$ is the permanent variable price impact measure for stock *s* in month *t*. $\overline{\Psi}_{s,t}$ is the transitory fixed price impact measure for stock *s* in month *t*. $\overline{\lambda}_{s,t}$ is the transitory variable price impact measure 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. Our price impact statistics indicate that there can be substantial price impact from trades: an unexpected buy order is found to permanently increase price by 28 basis points with the temporary fixed effects being as high as 42 bps. The average transitory variable effect is negative, similar to the findings for the US (Sadka (2006). All of our seven liquidity measures are winsorised at the 1% and 99% percentiles to reduce the effect of outliers (Korajczyk and Sadka (2008)).

5. Pricing of Liquidity Risk in Linear Asset Pricing Models

In this section we investigate the pricing of liquidity risk. First, we provide some preliminary discussion around the construction and properties of our market liquidity factors.

5.1. Constructing Liquidity Factors

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 for each liquidity measure we extract the first three principal components. 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 seven liquidity measures taken together. Here, we first stack the (T x n) matrices above to form a (T x 7n) matrix from which we again extract the first three principal components. We refer to these as our 'across-measure' (market) liquidity factors. In constructing these across-measure factors, the seven liquidity measure inputs are in different units of measurement. These scale differences mean that the resulting liquidity factors may overweight the larger unit liquidity measures without these being of any greater economic significance. To avoid this possible bias we first normalise all liquidity measures before extracting the principal components as follows: $NL^{i}_{s,t} = \frac{L^{i}_{s,t} - \hat{\mu}^{i}_{s,t}}{\hat{\sigma}^{i}_{s,t}}$. $\hat{\mu}^{i}_{s,t}$ 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 measure *i* for stock *s* up to time *t-1*.[6] We do this prior to the construction of both the within and across-measures factors.

In the case of some liquidity measures rising values represent reduced liquidity, e.g., quoted spread while for others the opposite is true, e.g., order imbalance. In turn, this complicates the interpretation of the extracted factors. For ease, we sign all factors so as to represent liquidity. Within-measure factors are signed to be negatively (positively) correlated with the time series of the monthly cross sectional average of the relevant measure if it represents illiquidity (liquidity). In the case of the across-measure factors the sign is chosen so that the factors are negatively correlated with the time series of the cross sectional average of the measures where here order imbalance is first multiplied by -1 before averaging.

5.2 Measuring Liquidity Shocks

In order to examine market liquidity shocks rather than anticipated changes in market liquidity, for each within-measure liquidity factor as well as for the across-measure factor we estimate the residuals of an AR(2) process fitted to the time series of the first extracted principal components. The results of this pre-whitening process are reported in Table 1 along with the proportion of a shock occurring at time *t* that remains at time *t+12* as implied by the AR(2) coefficients. Only the across-measure factor exhibits a significant coefficient on its second lagged value. The across-measure factor shows the greatest level of persistence with 61% of a shock at time *t* remaining at time *t+12*. The

[6] In order for there to be a feasible estimate of $NL^{i}_{s,t}$ 5 observations are required before inclusion in the sample.

order imbalance factor exhibits little persistence as almost none of the time *t* shock is transmitted to time *t+12*.

[Table 1]

5.3 Commonality Across Liquidity Measures

As we construct several different market liquidity factors (within and across liquidity measures) it is useful to provide a brief discussion of the extent to which these alternative extracted factors exhibit commonality across liquidity measures. As in Korajczyk and Sadka (2008) it is helpful here to use canonical correlation analysis. Specifically, for the first three extracted factors (principal components) across each pair of liquidity measures we calculate the first canonical correlation. We perform a similar canonical correlation analysis of the pre-whitened factors. We also look at the canonical correlation between liquidity factors and returns. Results are presented in Table 2 for the factors and pre-whitened factors in Panel A and Panel B respectively. All correlations are significant at the 1% significance level. As might be expected the results are slightly weaker for the pre-whitened factors in Panel B though they generally still suggests that the canonicals are significantly correlated (with just a few exceptions among the price impact measures) including those of liquidity factors and returns. Order imbalance is the most strongly correlated with return, as buying pressure increases prices would be expected to increase. Overall, there appears to be strong commonality across the various liquidity measures and indeed our later results are quite consistent across the various liquidity measure factors suggesting that liquidity proxies may be capturing the same underlying property.

[Table 2]

5.4. The Pricing of Liquidity Risk

We now turn to examining the pricing of liquidity risk among stocks. To do this we attempt to capture liquidity risk in a 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. 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

$$r_{i,t} = \theta_i + \beta_i * F_t^L + \gamma_i * F_t^O + \varepsilon_{i,t} \qquad (6)$$

where F_t^L is the relevant (pre-whitened) market liquidity factor, L = 1, 2…8. 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 risk mimicking portfolios is then regressed on CAPM, Fama-French (1996) and Carhart (1997) asset pricing models to estimate the post liquidity risk ranking alphas.

In order to examine liquidity risk pricing during the financial crisis, we also include an intercept dummy variable to capture the period. We take this as being from August 2007 to the end of the sample[7]. If liquidity risk is not priced independently of market, size, value and momentum risk then the portfolio alphas should be zero. Alphas and their t-statistics are reported in Table 3.

[7] On the 9th August 2007 Bloomberg reported that BNP Paribas halted withdrawals from three investment funds because it couldn't ``fairly'' value their holdings after U.S. subprime mortgage losses roiled credit markets (Bloomberg (2007)). We use this as one of the early indications of the financial crisis.

It is immediately apparent from Table 3 that the CAPM and Fama-French alphas are generally statistically significant across all portfolios sizes and liquidity factors at 1% significance and occasionally at 5% and 10% statistical significance. The only exception is the permanent variable price impact factor where we tend to fail to reject the hypothesis that portfolio (i.e., high minus low liquidity risk portfolio) alphas are zero. The across- measure factor is priced for all portfolio sizes in the non-crisis period, its risk premium is quite large with a monthly CAPM alpha of 1.79% for portfolio 10-1, the corresponding 3 factor alpha is 1.55%. In terms of magnitude, the effective spread factor provides the highest risk premium, significant for all models and portfolio sizes with an extremely high CAPM alpha (20-1) of 2.69%, the Fama-French alpha is also very high at 2.16%. The relative alpha performance of factor mimicking portfolios suggests that the performance is more pronounced at the extreme ends of liquidity risk as the across-measure 20-1 portfolio earns a 4 factor alpha of 1.65% per month (significant at 1%) whereas the 3-1 portfolio earns 0.50% per month (significant at 10%). The inclusion of the momentum factor causes some of the portfolios to become insignificant. The most robust are the effective spread factor, the temporary fixed price impact factor, the quoted spread factor and the across-measure factor. The order imbalance and temporary variable price impact factors are almost entirely explained away by momentum. For all portfolios the momentum factor substantially reduces the premium even for those portfolios that remain statistically significantly priced.

The estimated coefficient on the crisis intercept dummy, denoted “crisis”, indicates that from August 2007 there is a rapid reversal in risk adjusted return. For example, the four-factor alpha for the across-measure factors falls by 8.12% (portfolio 10-1). Indeed, the alphas for most liquidity factors and performance models are rendered insignificant over the entire time period if we carry out the performance regressions without including a crisis dummy (results not shown). This effect is pervasive across liquidity factors with the exception of the permanent variable factor, which shows counter-intuitive negative but largely insignificant alphas.

[Table 3]

Several studies such as Amihud and Mendelsen (1986) and Lu and Hwang (2007) argue that liquidity is priced as a characteristic: it is possible that liquidity risk which is positively priced could be explained away by liquidity as a characteristic, for example if high liquidity stocks were also high liquidity risk stocks. We control for this effect by including a liquidity characteristic factor mimicking portfolio in our performance models. This portfolio is formed in a similar manner to the size risk factor (SMB): each month all stocks are sorted into decile portfolios based on quoted spread, equal weighted portfolio returns are calculated over the following one month holding period and the process is repeated over a one month rolling window. The liquidity characteristic mimicking portfolio is the difference between the returns of the top and bottom decile portfolios, or illiquid minus liquid stocks, which we denote as the IML portfolio. Table 4 presents the performance results for the same portfolios as in Table 3 but with each performance model augmented with the liquidity characteristic mimicking portfolio (IML).

[Table 4]

Overall, the inclusion of the liquidity characteristic portfolio in Table 4 does not explain the observed liquidity risk premia in Table 3 which generally remain. The across-measure portfolios are mostly still significant at between 1% and 10% statistical significance albeit with reductions in the size of the alphas. The crisis intercept dummy variable remains significant in most cases as before with the reduction in alpha during the crisis period being of similar magnitude[8].

5.5 Cross Sectional Liquidity Pricing Tests

As an alternative approach to testing liquidity pricing, Tables 5 shows the results from a simple cross sectional regression of estimated portfolio alphas on market liquidity betas. Specifically, as before we estimate Eq (6) over a one month rolling backward-looking 36

[8] The fact that the crisis period was so extreme indicates that liquidity timing may have been a valuable skill as was seen in the US by Cao et al. (2013). We leave this as an interesting avenue of future research.

month window from which stocks are assigned to vigintile, decile and quintile portfolios based on their estimated beta relative to the market liquidity factor, i.e., $\hat{\beta}_i$. Each portfolio return is the equal weighted average return of its constituent stocks over the following month. The time series of returns for each of these 20, 10 and 5 liquidity risk portfolios is then regressed on CAPM, Fama-French (1996) and Carhart (1997) asset pricing models to estimate the post liquidity risk ranking alphas. We also include an intercept dummy variable to capture the crisis period. However, in estimating Eq (6) monthly over the backward-looking 36 month window, each month for each portfolio we also calculate the cross sectional (across stocks) average $\hat{\beta}_i$. For each portfolio we then calculate the time series average of these cross sectional average $\hat{\beta}_i$ values. Table 5 presents results of simple cross sectional (across portfolios) regressions of the portfolio alphas on these (average) portfolio betas. Values reported are the slope coefficients and their t-statistics from this regression. (Values are scaled by 10^3 for ease of presentation).

[**Table 5]**

The qualitative conclusion from the results are similar to before. Liquidity risk is priced where we see a statistically significant positive relationship between alpha and the liquidity risk betas across all measures of liquidity. Indeed the relationship is significant at the 1% level of significance in the 20 portfolio observations regression and the 10 portfolio observations regression. As before, the only exception is the permanent variable price impact measure. Looking at the cross-sectional regressions of the four-factor alphas on liquidity risk betas (denoted 'Carhart') we see that the pricing of liquidity risk is somewhat more robust to the inclusion of momentum in this cross-sectional analysis when compared to the results in Table 3.

In Table 6 we present results of the same analysis as presented in Table 5 but where we again control for the pricing of liquidity as a characteristic. Here, we again augment the CAPM, Fama-French (1996) and Carhart (1997) asset pricing models with the liquidity characteristic factor mimicking portfolio (IML) when estimating the post liquidity risk ranking alphas. From Table 6 we continue to see a statistically significant positive relationship between portfolio alphas and the portfolio liquidity risk betas across all measures of liquidity (except for the permanent variable price impact measure). Overall, the inclusion of the liquidity characteristic factor mimicking portfolio in Table 6 does not alter the finding that market liquidity risk premia remain statistically significant, albeit reduced slightly in size.

In summary, our results point to a strong degree of commonalty in liquidity among UK stocks. In terms of market-wide liquidity, we find a high level of persistence in market liquidity shocks. Our findings around pricing indicate that liquidity risk is positively priced in normal market conditions. During the more recent financial crisis period however, liquidity risk sensitive stocks yielded significant abnormal negative returns.

[Table 6]

Conclusion

In this study we employ a high frequency intra-day dataset, unprecedented in scale for the UK equity market, to investigate the asset pricing effects of market liquidity shocks. Our tick and best price data permit a richer analysis of liquidity by enabling the construction of liquidity measures which could not be calculated using lower frequency daily data. We construct time series of seven liquidity measures for each of the FTSE All Share constituent stocks during our sample period. We then construct systematic market liquidity factors for each measure as well as an across measure factor which captures commonality both across stocks and across liquidity measures. Our preliminary data analysis indicates strong commonality across liquidity measures and also shows that market liquidity shocks persist for up to one year. In our main results, liquidity risk mimicking portfolios exhibit a statistically significant return premium among high liquidity risk stocks. Controlling for liquidity level as a stock characteristic does not alter our conclusions. These are strongly robust to market, size and value risk. The inclusion of a momentum factor partially explains some of the liquidity premia but they remain statistically significant. We extend the literature by providing evidence on the pricing of liquidity risk during the financial crisis. In contrast to more normal market conditions our findings highlight that liquidity risk mimicking portfolios experienced significant losses during the crisis period. Overall, our results suggest that liquidity risk makes a significant contribution to asset pricing and point to a need to examine the liquidity exposure and liquidity risk adjusted returns of actual UK equity funds.

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Table 1: Estimation of Liquidity Shocks

Table 1 presents the results of AR(2) regressions of the first extracted principal components. Y_{t-1} represents the first lag and Y_{t-2} the second lag. The fraction of a shock at time *t* that is expected to remain at time *t+12* is also reported. Liquidity measures are estimated each month from tick data for the period January 1997 to February 2009. All the liquidity estimates are winsorised at 1% each month. Stocks' liquidity estimates are normalised by subtracting the mean and dividing by the standard deviation that are observed up to time *t-1*. The first principal component is extracted across stocks for each individual liquidity measure and across all liquidity measures. Extracted factors are then put through an AR(2) process, the residuals from which are taken as measures of market liquidity shocks. The coefficient estimates are then used to estimate the proportion of a shock at time *t* that remains at time *t+12*.

	Y_{t-1}	Y_{t-2}	Fraction of Shock Remaining after 12 months
Across Measure	1.23	-0.28	0.61
p-value	0.00	0.04	
Quoted Spread	1.09	-0.16	0.43
p-value	0.00	0.24	
Effective Half Spread	1.09	-0.16	0.42
p-value	0.00	0.24	
Temporary Fixed	1.09	-0.17	0.39
p-value	0.00	0.24	
Temporary Variable	0.76	0.10	0.17
p-value	0.00	0.19	
Permanent Fixed	1.08	-0.14	0.51
p-value	0.00	0.19	
Permanent Variable	0.74	0.20	0.41
p-value	0.00	0.17	
Order Imbalance	0.32	0.10	0.00
p-value	0.01	0.31	

Table 2: Canonical Correlation Analysis of Factors and Returns
Monthly stock's liquidity estimates are normalised by subtracting the mean and dividing by the standard deviation of returns observed up to time *t-1*. The first 3 common factors are extracted using principal component analysis for each individual measure and across all measures. The first 3 common factors are also extracted for returns. Panel A presents canonical correlations of the liquidity factors and return factors. In Panel B the factors are first pre-whitened by an AR(2) process to capture only shocks to liquidity before canonical correlations are calculated. * represents significance at 10%, ** represents significance at 5% and *** represents significance at 1%. QS = Quoted Spread, ES= Effective Spread, TF = Temporary Fixed (price impact), TV = Temporary Variable, PF = Permanent Fixed, PV = Permanent Variable, OIB = Order Imbalance.

Panel A

	Across Measure	**QS**	**ES**	**TF**	**TV**	**PF**	**PV**	**OIB**
QS	0.99***							
ES	0.99***	0.98***						
TF	0.99***	0.98***	0.98***					
TV	0.84***	0.81***	0.79***	0.80***				
PF	0.98***	0.97***	0.97***	0.96***	0.81***			
PV	0.87***	0.84***	0.87***	0.77***	0.72***	0.75***		
OIB	0.75***	0.78***	0.72***	0.76***	0.64***	0.67***	0.61***	
Return	0.58***	0.56***	0.65***	0.54***	0.57***	0.38**	0.71***	0.74***

Panel B

	Across Measure	**QS**	**ES**	**TF**	**TV**	**PF**	**PV**	**OIB**
QS	0.94***							
ES	0.86***	0.80***						
TF	0.87***	0.66***	0.79***					
TV	0.54***	0.32*	0.30	0.30				
PF	0.85***	0.62***	0.70***	0.81***	0.30			
PV	0.54***	0.40***	0.38***	0.27	0.42***	0.27		
OIB	0.36**	0.48***	0.32*	0.35**	0.22	0.37**	0.17	
Return	0.62***	0.63***	0.55***	0.45***	0.42***	0.36**	0.50***	0.73***

Table 3: Pricing of Liquidity Risk

Each month liquidity risk for stock *i* is estimated by regressing its returns over the previous 36 months on the market liquidity factor along with market, size, value and momentum factors. The market liquidity factor is the first extracted principal component pre-whitened to represent market liquidity shocks. This is done separately for each within-measure liquidity factor and the across-measure factor. A stock's liquidity risk is the beta on this market liquidity factor. (We require observations for 24/36 months for a stock to be included). Stocks are sorted into either 20, 10, 5 or 3 equal weighted portfolios and held for 1 month before reforming the portfolios. The time series of the high liquidity beta portfolio minus the low liquidity beta portfolio is tested against the CAPM, Fama French (1996) 3 factor and Carhart (1997) 4 factor models. Table 3 reports the alphas of these regressions. We also include an intercept dummy variable for the crisis period from August 1997 to the end of the sample, the estimated dummy coefficient is denoted "crisis". * represents significance at 10%, ** represents significance at 5% and *** represents significance at 1%. t-stats are Newey West (1987) adjusted for autocorrelation lag order 2. The FTSE All Share return is used to represent the market return. The SMB factor is the holding period (equally weighted) return on a portfolio that is long the smallest decile stocks and short the biggest decile stocks from the previous month, reformed monthly. The HML factor portfolio is the difference in returns between the MSCI Value Index and the MSCI Growth Index. The Momentum (MOM) portfolio is the holding period (equally weighted) return on a portfolio that is long the top performing 1/3 of stocks and short the worst performing 1/3 of stocks over the previous 11 months, reformed monthly. The risk free rate is the yield on 3 month sterling denominated gilts. QS = Quoted Spread, ES= Effective Spread, TF = Temporary Fixed (price impact), TV = Temporary Variable, PF = Permanent Fixed, PV = Permanent Variable, OIB = Order Imbalance.

	CAPM				**Fama-French**				**Carhart**			
	20-1	**10-1**	**5-1**	**3-1**	**20-1**	**10-1**	**5-1**	**3-1**	**20-1**	**10-1**	**5-1**	**3-1**
Across Measure	2.58***	1.79***	1.17***	0.85***	2.25***	1.55***	1.00**	0.75**	1.65***	1.03**	0.62*	0.50*
	3.66	3.43	2.94	2.90	3.32	3.07	2.56	2.55	2.70	2.38	1.81	1.87
Crisis	-9.41***	-8.07***	-5.61***	-4.20***	-9.78***	-8.52***	-5.93***	-4.45***	-9.31***	-8.12***	-5.63***	-4.26***
	-5.00	-5.68	-5.33	-5.56	-4.48	-5.31	-5.16	-5.23	-4.47	-5.22	-4.81	-4.92
QS	2.07***	1.79***	1.05***	0.77***	1.52**	1.46***	0.89***	0.65**	1.03**	1.11***	0.66**	0.48**
	3.09	3.39	3.48	3.32	2.62	3.12	3.23	2.91	2.03	2.75	2.59	2.39
Crisis	-3.26*	-2.77**	-2.67***	-2.00***	-3.67*	-3.08**	-2.94***	-2.13***	-3.29	-2.81**	-2.77***	-2.00**
	-1.68	-2.11	-3.07	-3.02	-1.84	-2.11	-2.94	-2.88	-1.62	-1.90	-2.71	-2.58
ES	2.69***	2.06***	1.48***	1.08***	2.16***	1.72***	1.25***	0.96***	1.33**	1.08**	0.78**	0.66***
	3.50	3.59	3.62	3.99	2.95	3.17	3.22	3.53	2.44	2.45	2.52	2.89
Crisis	-6.19***	-5.74***	-3.67***	-2.76***	-6.18***	-5.90***	-3.92***	-2.93***	-5.53***	-5.40***	-3.56***	-2.70***
	-2.99	-3.62	-3.98	-4.02	-3.02	-3.43	-3.61	-3.68	-2.79	-3.23	-3.41	-3.48
TF	1.81**	1.71***	1.14***	0.82***	1.36*	1.44***	1.00**	0.74***	0.50	0.95**	0.68**	0.52**
	2.46	3.33	3.05	3.16	1.90	2.89	2.60	2.73	0.87	2.24	2.02	2.11

Crisis	-5.61***	-6.00***	-3.54***	-2.26***	-6.06***	-6.18***	-3.81***	-2.41***	-5.39***	-5.80***	-3.57***	-2.24***
	-3.42	-3.73	-3.69	-4.00	-3.35	-3.66	-3.35	-3.56	-3.19	-3.40	-3.13	-3.22
TV	1.89***	1.54***	1.17***	0.69***	1.35**	1.14**	0.96***	0.53**	0.73	0.58	0.51*	0.23
	2.85	3.08	3.20	2.94	2.12	2.41	2.68	2.28	1.33	1.47	1.72	1.21
Crisis	1.34	-0.47	-0.33	-0.18	0.40	-1.29	-0.73	-0.49	0.88	-0.86	-0.38	-0.26
	0.65	-0.34	-0.41	-0.32	0.23	-1.07	-0.95	-1.00	0.53	-0.76	-0.58	-0.64
PF	2.23***	1.65***	1.19***	0.84***	1.75**	1.35**	1.01***	0.78***	1.12*	0.75*	0.60**	0.48*
	2.87	2.89	3.24	3.11	2.46	2.58	2.88	2.90	1.95	1.86	2.06	2.18
Crisis	-4.26**	-4.00***	-2.60**	-1.87**	-4.78**	-4.51***	-2.90**	-2.04**	-4.30*	-4.04**	-2.58**	-1.82**
	-2.10	-2.74	-2.42	-2.43	-2.03	-2.70	-2.40	-2.35	-1.86	-2.55	-2.24	-2.21
PV	-0.83	-0.73*	-0.24	-0.33*	-0.80	-0.64*	-0.15	-0.24	-0.22	-0.21	0.16	-0.06
	-1.53	-1.86	-1.02	-1.98	-1.39	-1.71	-0.61	-1.33	-0.41	-0.66	0.68	-0.32
Crisis	-0.26	0.42	0.11	-0.26	-0.39	0.17	-0.14	-0.25	-0.84	-0.16	-0.37	-0.39
	-0.12	0.40	0.14	-0.38	-0.18	0.16	-0.18	-0.42	-0.43	-0.18	-0.50	-0.65
OIB	2.61***	2.23***	1.60***	1.15***	2.17**	1.66**	1.19**	0.85**	0.85	0.63	0.42	0.28
	2.68	2.91	3.02	2.88	2.32	2.47	2.47	2.33	1.35	1.48	1.27	1.05
Crisis	-0.47	-1.34	-1.41	-1.51*	-1.45	-2.56**	-2.19**	-2.07***	-0.43	-1.76**	-1.60**	-1.63***
	-0.23	-0.84	-1.24	-1.88	-0.77	-2.15	-2.28	-3.07	-0.34	-2.32	-2.39	-3.16

Table 4: Pricing of Liquidity Risk Controlling for Liquidity as a Characteristic

Each month liquidity risk for stock *i* is estimated by regressing its returns over the previous 36 months on the market liquidity factor along with market, size, value and momentum factors. The market liquidity factor is the first extracted principal component pre-whitened to represent market liquidity shocks. This is done separately for each within-measure liquidity factor and the across-measure factor. A stock's liquidity risk is the beta on this market liquidity factor. (We require observations for 24/36 months for a stock to be included). Stocks are sorted into either 20, 10, 5 or 3 equal weighted portfolios based on the liquidity beta and held for 1 month before reforming the portfolios. The time series of the high liquidity beta portfolio minus the low liquidity beta portfolio is tested against the CAPM, Fama French (1996) 3 factor and Carhart (1997) 4 factor models. However, in order to control for the possible pricing of liquidity as a characteristic we augment these factor models with a liquidity characteristic mimicking portfolio. Each month all stocks are sorted into decile portfolios based on quoted spread, equal weighted portfolio returns are calculated over the following one month holding period and the process is repeated over a one month rolling window. The liquidity characteristic mimicking portfolio is the difference between the returns of the top and bottom decile portfolios, or illiquid minus liquid stocks, which we denote as the IML portfolio. Table 4 reports the alphas of these regressions. We also include an intercept dummy variable for the crisis period from August 1997 to the end of the sample, the estimated dummy coefficient is denoted "crisis". * represents significance at 10%, ** represents significance at 5% and *** represents significance at 1%. t-stats are Newey West (1987) adjusted for autocorrelation of lag order 2. The FTSE All Share return is used to represent the market return. The SMB factor is the holding period (equally weighted) return on a portfolio that is long the smallest decile stocks and short the biggest decile stocks from the previous month, reformed monthly. The HML factor portfolio is the difference in returns between the MSCI Value Index and the MSCI growth index. The Momentum (MOM) portfolio is the holding period (equally weighted) return on a portfolio that is long the top performing 1/3 of stocks and short the worst performing 1/3 of stocks over the previous 11 months, reformed monthly. The risk free rate is the yield on 3 month sterling denominated gilts. QS = Quoted Spread, ES= Effective Spread, TF = Temporary Fixed (price impact), TV = Temporary Variable, PF = Permanent Fixed, PV = Permanent Variable, OIB = Order Imbalance.

	CAPM+IML				**Fama-French+IML**				**Carhart+IML**			
	20-1	**10-1**	**5-1**	**3-1**	**20-1**	**10-1**	**5-1**	**3-1**	**20-1**	**10-1**	**5-1**	**3-1**
Across Measure	1.23**	1.25***	0.88**	0.67**	1.04*	1.23**	0.83**	0.64**	0.74	1.02**	0.69*	0.56**
	2.05	2.71	2.39	2.37	1.76	2.50	2.17	2.24	1.34	2.23	1.92	2.05
Crisis	-9.10***	-8.22***	-6.11***	-4.39***	-7.63***	-7.70***	-5.56***	-4.04***	-7.85***	-7.86***	-5.66***	-4.10***
	-4.95	-4.54	-4.61	-4.69	-4.76	-4.87	-5.08	-4.85	-5.07	-4.81	-4.88	-4.63
QS	1.54***	1.44***	0.79**	0.50**	1.40**	1.40***	0.78**	0.46*	1.18**	1.25***	0.68**	0.38*
	2.67	3.39	2.61	2.06	2.41	3.33	2.56	1.91	2.14	3.19	2.42	1.78
Crisis	-3.73	-4.24***	-3.20***	-2.74***	-3.02	-4.04***	-3.05***	-2.39***	-3.18	-4.15***	-3.13***	-2.44***
	-1.65	-3.00	-3.35	-3.31	-1.53	-3.01	-3.16	-3.09	-1.48	-2.82	-2.90	-2.85
ES	2.26***	1.47***	1.02***	0.72***	1.90***	1.30**	0.92**	0.65**	1.72***	1.19**	0.86**	0.64**

	3.46	2.87	3.00	2.87	2.95	2.44	2.61	2.52	2.93	2.21	2.46	2.45
Crisis	-9.87***	-7.59***	-5.4***3	-4.9***	-7.76***	-6.47***	-4.71***	-3.76***	-7.89***	-6.55***	-4.75***	-3.77***
	-3.71	-4.22	-3.76	-3.84	-3.54	-3.82	-3.59	-3.79	-3.33	-3.66	-3.46	-3.71
TF	1.00*	1.17**	0.79**	0.53*	0.74	1.03**	0.67*	0.46*	0.47	0.85	0.56	0.38
	1.70	2.39	2.15	1.93	1.26	2.05	1.82	1.67	0.89	1.81	1.61	1.41
Crisis	-5.34***	-4.85***	-3.23***	-2.29***	-3.70***	-3.63***	-2.27***	-1.63***	-3.89***	-3.77***	-2.36***	-1.69**
	-3.40	-3.16	-2.91	-2.89	-3.24	-3.04	-2.78	-2.67	-2.96	-2.99	-2.73	-2.62
TV	0.66	0.90*	0.68**	0.51*	0.64	0.88**	0.68**	0.50*	0.35	0.60	0.38	0.26
	1.30	1.97	2.03	1.82	1.33	1.99	2.04	1.82	0.74	1.45	1.27	1.07
Crisis	3.66	2.18	1.27	1.34	3.97	2.56	1.48	1.48*	3.75*	2.35*	1.25	1.30**
	1.50	1.35	1.14	1.53	1.65	1.61	1.32	1.68	1.68	1.67	1.52	2.08
PF	1.04*	0.68	0.74**	0.63**	0.86	0.57	0.65*	0.58**	0.69	0.36	0.51	0.47**
	1.85	1.51	2.14	2.48	1.60	1.26	1.89	2.24	1.35	0.92	1.64	2.05
Crisis	-3.73*	-3.17*	-2.20*	-1.40	-2.28	-2.15	-1.41	-0.87	-2.41	-2.31	-1.52	-0.95
	-1.67	-1.96	-1.77	-1.57	-1.22	-1.59	-1.34	-1.20	-1.22	-1.64	-1.41	-1.33
PV	-0.55	-0.11	-0.10	-0.11	-0.42	0.02	-0.03	-0.09	-0.30	0.07	0.00	-0.08
	-0.98	-0.27	-0.35	-0.66	-0.81	0.07	-0.12	-0.57	-0.58	0.20	-0.02	-0.47
Crisis	1.43	1.75	1.00	0.69	0.80	1.35	0.81	0.68	0.88	1.38	0.83	0.69
	0.77	1.60	0.94	0.85	0.47	1.38	0.82	0.90	0.54	1.44	0.84	0.91
OIB	1.27	1.22**	0.88**	0.72**	1.17	1.15**	0.79*	0.66*	0.67	0.76*	0.51	0.46
	1.58	2.08	2.04	2.06	1.50	2.03	1.88	1.95	0.97	1.66	1.38	1.50
Crisis	-1.16	-2.02*	-1.77**	-1.82**	-0.02	-1.33	-1.10	-1.35**	-0.39	-1.62	-1.31*	-1.50**
	-0.66	-1.77	-2.45	-3.18	-0.01	-1.19	-1.60	-2.31	-0.28	-1.60	-1.96	-2.57

Table 5. Cross sectional Regression of Portfolio Alpha on Portfolio Liquidity Risk.
Each month stocks are sorted into either 20, 10 or 5 equal weighted portfolios based on their liquidity beta and held for 1 month before reforming. Each month for each portfolio we also calculate the cross sectional (across stocks) average $\hat{\beta}_i$. For each portfolio we then calculate the time series average of these cross sectional averages. The time series of the portfolio returns are tested against the CAPM, Fama French (1996) 3 factor and Carhart (1997) 4 factor models (we also include the crisis period intercept dummy variable) and the portfolio alphas are estimated. In a second stage cross sectional regression the alpha of each portfolio is regressed against each portfolio's average beta. Table 5 reports the slope coefficients from this regression. Coefficients are scaled by 10^3 for ease of presentation. * represents significance at 10%, ** represents significance at 5% and *** represents significance at 1%. t-stats are Newey West (1987) adjusted for heteroskedasticity.

	CAPM			**Fama-French**			**Carhart**		
	20	**10**	**5**	**20**	**10**	**5**	**20**	**10**	**5**
Across Measure	1.83***	1.70***	1.62*	1.61***	1.50***	1.41**	1.10***	1.00***	0.92**
	4.46	3.47	2.77	5.90	4.89	3.98	5.08	5.24	3.89
Quoted Spread	2.89***	2.82**	2.49	2.29**	2.35***	2.11*	1.64***	1.75***	1.57**
	3.77	2.72	1.91	4.31	3.36	2.57	4.35	3.69	3.40
Effective Spread	3.72***	3.57***	3.52*	3.07***	3.03***	3.00**	1.96***	1.95***	1.93**
	5.23	3.63	2.59	6.58	5.17	3.66	6.32	5.62	5.30
Temporary Fixed	1.49***	1.86***	1.78*	1.58***	1.62***	1.59**	0.97***	1.11***	1.10***
	4.89	3.40	2.37	5.41	5.19	3.74	3.80	7.75	5.94
Temporary Variable	3.64***	3.55***	3.56**	2.67***	2.70***	2.84**	1.32***	1.34***	1.43*
	6.36	4.85	3.38	6.68	6.38	4.57	4.29	4.08	3.01
Permanent Fixed	1.78***	1.68***	1.67*	1.50***	1.45***	1.47**	0.92***	0.84***	0.88***
	4.68	3.70	3.04	6.38	5.92	5.33	5.38	5.43	6.10
Permanent Variable	-1.61*	-1.73	-1.23	-1.48**	-1.44	-0.86	-0.30	-0.25	0.34
	-1.85	-1.32	-0.77	-2.52	-1.72	-1.00	-0.51	-0.32	0.45
Order Imbalance	7.67***	7.57***	7.05**	5.82***	5.61***	5.14**	2.23***	1.20	1.75
	6.30	4.31	3.47	6.16	4.23	3.87	2.92	1.26	2.07

Table 6. Cross sectional Regression of Portfolio Alpha on Portfolio Liquidity Risk Controlling for Liquidity as a Characteristic

Each month stocks are sorted into either 20, 10 or 5 equal weighted portfolios based on their liquidity beta and held for 1 month before reforming the portfolios. Each month for each portfolio we also calculate the cross sectional (across stocks) average $\hat{\beta}_i$. For each portfolio we then calculate the time series average of these cross sectional averages. The time series of the portfolio returns are tested against the CAPM, Fama French (1996) 3 factor and Carhart (1997) 4 factor models. However, in order to control for the possible pricing of liquidity as a characteristic we augment these factor models with a liquidity characteristic mimicking portfolio: each month all stocks are sorted into decile portfolios based on quoted spread, equal weighted portfolio returns are calculated over the following one month holding period and the process is repeated over a one month rolling window. The liquidity characteristic mimicking portfolio is the returns of the top decile minus bottom decile portfolios, or illiquid minus liquid stocks, which we denote as the IML portfolio. Portfolio alphas are then estimated. In a second stage cross sectional regression the alpha of each portfolio is regressed against each portfolio's average beta. Table 6 reports the slope coefficients from this regression. Coefficients are scaled by 10^3 for ease of presentation. * represents significance at 10%, ** represents significance at 5% and *** represents significance at 1%.t-stats are Newey West (1987) adjusted for heteroskedasticity.

	CAPM+IML			**Fama-French+IML**			**Carhart+IML**		
	20	**10**	**5**	**20**	**10**	**5**	**20**	**10**	**5**
Across Measure	1.12***	1.21***	1.17***	1.05***	1.18***	1.11***	0.86***	0.99***	0.93***
	8.78	10.42	8.99	6.86	10.12	9.86	5.52	10.46	16.68
Quoted Spread	1.91***	2.09***	1.79***	1.80***	2.01***	1.73**	1.55**	1.76***	1.49**
	6.82	5.84	6.40	6.17	5.60	5.38	5.58	5.21	4.12
Effective Spread	2.44***	2.32***	2.30***	2.14***	2.07***	2.08***	1.99***	1.94***	1.98***
	6.90	9.69	9.73	6.34	8.93	9.79	6.44	11.57	18.20
Temporary Fixed	1.13***	1.22***	1.20***	0.90***	1.06***	1.04***	0.70***	0.87***	0.86***
	7.88	7.53	8.48	5.40	6.13	6.73	3.91	5.17	14.46
Temporary Variable	1.87***	2.18**	2.15***	1.87***	2.16***	2.15***	1.01**	1.29**	1.13*
	4.77	6.06	6.27	4.69	6.42	6.43	2.47	3.27	2.68
Permanent Fixed	0.97***	0.94***	1.09**	0.85***	0.83***	0.97**	0.66***	0.61**	0.76**
	4.89	4.35	5.27	4.51	4.05	5.53	3.40	2.84	4.55
Permanent Variable	-0.92*	-0.49	-0.42***	-0.61	-0.17	-0.15	-0.46	-0.07	-0.06
	-1.95	-1.15	-7.98	-1.32	-0.41	-1.64	-0.93	-0.14	-0.21
Order Imbalance	3.86***	4.04***	3.79**	3.58***	3.74***	3.41*	2.32***	1.18	2.22
	5.78	4.49	3.66	5.37	4.21	3.26	3.49	1.47	2.20

Figure 1: Intra-day Plots of Spread and Volatility (upper and lower panel respectively).
For each stock we estimate the quoted spread for each 15 minute period within the trading day. We then average across stocks and across days to obtain the intra-day pattern. We estimate intra-day volatility as in Abhyankar et al. (1997), 1 minute returns are calculated from changes in the midpoints of quotes to avoid any bid-ask bounce, the absolute value of the returns are then summed into 15 minute intervals. We then average across stocks over all days.