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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. We also find a positive relation between liquidity timing ability and fund abnormal performance where skilled liquidity timers outperform unskilled timers by around 3% p.a. - though this finding is driven by poor liquidity timing funds going on to yield negative alpha. However, despite the evidence of volatility and liquidity timing ability among funds, we fail to find in support of persistence in this timing. We find little evidence supporting market return timing ability.

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

In this paper we investigate whether UK equity 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 time volatility in this way.

Busse (1999) theorises a probably negative relation between market return and market volatility. This is empirically confirmed in the US 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 also 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 a fund's 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 that fund managers may attempt to time 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.

[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 higher 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 publicly available 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 remain in our sample of funds after controlling for the predictive power of publicly available information. We document a significant relation between fund liquidity timing and fund abnormal performance though the latter does not appear to be linked to volatility timing ability. However, we find no evidence in support of persistence among funds in either market volatility or market liquidity 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 expected market volatility and expected market liquidity shocks next period. Subbing [2] into [1] gives the timing augmented performance model

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

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 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 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) UK stock market 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

[3] 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.

afternoon time). Calculating liquidity using daily stock closing prices could give a false impression of liquidity 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: $NL^{i}_{s,t} = \dfrac{L^{i}_{s,t} - \hat{\mu}^{i}_{s,t}}{\hat{\sigma}^{i}_{s,t}}$,

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 investigate 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

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

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 in [5].

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) as follows.

The 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, 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'.

The 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:

$$r_{i,t} = \theta_i + \beta_i * F_t^L + \gamma_i * F_t^O + \varepsilon_{i,t} \quad [6]$$

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 lower contemporaneous returns and market 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 respectively as follows:

$$\begin{aligned} R_{i,t+1} &= \alpha_i + \theta_0 R_{m,t+1} + \beta_2 SMB_{t+1} + \beta_3 HML_{t+1} + \beta_4 MOM_{t+1} + \beta_5 IML_{t+1} + \beta_6 HML_{LR,t+1} \\ &+ \theta_1 R^2_{m,t+1} + \theta_2 \left[\left(\sigma_{m,t+1} - \bar{\sigma}_m \right) . \left(R_{m,t+1} \right) \right] + \theta_3 \left[\left(L_{m,t+1} - \bar{L}_m \right) . \left(R_{m,t+1} \right) \right] + \varepsilon_{i,t+1} \end{aligned} \quad [7]$$

$$\begin{aligned} R_{i,t+1} &= \alpha_i + \theta_0 R_{m,t+1} + \beta_2 SMB_{t+1} + \beta_3 HML_{t+1} + \beta_4 MOM_{t+1} + \beta_5 IML_{t+1} + \beta_6 HML_{LR,t+1} \\ &+ \theta_1 R^2_{m,t+1} + \theta_2 \left[\left(\sigma_{m,t+1(res)} \right) . \left(R_{m,t+1} \right) \right] + \theta_3 \left[\left(L_{m,t+1(res)} \right) . \left(R_{m,t+1} \right) \right] + \varepsilon_{i,t+1} \end{aligned} \quad [8]$$

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 (time series and cross-sectional averages). 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 monthly returns across funds 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 from 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

[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.

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.

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 briefly report on 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 [7] 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. For example, 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 and so on. 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. The bootstrap is performed on a fund-by-fund basis, rather than a cross-sectional bootstrap procedure. 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 4 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 fund performance 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 14.7% – 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).

From panel B, 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 3.2% 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 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, 10.8% of funds exhibit significant liquidity timing ability at 5% significant or 5.5% 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, 22.5% of funds do so with statistical significance or 9.7% of funds by the bootstrap p-value.

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.

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 5.5% 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. These findings in relation to the UK mutual fund industry are consistent with those of the Busse (1999) and Cao et al. (2013) US studies. 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. From section 2.3, 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 results of the two sets of private timing tests are qualitatively very similar. As such, a detailed discussion here would offer little new evidence and in order to conserve space we do not tabulate all results. Full results are available on request. However, briefly, on the whole we find that UK mutual funds can time market volatility based on public and private information equally well, i.e., we do not find reduced prevalence of volatility timing skill after controlling for publicly available information. On private market liquidity timing, we find that just 1% of funds continue to demonstrate private timing skill, down from 5.5% of funds previously.

Before continuing our discussion of empirical results, we note that the Carhart model has been questioned in some recent literature, e.g., Cremers, Petajisto and Zitzewitz (2010), where benchmark indices have been found to generate non-zero alpha. Cremers et al. suggest using investible indices as benchmark factors. As a robustness test, we repeat our tests above using the Morgan Stanley Capital International (MSCI inc) UK investable market index in place of the FTSE All Share index. We find the results are qualitatively very similar to those presented in the paper. As such there is little value to tabulating these results. However, all results are available on request.[7]

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 our accounting for non-normality in the regressions which we measure directly and find to be widespread.

[7] We thank an anonymous referee for suggesting this robustness test.

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 $\gamma = 5\%$ 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. (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

[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).

$$\mathrm{FDR}_{\gamma}^{+} = \frac{\pi_0(\gamma / 2)}{S_{\gamma}^{+}} \quad [9]$$

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 γ = 0.05 throughout. A similar formula applies in order to estimate $\mathrm{FDR}_{\gamma}^{-}$, 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 procedure to calculate p-values of estimated t-statistics and we apply the FDR procedure to these p-values.

We report our findings on the false discovery rates in estimating timing performance among funds in table 3. 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 in parentheses) of truly skilled timers. These figures are reported for market return, market volatility and market liquidity timing tests. Also shown are the estimates of π_0 above.

[Table 3 here]

From table 3 (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 27.97%, leaving 40 truly skilled volatility timers (or 6.1% of the sample).[9] Therefore, our initial finding of the existence of volatility timing skill among UK equity mutual funds is generally robust despite some false discoveries. On market liquidity timing, table 5 shows that 36 funds (or 5.5% of the sample) exhibit statistically significant liquidity timing. While this figure falls to 3.2% of the sample after the applying the estimated FDR, it remains indicative of some liquidity timing skill among funds. 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. 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% of funds demonstrate the ability to time market volatility. This figure falls to around 3% 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 Carhart (1997) and others.

For each fund, at time t we estimate Eq. [10], i.e., Eq. [7] from above, over the period t to t-36 (minimum 24 month requirement for fund inclusion) as follows:

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[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.

$$R_{i,t+1} = \alpha_i + \theta_0 R_{m,t+1} + \beta_2 SMB_{t+1} + \beta_3 HML_{t+1} + \beta_4 MOM_{t+1} + \beta_5 IML_{t+1} + \beta_6 HML_{LR,t+1}$$
$$+ \theta_1 R^2_{m,t+1} + \theta_2 \left[\left(\sigma_{m,t+1} - \bar{\sigma}_m \right) . \left(R_{m,t+1} \right) \right] + \theta_3 \left[\left(L_{m,t+1} - \bar{L}_m \right) . \left(R_{m,t+1} \right) \right] + \varepsilon_{i,t+1} \quad [10]$$

In three separate procedures we sort funds into deciles according to their measures of market return timing ability, as measured by the t-statistic of $\hat{\theta}_1$, market volatility timing ability, as measured by the t-statistic of $\hat{\theta}_2$ and market liquidity timing ability, as measured by the t-statistic of $\hat{\theta}_3$. In the case of return timing ability, $t_{\hat{\theta}_1}$, 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., $t_{\hat{\theta}_2}$ and $t_{\hat{\theta}_3}$ 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 $t_{\hat{\theta}_1}, t_{\hat{\theta}_2}$ and $t_{\hat{\theta}_3}$), this forward looking or *ex-ante* time series is then regressed on the timing model as follows:

$$R_{p,t+1} = \alpha_i + \delta_1 R^2_{m,t+1} + \delta_2 \left[\left(\sigma_{m,t+1} - \bar{\sigma}_m \right) . \left(R_{m,t+1} \right) \right] + \delta_3 \left[\left(L_{m,t+1} - \bar{L}_m \right) . \left(R_{m,t+1} \right) \right] + \varepsilon_{i,t+1} \quad [11]$$

where $R_{p,t+1}$ is the time series of forward looking returns. On sorting by $t_{\hat{\theta}_1}$, 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 $t_{\hat{\theta}_2}$ 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, on sorting by $t_{\hat{\theta}_3}$ the null hypothesis of no persistence in liquidity timing ability may be tested as $H_0: \hat{\delta}_3 = 0, H_A: \hat{\delta}_3 < 0$.

We present results on the persistence of timing skill among funds in table 4. In the first column of results denoted "Return Timing $t_{\hat{\theta}_1}$" where we test persistence in market return timing skill, the resulting coefficient estimate of δ_1 in [11] is 0.00 with a t-statistic of 0.30 and a bootstrap p-value of the t-statistic of 0.77. 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. In the second column of results denoted "Volatility Timing $t_{\hat{\theta}_2}$", we test persistence in market volatility timing skill, i.e., we sort on $t_{\hat{\theta}_2}$ from [10]. Here, the resulting coefficient estimate of δ_2 in [11] is 0.01 with a t-statistic of 0.22 and a bootstrap p-value of 0.83. Hence, we fail to reject the null hypothesis of no persistence in market volatility timing ability. In the third column of results denoted "Liquidity Timing $t_{\hat{\theta}_3}$" we test persistence in liquidity timing skill. Sorting on $t_{\hat{\theta}_3}$ in [10], the resulting coefficient estimate of δ_3 in [11] is -0.58 with a t-statistic of -0.77 and a bootstrap p-value of 0.44. Hence, again we fail to reject the null hypothesis of no persistence in liquidity timing skill.

Overall, while stock returns may be unpredictable, there is considerable evidence that both market volatility and market illiquidity persist over time (Busse, 1999; Bollerslev et al., 1992; Amihud, 2002; Chordia et al., 2000; Hasbrouck and Seppi, 2001; Pastor and Stambaugh, 2003). Although our results here find in support of some volatility and liquidity timing skill among funds, we find no evidence of persistence in this ability. However, our data restricts our analysis to monthly fund performance and there may well be a mismatch between possible higher frequency persistence in market volatility and market liquidity versus the monthly fund performance analysis here. We leave such an investigation to future research.

[Table 4 here]

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 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. Do funds that have the skill to anticipate market volatility and liquidity, and reduce systematic risk when conditional volatility and illiquidity is high, earn higher risk-adjusted returns? To examine this question we perform a similar recursive portfolio rebalancing procedure to that of the previous section. 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 funds are sorted into deciles based on the t-statistic of the timing coefficient. In each case we hold for 12 months before repeating recursively. In each case, this forward looking or *ex-ante* time series is then regressed on our six factor model, i.e., the Carhart four factor model augmented with the two liquidity risk factors, $HML_{LR,t}$ and IML_t, and the model alpha is estimated. If fund timing ability is associated with superior performance, we expect this alpha to be positive and statistically significant.

We present the results of this analysis in table 5. Panel A presents results for the top *minus* bottom decile portfolio of timers in each case while in panels B and C we report results for the top and bottom decile portfolios separately respectively. 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 risk adjusted performance respectively. We report the six-factor alpha and its t-statistic as well as the bootstrap p-value of the t-statistic (bootstrapping on a fund-by-fund basis). The results in panel A (column 3) provide strong evidence of a positive association between liquidity timing skill and fund abnormal performance where the top minus bottom decile portfolio alpha is 0.26% per month with a t-statistic of 2.23 and a bootstrap p-value of 0.03. However, looking at the results for the top and bottom deciles separately in panels B and C, we see that this finding is driven by the bottom (worst) decile of liquidity timers going on to yield statistically significant negative alphas (panel C) while the top decile of liquidity timers do not yield positive and significant alphas (panel B). It appears that investors seeking fund abnormal performance should at least avoid poor market liquidity timing funds.

From column 2, the top minus bottom decile of volatility timing funds does not yield significant alpha, although perversely, the top decile of volatility timers goes on to yield negative abnormal performance – significant at the 10% significance level. This result provides *prima facie* evidence that funds that are successful at anticipating market volatility by reducing (increasing) the fund beta in advance of higher (lower) market volatility do so at the expense of successful security selection.

Overall, we find strong evidence that among the cross-section of funds, liquidity timing skill is associated with positive abnormal performance: funds that successfully anticipate market liquidity by reducing (increasing) the fund beta in advance of worsening (improving) market liquidity earn significant risk adjusted returns.

[Table 5 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.

Investigating volatility and liquidity timing in the mutual fund industry is of interest for several reasons. First, past literature has shown that compensation incentives affect fund managers' risk choices. 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. Second, 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. Hence, there is significant advantage to timing market liquidity conditions as well. Third, there is considerable evidence that while stock market returns may not persist, market volatility and liquidity do persist, thus rationalising fund manager's attempt to time it. Finally, with billions of dollars wiped the value of global stocks markets following worsening volatility and liquidity conditions post the 2008 crisis period, there is clear value in an ability to time these conditions.

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. The evidence around market liquidity timing is broadly similar though its prevalence is slightly less compared to volatility timing. We also find a positive relation between liquidity timing ability and future fund abnormal performance - though this is driven by avoiding poor liquidity timing funds rather than investing in skilful ones. Overall, 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. However, while there is evidence of both market volatility and liquidity timing, we find no evidence that it persists. This, despite evidence that both market volatility and liquidity are themselves somewhat persistent.

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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 – all at the 5% significance level. The results are based on a cross-section of 657 funds.

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	0.01	0.01	0.03	0.06	0.23	0.27	0.85	1.00	0.68	0.40	0.29	0.17	0.17	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	0.01	0.01	0.01	0.06	0.17	0.41	0.60	0.70	0.39	0.15	0.09	0.04	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	0.00	0.02	0.05	0.15	0.52	0.96	0.67	0.31	0.15	0.07	0.02	0.01	0.01	0.00	0.00

Panel D: Percentage of Funds Exhibiting Timing

	Positive (Bootstrap)	Negative (Bootstrap)
Return Timing	2.0 (0.6)	34.0 (14.7)
Volatility Timing	11.0 (3.2)	21.0 (8.4)
Liquidity Timing	22.5 (9.6)	10.8 (5.5)

Table 3. False Discovery Rates in Timing Performance

Table 3 presents the results of the false discovery rate (FDR) estimation. 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. Also shown are the estimated proportions of truly null funds in the case of each timing ability – typically denoted $\hat{\pi}_0$ in the false discovery literature.

	Estimated Proportion of Truly Null $(\hat{\pi}_0)$	**Significant Positive (percentage)**	**FDR^+**	**Truly Positive (percentage)**	**Significant Negative (percentage)**	**FDR^-**	**Truly Negative (percentage)**
Return Timing	90%	4(0.61%)	100%	0(0%)	97(14.7%)	15.31%	82(12.5%)
Volatility Timing	94%	21(3.2%)	73.43%	6(0.9%)	55(8.4%)	27.97%	40(6.1%)
Liquidity Timing	90%	63(9.6%)	23.43%	48(7.3%)	36(5.5%)	41%	21(3.2%)

Table 4. Persistence in Timing Skills

Table 4 present results of tests of persistence in timing skill. Based on a backward looking window of 36 months we (separately) form portfolios (based on the t-statistic of the timing coefficient) 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.

Persistence in Timing Skill

	Return Timing $t_{\hat{\theta}_1}$	**Volatility Timing** $t_{\hat{\theta}_2}$	**Liquidity Timing** $t_{\hat{\theta}_3}$
Coefficient $\hat{\delta}_1, \hat{\delta}_2, \hat{\delta}_3$	0.00	0.01	-0.58
t-stat	0.30	0.22	-0.77
Bootstrap p-value	0.77	0.83	0.44

Table 5. Fund Timing Skill and Fund Abnormal Performance

Table 5 presents results on the relation between fund timing ability and fund abnormal performance. Based on a backward looking window of 36 months we (separately) form portfolios (based on the t-statistic of the timing coefficient) 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 a six 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 reports findings for the top (best) decile of timers minus the bottom (worst) decile of timers in the case of each of the three timing skills. Panel B and Panel C show the results for the top and bottom deciles separately respectively.

Panel A: Top (Best) Decile Minus Bottom (Worst) Decile

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 $\hat{\alpha}$
-0.26	-1.90	0.06	-0.10	-0.60	0.55	0.26	2.23	0.03

Panel B: Top (Best) Decile

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 $\hat{\alpha}$
-0.30	-2.05	0.04	-0.14	-1.78	0.08	0.10	0.88	0.38

Panel C: Bottom (Worst) Decile

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 $\hat{\alpha}$
-0.05	-0.52	0.61	-0.04	-0.26	0.80	-0.16	-2.14	0.04

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

$$Q_{s,m} = \frac{1}{qu_{s,m}} * \sum_{t=1}^{qu_{s,m}} \frac{P^A_{s,t} - P^B_{s,t}}{m_{s,t}} \tag{A1}$$

where $P^A_{s,t}$ is the ask price of quote *t* for stock *s*, $P^B_{s,t}$ is the bid price of quote *t* for stock *s*, $qu_{s,m}$ is the number of quotes in month *m* for stock *s*. $m_{s,t} = (P^A_{s,t} + P^B_{s,t})/2$ 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

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

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

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

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*. $\bar{\Psi}_{s,t}$ is the transitory fixed price impact measure for stock *s* in month *t*. $\bar{\lambda}_{s,t}$ 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.