Mutual Fund Skill in Timing Market Volatility and Liquidity

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Abstract
We investigate both market volatility timing and market liquidity timing for the first time among UK mutual funds. We find strong evidence that a small percentage of funds time market volatility successfully, i.e. when conditional market volatility is higher than normal, systematic risk levels are lower. The evidence around market liquidity timing ability is similar although it is slightly less prevalent compared to volatility timing. Here, funds lower the fund market beta in anticipation of reduced market liquidity. Tests indicate that both volatility and liquidity timing ability exceed that which may be attributed to publicly available information suggesting that managers have private timing skill. In contrast, we find little evidence supporting market return timing ability. We report that liquidity timing ability is also persistent and is strongly associated with superior fund abnormal performance though this is not the case for volatility timing ability.

Keywords: mutual fund performance, volatility, liquidity, timing.
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1. Introduction

In this paper, we investigate whether mutual funds are able to time fluctuations in both market volatility and market liquidity, assuming that managers attempt to do so in their investors' best interests. There is a sizeable extant literature on funds' ability to time fluctuations in market return, in particular in the US and UK fund industries, e.g. Treynor and Mazuy (1966), Henriksson (1984), Ferson and Schadt (1996), Jiang (2003), Cuthbertson et al. (2010). However, less work has been undertaken on market volatility timing, e.g. Busse (1999), Giambona and Golec (2007) while there has been a dearth of study on market liquidity timing (Cao et al. (2013). To our knowledge we are the first paper to set about the dual task of evaluating funds' skill in both market volatility and market liquidity timing in the UK mutual fund industry.

There are a number of reasons why market volatility timing is of interest. First, risk-averse investors are concerned about both risk and return. If funds can decrease (increase) beta when market volatility rises (falls), they have the potential to deliver returns with relatively low volatility. Busse (1999) finds that 80% of his 230 U.S. funds sample, covering the period 1985-1995, time volatility in this way.

Busse (1999) theorises a probably negative relation between market return and market volatility. This is empirically confirmed in his data which show a monthly correlation between the S&P 500 return and standard deviation of -0.47 between 1985-1995. This incentivises fund managers to reduce the fund market beta in anticipation of higher market volatility. Busse documents a significant relation between volatility timing and fund performance: funds that reduce systematic risk when conditional volatility is high earn higher risk-adjusted returns. Our UK data show a similar negative relationship between market volatility and market returns: the monthly correlation between the FTSE All share return and standard deviation is -0.50 over the sample period under consideration (January 1997 - February 2009). Based on this intuition, if managers can time market volatility, we expect a negative relation between funds' systematic risk (market beta) and market volatility.

Second, most measures of performance are risk adjusted (e.g. the Sharpe ratio, multi-factor model alphas). Since risk-adjusted performance affects fund cash flows (Massa, 2003; Nanda, Wang and Zheng, 2004; Kacperczyk and Seru, 2007), how funds manage risk has implications for assets under management (AUM), fund fees and manager compensation. Studies such as Brown, Harlow and Starks (1996), Chevalier and Ellison (1997), and Golec and Starks (2004) show that compensation incentives affect fund managers' risk choices. Therefore, fund managers may also attempt to time market volatility independently of its relationship with market return.

Finally, while stock returns may be unpredictable, there is persistence and predictability in volatility over time (Busse, 1999; Bollerslev et al., 1992). Therefore, there is greater reason, *a priori*, to believe fund managers may have skill in timing market volatility, if not market returns.

Cao et al. (2013), a study of the U.S. domestic equity mutual fund industry, is the only study of mutual fund liquidity timing. There are also a number of reasons to study market liquidity timing. First, clearly liquidity is of concern to mutual fund managers because an important function performed by mutual funds is to provide liquidity to investors. Second, the 2008 financial crisis established a link between market-wide liquidity and fund performance where reduced liquidity was accompanied by dramatic stock market declines. More formally, asset pricing literature has identified market liquidity as a risk factor in asset pricing[1]. As with volatility timing, if fund managers can anticipate market liquidity conditions, they can adapt their portfolio exposure accordingly to alleviate losses and improve performance.

Market liquidity, like market volatility, is persistent (Amihud, 2002; Chordia et al., 2000; Hasbrouck and Seppi, 2001; Pastor and Stambaugh, 2003), which again rationalises fund managers' attempt to time it.

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[1] Foran et al. (2014a) and Foran et al. (2015) establish a strong role for market liquidity risk in the pricing of UK equities while Foran et al. (2014b) describe the role for market liquidity risk in the performance of UK equity mutual funds.

Acharya and Pedersen (2005) develop a theoretical model of how asset prices are determined by three types of illiquidity risk[2]. The model shows that since illiquidity is persistent, it predicts future returns and is inversely related to contemporaneous returns. This is because an illiquidity shock predicts greater future illiquidity, this raises future required returns and lowers contemporaneous prices and contemporaneous returns. Hence, a market illiquidity shock is associated with low contemporaneous returns. Following Acharya and Pedersen (2005), Cao et al. (2013) contend that as market illiquidity shocks are contemporaneously and inversely related to market returns, fund managers with (il)liquidity timing ability reduce market exposure prior to greater market illiquidity and we expect a negative market beta – market illiquidity relation.

The above discussion links the sensitivity of a fund's market beta to anticipated market volatility and market liquidity. In a related stream of research, Huang (2015) examines the relationship between expected market volatility and mutual funds' demand for liquidity. During periods of market volatility, there is a need for funds to create a liquidity cushion to manage liquidity risk, Scholes (2000). As described by Huang (2015), periods of high market volatility are associated with higher probability and magnitude of investor redemptions. Liquidity mitigates against the adverse effects of investor outlfows by enabling funds to better meet redemptions without the need to liquidate investments, which can be costly (Nanda et al., 2000; Chen et al., 2010).

Huang argues that to the extent that expected market volatility can serve as a signal of future redemptions, as part of a liquidity risk timing strategy fund managers can reduce the fund market beta (e.g. higher cash holdings) during periods when expected market volatility is high. Therefore, fund managers may attempt to time market illiquidity independently of its relationship with market return.

[2] Specifically, (i) the covariance between the illiquidity of stock *i* and the illiquidity of the market (commonality), (ii) the covariance between the return on stock *i* and the illiquidity of the market and (iii) the covariance between the illiquidity of stock *i* and the return on the market.

In this paper, we address a number of questions. We investigate whether market volatility and market liquidity conditions motivate fund managers' stock selection and asset allocations decisions and whether managers possess the ability to time these conditions. We further evaluate whether managers have private timing skill, i.e. an ability to predict market volatility and liquidity beyond that which may be predicted by public information. Third, we examine whether there is persistence in these skills - is it possible *ex-ante* to select skilful timing funds? Finally, we ask whether volatility and liquidity timing ability predict fund performance. To our knowledge we are the first paper to investigate these questions in the UK fund industry.

We find that a small percentage of funds are skilful volatility timers and reduce systematic risk in advance of higher conditional market volatility. A slightly smaller number of funds are similarly found to reduce the fund beta in anticipation of market illiquidity. It is clear that these timing abilities are private in that they are not fully explained by the predictive power of public information. We report some evidence of persistence in liquidity timing ability. Finally, we document a relation between fund liquidity timing and fund abnormal performance though the latter does not appear to be linked to volatility timing ability.

The remainder of the paper is structured as follows: In section 2, we discuss our method to test fund timing skills as well as the construction of the market liquidity variable and liquidity risk control variables while in section 3 we describe our data set. In Section 4, we discuss our empirical findings. Section 5 concludes.

2. Method

In this section we outline our method for testing funds' ability to time fluctuations in market volatility and market liquidity. Although the main focus of the paper is on volatility and liquidity timing, it is straightforward in the testing methodology to also examine funds' skill in correctly anticipating future market returns.

2.1 Market return, volatility and liquidity timing tests

We begin with the well-established Carhart (1997) four-factor model with benchmark factors for market, size, value and momentum risk as follows:

$$R_{i,t+1} = \alpha_i + \beta_1 R_{m,t+1} + \beta_2 SMB_{t+1} + \beta_3 HML_{t+1} + \beta_4 MOM_{t+1} + \varepsilon_{i,t+1} \qquad [1]$$

where $R_{i,t+1}$ is the monthly excess return (over the risk free rate) of fund *i* in month *t+1*, $R_{m,t+1}$ is the monthly excess market return in month *t+1* (we use the returns on the FTSE All Share index as our market benchmark and the 1 month UK TBill yield as the risk free rate). SMB_{t+1}, HML_{t+1}, and MOM_{t+1} are the size, value and momentum benchmark factors in month *t+1* respectively, while β_k, k = 1,2..4, are risk factor loadings for fund *i*. (We provide further details on the construction of SMB_{t+1}, HML_{t+1} and MOM_{t+1} in section 3).

In a method that can be traced back to Treynor and Mazuy (1966), Henriksson and Merton (1981), Ferson and Schadt (1996) and others, to test for market return timing we condition the market beta, β_1, in [1] on future (next-period) market returns. Here, we extend this specification and condition β_1 on future market returns, future (de-meaned) market volatility $(\sigma_{m,t+1} - \bar{\sigma}_m)$ and future (de-meaned) market liquidity $(L_{m,t+1} - \bar{L}_m)$ as follows:

$$\beta_{1,t} = \theta_0 + \theta_1 R_{m,t+1} + \theta_2 \left(\sigma_{m,t+1} - \bar{\sigma}_m\right) + \theta_3 \left(L_{m,t+1} - \bar{L}_m\right) \qquad [2]$$

where $\bar{\sigma}_m$ and $\bar{L}_m$ are the time series means of market volatility and market liquidity respectively over the sample period. Here, θ_0 may be considered the fund's long run strategic beta. However, at time *t* the timing fund manager adjusts the market beta, $\beta_{1,t}$, in anticipation of expected market return, as well as market volatility and market liquidity shocks next period. Subbing [2] into [1] gives the timing augmented performance model

$$\begin{aligned} R_{i,t+1} = {} & \alpha_i + \theta_0 R_{m,t+1} + \beta_2 SMB_{t+1} + \beta_3 HML_{t+1} + \beta_4 MOM_{t+1} + \theta_1 R_{m,t+1}^2 \\ & + \theta_2 \left[\left(\sigma_{m,t+1} - \bar{\sigma}_m \right) . \left(R_{m,t+1} \right) \right] + \theta_3 \left[\left(L_{m,t+1} - \bar{L}_m \right) . \left(R_{m,t+1} \right) \right] + \varepsilon_{i,t+1} \end{aligned} \quad [3]$$

The ability to time market return is indicated by a positive value of θ_1. We estimate monthly conditional volatility as the standard deviation of the daily market returns in the month as follows:

$$\sigma_{m,t} = \left[\sum_{d=1}^{n_t} (r_{m,t,d} - \bar{r}_{m,t})^2 \right]^{\frac{1}{2}} \quad [4]$$

where $r_{m,t,d}$ are the n_t daily market returns during month *t*. As described in section 1, in line with Busse (1999), we expect an inverse relation between the fund's market beta and next-period volatility and successful volatility timing is indicated by a negative value of θ_2 in [3].

Similarly, in line with Acharya and Pedersen (2005) and Cao et al. (2013), we hypothesise that as market illiquidity shocks are inversely related to contemporaneous market returns, fund managers with (il)liquidity timing ability would decrease market exposure prior to greater market illiquidity. Our market liquidity variable is signed to represent illiquidity (a rising value means the market is becoming more illiquid, see below). Hence if managers can time market (il)liquidity, we expect a negative relation between a fund's systematic risk (market beta) and market illiquidity and successful liquidity timing is indicated by a negative value of θ_3 in [3].[3] We now discuss the construction of the market liquidity variable.

2.2 The market liquidity variable

There are several measures of stock liquidity in the literature. Widely used measures include quoted spread, effective spread, turnover and order imbalance. Other measures of liquidity include price impact measures, which focus on the impact of trades on stock prices. Price impact measures may be categorised as transitory or permanent impacts and in each case may be subcategorized as fixed impacts (independent of trade size) or variable impacts (dependent on trade size) – see Amihud (2002), Chordia et al. (2000), Korajczyk and Sadka (2008), Sadka (2006), Foran et al. (2014a). As alternative measures of liquidity may capture slightly different facets of liquidity, we construct a market liquidity variable that encompasses as many facets of liquidity as possible.

Following the approach of Foran et al. (2014a), we begin with seven liquidity measures. These are quoted spread, effective spread and order imbalance as well as four price impact measures (permanent fixed, permanent variable, transitory fixed and transitory variable). As these measures are well documented in the literature, we do not propose to provide a detailed account here in the text. However, we provide a description in an appendix to the paper.

As detailed in the appendix, we estimate seven liquidity measures from the microstructure literature based on intra-day tick data and aggregate up to a monthly measure. We use intra-day data because as demonstrated by Foran et al. (2014a) liquidity varies considerably throughout the day (falling steadily over the course of the morning and flattening out in the afternoon, most likely due to the opening of the US market in the UK afternoon

[3] On semantics, the specification in [2] captures the fund manager's attempt to time above normal market illiquidity or a market illiquidity 'shock' (rather than the 'level' of liquidity), i.e. if $L_{m,t+1} = \overline{L}_m$ in [2], there is no market beta response as part of a market liquidity timing strategy. However, timing an illiquidity 'shock', e.g. $L_{m,t+1} > \overline{L}_m$ is also clearly timing a higher 'level' of illiquidity.

time). Calculating liquidity using daily stock closing prices could give a false impression and bias results. In our study, each liquidity measure is estimated for each stock each month and a time series of stock liquidity is generated for each liquidity measure and each stock. All measures are signed to represent illiquidity. We estimate liquidity in a given month only if the stock was a constituent of the FTSE All Share *that* month.

In a procedure similar to that of Korajczyk and Sadka (2008) and Foran et al. (2014a) we use asymptotic principal component analysis to construct the market liquidity variable. The procedure captures systematic variation or commonality in liquidity *both* across stocks and also across the alternative liquidity measures and therefore provides a proxy for overall market liquidity conditions which is what the manager is intuitively attempting to time.

Specifically, for each of the seven liquidity measure we have a (T x n) matrix of liquidity observations where T = number of months and n = number of stocks. We first stack the (T x n) matrices to form a (T x 7n) matrix. We extract the first principal component and refer to this as our 'across-measure' market liquidity variable.

In constructing the across-measure principal component, the seven liquidity measures are in different units of measurement. These scale differences mean that the resulting principal component 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 conducting the principal component analysis as follows: $NL^{i}_{s,t} = \frac{L^{i}_{s,t} - \hat{\mu}^{i}_{s,t}}{\hat{\sigma}^{i}_{s,t}}$, where $L^{i}_{s,t}$ is liquidity measure *i* for stock *s* at time *t*, $\hat{\mu}^{i}_{s,t}$ is the estimated mean of liquidity measure *i* for stock *s* up to time *t-1* and $\hat{\sigma}^{i}_{s,t}$ is the estimated standard deviation of measure *i* for stock *s* up to time *t-1*.[4]

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

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 principal component. For ease, we sign the across-measure principal component to represent illiquidity, i.e. rising values of the series represent illiquidity. The sign is chosen so that the principal component is positively correlated with the time series of the cross sectional average of the measures where here order imbalance is first multiplied by -1 before averaging.

The theory underpinning market liquidity timing is based on persistence in liquidity shocks. To examine this in the case of our UK data, we fit an AR(2) model to the market liquidity series (first extracted principal component) and estimate liquidity shocks as the residuals from the model. We measure persistence by calculating the fraction of a shock at time *t* that still impacts liquidity at time *t+12*. We find that 58% of a shock to market liquidity remains a year later. Using a similar method we also calculate the persistence of market volatility shocks. Instead of an AR(2) model, however, we model market volatility using an ARMA (1,1) specification. The results indicate strong short run persistence in market volatility from one month to the next (although only 1.3% of the volatility shock at time *t* still impacts volatility at time *t+12*)[5].

This strong persistence or predictability in both market liquidity and market volatility rationalises fund managers' attempts to time these market conditions and motivates our investigation of same.

2.3 Public versus private timing ability

The above market volatility and market liquidity timing tests can be extended to investigate whether fund managers can time variation in market volatility and liquidity beyond the

[5] In robustness tests we examine several alternative ARMA and AR specifications. The ARMA(1,1) and AR(2) are found to be the most parsimonious best fit.

variation that is predictable by public information – do managers respond to market volatility and liquidity fluctuations using *private* timing ability?

To do this we examine two alternative conditional models of market volatility (an ARMA (1,1) model and an instrumental variables model) and two alternative conditional models of market liquidity (an AR(2) model and an instrumental variables model). The residuals of these models represent the variation in market volatility and liquidity not explained by publicly available information. In the instrumental variables model our set of instruments are similar to those used by Busse (1999) and Ferson and Schadt (1996) and include the short term interest rate, market dividend yield, term structure, default spread and a January dummy. Testing managers' private timing skill involves repeating the above timing test in [3] replacing the market volatility and market liquidity variables with the residuals from these conditional models as follows

$$\begin{aligned} R_{i,t+1} = {} & \alpha_i + \theta_0 R_{m,t+1} + \beta_2 SMB_{t+1} + \beta_3 HML_{t+1} + \beta_4 MOM_{t+1} + \theta_1 R^2_{m,t+1} \\ & + \theta_2 \left[\left(\sigma_{m,t+1(res)} \right) . \left(R_{m,t+1} \right) \right] + \theta_3 \left[\left(L_{m,t+1(res)} \right) . \left(R_{m,t+1} \right) \right] + \varepsilon_{i,t+1} \end{aligned} \quad [5]$$

where $\sigma_{m,t+1(res)}$ and $L_{m,t+1(res)}$ are the residuals from the conditional model estimations. Private skill in market volatility and market liquidity timing is indicated by negative values of θ_2 and θ_3 respectively.

2.4 Controlling for characteristic liquidity risk and systematic liquidity risk

From asset pricing literature, the liquidity attributes of stocks are known to play a role in explaining stock returns (Pastor and Stambaugh, 2003; Korajczyk and Sadka, 2008; Sadka, 2006). When considering whether a fund is successful at timing market liquidity therefore, we should control for the liquidity attributes of the fund's stock holdings in explaining performance.

We are concerned with two types of liquidity 'attributes' that may be priced. First, liquidity as a priced *characteristic* refers to a stock's own liquidity level as a driver of its return. Amihud and Mendelson (1986) argue that illiquid stocks should earn a premium over liquid stocks to compensate investors for the trading costs incurred which reduce returns, e.g. wider bid-offer spreads. Second, *systematic liquidity risk* refers to the sensitivity of a stock's return to changes in market liquidity that may not be diversifiable and hence commands a premium, Korajczyk and Sadka (2008). In the UK, there is also strong evidence indicating that liquidity plays a role in asset pricing (Lu and Hwang, 2007; Foran et al. 2015, 2014a) and in UK mutual fund performance, Foran et al. (2014b).

In this paper, in our tests of market liquidity timing, we control for the role that both funds' illiquidity characteristic risk and systematic liquidity risk may play in fund returns. To do this we augment [3] and [5] with illiquidity characteristic risk and systematic liquidity risk benchmark factors (risk mimicking portfolios).

Illiquidity characteristic risk factor

We begin by constructing an illiquidity characteristic risk mimicking portfolio. This can be constructed for each liquidity measure. However, in order to avoid producing overly voluminous results and to conserve space, we base the characteristic risk mimicking portfolio on one liquidity measure. Here, we select the intuitive quoted spread. Each month all FTSE All share constituent stocks are sorted into decile portfolios based on their liquidity (quoted spread) where decile 1 represents high liquidity stocks while decile 10 represents low liquidity stocks. Equal weighted decile portfolio returns are calculated over the following one month holding period and the process is repeated over a one month rolling window. The illiquidity characteristic risk mimicking portfolio is the difference between the returns of the top decile

(decile 10) and bottom decile (decile 1) portfolios, or illiquid minus liquid stocks. We denote this control variable by 'IML'.

Systematic liquidity risk factor

In order to capture systematic liquidity risk in a mimicking portfolio, we do the following: using the market liquidity variable constructed previously, i.e. the across-measure first extracted principal component, each month individual stock (excess) returns are regressed on the market liquidity variable as well as factors for market, size, value and momentum risk. We estimate this regression over the previous 36 months (minimum 24 month requirement for stock inclusion). Stocks are then sorted into deciles according to their systematic liquidity risk, i.e. their estimated beta (sensitivity) relative to the market liquidity variable 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 market liquidity variable, F_t^0 is a matrix of the other risk factors, $r_{i,t}$ is the excess return on stock *i* at time *t*. Stocks are assigned to a portfolio based on $\hat{\beta}_i$, which measures sensitivity to market liquidity, in ascending order, e.g. portfolio 1 contains low liquidity risk (low beta) stocks while portfolio 10 contains high liquidity risk (high beta) stocks. Each portfolio return is the equal weighted average return of its constituent stocks for the *following* month, i.e. these portfolios are forward looking. Portfolios are reformed monthly. The systematic liquidity risk mimicking portfolio is taken to be the difference between the high minus low portfolios, i.e. 10-1. We denote this control variable by 'HML_{LR}' or 'high minus low liquidity risk'.

To clarify, the theory underpinning market liquidity timing is that a market illiquidity shock predicts greater future illiquidity, which raises the future required return and lowers contemporaneous prices and contemporaneous returns. Hence, a market illiquidity shock is associated with low contemporaneous returns and market (il)liquidity timing ability is indicated by a lower market beta during periods of greater market illiquidity. However, from asset pricing, high, relative to low, systematic liquidity risk stocks may have higher forward looking required returns. To control for this, we add the HML_{LR} explanatory factor to the performance model in the timing tests.

In our timing tests (including private timing tests) we augment [3] and [5] with the IML and HML_{LR} risk mimicking portfolios as control variables.

3. Data

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

In table 1 we report summary statistics of the mutual fund sample. Panel A presents the number of funds in the sample by year, ranging from 447 in 2000 (all investment styles) to 792 in 2005. The table shows a yearly breakdown of the numbers of funds entering and exiting the industry. We see a particularly large number of funds exiting the industry around 1999 following the Asian and Russian financial crisis periods and again in 2007/8 following the more recent financial crisis period. In panel B, we present descriptive statistics of returns. Equity income funds yield the highest average monthly return of 0.74% and the lowest standard deviation of 0.61% while at 0.44% small company funds yield the lowest return but the highest standard deviation of 0.89% (where, in results not shown, monthly returns range from 6.69% to -5.14%). All fund styles exhibit considerable variation in returns which is helpful in identifying whether volatility and liquidity timing is taking place across funds. There is a high degree of non-normality in the fund returns - we discuss this later in the context of the need to calculate nonparametric bootstrap p-values in tests of statistical significance.

[Table 1 here]

From section 2, Eq. [1], the FTSE All Share monthly returns are obtained from the London Share Price Database (LSPD). The size risk factor, small minus big (SMB), is calculated from the FTSE All share historic constituent stocks. (We cross-reference with the LSPD Archive file which records the constituents of the FTSE All Share index through time). Each month we form a portfolio that is long the decile of smallest stocks and short the decile of biggest stocks based on market capitalisation and hold for one month before reforming. SMB is the holding period difference in return between the deciles of small versus big stocks. The value factor, high book to market minus low book to market stocks (HML), is the return on the Morgan Stanley Capital International (MSCI) UK Value Index minus the return on the MSCI UK growth index. The momentum factor (MOM) is formed by ranking the FTSE All Share historic constituent stocks each month based on performance over the previous 11 months. A factor mimicking portfolio is formed by going long the top performing one-third of stocks and taking a short position in the worst performing one-third of stocks over the following month. All portfolios are equal weighted. The risk free rate is the yield on the 1 month UK TBill.

Our set of instruments in the conditional volatility and conditional liquidity models are the short term interest rate (UK 1month TBill rate), the market dividend yield (dividend yield on the FTSE All Share), the term structure (30 year UK gilt yield minus the UK 1 month TBill rate), the default spread (5 year UK swap rate minus the 5 year UK gilt yield) and a January dummy. These data are sourced in Datastream.

We construct a market liquidity variable as well as stock illiquidity characteristic risk and systematic liquidity risk mimicking portfolios (risk factors). These involve first generating monthly time series of liquidity for each stock in the FTSE All Share over the period (January 1997-February 2009). We use tick data and best price data to construct the liquidity variables (see Appendix for a description of the liquidity variables). We obtain the tick data and best price data from the London Stock Exchange (LSE) information products division[6]. The LSE tick data file contains all trades of which the LSE has a record. The data for each trade includes the trade time, publication time, price at which the trade occurs, the number of shares, the currency, the tradable instrument code (TIC) and SEDOL of the stock, the market segment and sector through which the trade was routed as well as the trade type. Our tick data files contain 792,995,147 trades. The best price files contain the best bid and ask prices available on the LSE for all stocks for the same time period; this includes the tradable instrument code (TIC), SEDOL, country of register, currency of trade and time stamp of best price. The files contain 1,956,681,874 best prices.

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

[6] We estimate a stock's liquidity in a given month only if the stock is a constituent of the FTSE All Share index that month. The LSE data are cross-referenced with the LSPD Archive file using SEDOL numbers. This dataset is the same as that used in Foran et al. (2014a) which provides further data discussion.

From section 2, we construct a time series of monthly market volatility by calculating the standard deviations of daily returns within each month. We obtain FTSE All Share daily returns from Datastream.

4. Empirical Results

In this section we report our empirical findings. We first examine funds' timing abilities where we do not distinguish between timing skill based on public versus private information. Next, we investigate private timing skill. We then examine persistence in timing abilities. Finally, we report on the relation between timing ability and fund abnormal performance.

4.1 Timing market return, volatility and liquidity

We begin by testing funds' ability to time the level of the market return, market volatility and market liquidity (unconditional upon whether timing is based on public information). We estimate [3] for the full set of funds in our sample. From section 2, successful return timing is indicated by $\theta_1 > 0$ while successful volatility timing and successful liquidity timing are indicated by $\theta_2 < 0$ and $\theta_3 < 0$ respectively.

In table 2, we present the results of these tests where market return timing, volatility timing and liquidity timing results are displayed in panel A, B and C respectively. In each case, we report findings at various points in the cross-section of timing performance as indicated. Results are sorted by the timing coefficient t-statistic from lowest t-statistic ("min") to highest ("max") and show the corresponding timing coefficient and bootstrap p-value of the t-statistic of that fund. The column headed "10 max" shows the coefficient, t-statistic and bootstrap p-value of the t-statistic of the fund with the tenth highest t-statistic, "max10%" reports results at the 90th percentile while "min10%" displays results at the 10th percentile etc. The t-statistics are calculated using Newey-West (1987) heteroscedasticity and autocorrelation-consistent standard errors with two lags.

Jarque-Bera tests reveals a high degree of non-normality in fund regression residuals across the fund sample. Therefore, in order to make more reliable statistical inferences, we report bootstrap p-values of the timing coefficient's t-statistic based on 1,000 bootstrap simulations under the null hypothesis of no timing ability. Here, we conduct separate bootstrap procedures for the return timing, volatility timing and liquidity timing coefficient t-statistics. We use the t-statistic as the performance statistic since it has superior statistical properties, in particular for short-lived funds. For further improved statistical inference we restrict our analysis to funds with a minimum of 36 monthly observations, leaving 657 funds in the sample.

[Table 2 here]

From panel A, in the upper side of the distribution, the fund with the best market return timing ability has a value of θ_1 = 0.034 with a t-statistic of 3.71 and bootstrap p-value of 0.01. The bootstrap p-value of 0.01 means that in the 1,000 simulations, only 1% of the θ_1 values generated under the null hypothesis have a t-statistic greater than 3.71. Zooming in on the upper side of the distribution between the indicated points in panel A reveals that 13 funds (or 2% of the fund sample) exhibit statistically significant (by t-statistic) positive market return timing ability at 5% significance (one-tail test). However, according to the non-parametric bootstrap p-value, this number falls to only four funds (or 0.6% of the sample). This highlights the importance of making adjustment for non-normality in our tests – an issue highlighted in past literature, Cuthbertson et al. (2008), Kosowski et al. (2006). Perversely, from the lower side of the distribution, our results show that a far higher proportion of the fund sample exhibit statistically significant negative market return timing. The worst fund has a value of θ_1 = -0.033 with a t-statistic of -7.82 and a bootstrap p-value of 0.00. (The bootstrap p-value of 0.00 means that in the 1,000 simulations, none of the θ_1 values generated under the null hypothesis has a t-statistic less than -7.82). In fact, by the t-statistic, 34% of the funds demonstrate significant negative return timing, although by the bootstrap p-value this number falls to 15.2% – both calculated at 5% significance. This preponderance of negative over positive return timing among UK equity mutual funds is consistent with previous UK findings (Cutherbertson et al., 2010).

Panel D of table 2 summarises the percentage of funds that exhibit statistically significant (by conventional t-statistic) positive and negative ability in timing market return, volatility and liquidity. Figures in parentheses are percentages derived from the bootstrap p-values.

From panel B in table 2, in the lower side of the distribution, the fund with the best market volatility timing ability has a value of θ_2 = -0.53 with a t-statistic of -6.79 and bootstrap p-value of 0.00. The θ_2 value of -0.53 indicates that in a month when market volatility is one standard deviation (i.e. 0.605) above its mean, *ceteris paribus*, this fund's market beta is lower by 0.32 (i.e. 0.53*0.605). Our results reveal quite a high prevalence of market volatility timing ability among the funds where, by the t-statistic, 21% of the sample exhibit significant volatility timing ability at 5% significance or 8.4% of the sample by the bootstrap p-value. It is noteworthy that the degree of volatility timing ability among funds is higher than that of return timing ability. At the upper end of the volatility timing distribution there is evidence of funds that counter-intuitively increase the market beta in advance of higher market volatility where 11% of funds do so with statistical significance (or 3.5% of funds according to the bootstrap p-value). Why funds would engage in such a strategy is puzzling. It is not explained by funds attempting to chase higher market returns as, as previously described, there is a strong negative contemporaneous correlation between market volatility and market returns.

From panel C in table 2, in the lower end of the distribution, the fund with the best market liquidity timing ability has a value of θ_3 = -13.61 with a t-statistic of -3.96 and bootstrap p-value of 0.00. The θ_3 value of –13.61 indicates that in a month when market illiquidity is one standard deviation (i.e. 0.032) above its mean, *ceteris paribus*, this fund's market beta is lower by 0.43 (i.e. 13.61*0.032). In total, 11% of funds exhibit significant liquidity timing ability at 5% significance or 4.7% of funds by the bootstrap p-value. At the upper end of the liquidity timing distribution there is evidence of funds that counter-intuitively increase the market beta in advance of higher than normal market illiquidity. Indeed, 22.4% of funds do so with statistical significance or 8.4% of funds by the bootstrap p-value.

Overall, we find a quite high degree of skilful market volatility timing among funds where 8.4% of funds are shown to significantly negatively time volatility at 5% significance by the bootstrap p-value. Although the prevalence of market liquidity timing is slightly lower at 4.7% of funds, there is nevertheless evidence of skill here also in the extreme tail of the cross-sectional distribution of funds with many funds exhibiting p-values far less than 0.05. The evidence of market return timing ability is considerably weaker where only 0.6% of funds demonstrate skill. Across the funds, there is no overlap in timing abilities between return, volatility and liquidity timing. That is, no fund demonstrates statistically significant timing ability in any two strategies. One possible explanation for the paucity of market return timing may be that the prevalent volatility timing is explaining return timing: successful volatility timing means that funds reduce the market beta when next period market volatility is higher. However, as market volatility and market return are strongly negatively correlated (correlation coefficient = -0.50), this means funds are also reducing beta when market return is lower and *vice-versa*, which is market return timing. Our results indicate that there is little return timing taking place independently of volatility timing. However, the cross-sectional (across funds) correlation coefficient between funds' market return timing coefficient and funds' market volatility timing coefficient is a high 0.60. This suggests that among the funds, volatility timing activity is inversely associated with return timing activity or, more specifically, funds that are better at timing market volatility are poorer at timing the market return fluctuations not explained by market volatility. However, in results not shown, we test funds' market return timing ability without simultaneously testing their attempts to also time market volatility and liquidity. We continue to find that only 0.46% of funds exhibit statistically significant return timing ability. This would indicate that funds are simply more engaged with volatility timing and liquidity timing than return timing or that they simply lack skill in return timing.

The time series correlation between market volatility and market liquidity is 0.59. Funds timing market volatility reduce the market beta in anticipation of higher next-period market volatility. However, the positive market volatility/liquidity time series correlation implies that these funds are also reducing the market beta during rising market illiquidity - which is market liquidity timing. This may suggest that for some funds, volatility timing is partly explaining liquidity timing and *vice-versa* which is why we fail to identify any funds that exhibit both significant volatility timing ability and significant liquidity timing ability. However, the cross-sectional correlation between funds' volatility timing coefficient and liquidity timing coefficient is a large -0.61. This negative cross-sectional correlation suggests that funds better engaged in volatility timing are poorer at timing the market liquidity variations not explained by market volatility.

4.2 Private Timing Ability

As described in section 2.3, there is also research appeal in investigating whether funds possess the ability to time fluctuations in market return, volatility and liquidity that is superior to timing ability attributable to publicly available information. Such superior or private timing skill on the part of fund managers better justifies active management fees. We estimate [5] and focus on funds' private skill in timing market volatility and market liquidity rather than market returns. Findings are presented in table 3 and table 4.

[Table 3 here]

[Table 4 here]

We first estimate an ARMA (1,1) conditional model of market volatility and an AR(2) conditional model of market liquidity.[7] The residuals of these models represent the variation in market volatility and market liquidity not explained by public information. Tests of private timing skill involve investigating whether funds can time this residual or unexplained component. We present results of these tests in table 3. The conclusions from these tests are,

[7] As indicated in section 2, the ARMA(1,1) and AR(2) specifications are found to be the most parsimonious best fit.

of course, contingent on the choice of conditional model. In order to test the robustness of our findings, we also estimate the residuals from separate regressions of market volatility and market liquidity on a set of instruments and implement similar fund private timing tests on these regression residuals. Our set of instruments are a short term interest rate, market dividend yield, term structure, default spread and a January dummy (Busse, 1999; Ferson and Schadt, 1996). Results of these tests are reported in table 4.

From table 3, panel B and C, the results indicate private volatility timing and private liquidity timing abilities respectively in the extreme left tails of the two distributions. This is the case by both the t-statistic and its bootstrap p-value. Panel D summarises the percentage of statistically significant positive and negative private timing coefficients by t-statistic (and by bootstrap p-value in parentheses). Here, we see that 9.6% of funds exhibit significant (by bootstrap p-value) private volatility timing ability based on the ARIMA (1,1) conditional model. This finding is broadly in line with overall timing ability (public and private) from table 2 (panel D). This indicates that, on the whole, UK mutual funds can time market volatility based on public and private information equally well. On private market liquidity timing based on the AR(2) model, from panel D just 1.1% of funds (by bootstrap p-value) demonstrate private skill, down from 4.7% in the case of public and private skill (from panel D, table 2).

In table 4, where private timing tests are based on the conditional instrumental variables models, results confirm those in table 3 in showing that a small number of funds continue to exhibit both market volatility and market liquidity timing skill after controlling for predictability based on public information. Although, panel D indicates a smaller percentage of private volatility timers and a larger percentage of private liquidity timers compared to the results in table 3.

Overall, we conclude from our private timing tests that private skill in timing both market volatility and market liquidity does exist among a small number of funds.

Throughout our analysis of both public and private timing ability among funds and across market return timing, volatility timing and liquidity timing, a consistent finding is that the prevalence of statistically significant timing ability among funds falls considerably when measured by a non-parametric bootstrap procedure compared to a conventional t-statistic. This highlights the importance of accounting for non-normality in the regressions which we measure directly and find to be widespread.

4.3 Pinpointing timing capabilities – false discovery rates.

In the above discussion we follow the standard approach to determine whether the timing performance of a single fund demonstrates skill or luck – we choose a rejection region and associated significance level, γ, and reject the null of no timing ability (or skill) if the test statistic lies in the rejection region. However, using γ = 5% when testing the timing ability for each of *m* funds, the probability of finding at least one lucky fund from a sample of *m* funds is much higher than 5% - even if all funds have true timing ability of zero[8]. Consider a case where we find 50 out of 500 funds (i.e. 10% of funds) with significant estimated timing coefficients when using a 5% significance level. Some of these will merely be lucky – indeed 5% of all true null-funds found to be significant will be false positives. The false discovery rate is the probability that the fund's performance is found to be significant, given that it is truly null. For example, suppose the FDR amongst 50 significant timing funds is 80% then this implies that only 10 funds (out of the 50) have truly significant timing ability.

In order to shed further light on true timing ability in the UK equity mutual fund industry, we extend our previous discussion by estimating the false discovery rate around timing ability in our fund sample.

The false discovery rate (FDR) estimation methodology is now well documented in the literature so we do not propose to provide detail on it here. We refer the reader to Barras et al.

[8] This probability is the compound type-I error. For example, if the *m* tests are independent then Pr(at least 1 false discovery) = $1 - (1-\gamma)^m = z_m$, which for a relatively small number of say $m = 50$ funds and conventional $\gamma=0.05$ gives $z_m = 0.92$ – a high probability of observing at least one false discovery, Cuthbertson et al. (2012).

(2010) and Cuthbertson et al. (2012) for a fuller discussion. Here, we estimate the FDR separately in the market return, market volatility and market liquidity timing tests and, in turn, in each case we estimate the FDR separately among the funds with the best and worst timing ability.

For example, the estimated FDR among positive significant timing funds is given as

$$FDR_{\gamma}^{+} = \frac{\pi_0(\gamma / 2)}{S_{\gamma}^{+}} \qquad [7]$$

where π_0 is the proportion of truly zero timing ability funds, S_{γ}^{+} is the estimated proportion of positive significant timers, and γ is the chosen significance level – we use $\gamma = 0.05$ throughout. A similar formula applies in order to estimate FDR_{γ}^{-} , i.e. the false discovery rate among negative significant timing funds. In our case, market return timing is indicated by a positive timing coefficient while market volatility timing and market liquidity timing are indicated by negative timing coefficients. To estimate the FDR we only require an estimate of π_0. To do this we use the result that truly alternative features have p-values clustered around zero, whereas truly null p-values are uniformly distributed. Again, we refer the reader at this point to, for example, Barras et al. (2010) and Cuthbertson et al. (2012) for a fuller discussion on FDR estimation methodology.

Calculation of the FDR depends on correct estimation of individual p-values. Because of the non-normality in regression residuals as discussed previously, we use the bootstrap pricedure to calculate p-values of estimated t-statistics and we apply the FDR procedure to these p-values. Furthermore, in results not shown, in each panel of Tables 2,3 and 4 discussed in the previous section, the null hypothesis that the cross-sectional distribution of the timing coefficients follows a normal distribution is strongly rejected (at 1% significance). Hence, for more reliable statistical inference we use the bootstrap p-values of the t-statistics.

We report our findings on the false discovery rates in estimating timing performance among funds in table 5. The table shows the number (and percentage in parentheses) of positive and negative significant funds by the bootstrap p-value as before but also shows the false discovery rate (FDR) among the positive significant funds and among the negative significant funds. We then report the number (percentage) of truly skilled timers. These figures are reported for market return, market volatility and market liquidity timing tests as well as for both public timing and private timing ability in each case. The upper panel presents findings from unconditional timing tests, i.e. based on both public and private information. The middle panel reports results from private timing tests which test whether funds can time market volatility, as measured by the residuals from the conditional ARMA (1,1) model, and market liquidity, as measured by the residuals from the conditional AR(2) model. In the bottom panel we report results of private volatility timing and private liquidity timing as measured by the funds' ability to time the residuals from the conditional instrumental variables model.

[Table 5 here]

In the upper panel of table 5 (and as reported in the previous section) we see that quite a high number of funds (55 funds or 8.4% of the sample) exhibit statistically significant market volatility timing ability. We estimate the FDR among these funds to be 23.73%, leaving 42 truly skilled volatility timers (or 6.4% of the sample).[9] Therefore, our initial finding of the existence of volatility timing skill among UK equity mutual funds is robust to false discoveries. Furthermore, we previously found that 63 funds (9.6% of the sample) showed private volatility timing ability (conditioning on the ARMA (1,1) model). The middle panel of table 5 reveals that the FDR among these funds is 23.39% indicating that a high 48 funds (7.3% of the sample) demonstrate true private volatility timing ability. Consistent with the finding in the previous

[9] While we say "true" timing ability, of course the FDR itself is subject to estimation error so we cannot be certain that a proportion of funds have true timing ability. Furthermore, the FDR analysis does not identify whether an individual fund is truly null or not – it is the estimated proportion of false discoveries among a group of funds.

section, this figure falls if we estimate private timing ability conditional on the IV model - lower panel of table 5).

On market liquidity timing, the upper panel of table 5 shows that 31 funds (or 4.7% of the sample) exhibit statistically significant liquidity timing. While this figure falls to 3.5% of the sample after the applying the estimated FDR it remains indicative of some liquidity timing skill among funds. Consistent with the discussion in the previous section, there are conflicting results around whether funds exhibit private liquidity timing ability depending on the conditional model chosen (middle and lower panels of table 5).

On market return timing, we previously found that a tiny proportion of funds (just 4 funds or 0.6% of the sample) demonstrate return timing ability (upper panel, table 5). The FDR analysis estimates that these are all false discoveries.

Overall, we conclude that the quite high prevalence of volatility timing skill in particular reported in our previous results remains generally robust to false discoveries and we can now more reliably conclude that around 6.4% of funds demonstrate the ability to time market volatility. This figure falls to around 3.5% of funds in the case of market liquidity timing.

4.4 *Persistence in Timing Skills*

Having identified some timing ability among funds, a further question of interest is whether this *ex-post* evidence of timing ability provides an *ex-ante* strategy for investors in fund selection. In short, does timing ability persist? To examine this we adopt a persistence testing methodology similar to Hendrick et al. (1993), Carhart (1997) and others.

For each fund, at time *t* we estimate Eq. [3] over the period *t* to *t*-36 (minimum 24 month requirement for fund inclusion) as follows:

$$
\begin{aligned}
R_{i,t+1} = {} & \alpha_i + \theta_0 R_{m,t+1} + \beta_2 SMB_{t+1} + \beta_3 HML_{t+1} + \beta_4 MOM_{t+1} + \theta_1 R^2_{m,t+1} \\
& + \theta_2\left[\left(\sigma_{m,t+1} - \overline{\sigma}_m\right).\left(R_{m,t+1}\right)\right] + \theta_3\left[\left(L_{m,t+1} - \overline{L}_m\right).\left(R_{m,t+1}\right)\right] + \varepsilon_{i,t+1}
\end{aligned} \qquad [3]
$$

In three separate procedures we sort funds into deciles according to their measures of market return timing ability, as measured by $\hat{\theta}_1$, market volatility timing ability, as measured by $\hat{\theta}_2$ and market liquidity timing ability, as measured by $\hat{\theta}_3$. In the case of return timing ability, $\hat{\theta}_1$, we sort funds from highest to lowest (most skilful to least skilful) while in the case of volatility timing and liquidity timing abilities, i.e. $\hat{\theta}_2$ and $\hat{\theta}_3$ respectively, we sort from lowest to highest (most skilful to least skilful). In all three cases, we form equally weighted decile portfolios and hold for 12 months. (If a fund ceases to exist during the 12 months, the portfolio is rebalanced equally between the remaining funds). We then calculate the difference in returns between the top (most skilful) and bottom (least skilful) decile portfolios each month during the 12 month holding period. This process is repeated recursively over the sample period. Put another way, we (separately) form portfolios that are (i) long the top decile of return timers and short the bottom decile of return timers, (ii) long the top decile of volatility timers and short the bottom decile of volatility timers and (iii) long the top decile of liquidity timers and short the bottom decile of liquidity timers and in each case we hold for 12 months before repeating recursively. In each case (i.e. sorting by $\hat{\theta}_1, \hat{\theta}_2$ and $\hat{\theta}_3$), this forward looking or *ex-ante* time series is then regressed on the timing model as follows:

$$
R_{i,t+1} = \alpha_i + \delta_1 R^2_{m,t+1} + \delta_2\left[\left(\sigma_{m,t+1} - \overline{\sigma}_m\right).\left(R_{m,t+1}\right)\right] + \delta_3\left[\left(L_{m,t+1} - \overline{L}_m\right).\left(R_{m,t+1}\right)\right] + \varepsilon_{i,t+1} \qquad [8]
$$

where $R_{i,t+1}$ is the time series of forward looking returns. On sorting by $\hat{\theta}_1$, the null hypothesis of no persistence in return timing ability may be tested as $H_0 : \hat{\delta}_1 = 0, H_A : \hat{\delta}_1 > 0$. Similarly, on sorting by $\hat{\theta}_2$ the null hypothesis of no persistence in volatility timing ability may be tested as

$H_0 : \hat{\delta}_2 = 0, H_A : \hat{\delta}_2 < 0$. Finally, having sorted by $\hat{\theta}_3$ the null hypothesis of no persistence in liquidity timing ability may be tested as $H_0 : \hat{\delta}_3 = 0, H_A : \hat{\delta}_3 < 0$.

The above methodology describes tests of persistence in market return, market volatility and market liquidity timing ability based on both public and private information. We implement a similar procedure to test for persistence in private timing ability in market volatility timing and market liquidity timing. Here, we first estimate the *private* timing performance model, Eq. [5], as follows:

$$\begin{aligned} R_{i,t+1} = \alpha_i + \theta_0 R_{m,t+1} + \beta_2 SMB_{t+1} + \beta_3 HML_{t+1} + \beta_4 MOM_{t+1} + \theta_1 R^2_{m,t+1} \\ + \theta_2 \left[\left(\sigma_{m,t+1(res)} \right) . \left(R_{m,t+1} \right) \right] + \theta_3 \left[\left(L_{m,t+1(res)} \right) . \left(R_{m,t+1} \right) \right] + \varepsilon_{i,t+1} \end{aligned} \quad [5]$$

Again, in three separate procedures we sort funds into deciles according to their measures of return timing ability, as measured by $\hat{\theta}_1$ in [5], private market volatility timing ability, as measured by $\hat{\theta}_2$ and private market liquidity timing ability, as measured by $\hat{\theta}_3$. In the same sorting and holding procedure as described previously, in each case (i.e. sorting by $\hat{\theta}_1, \hat{\theta}_2$ and $\hat{\theta}_3$), the forward looking or *ex-ante* time series of holding period returns is then regressed on the *private* timing model as follows:

$$R_{i,t+1} = \alpha_i + \delta_1 R^2_{m,t+1} + \delta_2 \left[\left(\sigma_{m,t+1(res)} \right) . \left(R_{m,t+1} \right) \right] + \delta_3 \left[\left(L_{m,t+1(res)} \right) . \left(R_{m,t+1} \right) \right] + \varepsilon_{i,t+1} \quad [9]$$

The null hypotheses of no persistence in return timing, private volatility timing and private liquidity timing ability is examined by testing the statistical significance of $\hat{\delta}_1, \hat{\delta}_2$ and $\hat{\delta}_3$ respectively as before. Note, in [5] and [9], $\sigma_{m,t+1(res)}$ and $L_{m,t+1(res)}$ are the residuals from conditional ARMA (1,1), AR(2) and instrumental variables (IV) models as described in 2.3. For robustness, we examine persistence in private timing ability using residuals from both types of conditioning model.

We present results on the persistence of timing skill among funds in table 6. Panel A presents findings from unconditional timing, i.e. based on both public and private information. Panel B reports results from private timing tests which test whether funds can time market volatility as measured by the residuals from the conditional ARMA (1,1) model and market liquidity as measured by the residuals from the conditional AR(2) model. In panel C, we report results of private volatility and private liquidity timing as measured by the funds' ability to time the residuals from the conditional instrumental variables model.

[Table 6 here]

From panel A, in the first column of results denoted "Return Timing $\hat{\theta}_1$" where we test persistence in market return timing skill, i.e. sorting on $\hat{\theta}_1$ from [3], the resulting coefficient estimate of $\hat{\delta}_1$ in [8] is 0.00 with a t-statistic of 0.05 and a bootstrap p-value of the t-statistic of 0.96. Hence, we fail to reject the null hypothesis of no persistence in market return timing ability. This is not surprising as we found little evidence of market return timing ability earlier. For completeness, we also test whether sorting funds on return timing ability, $\hat{\theta}_1$, predicts future volatility timing and liquidity timing ability. For example, sorting on $\hat{\theta}_1$ from [3] yields estimates of $\hat{\delta}_2$ = 0.10 and $\hat{\delta}_3$ = -0.15 in [8]. However, neither is statistically significant indicating that there no evidence that return timing ability predicts future volatility or liquidity timing ability. From panel A, in the second column of results denoted "Volatility Timing $\hat{\theta}_2$", we test persistence in market volatility timing skill, i.e. we sort on $\hat{\theta}_2$ from [3]. Here, the resulting coefficient estimate of $\hat{\delta}_2$ in [8] is 0.05 with a t-statistic of 0.80 and a bootstrap p-value of 0.43. Hence, we fail to reject the null hypothesis of no persistence in market volatility timing ability. Similarly, there is no evidence that sorting on volatility timing ability predicts either future return timing or liquidity timing skill. However, in the third column of results denoted "Liquidity Timing $\hat{\theta}_3$" we test persistence in liquidity timing skill. Sorting on $\hat{\theta}_3$ in [3], the resulting coefficient estimate of $\hat{\delta}_3$ in [8] is -4.05 with a t-statistic of -4.07 and a bootstrap p-value of 0.00. Hence, here we reject the null hypothesis of no persistence in market liquidity timing skill.

In panel B, which tests persistence in private timing skill, the most striking result is evidence of *negative* persistence in private market volatility timing skill among funds. In the second column of results denoted "Volatility Timing $\hat{\theta}_2$", we sort on $\hat{\theta}_2$ from [5]. The null hypothesis of no persistence involves testing $H_0 : \hat{\delta}_2 = 0, H_A : \hat{\delta}_2 < 0$ in [9]. The null is strongly rejected where $\hat{\delta}_2$ = 0.09 with a t-statistic of 4.36 and a bootstrap p-value of 0.00. However, as $\hat{\delta}_2 > 0$, these results indicate that the best private volatility timers over the previous 36 months go on to be poor private volatility timers over the following 12 months where they increase the fund beta in advance of higher market illiquidity. We see a similar finding in the second column of results in panel C, which also examines private market volatility timing under the alternative IV conditioning conditional model, though this finding is less statistically significant than in panel B.

From panel A previously we found evidence of persistence in (unconditional) liquidity timing. However, in both panel B and panel C in the third column of results in each case denoted "Liquidity Timing $\hat{\theta}_3$" there is no significant evidence of persistence in private liquidity timing ability among funds.

Overall, therefore, we find evidence of liquidity timing ability among funds and further evidence that it persists and can be used to predict future liquidity timing ability *ex-ante*. However, we find less evidence of private liquidity timing skill and no evidence that it persists. There is no evidence of persistence in either market return timing or market volatility timing and indeed there is an indication of an inverse or negative persistence in private market volatility timing.

4.5 Timing ability and fund performance

If funds have skill in timing market return, market volatility and market liquidity, and we have established that there is at least some evidence that they do in the case of market volatility and liquidity in particular, it prompts the question whether this skill is associated with superior fund performance. To examine this we perform a similar recursive portfolio rebalancing procedure to that of the previous section. From Eq. [3] and based on a 36 month evaluation period, we form equally weighted portfolios that are (i) long the top decile of return timers and short the bottom decile of return timers (ii) long the top decile of volatility timers and short the bottom decile of volatility timers and (iii) long the top decile of liquidity timers and short the bottom decile of liquidity timers. In each case we hold for 12 months before repeating recursively. In each case (i.e. sorting by $\hat{\theta}_1, \hat{\theta}_2$ and $\hat{\theta}_3$ from [3]), this forward looking or *ex-ante* time series is then regressed on a Carhart four-factor performance model and the Carhart alpha is estimated. If timing ability is associated with superior performance, we expect this Carhart alpha to be positive and statistically significant. We carry out this procedure to examine the relation between both timing skill based on public information as well as private timing skill and fund performance. In the latter case, we repeat the above procedure where we sort on the estimates of private timing ability from the estimation of [5] rather than [3].

We present the results of this analysis in table 7. Panel A relates to public timing skill while panel B and panel C relate to private timing ability - where private timing ability is measured as indicated and as explained previously. The first, second and third columns of results in each panel report on the relation between market return timing ability, volatility timing ability and liquidity timing ability and fund performance respectively. We report the Carhart four-factor alpha, the t-statistic of alpha and the bootstrap p-value of the t-statistic of alpha. The results in table 7 (panel A) reveal a positive association between liquidity timing skill and fund performance where the Carhart alpha is 0.38% per month with a t-statistic of 2.27 and a bootstrap p-value of 0.03. From panel C there is also some evidence that private liquidity timing ability is associated with positive abnormal performance – significant at the 10% significance level. We find no evidence of a relation between either market return or market volatility timing skill and fund abnormal performance.

[Table 7 here]

5. Conclusion

Market timing among mutual funds has attracted much attention in the literature. Specifically, this has focused on funds' ability to time market return. The ability to time market volatility has received less attention while there is a dearth of analysis of market liquidity timing ability among funds. To our knowledge, ours is the first examination of market volatility and market liquidity timing in the large UK mutual fund industry. We find strong evidence of skilful volatility timing among a small percentage of UK equity mutual funds: when conditional market volatility is higher than normal, systematic risk levels are lower. After controlling for the element of this timing that may be attributable to publicly available information, the timing ability remains suggesting that it is partly based on private information or private skill among managers. The evidence around market liquidity timing is broadly similar though its prevalence is slightly less compared to volatility timing but again there is evidence of skillful liquidity timing in the extreme tails of the cross-sectional distribution of funds and it is not entirely explained by publicly available information - when market illiquidity is worse than normal, fund systematic risk levels are lower. We find that funds are either more engaged in timing market volatility and liquidity than market return or simply that funds are less skilled in timing market return compared to market volatility and liquidity.

While there may be somewhat less prevalence of liquidity timing skill, we find evidence that it persists and can be used to predict future liquidity timing ability *ex-ante*. There is no evidence of persistence in either market return timing or market volatility timing and indeed there is an indication of an inverse or negative persistence in private market volatility timing.

The ability to time fluctuations in market liquidity is associated with superior abnormal performance. However, while there is evidence among funds of the ability to time market volatility, we find this is not associated with superior fund abnormal performance.

A consistent finding is that the prevalence of statistically significant timing ability among funds falls considerably when measured by a non-parametric bootstrap procedure compared to a conventional t-statistic. This highlights the importance of accounting for non-normality in the regressions which we measure directly and find to be widespread.

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Table 1: Descriptive Statistics of the Mutual Fund Sample

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

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

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

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

Table 2. Fund skill in timing market return, volatility and liquidity

Panels A, B and C present results of market return timing, volatility timing and liquidity timing respectively. Each panel shows the timing coefficient, its t-statistic and the bootstrap p-value of the t-statistic at various points in the cross-sectional distribution of funds. Results are sorted by the t-statistic from lowest t-statistic ("min") to highest ("max") and show the corresponding timing coefficient and bootstrap p-value of the t-statistic of that fund. For example, the column headed "10max" shows the coefficient, t-statistic and bootstrap p-value of the fund with the tenth highest t-statistic. Similarly, "max10%" reports results at the 90th percentile etc. Panel D reports the percentage of funds that exhibit statistically significant (by conventional t-statistic) positive and negative ability in timing market return, volatility and liquidity while figures in parentheses are percentages derived from non-parametric bootstrap p-values.

Panel A: Return Timing

	min	5 min	10 min	20 min	min5%	min10%	min20%	min30%	min40%	max30%	max20%	max10%	max5%	20 max	10 max	5 max	max
Coefficient	-0.033	-0.029	-0.031	-0.022	-0.025	-0.029	-0.026	-0.013	-0.007	-0.004	-0.000	0.012	0.008	0.016	0.010	0.015	0.034
t-stat	-7.82	-5.18	-4.61	-4.15	-3.54	-2.95	-2.28	-1.80	-1.40	-0.32	-0.01	0.58	0.99	1.35	1.75	1.98	3.71
p-value	0.00	0.00	0.00	0.00	0.01	0.02	0.06	0.18	0.31	0.82	1.00	0.66	0.41	0.25	0.21	0.19	0.01

Panel B: Volatility Timing

	min	5 min	10 min	20 min	min5%	min10%	min20%	min30%	min40%	max30%	max20%	max10%	max5%	20 max	10 max	5 max	max
Coefficient	-0.53	-0.38	-0.17	-0.36	-0.16	-0.17	-0.20	-0.67	-0.19	0.03	0.12	0.25	0.31	0.36	0.38	0.39	0.30
t-stat	-6.79	-4.31	-3.70	-3.31	-2.99	-2.37	-1.66	-1.10	-0.64	0.51	1.07	1.70	2.22	2.59	3.01	3.65	4.97
p-value	0.00	0.01	0.00	0.00	0.02	0.07	0.15	0.45	0.58	0.65	0.38	0.14	0.09	0.03	0.01	0.00	0.00

Panel C: Liquidity Timing

	min	5 min	10 min	20 min	min5%	min10%	min20%	min30%	min40%	max30%	max20%	max10%	max5%	20 max	10 max	5 max	max
Coefficient	-13.61	-12.30	-14.68	-11.20	-4.23	-6.05	-2.13	-0.15	0.49	4.47	3.23	4.19	7.52	3.39	2.73	5.67	11.02
t-stat	-3.96	-3.38	-3.20	-3.00	-2.43	-1.76	-0.70	-0.09	0.44	1.38	1.74	2.28	2.85	3.09	3.60	3.83	5.99
p-value	0.00	0.02	0.01	0.04	0.05	0.15	0.56	0.96	0.72	0.30	0.15	0.10	0.01	0.01	0.01	0.00	0.00

Panel D: Percentage of Funds Exhibiting Timing

	Positive (Bootstrap)	Negative (Bootstrap)
Market Timing	2.0 (0.6)	34.0 (15.2)
Volatility Timing	11.0 (3.5)	21.0 (8.4)
Liquidity Timing	22.4 (8.4)	11.0 (4.7)

Table 3. Private fund skill in timing market volatility and liquidity: shocks estimated from ARMA(1,1) and AR(2) models

Panels A, B and C present results of market return timing, private market volatility timing and private market liquidity timing respectively. Tests are based on the residuals from ARMA(1,1) and AR(2) estimations as indicated. Each panel shows the timing coefficient, its t-statistic and the bootstrap p-value of the t-statistic at various points in the cross-sectional distribution of funds. Results are sorted by the t-statistic from lowest t-statistic ("min") to highest ("max") and show the corresponding timing coefficient and bootstrap p-value of the t-statistic of that fund. For example, the column headed "10max" shows the coefficient, t-statistic and bootstrap p-value of the fund with the tenth highest t-statistic. Similarly, "max10%" reports results at the 90th percentile etc. Panel D reports the percentage of funds that exhibit statistically significant (by conventional t-statistic) positive and negative ability in timing market return, volatility and liquidity while figures in parentheses are percentages derived from non-parametric bootstrap p-values.

Panel A: Return Timing

	min	5 min	10 min	20 min	min5%	min10%	min20%	min30%	min40%	max30%	max20%	max10%	max5%	20 max	10 max	5 max	max
Coefficient	-0.064	-0.040	-0.036	-0.031	-0.047	-0.021	-0.019	-0.013	-0.012	-0.006	-0.001	0.004	0.008	0.032	0.010	0.022	0.049
t-stat	-6.06	-5.04	-4.55	-3.80	-3.47	-2.91	-2.27	-1.83	-1.40	-0.38	-0.05	0.58	0.89	1.26	1.55	1.95	2.42
p-value	0.00	0.00	0.00	0.01	0.01	0.04	0.07	0.18	0.27	0.74	0.98	0.70	0.47	0.33	0.22	0.10	0.08

Panel B: Private Volatility Timing (ARMA(1,1))

	min	5 min	10 min	20 min	min5%	min10%	min20%	min30%	min40%	max30%	max20%	max10%	max5%	20 max	10 max	5 max	max
Coefficient	-0.71	-0.32	-0.50	-0.31	-0.28	-0.21	-0.27	-0.10	-0.10	0.04	0.16	0.19	0.21	0.21	0.50	0.96	0.35
t-stat	-5.68	-4.65	-4.19	-3.55	-3.25	-2.52	-1.79	-1.27	-0.79	0.40	0.89	1.53	1.95	2.36	2.60	3.71	5.01
p-value	0.00	0.00	0.00	0.02	0.02	0.08	0.17	0.33	0.50	0.73	0.50	0.21	0.14	0.08	0.05	0.02	0.00

Panel C: Private Liquidity Timing (AR(2))

	min	5 min	10 min	20 min	min5%	min10%	min20%	min30%	min40%	max30%	max20%	max10%	max5%	20 max	10 max	5 max	max
Coefficient	-8.26	-12.25	-7.33	-21.53	-3.18	-11.58	-2.42	-1.14	-0.02	4.93	2.98	7.06	8.99	7.60	10.15	14.42	40.86
t-stat	-5.53	-2.98	-2.70	-2.28	-2.01	-1.45	-0.87	-0.41	-0.01	1.14	1.63	2.53	3.02	3.46	4.08	4.38	6.13
p-value	0.00	0.04	0.06	0.12	0.12	0.32	0.51	0.71	0.99	0.38	0.22	0.06	0.03	0.02	0.01	0.00	0.00

Panel D: Percentage of Funds Exhibiting Timing

	Positive (Bootstrap)	Negative (Bootstrap)
Market Timing	1.2 (0.0)	35.0 (15.1)
Volatility Timing	8.2 (2.0)	22.0 (9.6)
Liquidity Timing	19.8 (7.3)	7.6 (1.1)

Table 4. Private fund skill in timing market volatility and liquidity: shocks estimated from instrumental variables models

Panels A, B and C present results of market return timing, private market volatility timing and private market liquidity timing respectively. Tests are based on the residuals from instrumental variables models of market volatility and market liquidity. Each panel shows the timing coefficient, its t-statistic and the bootstrap p-value of the t-statistic at various points in the cross-sectional distribution of funds. Results are sorted by the t-statistic from lowest t-statistic ("min) to highest ("max") and show the corresponding timing coefficient and bootstrap p-value of the t-statistic of that fund. For example, the column headed "10max" shows the coefficient, t-statistic and bootstrap p-value of the fund with the tenth highest t-statistic. Similarly, "max10%" reports results at the 90th percentile etc. Panel D reports the percentage of funds that exhibit statistically significant (by conventional t-statistic) positive and negative ability in timing market return, volatility and liquidity while figures in parentheses are percentages derived from non-parametric bootstrap p-values.

Panel A: Return Timing																	
	min	5 min	10 min	20 min	min5%	min10%	min20%	min30%	min40%	max30%	max20%	max10%	max5%	20 max	10 max	5 max	max
Coefficient	-0.060	-0.051	-0.045	-0.025	-0.019	-0.027	-0.010	-0.018	-0.012	-0.005	-0.001	0.004	0.003	0.026	0.022	0.012	0.033
t-stat	-6.69	-5.59	-4.16	-3.63	-3.38	-2.78	-2.27	-1.87	-1.49	-0.52	-0.16	0.49	1.00	1.21	1.66	2.02	3.74
p-value	0.00	0.00	0.01	0.01	0.02	0.03	0.07	0.11	0.24	0.66	0.90	0.74	0.48	0.40	0.24	0.12	0.01
Panel B: Private Volatility Timing																	
	min	5 min	10 min	20 min	min5%	min10%	min20%	min30%	min40%	max30%	max20%	max10%	max5%	20 max	10 max	5 max	max
Coefficient	-0.45	-0.20	-0.17	-0.16	-0.35	-0.17	-0.07	-0.04	-0.06	0.06	0.10	0.23	0.26	0.09	0.28	0.20	0.24
t-stat	-5.15	-3.81	-3.35	-2.61	-2.40	-1.78	-1.20	-0.80	-0.42	0.55	0.90	1.55	2.01	2.24	2.58	3.23	4.63
p-value	0.00	0.01	0.02	0.10	0.06	0.17	0.32	0.58	0.78	0.70	0.53	0.23	0.12	0.08	0.10	0.04	0.01
Panel C: Private Liquidity Timing																	
	min	5 min	10 min	20 min	min5%	min10%	min20%	min30%	min40%	max30%	max20%	max10%	max5%	20 max	10 max	5 max	max
Coefficient	-7.94	-10.44	-7.70	-3.96	-3.43	-1.98	-2.82	-1.91	-0.49	1.34	1.06	18.01	5.66	1.87	2.97	4.64	5.40
t-stat	-5.41	-4.02	-3.83	-3.27	-2.96	-2.38	-1.62	-1.13	-0.74	0.61	1.13	1.93	2.77	3.05	3.70	4.37	5.51
p-value	0.00	0.01	0.01	0.01	0.01	0.06	0.21	0.37	0.54	0.55	0.39	0.15	0.03	0.03	0.00	0.00	0.01

Panel D: Percentage of Funds Exhibiting Timing

	Positive (Bootstrap)	Negative (Bootstrap)
Market Timing	1.5 (0.3)	36.2 (11.1)
Volatility Timing	8.8 (1.2)	13.6 (2.9)
Liquidity Timing	12.8 (5.9)	19.5 (7.9)

Table 5. False Discovery Rate in Timing Performance

Table 5 presents the results of the false discovery rate (FDR) estimation. The FDR is estimated for public (unconditional) timing skills denoted "public timing" in the upper panel as well as for private timing skills as indicated in the lower panels. In the middle panel, private volatility timing and private liquidity timing are measured as the ability to time residuals from an ARMA(1,1) model and an AR(2) respectively. In the bottom panel, private volatility timing and private liquidity timing are measured as the ability to time residuals from instrumental variables models. The instrumental variables are the short term interest rate, market dividend yield, term structure, default spread and a January dummy. In the case of all panels, we estimate the FDR for market return, market volatility and market liquidity timing. Calculation of the FDR depends on correct estimation of individual p-values. Because of the non-normality in regression residuals, we use the bootstrap approach to calculate p-values of estimated t-statistics and we apply the FDR procedure to these p-values. Figures shown are the numbers of statistically significant positive and negative funds at 5% significance, γ = 0.05, based on the bootstrap p-values. Figures in parentheses are percentages based on 657 funds used in the analysis. We then show the false discovery rates and the resulting numbers (and percentages) of 'truly' significant timing funds.

	Significant Positive (percentage)	**FDR^+**	**Truly Positive (percentage)**	**Significant Negative (percentage)**	**FDR^-**	**Truly Negative (percentage)**
Public Timing						
Return	4 (0.6)	100	0 (0)	100 (15.2)	13.39	87 (13.2)
Volatility	23 (3.5)	63.68	8 (1.2)	55 (8.4)	23.73	42 (6.4)
Liquidity	55 (8.4)	16.67	46 (7.0)	31 (4.7)	27.14	23 (3.5)
Private Timing						
Return	0 (0)	100	0 (0)	99 (15.1)	12.62	87 (13.2)
Volatility, ARMA (1,1)	13 (2.0)	100	0 (0)	63 (9.6)	23.39	48 (7.3)
Liquidity, AR(2)	48 (7.3)	31.43	33 (5.0)	7 (1.1)	100	0 (0)
Private Timing						
Return	2 (0.3)	100	0 (0)	73 (11.1)	13.64	63 (9.6)
Volatility (IV)	8 (1.2)	100	0 (0)	19 (2.9)	81.94	3 (0.46)
Liquidity (IV)	39 (5.9)	30.17	27 (4.1)	52 (7.9)	22.62	40 (6.1)

Table 6. Persistence in Timing Skills

Panels A, B and C present results of tests of persistence in public as well as private timing skill. Panel A reports findings based on public (unconditional) timing ability. In panel B, private volatility timing and private liquidity timing are measured as the ability to time residuals from an ARMA(1,1) model and an AR(2) model respectively. In panel C, private volatility timing and private liquidity timing are measured as the ability to time residuals from instrumental variables models. The instrumental variables are the short term interest rate, market dividend yield, term structure, default spread and a January dummy. Based on a backward looking window of 36 months we (separately) form portfolios that are (i) long the top decile of return timers and short the bottom decile of return timers, (ii) long the top decile of volatility timers and short the bottom decile of volatility timers and (iii) long the top decile of liquidity timers and short the bottom decile of liquidity timers and in each case we hold for 12 months before repeating recursively. We regress the time series of these *ex-ante* forward looking or holding period returns on the return, volatility and liquidity timing variables (as described in section 4.4). From these regressions, we report the coefficients, Newey-West adjusted t-statistics and bootstrap p-value of the t-statistics on the three timing variables.

Panel A: Public Timing Skill									
	Return Timing $\hat{\theta}_1$			**Volatility Timing** $\hat{\theta}_2$			**Liquidity Timing** $\hat{\theta}_3$		
	Return	Volatility	Liquidity	Return	Volatility	Liquidity	Return	Volatility	Liquidity
Coefficient $\hat{\delta}_1, \hat{\delta}_2, \hat{\delta}_3$	0.00	0.10	-0.15	0.02	0.05	-2.10	0.01	0.11	-4.05
t-stat	0.05	1.46	-0.06	1.38	0.80	-1.29	1.71	2.86	-4.07
p-value	0.96	0.15	0.95	0.17	0.43	0.20	0.09	0.01	0.00
Panel B: Private Timing Skill									
	Return Timing $\hat{\theta}_1$			**Volatility Timing** $\hat{\theta}_2$ **(ARMA 1,1)**			**Liquidity Timing** $\hat{\theta}_3$ **(AR 2)**		
	Return	Volatility	Liquidity	Return	Volatility	Liquidity	Return	Volatility	Liquidity
Coefficient $\hat{\delta}_1, \hat{\delta}_2, \hat{\delta}_3$	0.06	-0.24	-12.86	0.00	0.09	18.03	0.03	-0.14	-8.93
t-stat	3.82	-3.78	-0.78	-0.10	4.36	2.73	3.03	-3.80	-0.86
p-value	0.00	0.00	0.44	0.92	0.00	0.01	0.00	0.00	0.39
Panel C: Private Timing Skill									
	Return Timing $\hat{\theta}_1$			**Volatility Timing** $\hat{\theta}_2$ **(IV)**			**Liquidity Timing** $\hat{\theta}_3$ **(IV)**		
	Return	Volatility	Liquidity	Return	Volatility	Liquidity	Return	Volatility	Liquidity
Coefficient $\hat{\delta}_1, \hat{\delta}_2, \hat{\delta}_3$	-0.01	-0.22	0.33	0.02	0.14	0.24	0.00	-0.13	1.98
t-stat	-0.97	-2.10	0.27	1.99	1.56	0.27	0.07	-1.10	1.75
p-value	0.33	0.04	0.79	0.05	0.12	0.79	0.95	0.28	0.28

Table 7. Timing Skill and Fund Abnormal Performance

Table 7 presents results on the relation between fund timing ability and fund abnormal performance. Panel A reports findings based on public (unconditional) timing ability. In panel B, private volatility timing and private liquidity timing are measured as the ability to time residuals from an ARMA(1,1) model and an AR(2) respectively. In panel C, private volatility timing and private liquidity timing are measured as the ability to time residuals from instrumental variables models. The instrumental variables are the short term interest rate, market dividend yield, term structure, default spread and a January dummy. Based on a backward looking window of 36 months we (separately) form portfolios that are (i) long the top decile of return timers and short the bottom decile of return timers, (ii) long the top decile of volatility timers and short the bottom decile of volatility timers and (iii) long the top decile of liquidity timers and short the bottom decile of liquidity timers and in each case we hold for 12 months before repeating recursively. We then regress the time series of these *ex-ante* forward looking or holding period returns on the Carhart four-factor model. From these regressions, we report the alpha, the Newey-West adjusted t-statistic of alpha and the bootstrap p-value of the t-statistic of alpha.

Panel A: Public Timing Skill								
Return Timing $\hat{\theta}_1$			**Volatility Timing** $\hat{\theta}_2$			**Liquidity Timing** $\hat{\theta}_3$		
$\hat{\alpha}$	t-$\hat{\alpha}$	p-value $\hat{\alpha}$	$\hat{\alpha}$	t-$\hat{\alpha}$	p-value $\hat{\alpha}$	$\hat{\alpha}$	t-$\hat{\alpha}$	p-value $\hat{\alpha}$
-0.02	-0.08	0.94	-0.22	-1.11	0.27	0.38	2.27	0.03
Panel B: Private Timing Skill								
Return Timing $\hat{\theta}_1$			**Volatility Timing** $\hat{\theta}_2$ **(ARMA 1,1)**			**Liquidity Timing** $\hat{\theta}_3$ **(AR 2)**		
$\hat{\alpha}$	t-$\hat{\alpha}$	p-value $\hat{\alpha}$	$\hat{\alpha}$	t-$\hat{\alpha}$	p-value $\hat{\alpha}$	$\hat{\alpha}$	t-$\hat{\alpha}$	p-value $\hat{\alpha}$
0.35	1.04	0.30	0.21	0.99	0.32	0.27	1.07	0.29
Panel C: Private Timing Skill								
Return Timing $\hat{\theta}_1$			**Volatility Timing** $\hat{\theta}_2$ **(IV)**			**Liquidity Timing** $\hat{\theta}_3$ **(IV)**		
$\hat{\alpha}$	t-$\hat{\alpha}$	p-value $\hat{\alpha}$	$\hat{\alpha}$	t-$\hat{\alpha}$	p-value $\hat{\alpha}$	$\hat{\alpha}$	t-$\hat{\alpha}$	p-value $\hat{\alpha}$
0.15	0.91	0.37	-0.09	-0.64	0.53	0.23	1.72	0.09

APPENDIX

In this appendix we describe the construction of our seven liquidity measures. For a given liquidity measure *i*, *i* = 1,2…7 we construct a monthly time series of liquidity for each stock. We estimate liquidity in a given month only if the stock was a constituent of the FTSE All Share index that month. We cross-reference the London Stok Exchange (LSE) tick data with the London Share Price Database (LSPD) Archive file data using SEDOL number, using the latter to determine historically when a given stock was a constituent of the FTSE All Share index.

Liquidity Measures

We estimate seven liquidity measures from the microstructure literature based on intra-day tick data and aggregate up to a monthly measure. 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

$$Q_{s,m} = \frac{1}{qu_{s,m}} * \sum_{t=1}^{qu_{s,m}} \frac{P_{s,t}^{A} - P_{s,t}^{B}}{m_{s,t}} \tag{A1}$$

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

$$E_{s,m} = \frac{1}{tr_{s,m}} * \sum_{t=1}^{tr_{s,m}} \frac{P_{s,t}^{tr} - m_{s,t-5}}{m_{s,t-5}} \tag{A2}$$

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

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

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 indicate whether a trade is a buy or a sell. This is not uncommon and 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 (below the bid) are categorized as buys (sells). We categorise all other trades 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

$$OIB_{s,m} = \frac{100}{\sum_{t=1}^{tr_{s,m}} V_t} * \sum_{t=1}^{tr_{s,m}} D_t V_t \qquad \text{(A3)}$$

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. The model assumes that trades impact stock 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

$$\Delta p_t = \Psi \varepsilon_{\psi,t} + \lambda \varepsilon_{\lambda,t} + \bar{\Psi} \Delta D_t + \bar{\lambda} \Delta(DV_t) + y_t \qquad \text{(A4)}$$

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:

$$DV_t = n_0 + \sum_{`j=1}^{5} n_j DV_{t-j} + \varepsilon_{\lambda,t} \tag{A5}$$

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 (A4) is estimated by OLS each month. $\Psi_{s,t}$ is the permanent fixed price impact measure for stock *s* in month *t*. $\lambda_{s,t}$ 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.

As in Korajczyk and Sadka (2008), all seven liquidity measures are winsorised at the 1% and 99% percentiles to reduce the effect of outliers. All measures are signed to represent illiquidity.