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Liquidity risk and the performance of UK mutual funds☆

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ABSTRACT

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

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1. Introduction

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

The differing market structures of UK and US exchanges lead to large differences in liquidity characteristics (Huang & Stoll, 2001). Liquidity may be priced in two ways. Liquidity as a priced characteristic considers a stock's own liquidity as a determinant of its return. Amihud and Mendelson (1986) argue that illiquid stocks should earn a premium over liquid stocks to compensate investors for the trading costs incurred which reduce realisable returns, e.g., wider bid–offer spreads. Liquidity as a risk factor refers to systematic liquidity risk, i.e., the sensitivity of returns to changes in market liquidity that may not be diversifiable. A number of papers demonstrate commonality in liquidity across stocks (Chordia, Roll, & Subrahmanyam, 2000; Hasbrouck & Seppi, 2001) while Pastor and Stambaugh (2003), Acharya and Pedersen (2005), Chen (2005), Korajczyk and Sadka (2008) and Sadka (2006) provide evidence of a premium for this systematic liquidity risk. There is also strong evidence indicating that liquidity plays a role in asset pricing in UK equities. Lu and Hwang (2007) report counter-intuitive findings around the pricing of liquidity as a stock characteristic in the UK where liquid stocks are found to outperform illiquid stocks, Foran, Hutchinson, and O'Sullivan (2014b) confirm this result. Foran, Hutchinson, and O'Sullivan (2014a) report evidence of a premium for systematic liquidity risk in the UK equity market.

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

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

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

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

2. Data

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

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

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

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

Our mutual fund data set is obtained from Morningstar and contains monthly returns on 1141 actively managed UK equity unit trusts and Open Ended Investment Companies. 'UK Equity' funds (by definition) have at least 80% of the fund invested in UK equity. By restricting our analysis to funds investing in UK equities, more accurate performance benchmarks may be used. This data set represents almost the entire set of UK equity funds which have existed at any point during the period January 1997–June 2009, including 672 nonsurviving funds. Funds are also categorised by investment objectives: 'Equity income' funds (221 funds), which aim to achieve a dividend yield greater than 110% of the market, 'general equity' funds (779), which invest in a broad range of equity and small company funds (141), which are invested in stocks which form the lowest 10% of the market by market capitalization. Fund returns are measured before taxes on dividends and capital gains but net of management fees.

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

3. Methodology

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

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

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

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

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