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The liquidity timing ability of mutual funds

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ABSTRACT

We apply the nonparametric methodology of Jiang (2003) to test the market liquidity timing skills across individual equity mutual funds in three countries (the US, UK, and China). We calculate the monthly stock market liquidity using simple averages (across stocks) as well as the asymptotic principal component analysis (APCA) method based on six stock liquidity measures. Using an across-measure of market liquidity from APCA, we find a relatively small number of funds demonstrate statistically positive liquidity timing skills at a 5% significance level for the period of 2000–2021. After controlling for lagged market liquidity information, we still find a small number of mutual funds that have conditional liquidity timing ability using the nonparametric method.

1. Introduction

In a changing market environment, can professional investors predict and exploit changes in market conditions? Research on the timing ability of mutual fund managers has been conducted since the seminal papers of Treynor and Mazuy (1966) (henceforth, TM) and Henriksson and Merton (1981) (henceforth, HM). In the following decades, a great deal of literature has emerged on market timing skills, with various linear and nonlinear measures being proposed with or without conditional information to determine the presence of this skill. The evaluation of market timing performance is a topic of considerable interest to both academics and practitioners. For the former, it provides a test of the Efficient Market Hypothesis (EMH) since significant evidence of superior timing skills would violate the EMH. For the latter, investment fund managers can use it to evaluate their performance and the value added by their active management.

Literature is abundant on funds' ability to time fluctuations in market returns, especially in the US and UK fund industries, and most evidence suggests that fund managers lack the ability to time the market return by increasing portfolio exposure prior to a bull market or decreasing exposure before a bear market[1] (Treynor & Mazuy, 1966; Ferson & Schadt, 1996; Henriksson & Merton, 1981; Bollen & Busse, 2001; Jiang, 2003; Jiang et al., 2007; Cuthbertson et al., 2010).[2] The difficulty in predicting future market returns may explain why there is little evidence supporting mutual fund managers' market timing skills (Cao et al., 2013b).

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[1] Lunde and Timmermann (2004) provide a classification methodology of the bull and bear market phases using real and nominal price indices of stock price.

[2] Bollen and Busse (2001) and Jiang et al. (2007), however, find supportive evidence of market return timing ability in mutual funds by using daily return data and portfolio holding data, respectively, which indicates that timing results may be affected by the frequency or type of data collected.

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Based on return timing, two other perspectives have been developed on the timing abilities of mutual fund managers in the literature. On the one hand, fund managers may adjust their risk exposure to the market to protect fund performance from a higher level of volatility, i.e., market volatility timing. They may decide to decrease (increase) their exposure to equities when the market is expected to become more (less) volatile based on techniques that are relatively reliable in predicting return volatility. Using daily data, Busse (1999) shows that fund managers demonstrate the volatility timing ability to adjust funds' exposure to the market when it is more (less) volatile and that volatility timing ability leads to better risk-adjusted performance.

On the other hand, Cao et al. (2013b) explore the ability of mutual funds to time the market from the perspective of market-wide liquidity. They suggest that mutual fund managers may adjust their systematic risk exposure according to the condition of aggregated liquidity. As liquidity timers, mutual funds tend to increase their exposure to the market when market liquidity is higher while reducing it when market liquidity is lower.

There are a number of reasons to study market liquidity timing. First, market-wide liquidity represents a critical component of market conditions, and mutual fund performance is clearly correlated with market-wide liquidity. For example, as witnessed during the 2008–2009 financial crisis, market liquidity declines simultaneously when many investors exit the market. The deterioration of market liquidity leads to more liquidation and further reduction of market liquidity with dramatic stock market declines. Therefore, a skilled fund manager would reduce his/her fund's market exposure after correctly predicting a market-wide liquidity deterioration. Second, market liquidity is more persistent and reliably predictable than the market return. Consequently, it might be easier for fund managers to time market liquidity than market returns. Finally, market liquidity is identified as a state variable in the asset pricing literature. There is a positive correlation between the market return and measures of market liquidity (Chordia et al., 2001; Pástor & Stambaugh, 2003; Acharya & Pedersen, 2005; Liu, 2006; Lee, 2011). Acharya and Pedersen (2005) show that liquidity predicts future returns and co-moves with contemporaneous returns. Given the correlation between market liquidity and market returns, it is natural to ask whether market liquidity plays a significant role in asset allocation. Accordingly, if fund managers can anticipate market liquidity conditions in advance, they can adapt their portfolio exposure to the market to reduce losses and improve performance. Karstanje et al. (2013) find that investors who predict stock returns using lagged market liquidity conditions get significant risk-adjusted returns, implying that the liquidity timing strategy leads to tangible economic gains.

The small number of empirical studies on market liquidity timing demonstrates significant positive liquidity timing skills. Cao et al. (2013b) is the first study to examine mutual fund managers' ability to time market liquidity. Using the TM test procedure for multi-factor models, they find that US mutual fund managers decrease their market exposure when aggregate liquidity is low, supporting the idea that mutual fund managers have liquidity timing abilities. Bodson et al. (2013) use the Kalman filter to model time-varying market exposure (betas) due to the market timing ability. With dynamic estimates, they find liquidity timing abilities at the portfolio and individual fund levels in the US. There is also evidence of significant positive liquidity timing in the UK. Using asymptotic principal component analysis to extract the latent market liquidity factor, Foran and O'Sullivan (2017) find evidence of skillful liquidity timing among a small percentage of UK equity mutual funds. Li et al. (2015) explore the liquidity timing ability of mutual funds in China. Based on monthly data from October 2001 to February 2014, they find significant positive liquidity timing ability in actively managed open-end equity funds in China. Following their study, Huang et al. (2018) further explore the liquidity timing ability of equity funds at the individual fund level in China. They find that nearly 30% of the 427 funds demonstrate liquidity timing ability. Yi et al. (2018) explore the market timing abilities from all three dimensions, and they find strong evidence of volatility timing and liquidity timing of China mutual fund managers.

In contrast to previous studies focusing exclusively on market exposure, Bazgour et al. (2017) argue that fund managers may also adjust fund exposure to the style factors in anticipation of market liquidity. The fund manager may be able to take advantage of other liquidity timing opportunities, such as size (SMB) liquidity timing, growth (HML) liquidity timing, and momentum (MOM) liquidity timing. This is because liquidity risk has a positive relationship with small stock and momentum returns but a negative relationship with value return (Pástor & Stambaugh, 2003; Sadka, 2006). By implementing a multi-factor liquidity timing framework, the authors extend Cao et al. (2013b) liquidity timing model to account for the four liquidity timing opportunities available to fund managers. They find no evidence of market liquidity timing after controlling for style liquidity timing and liquidity reaction.

In this paper, we revisit the issue of mutual fund liquidity timing from a new perspective. Due to the co-movement of market liquidity and market returns, Cao et al. (2013b) assume that fund managers with liquidity timing abilities shift their cash into stocks to increase the fund's systematic risk (market beta) before markets are more liquid and reduce market beta prior to more illiquid markets by shifting stocks to cash. We argue that mutual fund managers may directly adjust their funds' sensitivity (exposure) to the market liquidity after anticipating movements of market-wide liquidity.[3] That is, by rebalancing the proportion of risky equity holdings and cash, a fund manager may increase fund exposure to market liquidity before the market is more liquid and decrease exposure before the market becomes illiquid. This strategy is beneficial during financial or liquidity crises when liquidity spirals dry up market liquidity.

In this paper, we conduct a comprehensive study of mutual funds' liquidity timing ability using a large sample of funds over the period from 2000 to 2021 from the US, UK, and China. To mitigate survivorship bias, we include both live and dead funds in our sample for the three countries. Results suggest that, on average, live funds are more successful market liquidity timers. As expected, funds with liquidity timing ability are more likely to survive than those without liquidity timing. Thus, our results demonstrate the critical role market liquidity plays in asset allocation decisions for fund managers.

[3] Of course, not all investors reduce their exposure to market liquidity when it deteriorates. However, this analysis can be regarded as a test of whether fund managers are among those investors that reduce liquidity exposure when liquidity deteriorates.

Using regression-based multi-factor models, Cao et al. (2013b), Foran and O'Sullivan (2017) and Li et al. (2015) find significant market liquidity timing ability in the US, UK and China, respectively, at the individual fund level. The proportions of significant positive liquidity timing are around 25%, 27% and 10% for the sample of US, UK and China funds. Compared with these studies, we find less significant evidence of positive liquidity timing using the nonparametric approach. (2%, 0.3% and 0.7% for the US, UK and China, respectively). Our results support the findings of Bazgour et al. (2017), which demonstrate that the market liquidity timing coefficient becomes insignificant timing after controlling for style liquidity factors. Thus, the significant results of liquidity timing by previous studies may be partially explained by other liquidity timing strategies, such as size (SMB) liquidity timing, growth (HML) liquidity timing, and momentum (MOM) liquidity timing. After controlling for these alternative style liquidity strategies, only a small amount of funds directly adjust their portfolio exposure to the market liquidity after anticipating market liquidity movement.

Our study has several distinguishing features. First, we use a set of liquidity proxies to measure stock liquidity. Measuring market liquidity is not easy as it is not observed directly but has several aspects that cannot be captured in a single measure (Amihud, 2002). We calculate market-wide liquidity using two different methods: cross-sectional average stock liquidity and asymptotic principal component analysis (APCA), since liquidity timing skills may be sensitive to specific liquidity proxies.

Second, we apply the nonparametric procedure of Jiang (2003) to examine the individual fund's exposure to market-wide liquidity. To our knowledge, this is the first paper to use this nonparametric method to assess mutual fund managers' liquidity timing skills. For comparison, we also apply the regression-based (parametric) approach of Cao et al. (2013b). In empirical studies, using parametric and nonparametric measures together can provide a more comprehensive picture of the market timing performance of fund managers (Jiang, 2003). Compared with parametric tests, we find a smaller number of significant positive liquidity timers in the nonparametric test across various market liquidity measures. The difference between nonparametric and parametric methods may arise because the nonparametric method directly measures fund exposure to market liquidity. The parametric method assumes the fund manager adjusts the fund's exposure to the market portfolio rather than market liquidity after anticipating market liquidity changes. Besides, unlike the nonparametric test, the parametric measures both the probability of correct forecast in liquidity timing and the aggressiveness of timing response.

Third, we investigate the difference in liquidity timing skills between funds with different investment styles. We find that there are more statistically significant liquidity timers in large funds. In addition to examining the liquidity timing performance of onshore (domestic) funds (e.g., Cao et al., 2013b), we also examine the performance of offshore funds to test whether geographical location produces information asymmetries and, thus, performance differences. In terms of location, there is no evidence that the more geographically distant offshore funds underperform onshore funds in liquidity timing.

Finally, we analyze conditional liquidity timing in this paper. Conditional market timing evaluation provides a test of private timing skills by the fund after controlling for timing ability attributable to public information (Graham & Harvey, 1996; Becker et al., 1999; Ferson & Schadt, 1996; Ferson & Khang, 2002). Ferson and Schadt (1996) describe the time-varying portfolio beta as a function of a series of lagged public information variables and relying only on publicly available information does not reflect abnormal timing ability. Fund managers who simply adjust betas based on lagged market liquidity levels do not reflect real liquidity timing skills because lagged market conditions are public information (Cao et al., 2013a).

The rest of this paper is organized as follows. In Section 2, we discuss our method to test timing skills. Section 3 shows the data for individual funds and stocks and explains how to construct monthly liquidity proxies. Section 4 describes how to construct monthly market liquidity variables. Section 5 shows the empirical results for three countries, and Section 6 concludes.

2. Method

2.1. Nonparametric liquidity timing

Jiang (2003) proposes a nonparametric method for market timing of mutual funds (applied to the US) because of the difficulties in parametric market timing tests. We extend the nonparametric framework to examine liquidity timing ability. With independent selectivity and timing (Grinblatt & Titman, 1989), we have the following model of fund returns[4]:

$$r_{i,t+1} = \alpha_i + \beta_{i,t} L_{m,t+1} + \varepsilon_{i,t+1} \tag{1}$$

where r_i is the excess return on fund i and $L_{m,t+1}$ represents the market-wide liquidity at time t + 1. α_i measures the return attributed to security selectivity, assuming that the fund manager's timing ability is independent of security selection skills. The fund beta, $\beta_{i,t}$ measures the sensitivity of stock returns to the market liquidity variable and is assumed to vary with the information fund managers possess at time t. In the absence of security selection, liquidity timing is regarded as moving in and out of the equity market. In the simplest case, a market timer decides funds sensitivity ($\beta_{i,t}$) to market liquidity at time t and adjust it in time t + 1. The successful liquidity timer is identified by correctly anticipating market liquidity movements.

Let $\widehat{L}_{m,t+1} = \mathrm{E}\left(L_{m,t+1}|I_t\right)$ be the manager's forecast for the time t +1 based on the information set (both public and private) I_t at time

[4] Note that this equation is not a model for asset pricing, but rather aims to test how mutual funds time market liquidity. Thus, we omit other variables that may affect the expected return of the portfolio, such as size or book-to-market. It is very likely that α_i will include returns due to omitted risk factors, but the method remains valid if we are merely interested in determining whether fund successfully time market liquidity. See Jiang (2003) for a detailed discussion.

t. For two periods ($t_1 \neq t_2$), the parameter v, which measures the time information, is defined as:

$$\begin{aligned} v &= Pr\left(\widehat{L}_{m,t_2+1} > \widehat{L}_{m,t_1+1} | L_{m,t_2+1} > L_{m,t_1+1}\right) - Pr\left(\widehat{L}_{m,t_2+1} < \widehat{L}_{m,t_1+1} | L_{m,t_2+1} > L_{m,t_1+1}\right) \\ &= 2Pr\left(\widehat{L}_{m,t_2+1} > \widehat{L}_{m,t_1+1} | L_{m,t_2+1} > L_{m,t_1+1}\right) - 1 \end{aligned} \tag{2}$$

The parameter v is equal to zero if no liquidity timing ability exists since the probability of correct prediction offsets the probability of incorrect prediction. Therefore, $v \in [-1, 1]$ represents the liquidity timing ability where $v = -1$ represents perfectly negative (i.e., false) liquidity timing and $v = 1$ indicates perfectly positive (i.e., successful) liquidity timing.

The next step connects the manager's prediction of the market liquidity ($\widehat{L}_{m,t+1}$) with their response ($\beta_{i,t}$).[5] Since fund managers can benefit from increasing (decreasing) their exposure (β) to market-wide liquidity in good (bad) conditions, i.e., $\frac{\partial \beta_t}{\partial \widehat{L}_{m,t+1}} > 0$, Eq. (2) becomes:

$$v = 2Pr\left(\beta_{i,t_2} > \beta_{i,t_1} | L_{m,t_2+1} > L_{m,t_1+1}\right) - 1 \tag{3}$$

Based on Eq. (3), the nonparametric test statistic is constructed. For any trio of observations of market liquidity sampled from any three periods where $L_{m,t_1} < L_{m,t_2} < L_{m,t_3}$, an informed market timer should keep the average exposure to liquidity at a higher level over the $[L_{m,t_2}, L_{m,t_3}]$ range than the $[L_{m,t_1}, L_{m,t_2}]$ range, i.e., $\beta_{i,t_2} > \beta_{i,t_1}$. The nonparametric beta estimates for these two ranges are $\beta_{i,t_1} = (r_{i,t_2} - r_{i,t_1})/(L_{m,t_2} - L_{m,t_1})$ and $\beta_{i,t_2} = (r_{i,t_3} - r_{i,t_2})/(L_{m,t_3} - L_{m,t_2})$. Therefore, a convex relationship between the fund return and market liquidity holds when fund managers possess superior timing information:

$$\frac{r_{i,t_3} - r_{i,t_2}}{L_{m,t_3} - L_{m,t_2}} > \frac{r_{i,t_2} - r_{i,t_1}}{L_{m,t_2} - L_{m,t_1}} \tag{4}$$

Assume θ measures the *probability* that fund returns hold a convex relationship with market liquidity:

$$\theta = 2Pr\left(\frac{r_{i,t_3} - r_{i,t_2}}{L_{m,t_3} - L_{m,t_2}} > \frac{r_{i,t_2} - r_{i,t_1}}{L_{m,t_2} - L_{m,t_1}}\right) - 1 \tag{5}$$

Here, θ is a valid proxy for v, and superior timing information $v > 0$ is approximately equal to $\theta > 0$.
The sample statistic of θ is constructed as:

$$\widehat{\theta}_n = \binom{n}{3}^{-1} \sum\nolimits_{L_{m,t_1} < L_{m,t_2} < L_{m,t_3}} sign\left(\frac{r_{i,t_3} - r_{i,t_2}}{L_{m,t_3} - L_{m,t_2}} > \frac{r_{i,t_2} - r_{i,t_1}}{L_{m,t_2} - L_{m,t_1}}\right) \tag{6}$$

The sample statistic is a U-statistic with kernel of order three. $\widehat{\theta}_n$ is a $\sqrt{n}$-consistent and asymptotically normal estimator for θ. Therefore, $\sqrt{n}(\widehat{\theta}_n - \theta) \rightarrow N\left(0, \sigma^2_{\theta_n}\right)$. $\widehat{\theta}$ is the least variance estimator for the population coefficient θ in the set of all unbiased estimators. A consistent estimator of the standard error of $\widehat{\theta}_n$ is as defined as follows (Abrevaya & Jiang, 2005):

$$\widehat{\sigma}^2_{\hat{\theta}_n} = \frac{9}{n} \sum\nolimits_{t_1=1}^{n} \left(\binom{n}{2}^{-1} \sum\nolimits_{t_2,t_3} h\left(z_{t_1}, z_{t_2}, z_{t_3}\right) - \widehat{\theta}_n \right)^2 \tag{7}$$

where:

$$h\left(z_{t_1}, z_{t_2}, z_{t_3}\right) = sign\left(\frac{r_{i,t_3} - r_{i,t_2}}{L_{m,t_3} - L_{m,t_2}} > \frac{r_{i,t_2} - r_{i,t_1}}{L_{m,t_2} - L_{m,t_1}} | L_{m,t_1} < L_{m,t_2} < L_{m,t_3}\right) \tag{8}$$

The test statistic, $z = \sqrt{n}\widehat{\theta}_n / \widehat{\sigma}_{\hat{\theta}_n}$, is asymptotically distributed as N (0,1) under the null hypothesis of no liquidity timing ability. The positive θ suggests the probability that fund managers move funds' exposure to the market liquidity in the correct direction is greater than the probability of a move in the wrong direction.

As discussed, the regression-based (parametric) methods of Cao et al. (2013a) and Cao et al. (2013b) assume that fund managers adjust funds' exposure to the market risk factor after anticipating market liquidity moves. Compared with parametric methods, our nonparametric method directly measures the fund's exposure (sensitivity) to the market liquidity rather than the fund's exposure to the market risk. A fund manager holding such a liquidity timing strategy may increase (decrease) fund exposure to market liquidity when the market is expected to be more liquid (illiquid) by rebalancing the proportion of risky equity holdings and cash.

The nonparametric method also has the following properties. First, the nonparametric statistics measure the quality component of the fund manager's timing information rather than their response to the information, whereas the parametric test fails to separate these elements of market timing. The quality component is more important to investors because they can control the aggressiveness of their own actions. In addition, the nonparametric approach examines timing over multiple frequency ranges instead of assuming timing frequency to be uniform across funds. Therefore, the nonparametric liquidity timing result is robust even when the timing frequency

[5] Beta at any point is the slope of fund return against market liquidity and reflects both the precision of the forecast and the aggressiveness of the manager's response to informed information.

differs from the sample data frequency. The timing measure in the nonparametric test also has little correlation with the estimates of standard selectivity measures. Finally, the asymptotic distribution of the nonparametric test is robust and unaffected by heteroscedasticity or skewness.

2.2. Parametric market liquidity timing

The study of liquidity timing is pioneered by Cao et al. (2013a) for hedge funds, and their work is extended to mutual fund managers by Cao et al. (2013b), who develop a conditional beta model of liquidity timing with Carhart (1997) four-factor models. The liquidity timing model can be expressed in the following generic form:

$$r_{i,t+1} = \alpha_i + \beta_i MKT_{t+1} + \theta_1 MKT_{t+1}\left(L_{m,t+1} - \overline{L}_m\right) + \sum_{j=1}^{J} \beta_j f_{j,t+1} + \varepsilon_{i,t+1} \tag{9}$$

where $r_{i,t+1}$ is the monthly excess return of fund i in month t + 1, MKT_{t+1} is the monthly excess market return in month t + 1. $f_{j,t+1}$ denotes risk factors besides equity market risk factor. The market beta is a linear function of market liquidity in excess of its time-series average, i.e., first-order Taylor series expansion, $\beta_m = \beta_i + \theta_1\left(L_{m,t+1} - \overline{L}_m\right)$. This model is in line with Treynor and Mazuy (1966), Ferson and Schadt (1996), and Busse (1999), in which time-varying beta is a linear function of market conditions (returns or volatiles). The ability to time market liquidity is indicated by a positive and significant value of θ_1. We calculate t-statistics using the Newey and West (1987) heteroscedasticity and autocorrelation adjusted standard errors.

2.3. Conditional liquidity timing

The literature on conditional timing ability examines whether fund managers could forecast the level of market conditions after controlling for publicly available information. The conditional performance highlights the importance of distinguishing performance merely attributed to publicly available information from performance due to better private information (Ferson & Schadt, 1996; Graham & Harvey, 1996; Becker et al., 1999; Ferson & Khang, 2002). It is natural to ask whether fund managers have the ability to time the market after taking public information into account.

A fund manager may adjust fund exposure based on lagged values of market liquidity conditions since they are generally serially correlated, and their values in month $t + 1$ contain information from prior months. If a fund manager uses observed liquidity in month t to predict market liquidity and adjusts the fund's beta accordingly, he has no timing skills but simply reacts to past liquidity conditions since adjusting fund betas based on public information does not reflect true timing skills (Ferson & Schadt, 1996). Accordingly, Cao et al. (2013a) highlight the difference between liquidity timing and liquidity reaction. That is, liquidity reactors adjust fund betas based on observed market liquidity in month t, but liquidity timers manage market exposure using their forecast of market liquidity in month $t + 1$.

To distinguish liquidity timing skills from liquidity reaction, we estimate the following model in which both liquidity timing and liquidity-reaction terms are included:

$$\begin{aligned} r_{i,t+1} \quad &= \alpha_i + \beta_i MKT_{t+1} + \gamma_i MKT_{t+1}\widetilde{L}_{m,t+1} \\ &\quad + \phi_i MKT_{t+1}\left(L_{m,t} - \overline{L}_m\right) + \sum_{j=1}^{J} \beta_j f_{j,t+1} + \varepsilon_{i,t+1} \end{aligned} \tag{10}$$

In this regression, $L_{m,t}$ is one-month lagged market liquidity and represents the predictable component of liquidity. $\widetilde{L}_{m,t+1}$ is the innovation in market liquidity from an AR(2) process, which represents the unpredictable component of market liquidity. The coefficients γ and ϕ measure liquidity timing and liquidity reaction, respectively. If a fund manager solely reacts to past liquidity conditions, we expect his/her timing coefficient to be insignificant after controlling for lagged market liquidity variable.

The nonparametric measure can also be applied to the conditional liquidity timing test. We first obtain the fund return residuals by regressing fund returns on lagged market liquidity variables with two lags and then calculate the market liquidity residuals using an AR (2) model. These residuals represent the variation in the fund return and market liquidity that are not explained by public information. The nonparametric test statistic is then applied to market liquidity and fund return residuals, yielding a conditional timing measure.

$$\widetilde{\theta}_n = \binom{n}{3}^{-1} \sum_{\widetilde{L}_{m,t_1} < \widetilde{L}_{m,t_2} < \widetilde{L}_{m,t_3}} sign\left(\frac{\widetilde{r}_{i,t_3} - \widetilde{r}_{i,t_2}}{\widetilde{L}_{m,t_3} - \widetilde{L}_{m,t_2}} > \frac{\widetilde{r}_{i,t_2} - \widetilde{r}_{i,t_1}}{\widetilde{L}_{m,t_2} - \widetilde{L}_{m,t_1}}\right) \tag{11}$$

where $\widetilde{r}_{i,t}$ and $\widetilde{L}_{m,t}$ are the fund return residual and market liquidity residual, respectively. $\widetilde{\theta}_n$ represents the conditional probability that fund managers increase beta when the market liquidity is higher after controlling for public information in both market liquidity and fund returns. $\widetilde{\theta}$ in equation (11) may be different from $\widehat{\theta}$ (equation (5) in terms of magnitudes or even signs because these probabilities are conditional on different assumptions. A fund with $\widehat{\theta} > 0$ and $\widetilde{\theta} \leq 0$ has liquidity timing ability that is solely attributable to public information.

3. Data

In this section, we report the data source of mutual funds, liquidity measures and stock market factors.

3.1. Fund data

Our mutual fund data is from Morningstar from January 2000 to June 2021 for the US, UK, and China, which represent almost the entire set of equity funds that have existed in each region during the sample period under consideration. We apply several filters to our initial set of observations. We have removed "second units" of the funds because second units report relatively few independent returns. Furthermore, we exclude the index funds because these funds replicate an index and are unlikely to exhibit timing characteristics. In addition, we require that the funds have a minimum of 36 monthly observations in our sample to improve statistical reliability. Mutual fund monthly returns are measured gross of taxes on dividends and capital gains and net of management fees, i.e., net returns.

Our mutual fund data contains 4616 open-ended US mutual funds from Morningstar. Based on the Morningstar global categories, there are Large Blend (1267), Large Growth (914), Large Value (692), Medium (798), and Small (945) funds. The data set includes both surviving funds (2219) and non-surviving funds (2397) to eliminate survivorship bias. Our sample also identifies onshore funds (3814) managed in the US and offshore funds (802) operated outside the US.

There are 669 open-ended UK mutual funds in our sample from Morningstar. The UK equity funds are categorized based on the Morningstar global categories: Large (341), Small and Medium (105), Equity Income (91), and Flex Equity (132). The data set includes both surviving funds (308) and non-surviving funds (361) to mitigate survivorship bias. We identify onshore funds (548) managed in the UK and offshore funds (121) operated outside the UK in the sample.

Our fund sample contains 439 open-ended Chinese mutual funds. These funds are grouped based on the Morningstar categories. There are five categories of investment styles: Large Blend (154), Large Growth (191), Medium Blend (44), Medium Growth (36), and others (14). We exclude sector funds as sector funds may exclusively focus on sector-related stocks and ignore the movement of overall market liquidity. The data set includes both surviving funds (394) and non-surviving funds (45). All these funds are onshore funds managed in mainland China.

3.2. Liquidity measures

Liquidity is an elusive concept that is not observed directly but instead has several aspects[6] that cannot be captured in a single measure (Amihud, 2002).

This study has six liquidity proxies to measure stock liquidity: quoted spread (Chung & Zhang, 2014), High-Low spread (Corwin & Schultz, 2012), Roll (1984) effective spread, Amihud (2002) impact, turnover rate, and Pástor and Stambaugh (2003) gamma. These monthly liquidity proxies are shown to be highly correlated with the liquidity benchmarks from high-frequency data. (Hasbrouck, 2009; Fong et al., 2017[7]).

Our liquidity measures are constructed using daily stock data in the US, UK and China from Refinitiv Datastream during the period January 2000 to June 2021.[8] Our sample contains common shares of US firms in the three main stock exchanges (i.e., NYSE, AMEX, and NASDAQ). For UK stocks, we obtain common shares of UK firms on the London Stock Exchange (LSE). The common shares (A shares) of Chinese firms are from the two main stock exchanges in China (i.e., Shanghai Stock Exchange and Shenzhen Stock Exchange).

We obtain daily data on daily closing price, closing bid price, closing ask price, high price, low price, the number of shares traded, the number of shares outstanding, and daily stock returns. To avoid potential data bias, we apply both static and return screens for daily stock data, similar to Ince and Porter (2006) and Schmidt et al. (2019). The details of these liquidity measures and screens are discussed in the Appendix.

When calculating the monthly liquidity measures, we require stocks to have at least ten daily observations in the month for inclusion and winsorize the data at the 1st and 99th percentiles each month to reduce the outlier and possible data errors, similar to Korajczyk and Sadka (2008).

3.3. Stock market factors

For the US market, we obtain the market, size, value, and momentum factors from the French Data Library.[9] The risk-free rate is the one-month Treasury bill rate, which is also from the French library.

[6] Lybek and Sarr (2002) summarize five characteristics of market liquidity: tightness (costs), immediacy, depth, breadth, and resiliency.

[7] Fong et al. (2017) compare monthly liquidity proxies constructed from daily data to liquidity benchmarks computed from high-frequency data and identify some high-quality liquidity proxies such as closing percent quoted spread, high-low spread, and Amihud impact.

[8] Due to the data availability, the relevant data to calculate the quoted spread in the US is from March 2006.

[9] Available at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

We construct the Fama and French (1993) 3-factor model for the UK market using stock market index data from Datastream, following Cuthbertson et al. (2008).[10] The market factor is the difference in returns between the FTSE All Share Index (total returns) and the one-month UK Treasury bill rate. The size factor (SMB) is the difference between the monthly returns on the FTSE SmallCap Index and the returns on the FTSE 100 Index. The value factor (HML) is the difference between the monthly returns of the MSCI UK Value Index and the returns of the MSCI UK Growth Index.

We obtain the market, size, value, and momentum factors from the China Stock Market & Accounting Research (CSMAR) database. The risk-free rate is the monthly return of the three-month deposit rate from Datastream.

4. Market liquidity

We use two approaches to extract monthly market-wide liquidity: average and asymptotic principal component analysis (APCA).

In the first approach, an estimate for the time series of market-wide liquidity is computed simply as the cross-sectional average of liquidity across individual stocks in each month. For example, Chordia et al. (2000) and Pástor and Stambaugh (2003)[11] use this method for determining aggregated liquidity in equity markets. We have a (T x N) matrix of liquidity observations for each liquidity measure where T = the number of months and N = the number of stocks. In our setting, monthly market liquidity $L^j_{m,t}$ for a given measure of liquidity L^j for N stocks can be estimated as

$$L^j_{m,t} = \frac{1}{N}\sum\nolimits_{s=1}^{N} L^j_{s,t}$$

For ease of interpretation, we sign the market liquidity measures, $L^j_{m,t}$, to represent liquidity.[12]

Second, we use the asymptotic principal component analysis (APCA) to construct market liquidity factors across stocks, a procedure similar to that of Korajczyk and Sadka (2008).[13] The extracted latent market liquidity factors represent the systematic variation in liquidity or liquidity commonality across various stocks. We choose to standardize our liquidity proxies to avoid one liquidity measure driving the extracted factors because of its relative magnitude. If L^j is a (T x N) matrix of the observation for liquidity measure j, $NL^j_{s,t}$ is the standardized liquidity measure for stock s in month t:

$$NL^j_{s,t} = \frac{L^j_{s,t} - \widehat{\mu}^j_s}{\widehat{\sigma}^j_s}$$

where $\widehat{\mu}^j_s$ is the estimated mean of liquidity measure j for stock s. $\widehat{\sigma}^j_s$ is the estimated standard deviation of measure j for stock s.

From each matrix of liquidity measures, we extract the first three components, which capture common variation in liquidity across stocks, with the first principal component representing market-wide liquidity. We refer to these factors as within-measure market liquidity factors. We choose the sign of each within-measure factor to represent market liquidity rather than illiquidity, following Korajczyk and Sadka (2008). Specifically, we choose the sign of each within-measure factor (except for turnover rate) to be negatively correlated with the time series of the cross-sectional mean of that measure, since the positive values of Quoted spread, High-Low spread, Roll spread and Amihud impact represent market illiquidity. For the turnover rate, we set the sign of the first principal component to be positively correlated with the time series of its cross-sectional mean as positive values of turnover rate measure market liquidity.

In addition to extracting market liquidity factors from each liquidity measure, we construct latent market liquidity factors across five liquidity measures. Here, we first stack the (T x N) matrices above to form a (T x 5N) matrix from which we again extract the first three components. We refer to the first principal component as our across-measure market liquidity factor. The extracted latent market liquidity factors are signed to represent liquidity. Similarly, the sign of the across-measure factor is chosen to be negatively correlated with the time series of the cross-sectional averages of all five liquidity measures, where the turnover rate is first multiplied by −1 before averaging.

Table 1 reports the first three principal components of the APCA method. We find that the first three components (PC1-PC3) collectively explain the total variance of liquidity up to 46% among all liquidity proxies. In both the US and China, the first principle components (PC1s) of the Amihud impact factor explain the highest proportion of liquidity variance with the highest standard deviation compared to PC1s of other liquidity measures. In the UK, the PC1 of Quoted spread explains the highest proportion (15%) of total liquidity variance compared to other liquidity proxies. In terms of latent market factor, its PC1, i.e., across-measure of market liquidity, on average, captures around 10% of total liquidity variance. In other words, co-movement of liquidity (liquidity commonality), on average, accounts for around 10% of market liquidity movements in these three countries.

[10] According to Cuthbertson et al. (2008), momentum factor is not statistically significant at the individual UK funds level. Therefore, we do not include the momentum factor in the UK study.

[11] Pástor and Stambaugh (2003) suggests the ordinary least squares slope coefficient $\widehat{\gamma}_{s,t}$ is used to compute the market average liquidity in month t as it is an imprecise estimate of a given stock's $\gamma_{s,m}$. The unobserved market average liquidity $\widehat{\gamma}_{m,t}$ become more precisely when the number of stocks, N, is large, $\widehat{\gamma}_{m,t} = \frac{1}{N}\sum_{s=1}^{N}\widehat{\gamma}_{s,t}$.

[12] Since the quote spread, High-Low spread, Roll spread, and Amihud impact are proxy for market illiquidity, we multiply these measures by negative one to represent market liquidity.

[13] Pástor and Stambaugh (2003) suggest gamma is a noise estimator at the individual stock level. We do not include gamma measure in the APCA analysis similar to Korajczyk and Sadka (2008) and Hasbrouck (2009).

Table 1
The Asymptotic Principal Component Analysis (APCA).

	Standard deviation			Proportion of variance explained			Cumulative Proportion		
Liquidity Proxies	PC1	PC2	PC3	PC1	PC2	PC3	PC1	PC2	PC3
Panel A: US									
Quoted Spread	3.55	3.41	2.30	0.15	0.14	0.06	0.15	0.28	0.34
High-low Spread	3.96	2.90	2.25	0.17	0.09	0.05	0.17	0.25	0.31
Roll Spread	3.00	1.97	1.84	0.08	0.04	0.03	0.08	0.12	0.15
Amihud Impact	4.13	2.81	2.70	0.18	0.08	0.08	0.18	0.26	0.34
Turnover	3.42	2.64	2.21	0.11	0.07	0.05	0.11	0.17	0.22
Latent Factor	3.24	2.84	2.29	0.10	0.08	0.05	0.10	0.18	0.23
Panel B: UK									
Quoted Spread	3.77	3.08	2.59	0.15	0.10	0.07	0.15	0.25	0.32
High-low Spread	2.96	2.50	2.17	0.10	0.07	0.05	0.10	0.17	0.22
Roll Spread	1.76	1.50	1.32	0.04	0.03	0.02	0.04	0.06	0.08
Amihud Impact	2.36	2.08	1.60	0.07	0.06	0.03	0.07	0.13	0.16
Turnover	2.77	1.65	1.48	0.09	0.03	0.03	0.09	0.13	0.15
Latent Factor	2.42	2.35	2.11	0.07	0.06	0.05	0.07	0.13	0.18
Panel C: China									
Quoted Spread	4.39	3.49	2.52	0.19	0.12	0.06	0.19	0.31	0.37
High-low Spread	3.76	2.33	1.82	0.12	0.05	0.03	0.12	0.17	0.20
Roll Spread	2.61	1.92	1.69	0.06	0.03	0.03	0.06	0.10	0.12
Amihud Impact	5.23	3.33	2.83	0.27	0.11	0.08	0.27	0.38	0.46
Turnover	4.21	2.58	2.32	0.18	0.07	0.05	0.18	0.24	0.30
Latent Factor	3.87	2.98	2.36	0.13	0.08	0.05	0.13	0.20	0.25

This table reports the first three principal components derived from the five liquidity proxies, including Quoted spread, High-Low spread, Roll spread, Amihud impact, and turnover rate. The definitions of these liquidity proxies are described in Appendix A. We also construct latent market liquidity factors across five liquidity proxies. PC1-PC3 denotes principal components in order.

We focus on using the across-measure of liquidity to analyze the liquidity timing strategy later, as the across-measure contains systematic variations in liquidity across various stocks and liquidity measures, i.e., commonality in liquidity, guaranteeing that our result is not sensitive to a specific liquidity measure. Fig. 1 shows the time series plots of market liquidity using the across-measure of market liquidity. As shown in Fig. 1, significant drops in market liquidity mainly occurred around March 2008 (the recent global financial crisis) and January 2020 (the Covid-19 pandemic) in both countries.

5. Empirical results

5.1. Empirical results: US

In this section, we use the nonparametric liquidity timing test to evaluate the liquidity timing ability of US individual mutual funds. We require each fund to have at least 36 monthly observations in the test, which leaves 4616 funds in our sample. For comparison, we also report the results of two parametric liquidity timing models, i.e., two forms of equation (9). In the first parametric model, we only include the market risk factor, which is the baseline model. The second model includes market, size, value, and momentum risk factors (Carhart, 1997). We focus on using the across-measure of market liquidity as it contains systematic variations in liquidity across various stocks and liquidity measures.

5.1.1. Liquidity timing using across-measure of market liquidity

Table 2 reports the cross-sectional distribution of z-statistics for liquidity timing coefficients across individual funds using the across-measure of liquidity. Row 1 displays the unconditional liquidity timing test statistic at various breakpoints in the cross-sectional distribution of liquidity timing performance. The test statistic, $z = \sqrt{n}\hat{\theta}_n/\hat{\sigma}_{\hat{\theta}_n}$, is asymptotically distributed as N (0,1) under the null hypothesis of no liquidity timing ability. We use the 5% significance level (one-tail test) in the following analysis. The second row reports the liquidity-timing coefficients, $\hat{\theta}_n$, corresponding to the test statistic in row 1. As discussed in Section 2, compared with parametric models, our nonparametric methods directly measure the fund's exposure to market liquidity. According to equation (5), the positive θ suggests the probability that fund managers move funds' exposure to the market liquidity in the correct direction is greater than the probability of a move in the wrong direction. From the z-statistic in Row 1, it is evident there are only a small number of skilled liquidity timers. More specifically, we find that 102 funds demonstrate statistically significant positive liquidity timing skills, around 2.20% of the sample of funds.[14] The total number of individual funds with significant z-statistics on the positive side is greater

[14] When discussing the proportion of funds that have a statistically significant value, we are talking about significance level for each fund individually in a multiple testing framework which would be different from the overall proportion of significant funds due to the compound type I errors, see Barras et al. (2010).

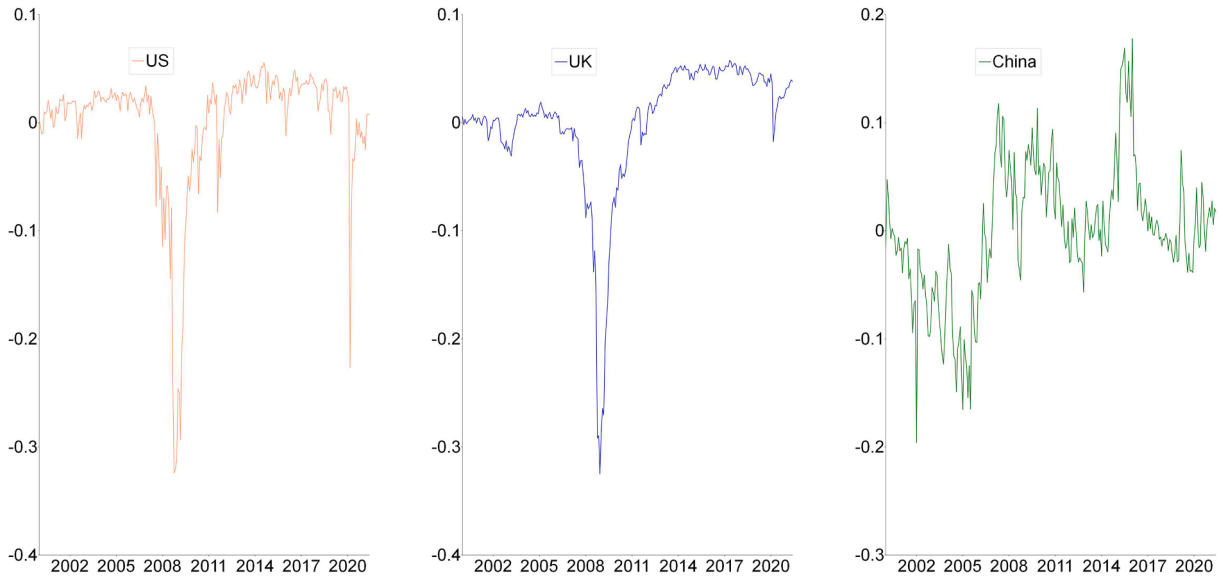

Fig. 1. Time series of monthly market liquidity using across-measure of market liquidity.

Table 2
US Mutual Fund Liquidity Timing Performance.

	1 %	5 %	10 %	25 %	50 %	75 %	90 %	95 %	99 %
z	−1.76	−1.02	−0.73	−0.27	0.23	0.73	1.14	1.40	1.92
$\widehat{\theta}_n$	−0.13	−0.02	−0.03	−0.01	0.01	0.04	0.02	0.12	0.13
t(1F)	0.25	−0.13	−0.24	0.28	0.21	−4.28	1.54	2.30	−0.67
t(4F)	−0.11	3.38	0.54	0.47	0.26	−0.67	1.93	2.16	−0.68
Type	1	5	2	2	1	5	1	4	1
Location	1	1	1	0	0	1	1	1	0
Dead	1	0	1	0	0	0	0	1	1
No. obs.	36	256	84	168	207	72	258	38	48

This table reports the values of unconditional liquidity timing nonparametric z-statistics at percentiles in the cross-sectional distribution. Funds are sorted from lowest to highest based on the statistic, $\mathbf{z} = \sqrt{\boldsymbol{n}}\widehat{\theta}_{\mathbf{n}}/\widehat{\sigma}_{\widehat{\theta}_n}$, and column headings show the position of percentiles where funds are ranked in the distribution. Row 1 presents the nonparametric test statistic, using the across-measure of market liquidity. Row 2 shows the market timing coefficient $\widehat{\theta}_{\boldsymbol{n}}$ corresponding to the funds sorted in row 1. Row 3 and row 4 present the Newey-West adjusted t-statistics for the single-factor (1F) liquidity timing model and four-factor (4F) liquidity timing model, respectively. Row 5 describes the fund categories: 1 = Large Blend fund, 2 = Large Growth fund, 3 = Large Value fund, 4 = Medium fund, 5 = Small fund. Row 6 shows the fund location: 0 = offshore fund, 1 = onshore fund. Row 7 describes whether the fund is dead or alive: 0 = alive, 1 = dead. Row 8 displays the number of monthly observations. The analysis covers 4616 funds from 2000 M1 to 2021 M6 with a minimum of 36 monthly observations.

than the number on the opposing side. Around 62% of funds demonstrate positive liquidity timing skills, while 38% of funds show negative liquidity timing (1.20% of funds are statistically significant negative). As the proportion of positive liquidity timers is greater than the negative ones, the cross-sectional distribution of z-statistics tends to be negatively skewed. The cross-sectional averages of timing coefficients $\widehat{\theta}_n$ and test statistics z_t are 0.65% and 0.212, respectively. Therefore, as a group, the probability that mutual fund managers move the fund's exposure to the market liquidity in the correct direction is 0.65% on average higher than the probability of a move in the wrong direction. The average $\widehat{\theta}_n$ value of live funds (1.04%) is greater than that of dead funds (0.29%), suggesting dead funds are less successful at liquidity timing.

5.1.2. Liquidity timing and investment style

We now examine possible differences in liquidity timing skills between funds with different investment objectives. There are five categories: Large Blend, Large Value, Large Growth, Medium, and Small funds. The liquidity timing ability of these groups is evaluated using the across-measure of market liquidity as it contains information from various liquidity measures.

Table 3 reports the liquidity timing results by investment style where funds are evaluated against the across-measure of market liquidity. There is strong evidence of positive liquidity timing ability for Large Growth funds in the right tail of the distribution. From the total sample of Large Growth funds, 84 funds show statistically significant positive liquidity timing at a 5% significance level,

accounting for 9.20% of the total sample. There is considerably less statistically significant negative liquidity timing for the Large Growth fund. In the left tail of the distribution, only 11 Large Growth funds (1.2% of the sample) show statistically negative liquidity timing skills. As a group, Large Growth funds positively time the market liquidity on average. In detail, the cross-sectional averages of timing coefficients $\widehat{\theta}_n$ and test statistics z_t are 1.36% and 0.542, respectively.

There is little evidence of liquidity timing for Large Blend, Large Value, Medium, and Small funds. The percentage of significant liquidity timers on the positive side ranges from 0.42% to 0.88% for these funds. The cross-sectional averages of test z-statistics are 0.238, 0.024, 0.105, and 0.086 for Large Blend, Large Value, Medium, and Small funds, respectively. Therefore, although there are a small number of top liquidity timers, nevertheless, as groups, these classes of funds time the market liquidity in the correct direction.

5.1.3. Liquidity timing and location

The performance of onshore and offshore mutual funds is evaluated in Table 4. Here, we examine whether geographical location gives rise to fund performance differences. Panel A presents results for 802 offshore US funds, while Panel B reports results for 3814 onshore US funds. A small number of both onshore and offshore funds (around 2.12% and 2.23%, respectively) exhibit statistically significant positive market timing skills when using the nonparametric z-statistics, and the proportions of significant negative liquidity timers are quantitatively similar (1.37% for offshore funds and 1.15% for onshore funds). The cross-sectional averages of z-statistics for offshore funds and onshore funds are 0.24 and 0.21, respectively. Hence, as groups, both offshore and onshore funds positively time the market liquidity, although not significantly. The average $\widehat{\theta}_n$ value of onshore funds (0.66%) is slightly greater than that of dead funds (0.59%). There is no evidence that the more geographically distant offshore funds underperform onshore funds in terms of liquidity timing. This may be because there is less or no informational asymmetry when predicting macro-level market liquidity movements than the micro-level security selection required to generate positive alpha.

5.1.4. Conditional liquidity timing

The conditional liquidity timing test can be used to control for liquidity timing skills attributable to publicly available information and hence can determine whether evidence of successful liquidity timing is attributable to private timing signals. As Cao et al. (2013a) discussed, fund managers who adjust fund's exposure simply based on past information of market liquidity (public information) in month t are liquidity reactors rather than liquidity timers. True liquidity timers adjust the fund's exposure using their forecasts of market liquidity in month $t+1$. Similar to Cao et al. (2013) and Foran and O'Sullivan (2017), we use innovation in market liquidity from the AR(2) process to control lagged market liquidity. The residuals of the AR(2) model represent the variation in market liquidity not explained by publicly available information.

Table 5 presents the cross-sectional distribution of the z-statistic for the conditional liquidity timing using the across-measure of market liquidity. Row 1 presents the conditional nonparametric z-statistic for funds sorted from lowest to highest. For comparison, row 3 reports unconditional z-statistics corresponding to the funds sorted in row 1. As discussed in Section 2, the sign and magnitude of conditional timing coefficients ($\widetilde{\theta}_n$) may be different from unconditional ones ($\widehat{\theta}_n$). From conditional z-statistics in Row 1, we find that the proportion of positive liquidity timers is greater than that of negative liquidity timers. However, only a relatively smaller number of funds show significantly positive liquidity timing in the conditional nonparametric test compared with the unconditional one. In the conditional nonparametric test, the top 92 funds demonstrate statistically significant positive liquidity timing after controlling for lagged market liquidity information, around 2% of the sample (compared with 2.2% of funds for the unconditional test). There is also a smaller number of significantly negative liquidity timing in the conditional nonparametric test. In the left tail of the conditional distribution, only six funds negatively time the market liquidity at a 5% significance level (compared with 55 funds for the unconditional test). The cross-sectional averages of timing coefficients $\widetilde{\theta}_n$ and z-statistics in the conditional nonparametric test are 1.65% and 0.42, respectively. These values imply that as a group, mutual fund managers positively time the market liquidity using the private information they possess. For comparison, Table 5 also shows the t-statistics of the conditional market liquidity timing coefficients for the single-factor and four-factor parametric tests. Similarly, we find more significant positive market liquidity timers in the conditional

Table 3
US Mutual Fund Liquidity Timing Performance-by Fund Type.

Fund Group	Nobs	Mean $\widehat{\theta}_n$	Mean z	$\widehat{\theta}_n > 0$	$\widehat{\theta}_n < 0$	$\%\widehat{\theta}_n > 0$ sig 5%	$\%\widehat{\theta}_n < 0$ sig 5%
Large Blend	1267	0.61	0.238	840	427	0.39	1.66
Large Growth	914	1.36	0.542	688	226	9.19	1.20
Large Value	692	0.08	0.024	377	315	0.29	1.01
Medium	798	0.40	0.105	461	337	0.88	1.25
Small	945	0.62	0.086	513	432	0.42	0.63

This table summarizes the unconditional nonparametric timing measures of mutual funds by fund type using the across measure of market liquidity. The first column lists the number of funds within the group. The second column lists the average value of $\widehat{\theta}_n$ (in percentage) of all funds in the group. The mean value of nonparametric test statistic $\boldsymbol{z}$ is reported in the third column. The fourth (fifth) column shows the number of funds that have $\widehat{\theta}_n > 0 (\widehat{\theta}_n < 0)$. The sixth (seventh) column reports the percentage of funds in each group that have $\widehat{\theta}_n > 0 (\widehat{\theta}_n < 0)$ at a 5% significance level. The analysis covers 4616 funds with a minimum of 36 monthly observations from 2000 M1 to 2021 M6, leaving 1267 Large Blend funds, 914 Large Growth funds, 692 Large Value funds, 798 Medium Funds, and 945 Small funds.

Table 4
US Mutual Fund Liquidity Timing Performance −by Fund Location.

Panel A: Offshore Fund									
	1 %	5 %	10 %	25 %	50 %	75 %	90 %	95 %	99 %
z	−1.97	−1.14	−0.80	−0.22	0.26	0.76	1.17	1.38	1.92
$\widehat{\theta}_n$	−0.09	−0.04	−0.04	−0.01	0.01	0.03	0.03	0.05	0.13
t(1F)	0.41	1.97	3.27	−2.65	−2.22	−0.56	2.27	−2.19	−0.67
t(4F)	0.47	1.70	2.95	−1.01	−0.61	−0.45	2.44	−1.04	−0.68
Type	1	1	3	1	1	2	1	1	1
Location	0	0	0	0	0	0	0	0	0
Dead	1	1	1	0	0	1	1	0	1
No. obs.	68	125	59	57	100	107	180	148	48
Panel B: Onshore Fund									
	1 %	5 %	10 %	25 %	50 %	75 %	90 %	95 %	99 %
z	−1.74	−1.01	−0.73	−0.28	0.22	0.72	1.13	1.41	1.92
$\widehat{\theta}_n$	−0.04	−0.05	−0.02	−0.01	0.00	0.04	0.02	0.03	0.05
t(1F)	−1.31	−0.77	0.39	2.42	−0.74	−0.54	2.71	2.59	0.63
t(4F)	0.80	−0.28	1.40	3.17	0.03	−0.85	2.62	0.63	−0.96
Type	4	2	5	1	5	2	1	2	2
Location	1	1	1	1	1	1	1	1	1
Dead	1	1	0	1	0	0	0	0	0
No. obs.	216	61	191	150	258	75	258	258	208

This table reports the values of unconditional liquidity timing nonparametric z-statistics at percentiles in the cross-sectional distribution. Funds are sorted from lowest to highest based on the statistic, $\mathbf{z} = \sqrt{\boldsymbol{n}}\widehat{\theta}_{\mathbf{n}}/\widehat{\sigma}_{\widehat{\theta}_n}$, and column headings show the position of percentiles where funds are ranked in the distribution. Panel A and B show the performance of offshore and onshore funds, respectively. In each panel, row 1 presents the nonparametric test statistic using the across-measure of market liquidity. Row 2 shows the market timing coefficient $\widehat{\theta}_{\boldsymbol{n}}$ corresponding to the funds sorted in Row 1. Row 3 and row 4 present the Newey-West adjusted t-statistics for the single-factor (1F) liquidity timing model and four-factor (4F) liquidity timing model, respectively. Row 5 describes the fund categories: 1 = Large Blend fund, 2 = Large Growth fund, 3 = Large Value fund, 4 = Medium Fund, 5 = Small fund. Row 6 shows the fund location: 0 = offshore fund, 1 = onshore fund. Row 7 describes whether the fund is dead or alive: 0 = alive, 1 = dead. Row 8 displays the number of monthly observations. The analysis covers funds with a minimum of 36 monthly observations from 2000 M1 to 2021 M6, leaving 802 offshore funds and 3814 onshore funds.

Table 5
US Mutual Fund Conditional Liquidity Timing Performance.

	1 %	5 %	10 %	25 %	50 %	75 %	90 %	95 %	99 %
$\widetilde{z}$	−0.85	−0.41	−0.24	0.07	0.41	0.73	1.10	1.32	1.81
$\widetilde{\theta}_n$	−0.02	−0.01	−0.01	0.00	0.01	0.03	0.08	0.04	0.07
z	−0.07	1.56	0.36	−0.73	−0.25	0.26	1.17	−0.33	−0.82
t(1F)	−0.36	2.89	0.19	−1.22	1.06	−11.67	0.74	0.11	0.07
t(4F)	−1.14	0.93	0.02	−1.43	0.69	−4.26	0.90	0.45	0.07
Type	5	2	5	5	5	5	1	2	2
Location	1	1	1	1	1	1	1	1	1
Dead	0	0	1	0	1	0	1	1	1
No. obs.	258	258	150	171	206	117	41	171	66

This table reports the values of conditional liquidity timing nonparametric z-statistics at percentiles in the cross-sectional distribution. Funds are sorted from lowest to highest based on the statistic, $\widetilde{\boldsymbol{z}} = \sqrt{\boldsymbol{n}}\widetilde{\theta}_{\boldsymbol{n}}/\widetilde{\sigma}_{\widetilde{\theta}_n}$, and column headings show the position of percentiles where funds are ranked in the distribution. Row 1 presents the nonparametric test statistic, using the across-measure of market liquidity. Row 2 shows the market timing coefficient $\widetilde{\theta}_{\boldsymbol{n}}$ corresponding to the funds sorted in row 1. Row 3 reports the unconditional liquidity timing test statistics, $\boldsymbol{z} = \sqrt{\boldsymbol{n}}\widehat{\theta}_{\mathbf{n}}/\widehat{\sigma}_{\widehat{\theta}_n}$ corresponding to the funds as sorted in row 1. Row 4 and row 5 present the Newey-West adjusted t-statistics of the single-factor (1F) conditional liquidity timing model and four-factor (4F) conditional liquidity timing model, respectively. Row 6 describes the fund categories: 1 = Large Blend fund, 2 = Large Growth fund, 3 = Large Value fund, 4 = Medium Fund, 5 = Small fund. Row 7 shows the fund location: 0 = offshore fund, 1 = onshore fund. Row 8 describes whether the fund is dead or alive: 0 = alive, 1 = dead. Row 9 displays the number of monthly observations. The analysis covers 4616 funds from 2000 M1 to 2021 M6 with a minimum of 36 monthly observations.

regression-based tests (8.80% for the single-factor model and 5.85% for the four-factor model, respectively).

5.1.5. Liquidity timing using various liquidity measures

For robustness test, the results of alternative liquidity measures are also reported in Table 6, which shows the proportion of statistically significant results of all three models using various liquidity measures. From the z-statistics in Table 6, we find there is some

evidence that top mutual fund managers possess superior liquidity timing ability in the nonparametric test, which is consistent with previous results. The proportion of significantly positive liquidity timers ranges from 0.04% to 3.53% (except for the within-measure of Amihud impact).

Compared with the nonparametric method, we find a higher proportion of significant positive liquidity timers in the two regression models for most liquidity measures. We find that the price impact liquidity proxies, such as Amihud impact or PS gamma, show significant results of liquidity timing in the parametric models. For example, 27.55% (23.45%) of funds show positive significant liquidity timing ability using average Amihud (PS) liquidity measures. These parametric market timing results for the US mutual funds are consistent with those of Cao et al. (2013b), who apply the bootstrap approach at the individual fund level with the null hypothesis of no liquidity timing ability. After examining the 4173 funds, they report that above 25% of funds possess statistically significant positive timing skills using Amihud and PS liquidity measures. The result suggests that the parametric liquidity timing models are easier to find more statistically significant liquidity timers.

In Table 6, the percentage of significant positive liquidity timing varies across various liquidity measures and various liquidity timing models. The result suggests that liquidity timing is sensitive to the choice of liquidity measure and liquidity timing models. The difference between nonparametric and parametric methods may arise because the nonparametric method directly measures fund exposure to market liquidity. The parametric method assumes the fund manager adjusts the fund's exposure to the market portfolio rather than market liquidity after anticipating market liquidity changes. Besides, the parametric test measures both the probability of correct forecast in liquidity timing and the aggressiveness of timing response, unlike the nonparametric test.

5.2. Empirical results: UK

In this section, we use the nonparametric liquidity timing test to evaluate the liquidity timing ability for UK individual mutual funds. We require each fund to have at least 36 monthly observations in the test, which leaves 669 funds in our sample. Unless stated otherwise, we use the 5% significance level (one-tail test) in the following analysis. For comparison, we also report the results of two parametric liquidity timing models. In the first parametric model, we only include the market risk factor, which is the baseline model. The second model includes market, size, and value risk factors (Fama & French, 1993).[15] We focus on using the across-measure of market liquidity as it contains systematic variations in liquidity across various stocks and liquidity measures.

5.2.1. Liquidity timing using across-measure of market liquidity

Table 7 reports the cross-sectional distribution of z-statistics for liquidity timing coefficients across individual funds using the across-measure of liquidity. The across-measure of market liquidity contains systematic variations in liquidity across various stocks and liquidity measures. From the z-statistic in Row 1, it is evident there are only a small number of skilled liquidity timers. More specifically, we find that only the top 2 funds demonstrate statistically significant positive liquidity timing skills, around 0.3% of the sample of funds. The total number of individual funds with significant z-statistics on the positive side is less than the number on the opposing side. Around 26% of funds demonstrate positive liquidity timing skills, while 74% of funds show negative liquidity timing (6.7% of funds are statistically significant negative). As the proportion of positive liquidity timers is far less than the negative ones, the cross-sectional distribution of z-statistics tends to be positively skewed. The cross-sectional averages of timing coefficients $\widehat{\theta}_n$ and test statistics z_t are −2.18% and −0.51, respectively. Therefore, as a group, the probability that mutual fund managers move the fund's exposure to the market liquidity in the correct direction is 2.18% on average lower than the probability of a move in the wrong direction. The average $\widehat{\theta}_n$ values are −1.62% and −2.66% for live and dead funds, respectively. As expected, dead funds are less successful at liquidity timing.

5.2.2. Liquidity timing and investment style

We now examine possible differences in liquidity timing skills between funds with different investment objectives. There are four categories: Large, Medium and Small, Equity Income, and Flex Equity. The liquidity timing ability of these groups is evaluated using the across-measure of market liquidity as it contains information from various liquidity measures.

Table 8 reports the nonparametric liquidity timing results for UK funds using the across-measure of market liquidity. There is some evidence of positive liquidity timing ability for Large and Flex Equity funds in the right tail of the distribution, while no Small and Medium Funds or Equity Income funds exhibit statistically significant positive liquidity timing. The cross-sectional average of nonparametric test statistics is −1.408, −0.325, −0.667, and −0.545 for Large, Small and Medium, Equity Income, and Flex Equity funds, respectively. Hence, as groups, these classes of funds perform poorly on average.

5.2.3. Liquidity timing and location

The performance of onshore and offshore UK mutual funds is evaluated in Table 9. Here, we examine whether geographical location gives rise to fund performance differences. Panel A presents results for the 121 offshore UK funds, while Panel B reports results for the 548 onshore UK funds. A small number of both offshore and onshore funds (around 0.83% and 0.18%, respectively) exhibit statistically significant positive market timing skills when using the nonparametric z-statistics, and the proportion of significant

[15] We use the Fama and French (1993) three factor model as the momentum risk factor is insignificant for UK mutual fund returns, similar to Cuthbertson et al. (2008).

Table 6
US Cross-Section Distribution of Test Statistics for the Liquidity Timing Coefficients across Liquidity Measures.

	Nonparametric		1-factor		4-factor	
Market liquidity measures	$z \leq -1.65$	$z \geq 1.65$	$t \leq -1.65$	$t \geq 1.65$	$t \leq 1.65$	$t \geq 1.65$
Panel A: APCA						
Across-Measure	1.19	2.21	14.49	25.21	10.68	31.26
Quoted Spread	0.95	1.04	26.88	4.29	32.08	4.31
High-low Spread	0.26	3.53	21.83	14.32	24.20	10.79
Roll Spread	2.53	0.04	40.34	13.15	38.82	13.80
Amihud Impact	0.48	33.80	9.40	17.70	6.74	16.55
Turnover	0.25	0.13	14.69	25.61	10.98	31.46
Panel B: Cross-sectional average						
Quoted Spread	1.82	1.34	12.98	16.49	8.66	21.66
High-low Spread	1.17	0.95	15.07	14.75	17.05	8.96
Roll Spread	2.12	1.26	36.58	13.11	10.16	47.96
Amihud Impact	2.71	0.69	10.53	18.94	10.18	27.55
Turnover	57.3	0.43	16.91	9.18	2.37	23.45
PS	28.37	0.09	13.38	15.88	13.47	8.58

This table summarizes the distribution of the nonparametric liquidity timing test statistics, $\mathbf{z} = \sqrt{\boldsymbol{n}}\widehat{\theta}_{\mathbf{n}}/\widehat{\sigma}_{\widehat{\theta}_n}$ and two parametric liquidity timing tests t-statistics, $t = \widehat{\theta}_1/\widehat{\sigma}_{\widehat{\theta}_1}$. The table shows the percentage of test statistics exceeding the indicated cut-off values at a 5% significance level (one-tail test). Panel A shows the percentage of test statistics using the first principal component of each liquidity measure (within-measure) and the first principal component of latent market liquidity factors (across-measure) as market liquidity proxies, while Panel B presents the percentage of test statistics using the cross-sectional average of each liquidity measure as market liquidity proxies.

Table 7
UK Mutual Fund Liquidity Timing Performance.

	1 %	5 %	10 %	25 %	50 %	75 %	90 %	95 %	99 %
z	−2.26	−1.81	−1.51	−1.06	−0.42	0.02	0.41	0.63	1.20
$\widehat{\theta}_n$	−0.15	−0.07	−0.06	−0.04	−0.01	0.00	0.01	0.02	0.03
t(1F)	−0.05	0.21	0.45	1.45	0.92	1.75	0.54	1.40	1.81
t(3F)	−0.05	−0.54	−1.18	−0.39	−0.10	1.05	0.10	−0.23	−0.45
Type	1	1	1	2	3	1	1	2	2
Location	0	1	1	1	1	1	1	1	1
Dead	1	1	0	1	0	0	0	0	0
No. obs.	61	108	89	94	244	258	258	256	258

This table reports the values of unconditional liquidity timing nonparametric z-statistics at percentiles in the cross-sectional distribution. Funds are sorted from lowest to highest based on the statistic, $\mathbf{z} = \sqrt{\boldsymbol{n}}\widehat{\theta}_{\mathbf{n}}/\widehat{\sigma}_{\widehat{\theta}_n}$, and column headings show the position of percentiles where funds are ranked in the distribution. Row 1 presents the nonparametric test statistic, using the across-measure of market liquidity. Row 2 shows the market timing coefficient $\widehat{\theta}_n$ corresponding to the funds sorted in row 1. Row 3 and row 4 present the Newey-West adjusted t-statistics for the single-factor (1F) liquidity timing model and three-factor (3F) liquidity timing model, respectively. Row 5 describes the fund categories: 1 = Large fund, 2 = Small and Medium fund, 3 = Equity Income fund, 4 = Flex Equity fund. Row 6 shows the fund location: 0 = offshore fund, 1 = onshore fund, Row 7 describes whether the fund is dead or alive: 0 = alive, 1 = dead. Row 8 displays the number of monthly observations. The analysis covers 669 funds from 2000 M1 to 2021 M6 with a minimum of 36 monthly observations.

negative liquidity timers in offshore funds is slightly greater than the proportion of onshore funds (9.09% for offshore funds and 6.20% for onshore funds). The cross-sectional averages of z-statistics for offshore and onshore funds are −0.59 and −0.49, respectively. Hence, as groups, offshore and onshore funds negatively time the market liquidity. The average $\widehat{\theta}_n$ value of onshore funds (−2.05%) is slightly greater than that of offshore funds (−2.78%). There is no evidence that the more geographically distant offshore funds underperform onshore funds in terms of liquidity timing. This may be because there is less or no informational asymmetry when predicting macro-level market liquidity movements than the micro-level security selection required to generate positive alpha.

5.2.4. Conditional liquidity timing

Table 10 presents the cross-sectional distribution of the z-statistic for the conditional liquidity timing using the across-measure of market liquidity. Row 1 presents the conditional nonparametric z-statistic for funds sorted from lowest to highest. For comparison, row 3 reports unconditional z-statistics corresponding to the funds sorted in row 1. As discussed in Section 2, the sign and magnitude of conditional timing coefficients ($\widetilde{\theta}_n$) may be different from unconditional ones ($\widehat{\theta}_n$). From conditional z-statistics in row 1, we find that the proportion of positive liquidity timers is less than that of negative liquidity timers. There are a small number of funds showing significantly positive liquidity timing in the conditional nonparametric test − the top 2 funds demonstrate statistically significant

Table 8
UK Mutual Fund Liquidity Timing Performance − by Fund Type.

Fund Group	Nobs	Mean $\widehat{\theta}_n$	Mean z	$\widehat{\theta}_n > 0$	$\widehat{\theta}_n < 0$	$\%\widehat{\theta}_n > 0$ sig 5%	$\%\widehat{\theta}_n < 0$ sig 5%
Large	341	−6.18	−1.408	99	242	0.85	20.54
Small and Medium	105	−1.43	−0.325	39	66	0.00	4.68
Equity Income	91	−0.02	−0.667	6	85	0.00	0.08
Flex Equity	132	−0.02	−0.545	33	99	0.01	0.05

This table summarizes the unconditional nonparametric timing measures of mutual funds using the across measure of market liquidity. The first column lists the number of funds within the group. The second column lists the average value of $\widehat{\theta}_n$ (in percentage) of all funds in the group. The mean value of nonparametric test statistic z_t is reported in the third column. The fourth (fifth) column shows the number of funds that have $\widehat{\theta}_n > 0 (\widehat{\theta}_n < 0)$. The sixth (seventh) column reports the percentage of funds in each group that have $\widehat{\theta}_n > 0 (\widehat{\theta}_n < 0)$ at a 5% significance level. The analysis covers 669 funds with a minimum of 36 monthly observations from 1990 M1 to 2021 M6, leaving 341 Large funds, 105 Small and Medium Funds, 91 Equity Income funds, and 132 Flex Equity funds.

Table 9
UK Mutual Fund Liquidity Timing Performance −by Fund Location.

Panel A: Offshore Fund									
	1 %	5 %	10 %	25 %	50 %	75 %	90 %	95 %	99 %
z	−2.58	−1.94	−1.59	−1.18	−0.61	0.04	0.35	0.46	1.02
$\widehat{\theta}_n$	−0.11	−0.07	−0.06	−0.04	−0.02	0.00	0.02	0.01	0.04
t(1F)	1.71	1.18	−0.19	2.24	0.86	1.38	0.76	2.55	1.57
t(3F)	2.02	0.47	−0.01	2.03	0.37	1.21	0.31	2.08	0.81
Type	1	1	1	2	1	1	2	1	1
Location	0	0	0	0	0	0	0	0	0
Dead	1	1	0	1	1	1	0	0	1
No. obs.	67	112	127	127	141	174	60	258	127
Panel B: Onshore Fund									
	1 %	5 %	10 %	25 %	50 %	75 %	90 %	95 %	99 %
z	−2.16	−1.72	−1.48	−1.04	−0.40	0.02	0.43	0.66	1.20
$\widehat{\theta}_n$	−0.08	−0.06	−0.06	−0.04	−0.01	0.00	0.01	0.04	0.03
t(1F)	2.15	0.47	0.76	1.27	0.77	−0.42	0.32	−0.29	1.81
t(3F)	0.28	0.74	0.33	0.59	−0.08	−1.84	−0.71	−2.79	−0.45
Type	2	1	1	1	3	4	2	2	2
Location	1	1	1	1	1	1	1	1	1
Dead	1	0	0	1	1	0	0	0	0
No. obs.	100	126	117	136	258	145	258	60	258

This table reports the values of unconditional liquidity timing nonparametric z-statistics at percentiles in the cross-sectional distribution. Funds are sorted from lowest to highest based on the statistic, $\mathbf{z} = \sqrt{\boldsymbol{n}}\widehat{\theta}_{\mathbf{n}}/\widehat{\sigma}_{\widehat{\theta}_n}$, and column headings show the position of percentiles where funds are ranked in the distribution. Panel A and B show the performance of offshore and onshore funds, respectively. In each panel, row 1 presents the nonparametric test statistic using the across-measure of market liquidity. Funds are sorted from lowest to highest based on these statistics. Row 2 shows the market timing coefficient $\widehat{\theta}_n$ corresponding to the funds sorted in Row 1. Row 3 and row 4 present the Newey-West adjusted t-statistics for the single-factor (1F) liquidity timing model and three-factor (3F) liquidity timing model, respectively. Row 5 describes the fund categories: 1 = Large fund, 2 = Small and Medium fund, 3 = Equity Income fund, 4 = Flex Equity fund. Row 6 shows the fund location: 0 = offshore fund, 1 = onshore fund. Row 7 describes whether the fund is dead or alive: 0 = alive, 1 = dead. Row 8 displays the number of monthly observations. The analysis covers funds with a minimum of 36 monthly observations from 2000 M1 to 2021 M6, leaving 121 offshore funds and 548 onshore funds.

positive liquidity timing after controlling for lagged market liquidity information, around 0.3% of the sample, which is similar to the unconditional test. However, there is a greater number of significantly negative liquidity timing in the conditional nonparametric test (12.1% of the sample) compared to 6.7% of the unconditional test. The cross-sectional averages of timing coefficients $\widetilde{\theta}_n$ and z-statistics in the conditional nonparametric test are −3.3% and −1.01, respectively. These values imply that, as a group, mutual fund managers negatively time the market liquidity using the private information they possess. Table 10 also shows the t-statistics of the conditional market liquidity timing coefficients for the single-factor and three-factor parametric tests. Similarly, we find more significant positive market liquidity timers in the conditional regression-based tests (37.22% for the single-factor model and 29.75% for the three-factor model, respectively).

5.2.5. Liquidity timing using various liquidity measures

The results of alternative liquidity measures are also reported as a robustness test. Table 11 shows the proportion of statistically significant results of all three models using various liquidity measures. From the z-statistics in Table 11, we find there is some evidence

Table 10
UK Mutual Fund Conditional Liquidity Timing Performance.

	1 %	5 %	10 %	25 %	50 %	75 %	90 %	95 %	99 %
$\widetilde{z}$	−2.52	−1.94	−1.73	−1.41	−1.03	−0.68	−0.33	−0.11	0.47
$\widetilde{\theta}_n$	−0.07	−0.05	−0.04	−0.03	−0.06	−0.03	−0.02	−0.01	0.03
z	−0.01	0.07	−1.03	0.35	−1.47	−1.49	−0.16	0.06	−0.15
t(1F)	2.90	2.83	3.19	3.36	−1.81	−1.84	−0.31	0.45	−2.11
t(3F)	1.63	2.36	2.47	3.34	−2.40	−3.74	−1.02	0.23	−1.75
Type	1	1	3	1	3	3	2	1	4
Location	0	0	1	0	1	0	1	1	1
Dead	1	0	0	1	1	1	1	1	0
No. obs.	152	169	258	258	61	103	37	47	47

This table reports the values of conditional liquidity timing nonparametric z-statistics at percentiles in the cross-sectional distribution. Funds are sorted from lowest to highest based on the statistic, $\widetilde{\boldsymbol{z}} = \sqrt{\boldsymbol{n}}\widetilde{\theta}_{\boldsymbol{n}}/\widetilde{\sigma}_{\widetilde{\theta}_n}$, and column headings show the position of percentiles where funds are ranked in the distribution. Row 1 presents the nonparametric test statistic, using the across-measure of market liquidity. Row 2 shows the market timing coefficient $\widetilde{\theta}_{\boldsymbol{n}}$ corresponding to the funds sorted in row 1. Row 3 reports the unconditional liquidity timing test statistics, $\boldsymbol{z} = \sqrt{\boldsymbol{n}}\widehat{\theta}_{\mathbf{n}}/\widehat{\sigma}_{\widehat{\theta}_n}$ corresponding to the funds as sorted in row 1. Row 4 and row 5 present the Newey-West adjusted t-statistics of the single-factor (1F) conditional liquidity timing model and three-factor (3F) conditional liquidity timing model, respectively. Row 6 describes the fund categories: 1 = Large fund, 2 = Small and Medium fund, 3 = Equity Income fund, 4 = Flex Equity fund. Row 7 shows the fund location: 0 = offshore fund, 1 = onshore fund. Row 8 describes whether the fund is dead or alive: 0 = alive, 1 = dead. Row 9 displays the number of monthly observations. The analysis covers 669 funds from 2000 M1 to 2021 M6 with a minimum of 36 monthly observations.

that top mutual fund managers possess superior liquidity timing ability in the nonparametric test using various market liquidity measures, which is consistent with previous results.

From Table 11, we also see that the result of liquidity timing is sensitive to the choice of liquidity measures. In the nonparametric test, we find a high proportion (above 10%) of significant test statistics for the cross-sectional average of Roll, Amihud impact, and PS measures. However, the proportion of positive significant liquidity timers ranges from 0.00% to 2.24% for most of the liquidity measures.

Compared with the nonparametric method, we find a higher proportion of significant positive liquidity timers in the two regression (parametric) models for most liquidity measures. Using the parametric models, the number of significant positive timers ranges from 1.04% to 28.25%. These parametric market timing results for the UK mutual funds are consistent with those of Foran and O'Sullivan (2017), who apply the bootstrap approach at the individual fund level with the null hypothesis of no liquidity timing ability. After examining the 657 funds, they report that above 10% of funds possess statistically significant positive timing skills at a 5% significance level using the across-measure of liquidity.

5.3. Empirical results: China

In this section, we use the nonparametric method to evaluate the liquidity timing ability of individual Chinese mutual funds. Unless stated otherwise, we use the 5% significance level (one-tail test) in the following analysis. We require each fund to have at least 36 monthly observations in the test, which leaves 439 funds in our sample. All these funds are onshore funds. For comparison, we also report the results of two parametric liquidity timing models. In the first parametric model, we only include the market risk factor, which is the baseline model. The second model includes market, size, value, and momentum risk factors (Carhart, 1997).

5.3.1. Liquidity timing using across-measure of market liquidity

Table 12 reports the cross-sectional distribution of z-statistics for liquidity timing coefficients across individual funds using the across-measure of liquidity. The across-measure of market liquidity captures systematic variations in liquidity across various stocks and across liquidity measures. From the z-statistic in row 1, only a small number of skilled liquidity timers exist. More specifically, we find that three (six) funds demonstrate statistically significant positive liquidity timing skills at a 5% (10%) significance level, around 0.7% (1.4%) of the sample of funds. The total number of individual funds with significant z-statistics on the positive side is less than the number on the negative side. Around 37% of funds demonstrate positive liquidity timing skills, while 63% of funds show negative liquidity timing (2.3% of funds are statistically significant and negative). As the proportion of positive liquidity timers is less than the negative ones, the cross-sectional distribution of z-statistics tends to be positively skewed. The cross-sectional averages of timing coefficients $\widehat{\theta}_n$ and test statistics z_t are −1.48% and −0.346, respectively. Therefore, as a group, the probability mutual fund managers move the fund's exposure to the market liquidity in the correct direction is 1.48% on average lower than the probability of a move in the wrong direction. The average $\widehat{\theta}_n$ value of live funds is −1.26% while that of dead funds is −3.35%, suggesting live funds are more successful at liquidity timing. Overall, there is little evidence that mutual fund managers possess superior liquidity timing ability in the nonparametric test.

Table 11
UK Cross-Section Distribution of Test Statistics for the Liquidity Timing Coefficients across Liquidity Measures.

	Nonparametric		1-factor		3-factor	
Market liquidity measures	$z \leq -1.65$	$z \geq 1.65$	$t \leq -1.65$	$t \geq 1.65$	$t \leq 1.65$	$t \geq 1.65$
Panel A: APCA						
Across-Measure	6.72	0.29	0.74	20.77	5.38	7.17
Quoted Spread	0.59	2.24	1.34	13.90	4.03	8.07
High-low Spread	0.74	0.59	0.59	25.41	6.57	8.67
Roll Spread	20.17	0.74	2.54	9.86	9.86	9.86
Amihud Impact	7.62	0.00	2.24	16.29	7.47	10.05
Turnover	31.24	0.14	2.54	9.86	22.72	2.09
Panel B: Cross-sectional average						
Quoted Spread	0.59	0.00	8.96	6.57	4.03	8.07
High-low Spread	48.28	1.34	2.39	28.25	2.23	20.17
Roll Spread	11.21	14.94	0.59	17.63	5.68	13.60
Amihud Impact	0.59	12.25	30.49	1.04	6.72	9.11
Turnover	23.91	0.00	21.22	1.34	6.57	5.83
PS	11.21	14.97	17.63	0.59	13.60	5.68

This table summarizes the distribution of the nonparametric liquidity timing test statistics, $\mathbf{z} = \sqrt{\boldsymbol{n}}\widehat{\theta}_{\mathbf{n}}/\widehat{\sigma}_{\widehat{\theta}_{\boldsymbol{n}}}$ and two parametric liquidity timing tests t-statistics, $t = \widehat{\theta}_1/\widehat{\sigma}_{\widehat{\theta}_1}$. The table shows the percentage of test statistics exceeding the indicated cut-off values at a 5% significance level (one-tail test). Panel A shows the percentage of test statistics using the first principal component of each liquidity measure (within-measure) and the first principal component of latent market liquidity factors (across-measure) as market liquidity proxies, while Panel B presents the percentage of test statistics using the cross-sectional average of each liquidity measure as market liquidity proxies.

Table 12
China Mutual Fund Liquidity Timing Performance.

	1 %	5 %	10 %	25 %	50 %	75 %	90 %	95 %	99 %
z	−2.06	−1.53	−1.31	−0.92	−0.42	0.19	0.57	0.79	1.27
$\widehat{\theta}_n$	−0.08	−0.09	−0.06	−0.04	−0.02	0.01	0.05	0.04	0.07
t(1F)	−1.20	0.81	1.20	0.99	−1.48	−0.37	0.43	−0.28	−0.27
t(4F)	−3.67	0.19	0.16	−1.03	−1.41	−0.81	0.74	−0.35	0.00
Type	2	3	3	4	2	1	1	2	1
Dead	0	0	0	0	0	1	0	0	0
No. obs.	124	73	113	111	103	39	38	72	57

This table reports the values of unconditional liquidity timing nonparametric z-statistics at percentiles in the cross-sectional distribution. Funds are sorted from lowest to highest based on the statistic, $\mathbf{z} = \sqrt{\boldsymbol{n}}\widehat{\theta}_{\mathbf{n}}/\widehat{\sigma}_{\widehat{\theta}_{\boldsymbol{n}}}$, and column headings show the position of percentiles where funds are ranked in the distribution. Row 1 presents the nonparametric test statistic using the across-measure of market liquidity. Row 2 shows the market timing coefficient $\widehat{\theta}_{\boldsymbol{n}}$ corresponding to the funds sorted in Row 1. Row 3 and row 4 present the Newey-West adjusted t-statistics of the single-factor (1F) liquidity timing model and four-factor (4F) liquidity timing model, respectively. Row 5 describes the fund categories: 1 = Large Blend fund, 2 = Large Growth fund, 3 = Medium Blend fund, 4 = Medium Growth fund, 5 = other fund. Row 6 describes whether the fund is dead or alive: 0 = alive, 1 = dead. Row 7 displays the number of monthly observations. The analysis covers 439 funds from 2000 M1 to 2021 M6 with a minimum of 36 monthly observations.

5.3.2. *Investment style and liquidity timing*

We now examine possible differences in liquidity timing skills between funds with different investment styles. There are four categories of investment styles: Large Blend, Large Growth, Medium Blend, and Medium Growth. We ignore other funds due to the small sample size. The liquidity timing ability of these groups is evaluated using the across-measure of market liquidity.

Table 13 reports the nonparametric liquidity timing results by investment style. Using the across-measure of market liquidity, there are a few significant positive liquidity timers in the nonparametric test. There is little evidence of positive liquidity timing ability for Large Blend funds (1 fund) in the right tail of the distribution, while no evidence of positive liquidity timing for Large Growth funds, Medium Blend funds, and Medium Growth funds. The cross-sectional average of z-statistics is −0.43, −0.21, −0.65 and −0.32 for Large Blend, Large Growth, Medium Blend and Medium Growth, respectively. As groups, all classes of fund groups negatively time the market liquidity in the nonparametric test with the cross-sectional averages of z-statistics less than zero.

5.3.3. *Conditional liquidity timing*

Table 14 presents the cross-sectional distribution of the z-statistic for the conditional liquidity timing using the across-measure of market liquidity. Row 1 presents the conditional nonparametric z-statistic for funds sorted from lowest to highest. For comparison, row 3 reports unconditional z-statistics corresponding to the funds sorted in row 1. As discussed in Section 2, the sign and magnitude of

Table 13
China Mutual Fund Liquidity Timing Performance-by Fund Type.

Fund Group	Nobs	Mean $\widehat{\theta}_n$	Mean z	$\widehat{\theta}_n > 0$	$\widehat{\theta}_n < 0$	$\%\widehat{\theta}_n > 0$ sig 5%	$\%\widehat{\theta}_n < 0$ sig 5%
Large Blend	154	−1.97	−0.438	49	105	0.65	2.60
Large Growth	191	−0.79	−0.211	78	113	0.00	1.05
Medium Blend	44	−3.01	−0.652	11	33	0.00	2.27
Medium Growth	36	−1.50	−0.327	16	20	0.00	0.00

This table summarizes the unconditional nonparametric timing measures of mutual funds using the across measure of market liquidity. The first column lists the number of funds within the group. The second column lists the average value of $\widehat{\theta}_n$ (in percentage) of all funds in the group. The mean value of nonparametric test statistic z_t is reported in the third column. The fourth (fifth) column shows the number of funds that have $\widehat{\theta}_n > 0 (\widehat{\theta}_n < 0)$. The sixth (seventh) column reports the percentage of funds in each group that have $\widehat{\theta}_n > 0 (\widehat{\theta}_n < 0)$ at a 5% significance level. The analysis covers 439 funds with a minimum of 36 monthly observations from 1990 M1 to 2021 M6, leaving 154 Large Blend funds, 191 Large Growth funds, 44 Medium Blend funds, and 36 Medium Growth funds.

conditional timing coefficients ($\widetilde{\theta}_n$) may be different from unconditional ones ($\widehat{\theta}_n$). From conditional z-statistics in row 1, we find a number of funds show significantly positive liquidity timing in the conditional nonparametric test. In the conditional nonparametric test, the top 31 funds demonstrate statistically significant positive liquidity timing at a 5% significance level, after controlling for lagged market liquidity information, around 7.06% of the sample (compared with 0.68% of funds for the unconditional test). The cross-sectional averages of timing coefficients $\widetilde{\theta}_n$ and z-statistics in the conditional nonparametric test are 4.95% and 0.942, respectively. These values imply that, as a group, mutual fund managers positively (although not significantly) time market liquidity using the private information they possess. For comparison, Table 14 also shows the t-statistics of the conditional market liquidity timing coefficients for the single-factor and four-factor parametric tests. Similarly, we find more significant positive market liquidity timers in the conditional regression-based tests (10.02% for the single-factor model and 12.98% for the four-factor model, respectively).

5.3.4. Liquidity timing using various liquidity measures

For comparison, Table 15 shows the proportion of statistically significant results of all three models using various liquidity measures. From the z-statistics in Table 15, we find there is some evidence that top mutual fund managers possess superior liquidity timing ability in the nonparametric test, which is consistent with previous results.

In Table 15, we see that the proportion of positive significant liquidity timers varies across various liquidity measures in the nonparametric test. Using the average Amihud impact, we find that 8.65% of funds show positive liquidity timing ability. For other liquidity measures, the percentage of positive liquidity timing ranges from 0.45% to 3.87%. Compared with the nonparametric test, we find a higher proportion of significant positive liquidity timers in the two regression models for most liquidity measures. The proportion of significant positive liquidity timers in the two regression models ranges from 1.59% to 23.46%. These parametric market timing results for the Chinese mutual funds are consistent with those of previous studies (Li et al., 2015; Huang et al.,2018; Yi et al., 2018), which report evidence of statistically significant positive timing skills using Amihud and PS liquidity measures.

5.4. Summary

Overall, we find a small proportion of funds that have positive liquidity timing ability at the individual level, across the US, UK, and China, based on the nonparametric test. Using the across-measure of market liquidity, we find that 2%, 0.3% and 0.7% of funds show significant positive liquidity timing in the US, UK and China, respectively. The US funds show more evidence of liquidity timing compared to funds in the UK and China. This may be due to different financial constraints faced by the mutual funds. Liquidity timing strategies are implemented by tactical asset allocation, derivatives, and rebalancing funds' equity holdings to adjust funds' exposure after anticipating bull or bear markets. There are fewer restrictions for US funds to use derivatives to short/long equities (Almazan et al., 2004; Chen et al., 2013)[16] while derivative securities are restricted for UK mutual funds since assets must be sufficient to cover any liabilities incurred by utilizing derivatives (Cuthbertson et al., 2010). In China, the use of derivative contracts is strictly restricted for mutual funds.

6. Conclusion

We use various liquidity proxies to measure market liquidity to avoid potential bias caused by specific liquidity measures. Our study applies the APCA method to form a latent factor of market liquidity across five liquidity measures. The latent (across-measure) market liquidity variable represents the systematic variation or commonality in liquidity across stocks and various liquidity measures. Therefore, it provides a proxy for overall market liquidity conditions by combining information from various measures. To our

[16] See Almazan et al. (2004), and Chen et al. (2013) for a discussion of the history of regulations on mutual fund short selling in the US mutual fund industry.

Table 14
China Mutual Fund Conditional Timing Performance.

	1 %	5 %	10 %	25 %	50 %	75 %	90 %	95 %	99 %
$\widetilde{z}$	−0.45	0.06	0.25	0.58	0.98	1.28	1.57	1.74	2.07
$\widetilde{\theta}_n$	−0.02	0.00	0.01	0.03	0.03	0.06	0.08	0.10	0.11
z	−0.35	−0.28	0.17	0.04	0.34	−0.89	−0.93	−0.06	0.37
t(1F)	2.01	−1.36	−0.02	−0.34	−0.19	−0.42	−0.01	−1.16	0.34
t(4F)	2.28	−1.52	0.02	−0.27	0.25	0.07	0.73	−0.39	1.06
Type	2	2	5	4	2	4	3	2	2
Dead	0	0	1	0	0	0	0	0	0
No. obs.	75	46	65	86	202	111	99	67	83

This table reports the values of conditional liquidity timing nonparametric z-statistics at percentiles in the cross-sectional distribution. Funds are sorted from lowest to highest based on the statistic, $\widetilde{\boldsymbol{z}} = \sqrt{\boldsymbol{n}}\widetilde{\boldsymbol{\theta}}_{\boldsymbol{n}}/\widetilde{\sigma}_{\widetilde{\theta}_{\boldsymbol{n}}}$, and column headings show the position of percentiles where funds are ranked in the distribution. Row 1 presents the nonparametric test statistic, using the across-measure of market liquidity. Row 2 shows the market timing coefficient $\widetilde{\theta}_{\boldsymbol{n}}$ corresponding to the funds sorted in row 1. Row 3 reports the unconditional liquidity timing test statistics, $\boldsymbol{z} = \sqrt{\boldsymbol{n}}\widehat{\boldsymbol{\theta}}_{\mathbf{n}}/\widehat{\sigma}_{\widehat{\theta}_{\boldsymbol{n}}}$ corresponding to the funds as sorted in row 1. Row 4 and row 5 present the Newey-West adjusted t-statistics of the single-factor (1F) conditional liquidity timing model and four-factor (4F) conditional liquidity timing model, respectively. Row 6 describes the fund categories: 1 = Large Blend fund, 2 = Large Growth fund, 3 = Medium Blend fund, 4 = Medium Growth fund, 5 = other fund, Row 7 describes whether the fund is dead or alive: 0 = alive, 1 = dead. Row 8 displays the number of monthly observations. The analysis covers 439 funds from 2000 M1 to 2021 M6 with a minimum of 36 monthly observations.

Table 15
China Cross-Section Distribution of Test Statistics for the Liquidity Timing Coefficients across Liquidity Measures.

	Nonparametric		1-factor		4-factor	
Market liquidity measures	$z \leq -1.65$	$z \geq 1.65$	$t \leq -1.65$	$t \geq 1.65$	$t \geq 1.65$	$t \geq 1.65$
Panel A: APCA						
Across-Measure	2.27	0.68	22.55	7.06	25.96	9.79
Quoted Spread	30.06	0.22	3.87	20.27	15.03	9.11
High-low Spread	15.71	0.91	5.23	12.52	7.28	23.46
Roll Spread	2.05	1.36	5.01	20.50	8.88	23.46
Amihud Impact	3.64	0.68	3.64	6.60	7.74	15.94
Turnover	19.36	0.45	21.64	6.60	28.70	6.37
Panel B: Cross-sectional average						
Quoted Spread	15.03	0.68	35.30	1.59	30.97	4.10
High-low Spread	0.00	3.87	12.52	18.67	12.30	25.51
Roll Spread	1.59	0.91	15.03	18.67	11.84	20.72
Amihud Impact	3.41	8.65	27.10	10.02	21.60	15.71
Turnover	39.40	0.45	21.18	11.84	25.51	12.30
PS	1.59	0.91	30.97	3.18	23.23	13.89

This table summarizes the distribution of the nonparametric liquidity timing test statistics, $\mathbf{z} = \sqrt{\boldsymbol{n}}\widehat{\boldsymbol{\theta}}_{\mathbf{n}}/\widehat{\sigma}_{\widehat{\theta}_{\boldsymbol{n}}}$ and two parametric liquidity timing tests t-statistics, $t = \widehat{\theta}_1/\widehat{\sigma}_{\widehat{\theta}_1}$. The table shows the percentage of test statistics exceeding the indicated cut-off values at a 5% significance level (one-tail test). Panel A shows the percentage of test statistics using the first principal component of each liquidity measure (within-measure) and the first principal component of latent market liquidity factors (across-measure) as market liquidity proxies, while Panel B presents the percentage of test statistics using the cross-sectional average of each liquidity measure as market liquidity proxies.

knowledge, our study is the first examination of liquidity timing using both nonparametric and APCA methods for a large sample of mutual funds from the US, UK, and China. Our results are robust in terms of sample size, timing frequency, liquidity measures, and underlying distributions.

In the unconditional test, we only find evidence of liquidity timing for a small number of funds in the US, UK and China. In terms of investment style, we find large funds tend to be more successful liquidity timers in all three countries. In terms of location, we do not find the underperformance of offshore funds due to geographical distance. The results for conditional tests vary across three countries. We find less evidence of conditional liquidity timing for US and UK equity funds at the individual fund level. There are fewer statistically significant conditional liquidity timers compared to the unconditional test. For China equity funds, we find some evidence of conditional liquidity timing due to private information compared with the unconditional test.

Evidence shows that live funds are more successful at liquidity timing in all three countries, suggesting market liquidity is critical to mutual fund managers' asset allocation decisions. Overall, our study of fund managers' liquidity timing ability suggests that mutual fund managers should consider market liquidity conditions when making asset allocation decisions.

CRediT authorship contribution statement

Zhengnan Yin: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Niall O'Sullivan:** Conceptualization, Methodology, Software, Supervision, Validation, Writing – review & editing. **Meadhbh Sherman:** Conceptualization, Investigation, Validation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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Appendix A. Liquidity measures

Quoted spread

The bid-ask spread has been widely used to measure stock market liquidity in the literature. Chung and Zhang (2014) suggest using the closing ask and bid prices to calculate quoted spread, which is known as the closing percent quoted spread. Fong et al. (2017) show that the closing percent quoted spread is the best liquidity proxy among percent-cost liquidity measures. For stock s in month t, it is given by

$$S_{s,t}^{close} = \frac{1}{n_{s,t}} \sum\nolimits_{d=1}^{n_{s,t}} \frac{Ask_{s,d} - Bid_{s,d}}{M_{s,d}} \tag{A1}$$

where $Ask_{s,d}$ is the closing ask price of stock s on day d, bid is the closing bid price of stock s on day d, and $M_{s,d}$ is the mid-price (mean) of $Ask_{s,d}$ and $Bid_{s,d}$, $n_{s,t}$ is the number of trading days in month t. We calculate the monthly quoted spread as the simple average of daily measures.

High-low spread

Corwin and Schultz (2012) develop a bid-ask spread estimator from daily high and low prices as the high-low price ratio reflects both the actual variance of the stock price and the bid-ask spread. It is easy and straightforward to calculate without a heavy computation burden.[17] The High-Low spread is shown to be an accurate estimator among liquidity proxies (Corwin & Schultz, 2012; Fong et al., 2017). For month t, the High-Low spread is given by:

$$S_{s,t}^{HL} = \frac{1}{n_{s,t}} \sum\nolimits_{d=1}^{n_{s,t}} \frac{2(e^{\alpha} - 1)}{1 + e^{\alpha}} \tag{A2}$$

The α, β, and γ values are obtained from daily high and low prices and defined as:

$$\alpha = \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}}$$

$$\beta = \sum\nolimits_{j=0}^{1} \left[ln\left(\frac{P_{d+j}^{H}}{P_{d+j}^{L}} \right) \right]^2$$

$$\gamma = \left[ln\left(\frac{P_{d,d+1}^{H}}{P_{d,d+1}^{L}} \right) \right]^2$$

Where P_d^H is the observed high price for stock s on day d and P_d^L is the low price for stock s on day d. $P_{d,d+1}^H$ and $P_{d,d+1}^L$ are the high price and the low price, respectively, over the two days d and $d + 1$.

[17] The sample SAS code for High-low spread is provide by Corwin and Schultz (2012) at https://sites.nd.edu/scorwin/research/.

Roll effective spread

Roll (1984) develops an estimator of the effective spread based on the serial covariance of the changes in daily stock prices P. Hasbrouck (2009) finds a high correlation between Roll spread (replacing the missing value with zeros) and effective spread computed from high-frequency Trade and Quote (TAQ) data.

The monthly estimate of the Roll spread, for stock s, is given by:

$$S_{s,t}^{Roll} = 2\sqrt{-Cov(\Delta P_d, \Delta P_{d-1})} \tag{A3}$$

There is a problem with this approach as it requires negative covariance in returns, which in practice holds only about half of the time. When the sample serial covariance is positive, the formula above is undefined with missing values, and so we substitute a default numerical value of zero, similar to Goyenko et al. (2009) and Hasbrouck (2009).

The modified version of the Roll estimator is:

$$S_{s,t}^{Roll} = \begin{cases} 2\sqrt{-Cov(\Delta P_d, \Delta P_{d-1})} & -Cov(\Delta P_d, \Delta P_{d-1}) < 0 \\ 0 & -Cov(\Delta P_d, \Delta P_{d-1}) \geq 0 \end{cases} \tag{A4}$$

Amihud impact

Amihud (2002) provides a measure of liquidity that attempts to capture the tendency that the price of illiquid assets tends to be more sensitive to trades, similar to Kyle's λ (Kyle, 1985).

$$Amihud_{s,t} = \frac{1}{n_{s,t}} \sum\nolimits_{d=1}^{n_{s,t}} \frac{|r_{s,d}|}{dvol_{s,d}} \tag{A5}$$

where $r_{s,d}$ and $dvol$ are stock return and the dollar volume on day d, respectively. $n_{s,t}$ is the number of valid days in month t.

Turnover

Turnover is widely used as a measure of liquidity in several studies (Stoll, 1978; Subrahmanyam, 2005). Turnover is defined as the number of shares traded divided by the shares outstanding as follows:

$$Turnover_{s,t} = \frac{1}{n_{s,t}} \sum\nolimits_{d=1}^{n_{s,t}} \frac{vol_{s,d}}{SO_{s,d}} \tag{A6}$$

where $vol_{s,d}$ is the trading volume of stock s on day d, $SO_{s,d}$ is shares outstanding on day d.

Pástor and Stambaugh (PS) gamma

Pástor and Stambaugh (2003) suggest using the following regression models to measure stock liquidity because illiquid stocks correspond to greater volume-related return reversals.

$$r_{s,d+1,t}^{e} = \theta_{s,t} + \phi_{s,t} r_{s,d,t} + \gamma_{s,t} sign\left(r_{s,d,t}^{e}\right) v_{s,d,t} + \epsilon_{s,d+1,t} \tag{A7}$$

The variables are defined as follows: $r_{s,d,t}^{e}$ is the stock's excess return of market on day d in month t; $r_{s,d,t}$ is the return on stock s on day d in month t; $v_{s,d,t}$ is the volume of stock s on day d in month t. $r_{s,d,t}^{e} = r_{s,d,t} - r_{m,d,t}$, where $r_{m,d,t}$ is the return on the benchmark portfolio (the value-weighted market return) on day d in month t. The return in excess of the market also plays a role in signing volume. The coefficient $\hat{\gamma}_{s,t}$ of signed volume ($sign\left(r_{s,d,t}^{e}\right) v_{s,d,t}$) is viewed as a proxy variable for liquidity. $\hat{\gamma}_{s,t}$ is expected to be negative when liquidity is lower.

Appendix B. Static and return screens

The data in this section are retrieved from Refinitiv Datastream, which provides constituent lists of predefined groups for all live and dead stocks. The download order of constituent lists is ranked as (1) Worldscope, (2) research lists, and (3) dead lists. This way helps avoid missing defunct codes that may be moved to the dead lists during download time.

According to Ince and Porter (2006), the Datastream data mainly has the following issues that may affect the accuracy of results: (i) the classification of equities (TYPE = EQ) includes not only common stocks (ordinary shares) but also includes equity of firm incorporated outside the located country, close-ended funds, real estate investment instrument (REITs), share of beneficial interest, traded partnership units, and ADRs; (ii) The return index is reported to 1–2 decimal digits, leading to substantial inaccuracies in calculated returns. This rounding error is significant when the absolute value is small. (ii) Data errors also exist for the data type, such as return index and price.

We select candidate stocks from the Datastream constituents lists built upon Ince and Porter (2006) and Schmidt et al. (2019) by employing the following static and dynamic security selection processes.

(1) We only keep issues listed as major securities and primary listing in case of cross-listing (MAJOR = Y and ISINID = P).
(2) We select issues that are located on the domestic market, listed on domestic exchanges to exclude any firms incorporated outside the located country and not traded on the domestic exchanges (For the US, GEOGEN = United States, EXMNEM = NYS, ASE, NAS, NMS. For the UK, GEOGEN = UK, EXMNEM = LON. For China, GEOGEN = CHINA, EXMNEM = SHG, SHE.).
(3) We only consider issues that refer to equities (TYPE = EQ) and are neither depository receipts nor preferred equity. We use equity names (NAME) to search for keywords or phrases that may indicate that security is not common equity. Following Campbell et al. (2010), we exclude security if the name record on Datastream includes one of the following codes that indicate it is not an ordinary share issue: CV, CONV, CVT, FD, OPC, VM, PREF, PF, PFD, PFC, PFCL, RIGHTS, RTS, UNIT, UNITS, WTS, WT, WARR, WARRANT, WARRANTS.

After applying the above static filter, we use all stocks left in the constituent list to download the relevant data to construct liquidity measures.

We calculate the returns of the individual stocks from price, dividends, and capital adjustment indices (CAI) to avoid the rounding problem with Datastream returns reported by Ince and Porter (2006). The CAI provides adjustments for stock splits and other capital events. The daily return is calculated from the following formula:

$$r_d = \frac{(P_d + Dividend_d)^* \frac{CAI_d}{CAI_{d-1}}}{P_{d-1}} \tag{B1}$$

We then calculated the returns from the total return index as it contains adjustments for dividends and price by default. We use the returns calculated from price data if the difference between the two returns is less than 0.01. In case of a difference in two returns greater than 0.01, we use the returns from the return index, similar to Schmidt et al. (2019). Schmidt et al. (2019) point out a slight difference between returns from the total return index and the return based on price data. Generally, the latter is more reliable because it improves numerical accuracy. However, in the case of significant differences, the return index may give more reliable values.

We also remove penny stocks whose price is below one to avoid the rounding problem, and we remove large return reversals and set returns that exceed 300 % to be missing. That is, if r_t or r_{t-1} is greater than 300 % and $(1 + r_t)(1 + r_{t-1}) - 1 < 50\%$, we set r_t and r_{t-1} to be missing.

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