### Accepted Manuscript

Title: Timing the liquidity in the Foreign Exchange Market: Did the Hedge Funds do it?

Author: Ji Luo Kai-Hong Tee Baibing Li



| PII:           | S1042-444X(17)30016-6                              |
|----------------|--|
| DOI:           | http://dx.doi.org/doi:10.1016/j.mulfin.2017.04.001 |
| Reference:     | MULFIN 523   |
| To appear in:  | J. of Multi. Fin. Manag.                           |
| Received date: | 22-2-2017  |
| Revised date:  | 28-3-2017  |
| Accepted date: | 1-4-2017   |

Please cite this article as: Luo, J., Tee, K.-H., Li, B., Timing the liquidity in the Foreign Exchange Market: Did the Hedge Funds do it?, *Journal of Multinational Financial Management* (2017), http://dx.doi.org/10.1016/j.mulfin.2017.04.001

This is a PDF file of an unedited manuscript that has been accepted for publication. As a service to our customers we are providing this early version of the manuscript. The manuscript will undergo copyediting, typesetting, and review of the resulting proof before it is published in its final form. Please note that during the production process errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

### Highlights

- The currency and systematic futures hedge funds have different liquidity timing skills
- Liquidity timing after the credit crisis is related to the implementation of the QE programs.
- Timing volatility in the FX market benefits systematic futures hedge funds more than the currency hedge funds.

1

#### Timing the liquidity in the Foreign Exchange Market: Did the Hedge Funds do it?

Ji Luo, Kai-Hong, Tee\* and Baibing, Li

School of Business and Economics, Loughborough University Loughborough LE11 3TU, UK

#### Abstract

Risks associated with international investments such as the foreign exchange (FX) exposure have recently gained increasing attention, especially those originating from the liquidity conditions of the FX market after the financial crisis of 2007-2008. This paper investigates whether hedge funds time the liquidity in the FX market and to what extent this contributes to their investment returns. This paper focuses on hedge funds that invest globally and transact in the FX market. Our findings, which are statistically robust, show the liquidity timing abilities of these hedge funds may be attributed to their investing styles and the types of assets they manage, where a stronger liquidity timing ability may be demanded of the systematic futures hedge funds to cushion against the exposure underlying the foreign assets.

Keywords: Foreign exchange market; hedge funds; liquidity timing ability

**JEL classification:** *G1; F3* 

\* Corresponding author, School of Business and Economics, Loughborough University, Loughborough, LE11 3TU, United Kingdom; tel. +44 1509 222156; email <u>k.tee@lboro.ac.uk</u>.

#### Timing the liquidity in the Foreign Exchange Market: Did the Hedge Funds do it?

#### Abstract

Risks associated with international investments such as the foreign exchange (FX) exposure have recently gained increasing attention, especially those originating from the liquidity conditions of the FX market after the financial crisis of 2007-2008. This paper investigates whether hedge funds time the liquidity in the FX market and to what extent this contributes to their investment returns. This paper focuses on hedge funds that invest globally and transact in the FX market. Our findings, which are statistically robust, show the liquidity timing abilities of these hedge funds may be attributed to their investing styles and the types of assets they manage, where a stronger liquidity timing ability may be demanded of the systematic futures hedge funds to cushion against the exposure underlying the foreign assets.

Keywords: Foreign exchange market; hedge funds; liquidity timing ability

JEL classification: G1; F3

#### 1. Introduction

This paper aims to investigate if liquidity timing ability in the FX market is a determinant of hedge funds' returns, an area of the financial market that has not been addressed in the literature. Instead, most of the existing studies have been focused on the equity and bond markets. There has been evidence of market return/volatility timing abilities found in these two markets, but they are not necessarily applicable to the FX market. First, the FX market is the world's largest financial market in terms of trading volume, and regarded as extremely liquid (Mancini, Ranaldo, Wrampelmeyer, 2013): its estimated average daily trading volume was 5.1 trillion U.S. dollars in April 2016 (Bank for International Settlements, 2016). Secondly, apart from being the largest financial market, the FX market is also observed to have a different liquidity pattern due to their unique characteristics based on the research of Kamaukh, et al (2015) which measures FX liquidity using intra-day data. It is therefore worth investigating if the timing abilities found in the equity and bond markets also exist in the FX market.

Third, specific to the FX market, recent findings by Hsu, Taylor, and Wang (2016) revealed that more successful FX traders' strategies consist of market timing skills alongside technical trade rules that give good timing inputs to enter and exit the FX market. An example in which timing strategy is used in the FX trading is the exploitation of the London 4 pm fix<sup>1</sup>; FX traders are known frequently to use this timing to determine upon the entry or exit from the FX market in order to profit from their trading<sup>2</sup>. This leads to the investigation of a related and important issue underlying the Quantitative Easting (QE) programmes implemented in various countries that inject huge liquidity into the

<sup>&</sup>lt;sup>1</sup> The London 4pm fix was set up in 1994 and run by WM Company and Reuters. It is the most popular benchmark used. It is made by taking an average of the exchange rate in currency trades 30 seconds before and after 4pm in the London market. The benchmark rate for a range of currencies—including major exchange rates like dollar-sterling, dollar-yen and dollar-euro—is used to value trillions of dollars of assets, and is the rate at which some big investors agree with their banks to exchange currencies to settle accounts at the end of every day. <sup>2</sup> See https://www.theguardian.com/business/2014/mar/12/forex-trader-closer-4pm-less-risk for an example of how the 4 pm fix may be exploited for profit by the FX traders.

financial markets after the financial crisis of 2007-2008. The impact on the interest rate differential and the specific underlying currencies pairs is an issue worth investigating as to how international investors would respond via timing the liquidity conditions in the FX market. This would be a more relevant approach as compared to focusing on the market return timing and volatility timing as documented in the literature that have been applied to the equity and bond markets.

Market timing is a topic that has been extensively researched in the academic literature. According to Admati, Bhattacharya, Pfleiderer and Ross (1986), the superior performance of an investment is due to either the manager's timing ability or selection ability or a combination of the two. The academic literature treats market timing as a type of dynamic asset allocation strategy that adjusts a portfolio's market exposure based on the manager's forecast about the market (Admati et al., 1986; Chen, 2007; Chen and Liang, 2007). Therefore, the managers with a timing ability can increase portfolios' market exposure before a market rise and decrease the portfolios' market exposure prior to a market fall.

Market timing models are based on the pioneering market return timing model of Treynor and Mazuy (1966). Busse (1999) documents that fund managers demonstrate the ability to time market volatility by increasing (reducing) the portfolio exposure when the market is less (more) volatile. Research on timing ability has also focused on hedge funds due to their relatively more dynamic investment style. Chen and Liang (2007) develop two models to investigate the joint timing ability of market returns and market volatility of hedge funds. Arising from the 2008 financial crisis which demonstrated the importance of understanding liquidity conditions to manage the market exposure of investments, researches such as Cao, Chen, Liang and Lo (2013), and Li, Luo and Tee (2017) have recently investigated the liquidity timing ability of hedge funds in the equity market and bond market respectively. Other researches in the literature that investigate the timing ability of hedge funds include French and Ko (2007) who examine whether long-short equity hedge funds exhibit market timing skills.

In this paper, we select the strategy style of hedge funds that mainly invest in global futures and options and transact in the FX market. These are known as the global derivatives hedge funds which focus mainly on either the currency or foreign derivative assets. Global derivatives hedge funds transact in the FX market and many funds treat currencies as an asset class (Nucera and Valente, 2013). This implies two potential sources of exposure, one from the FX market and the other from the underlying market of the derivative assets, if applicable to the strategies. Naturally, it becomes important to ask whether global derivatives fund managers who trade on a global scale are well equipped with the liquidity timing ability in the FX market when facing the liquidity risk exposure.

This paper is structured as follows. Section 2 briefly describes the market data and the liquidity measures. Section 3 discusses the main research hypotheses, empirical model and the main findings. Section 4 discusses the robustness tests and considers an alternative explanation, including investigating the liquidity timing ability using the bootstrap approach. Finally, Section 5 concludes the paper.

#### 2. Data

This section discusses the data used in the empirical analysis. This includes the hedge fund returns, factor data for hedge funds, and the liquidity measures of the FX market.

#### 2.1. Hedge funds

Hedge funds are investments using pooled funds. Hedge funds have various strategies which are constructed to take advantages of certain identifiable market opportunities. Hedge funds are classified into different categories based on their investment strategies and styles. We source the hedge fund

data from Morningstar<sup>3</sup> which classifies hedge funds into six broad strategy categories: 'Directional Equity', 'Directional Debt', 'Event', 'Global Derivatives', 'Multi-strategy', and 'Relative Value'. Each of these is further broken down into several sub-categories.

To investigate hedge funds' liquidity timing ability in the FX market, this paper considers only those hedge funds which invest globally and need to manage risks associated with the foreign asset classes, as well as the underlying foreign exchange exposure. Unlike other strategies in the Morningstar database, the hedge funds in the 'Global Derivatives' category invest mainly in the global markets with optimal global asset allocations where the FX market plays an important role. We therefore focus on this category of hedge fund strategy. The 'Global Derivatives' category includes four sub-categories of hedge funds strategies, i.e., 'Systematic Futures', 'Currency', 'Global Macro' and 'Volatility'<sup>4</sup>. In the empirical analysis we require each hedge fund included to have at least 24 monthly returns to obtain meaningful results<sup>5</sup>, following for example, Eling and Faust (2010),

<sup>&</sup>lt;sup>3</sup> Other data vendors are also used in the academic research on hedge funds, such as TASS and HFR. Each differs in terms of the number of funds available and the extent of survivorship bias, which is addressed in Section 5.1. Our empirical findings, based on data from Morningstar, are also further bootstrapped for validation purposes (see Section 5.3). It is beyond the scope of this paper to investigate and discuss the differences among the various hedge fund databases. However, interested readers are referred to Joenväärä *et al.* (2013) for more details.

<sup>&</sup>lt;sup>4</sup> Different data vendors use different ways to separate the strategies and styles of hedge funds. According to Morningstar (2014), funds in the 'Systematic Futures' sub-category trade liquid global futures, options, and foreign-exchange contracts largely according to trendfollowing strategies (such as linking greater than 50% of fund's exposure to such strategies). These strategies are price-driven (technical) and systematic (automated) rather than fundamental or discretionary. Trend-followers typically trade in diversified global markets, including commodities, currencies, government bonds, interest rates, and equity indexes. However, some trend followers may concentrate in certain markets, such as interest rates. These strategies prosper when markets demonstrate sustained directional trends, either bullish or bearish. Some 'Systematic Futures' strategies involve mean-reversion or counter-trend strategies rather than momentum or trend-following strategies. At least 60% of the funds' exposure is obtained through derivatives. Funds in the 'Currency' sub-category invest in portfolios of multiple currencies through the use of short-term money market instruments; derivative instruments, including and not limited to, forward currency contracts, index swaps and options, and cash deposits. These funds include both systematic currency traders and discretionary traders. Funds in the "Global Macro" sub-category base investment decisions on an assessment of the broad macroeconomic environment. They look for investment opportunities by studying such factors as the global economy, government policies, interest rates, inflation, and market trends. As opportunists, these funds are not restricted by asset class and may invest across such disparate assets as global equities, bonds, currencies, derivatives, and commodities. These funds primarily invest through derivatives markets. They typically make discretionary trading decisions rather than using a systematic strategy. At least 60% of the funds' exposure is obtained through derivatives. Funds in the "Volatility" sub-category trade volatility as an asset class. Directional volatility strategies aim to profit from the trend in the implied volatility embedded in derivatives referencing other asset classes. Volatility arbitrage seeks to profit from the implied volatility discrepancies between related securities.

<sup>&</sup>lt;sup>5</sup> The arguments about sufficient history (as a sampling requirement) that a fund must have before it can lead to bias are mixed. In the literature, the duration for the sampling requirement varies. For example, Fung and Hsieh (1997) require 36 months of return history before including a fund in their empirical study, whereas Ackermann, McEnally and Ravenscraft (1999) require funds to have 24 months of return

Stefanova and Siegmann (2012) and Li et al. (2017). In addition, following the previous hedge-fundfocused literature (Chen 2007; Aggarwal and Jorion, 2010; Stefanova and Siegmann, 2012; Cao et al., 2013), we include only hedge funds with no less than 10 million dollars of assets under management (AUM).

As the euro was introduced on January 1, 1999, the time period of this study is chosen from January 1999 to December 2012 so that we are able to investigate the FX market after the launch of the euro. This also covers the recent financial crisis period so that we can investigate the impact of the financial crisis on hedge funds' liquidity timing. Summary statistics of the returns of the 'Global Derivatives' hedge funds are provided in Panel A, Table 1.

In this paper, hedge fund returns in the 'Global Derivatives' category are examined using an FX market factor, i.e. the change in the trade-weighted U.S. dollar exchange rate index (see Boyson, Stahel and Stulz, 2010). This trade-weighted U.S. dollar exchange rate index is published by the Board of Governors of the U.S. Federal Reserve System. To control for other factors for hedge funds, the factors in the seven-factor model proposed by Fung and Hsieh (2004)<sup>6</sup> are used in the paper.

Panel B of Table 1 shows a statistical summary for Fung and Hsieh's seven factors and the FX market factor. For example, the average equity market excess return during the sample period is 0.155% per month with a standard deviation of 4.568%.

[Table 1]

history for inclusion in their tests. There is evidence that this bias, if it exists, is very small (Fung and Hsieh, 2000). Other forms of data bias are discussed in Section 5.1.

<sup>&</sup>lt;sup>6</sup> The seven factors include both linear and option-like factors, and have been shown to explain variation in hedge fund returns well. Specifically, these factors include an equity market factor, a size factor, changes in the constant maturity yield on 10-year Treasury bonds, change in the spread between Moody's Baa and 10-year Treasury bonds, and three trend-following factors for bonds, currency, and commodities. These are available from <a href="http://faculty.fuqua.duke.edu/~dah7/HFRFData.htm">http://faculty.fuqua.duke.edu/~dah7/HFRFData.htm</a> and we thank the providers for these data.

#### 2.2. Liquidity measures

There is a large number of liquidity measures developed in the literature. Following Goyenko, Holden and Trzcinka (2009) and Mancini et al. (2013), these liquidity measures are classified into two broad categories: (a) price-impact based liquidity measures; and (b) spread-based liquidity measures. We first discuss the price-impact based liquidity measures.

Kyle (1985) argues that the price impact measures how much an order flow can induce the exchange rate changes. A higher price impact indicates more changes in the exchange rates, which reflects a lower level liquidity in the FX market. According to Campbell, Grossman and Wang (1993), a part of the price impact on an illiquid currency is temporary because the pressure from net selling (buying) to the currency can lead to excessive appreciation (depreciation), which is followed by a price reversal to its fundamental value. Mancini et al. (2013) consider several liquidity measures that include price impact, return reversal, trading cost, and price dispersion.

In the literature, some researchers adopt the price impact measure of Pastor and Stambaugh (2003) to model the liquidity in the FX market (Banti and Phylaktis, 2012; Banti, Phylaktis and Sarno, 2012; Menkhoff, Sarno, Schmeling and Schrimpf, 2012). The liquidity measure in Pastor and Stambaugh (2003) is based on price reversals, indicating that a lower liquidity level in the FX market means a larger price impact caused by order flow in the market.

Next, we consider spread-based liquidity measures. A widely used spread-based liquidity measure is the proportional quoted bid-ask spread (see, e.g., Kessler and Scherer, 2011; Mancini et al. 2013; Ding and Hiltrop, 2010). This measure gives an indication of the costs for the immediate sale of an asset and is calculated as:

$$L^{(ba)} = \frac{\left(P^A - P^B\right)}{P^M},\tag{1}$$

where  $P^A$  and  $P^B$  denote the ask and bid prices, respectively, and  $P^M$  is the mid quote equal to  $\frac{(P^A + P^B)}{2}$ . See, for example, Ates and Wang (2005), Kaul and Stefanescu (2011), Kessler and Scherer (2011), Banti and Phylaktis (2012), Menkhoff et al. (2012) and Wrampelmeyer (2012) in which bid and ask prices are used to measure the liquidity in the FX market. There are several variants of the bid-ask spread in the literature.

In this paper, considering the data availability and the ease of interpretation, we follow Kessler & Scherer (2011) and Karnaukh et al. (2015), and use the bid-ask prices to compute the illiquidity measure in the FX market based on Eq. (1). The market liquidity measure is taken as the negative illiquidity. More specifically, the liquidity measure  $L_{FX,t}$  in the FX market at each time period t is based on Eq. (1) aggregated across the n currencies under investigation as follows:

$$L_{FX,t} = -\frac{1}{n} \sum_{i=1}^{n} L_{t,i}^{(ba)}, \qquad (2)$$

where  $L_{i,i}^{(ba)}$  is the proportional quoted bid-ask spread for currency *i* at each time period *t* in Eq. (1).

The liquidity measure in the FX market defined in Eq. (2) is computed using a basket of *n* currencies. For consistency check, we choose three baskets of currencies in the empirical analysis to calculate the FX market liquidity. First, following the existing literature, we choose a basket containing 10 currencies against the U.S. dollar (USD), including Australian dollar (AUD), British pound (GBP), Canadian dollar (CAD), Danish krone (DKK), euro (EUR), Japanese yen (JPY), New Zealand dollar (NZD), Norwegian krone (NOK), Swedish krona (SEK), and Swiss franc (CHF) (see, for example, Menkhoff et al., 2012). The calculated liquidity measure is denoted as Liquidity (10) in this paper. The second currency basket contains G10 currencies comprising AUD, CAD, CHF, EUR, GBP, JPY, NOK, NZD, SEK, and USD (Jurek, 2008; Farhi, Fraiberger, Gabaix, Ranciere and Verdelhan, 2013); the obtained liquidity measure based on this basket is denoted as Liquidity(G10).

The final liquidity measure, Liquidity (6), is calculated using a basket with six major currencies that include AUD, CAD, CHF, EUR, GBP and JPY (Froot and Ramadorai, 2005).

In the subsequent empirical analysis, the daily bid-ask prices for all the currencies are sourced from Thomson DataStream and are used to calculate the above liquidity measures in the FX market. The monthly liquidity measures in the FX market are calculated as the negative average of daily bid-ask spreads within each month. Panel C of Table 1 shows the summary statistics of the FX market liquidity measures calculated for the empirical analysis. It can be seen that the three FX market liquidity measures in Table 1 have similar statistics.

#### 3. Research hypotheses and main results

In this section, we investigate whether hedge fund managers time the liquidity of the FX market. Very little research on timing has been done for the FX market in the literature. Instead, most have been focused on the equity market (such as Cao, et al. (2013)) and the bond market (such as Li, et al. (2017)). The FX market is the world's largest financial market and is even regarded as extremely liquid (Mancini et al., 2013). It is very relevant to apply to the case of international investors and investigate if they time the liquidity in this huge and extremely liquid market. Considering the degree of risk aversion and the relatively aggressive styles of trading, we tentatively hypothesize that those hedge funds that invest globally and transact in the FX market have the ability to time the liquidity in the FX market. We address this hypothesis in Sections 3.2 and 3.3 by statistically testing them at both the strategy and individual fund levels.

Our second research question concerns with the impact of the recent financial crisis and the subsequent quantitative easing (QE) programmes on hedge funds' liquidity timing behaviour in the FX market. The QE programmes in various countries have injected huge liquidity into the financial markets since the financial crisis of 2007-2008. We tentatively hypothesize that the hedge fund

managers behaved differently in timing the liquidity of the FX market since the financial crisis and this issue will be addressed in Section 3.4.

In addition to the above, our study also compares the different styles of hedge funds and their timing abilities and we ask the following questions: (a) do these different strategy styles exhibit similar liquidity timing abilities in the FX market? (b) do these different strategy styles also time the market volatility and market return, apart from liquidity timing? These research questions will be analysed in sections 3.4 and 3.5.

#### 3.1. Model for testing liquidity timing in the FX market

We investigate whether global derivatives hedge fund managers time the liquidity of the FX market by adjusting hedge funds' exposure to the FX market based on managers' forecasts of future FX market liquidity conditions. Following the timing ability model in the literature (Treynor and Mazuy, 1966; Merton, 1981; Admati et al., 1986; Shanken, 1990), the beta  $\beta_{p,t}$  of a fund or category p in time period t is modelled as a linear function of fund managers' expected market conditions, i.e.  $\beta_{p,t} = \beta_p + \lambda_p E(market condition_{t+1}|I_t)$ , where  $\beta_p$  captures the funds' average beta without timing,  $I_t$  is the market information set available to the fund manager in time period t, and  $\lambda_p$  is the timing coefficient. When the market liquidity condition is used to forecast the beta in the liquidity timing problem, we have

$$\boldsymbol{\beta}_{p,t} = \boldsymbol{\beta}_p + \lambda_p \left( \boldsymbol{L}_{M,t+1} - \boldsymbol{\bar{L}}_M + \boldsymbol{\upsilon}_{p,t+1} \right), \tag{3}$$

where  $L_{M,t+1}$  denotes the liquidity level of the market in period t+1 with an average of  $\overline{L}_{M}$ . As it is unrealistic for a timer to have a perfect signal,  $v_{p,t+1}$  represents a zero-mean forecast noise, unknown until period t+1. Note that following the market timing literature (e.g., Ferson and Schadt, 1996;

Busse, 1999), the manager's signal is de-meaned by subtracting  $\overline{L}_M$  for ease of interpretation. The expression in the parentheses represents the managers' forecast signal using the market liquidity. The coefficient  $\lambda_p$  measures hedge fund managers' liquidity timing ability in the market under investigation. A positive value of  $\lambda_p$  indicates that a hedge fund manager has liquidity timing skills by increasing (decreasing) the hedge fund's exposure to the market prior to the rise (fall) of the market liquidity.

This paper focuses on the FX market. To capture the movement of the FX market, we follow Boyson et al. (2010) and use a FX market factor  $FXF_t$  at each time period t that is defined to be the change in the trade-weighted U.S. dollar exchange rate index published by the Board of Governors of the U.S. Federal Reserve System.

In addition, to control for the other effects, we also consider a widely used model in the literature for assessing hedge fund performances, i.e. the seven-factor model proposed by Fung and Hsieh (2004). Hedge funds usually invest in derivatives and a number of other markets (e.g. equity, bond, commodity, etc.) and use dynamic trading strategies (Fung and Hsieh, 1997, 2001; Mitchell and Pulvino, 2001). Correspondingly the seven factors include the equity market factor, the size spread factor, the bond market factor, the credit spread factor, the bond trend-following factor, the currency trend-following factor and the commodity trend-following factor. Hence, we consider the following eight-factor model:

$$r_{p,t+1} = \alpha_p + \beta_{p,t} F X F_{t+1} + \sum_{j=1}^{7} \gamma_j f_{j,t+1} + \varepsilon_{p,t+1}, \qquad (4)$$

where  $r_{p,t+1}$  is the excess return of hedge fund p in time period t+1.  $f_{j,t+1}$  (j=1...7) stand for the seven factors in Fung and Hsieh (2004)'s seven-factor model.  $\varepsilon_{p,t+1}$  denotes the error term in period t+1.

For the FX market, Eq. (3) is re-written as  $\beta_{p,t} = \beta_p + \lambda_p \left( L_{FX,t+1} - \overline{L}_{FX} + v_{p,t+1} \right)$ , where  $L_{FX,t+1}$  denotes the liquidity level in the FX market in period t+1 and  $\overline{L}_{FX}$  is the average FX market liquidity level. Substituting this equation into (4) and including the forecast noise  $v_{p,t+1}$  within the error term, we obtain the following liquidity time model:

$$r_{p,t+1} = \alpha_p + \beta_p F X F_{t+1} + \lambda_p F X F_{t+1} \left( L_{FX,t+1} - \overline{L}_{FX} \right) + \int_{j=1}^{t} \gamma_j f_{j,t+1} + \varepsilon_{p,t+1}.$$
(5)

Clearly, by controlling for the seven factors in Eq. (5), we can estimate the timing ability coefficient  $\lambda_p$  more accurately.

With the above eight-factor-based liquidity timing model, we will test hedge fund managers' liquidity timing ability in the FX market based on the timing ability coefficient  $\lambda_p$  in the next sections.

#### 3.2. Liquidity timing test at the category level

To gain a full picture about the liquidity timing ability of the global derivatives hedge funds, we first pool all the hedge funds of the four strategy sub-categories in 'Global Derivatives'—that is, 'Currency', 'Systematic Futures', 'Global Macro', and 'Volatility'—to investigate the average liquidity timing ability across the entire 'Global Derivatives' category. As previously argued, global derivatives hedge funds transact in the FX market and may treat currencies as an asset class. Liquidity in the FX market is in general important to these funds. We therefore hypothesize that, overall, the global derivatives hedge funds have liquidity timing ability in the FX market.

To test this hypothesis, we perform an empirical analysis based on the liquidity timing model, Eq. (5), where the FX market liquidity is measured by Liquidity (10). The results, as reported in the

second column of Panel A in Table 2, show that, after controlling for the seven factors, the liquidity timing coefficient  $\lambda_p$  is positive and significant at the 1% significance level. This implies that, on average, the 'Global Derivatives' hedge fund managers use the FX market liquidity condition as input to forecast the FX market beta and adjust exposure in the globally focused market.

To check for consistency, we repeat the analysis with the other two liquidity measures, i.e. Liquidity (G10) and Liquidity (6), as displayed in Panels B and C of Table 2. We can see that the results in Panels B and C are consistent with those shown in Panel A. The test for the liquidity timing ability of the global derivatives hedge funds is therefore not dependent on the choice of the liquidity measure of the FX market. In summary, the statistical test confirms that, although the FX market is in general considered to be extremely liquid, there is evidence indicating that the global derivatives hedge funds did time the liquidity of the FX market.

Next we take a closer look at the four sub-categories of the 'Global Derivatives' hedge funds, i.e. 'Systematic Futures', 'Currency', 'Global Macro' and 'Volatility'.

Hedge fund managers in each of these four sub-categories make investment decisions based on different strategies and instruments; therefore, it is expected these hedge fund managers in different sub-categories to have different liquidity timing abilities. In particular, the managers in the 'Volatility' sub-category mainly treat volatility as asset class and attempt to profit from, for example, the trend underlying the implied volatility discrepancies between related securities for volatility arbitrage strategies<sup>7</sup>. The strategy of this sub-category is therefore largely concentrated on exploiting volatility patterns, rather than capturing the market liquidity. In addition, the managers in the 'Global Macro' sub-category base their investment decisions on the assessment of the broader macro-economic environment by studying factors such as the global economy, government policies, interest rates, inflation, and market trends, where the liquidity condition could be one of the trends, but unlikely to

<sup>&</sup>lt;sup>7</sup> Sources drawn from Morningstar (2014)

be the main focus of the strategy. We therefore formulate a hypothesis that, overall, the managers in the 'Volatility' and 'Global Macro' sub-categories do not implement liquidity timing in the FX market.

In contrast, the hedge fund managers in the 'Currency' strategy sub-category invest currency portfolios in multiple currencies through the use of short-term money market instruments, derivative instruments, and cash deposits. It is not uncommon for hedge fund to invest currency mainly as an asset class as research reported in Nucera and Valente (2013) shows that the currency hedge funds heavily involved in the money market and exploited on carry trades to generate returns. On the other hand, the managers in the 'Systematic Futures' strategy sub-category trade liquid global futures, options, and foreign-exchange contracts largely according to trend-following strategies. Hedge funds in both sub-categories involve various technical analyses. We therefore formulate a hypothesis that overall the managers in the 'Currency' and 'System Futures' sub-categories do implement liquidity timing in the FX market.

To test the above two hypotheses, we perform empirical analysis for each of the four subcategories. The results of the analysis are reported in columns 3 to 6 of Panel A in Table 2. We can see that there are indeed great differences among the four individual sub-categories in terms of their liquidity timing ability. Controlling for the seven factors, we find that the liquidity timing coefficients  $\lambda_p$  is significantly positive at the 1% level for the 'Currency' and 'Systematic Futures' strategy subcategories. However, the timing ability coefficient for the 'Global Macro' and 'Volatility' strategy sub-categories are not significant at the 1% significance level. We repeat the analysis with the Liquidity (G10) and Liquidity (6) measures with consistent results, as displayed in Panels B and C of Table 2.

From the above empirical analysis, the sub-categories 'Currency' and 'System Futures' show very strong liquidity timing ability in the FX market. On the other hand, there is not enough evidence

to support that the 'Global Macro' and Volatility' sub-categories time the market liquidity; the liquidity timing ability coefficient for the 'Global Macro' sub-category is only significant at the 10% significance level with Liquidity(10) and Liquidity(G10), but not significant even at the 10% level with Liquidity(6). Hence, overall the empirical analysis supports both hypotheses regarding these four sub-categories.

#### [Table 2]

#### 3.3. Liquidity timing test at the individual fund level

The findings from the previous sub-section reveal evidence of the liquidity timing ability at the aggregate strategy level in the FX market. To further substantiate these findings, we now investigate if the global derivatives hedge funds also acquire liquidity timing ability at the individual fund level.

### [Table 3]

Specifically, we estimate the regression coefficients using Eq. (5) for each fund in the 'Currency' and 'Systematic Futures' sub-categories, as well as the 'Global Derivatives' category. The null hypothesis of  $\lambda_p = 0$  is tested and the corresponding t-statistic is calculated for each fund p. Table 3 displays the distribution of the t-statistics for the individual hedge funds' liquidity timing coefficient, where the numbers in the table are the percentage of hedge funds with the t-statistics of the liquidity timing coefficient that exceeds the indicated values. For example, 21.5% of the 'Global Derivatives' hedge funds have a t-statistic of the estimated liquidity timing coefficient that is greater than 1.96. In general, Table 3 shows that a substantial portion (about 40%) of hedge funds is associated with a t-statistic of the liquidity timing coefficient greater than 1.28. This provides some evidence of liquidity timing skills at the individual fund level.

We also note from Table 3 that some hedge funds have t-statistics smaller than -1.28, implying that these hedge funds exhibit negative liquidity timing ability. As discussed in Cao et al. (2013), it is difficult to interpret a negative liquidity timing coefficient which suggests that fund managers adjust portfolios' market exposure in the opposite direction to the direction used by those managers with successful liquidity timing skills. We can see from Table 3, however, that the right tails of the distribution of t-statistics are much thicker than the left tails.

#### 3.4 Impact of the recent financial crisis on liquidity timing

Liquidity played an important role in the recent financial crisis (see, e.g., Lou and Sadka, 2011; Fahlenbrach, Prilmeier and Stulz, 2012). To evaluate if there is any impact of the recent financial crisis on the liquidity timing behaviour of hedge funds' managers, we compare the findings on the managers' liquidity timing ability in the time period before the recent financial crisis (January 1999 – July 2007) with the period since August 2007, where the period is chosen based on those in the literature (see, e.g., Ben-David, Franzoni and Moussawi, 2012).

Table 4 presents the comparison results for the before/after financial crisis periods. First, we note that the obtained results reaffirm the liquidity timing skills of the 'Global Derivatives' hedge funds since August 2007 at the 1% significance level, whereas in the pre-financial period there is no evidence of liquidity timing skills at the 1% significance level for the 'Global Derivatives' hedge funds as a whole. This suggests that the managers of 'Global Derivatives' hedge funds have paid more attention to the FX market liquidity condition since the recent financial crisis.

Next, Table 4 suggests that hedge fund managers in both 'Currency' and 'Systematic Futures' strategy sub-categories show stronger liquidity timing ability in the period since August 2007 than the pre-financial crisis period: (a) the liquidity timing coefficient for the 'Systematic Futures' sub-category is significant at the 1% significance level in the period since August 2007, whereas it is not significant at the 1% significance level prior to the recent financial crisis; and (b) for both 'Currency'

and 'Systematic Futures' strategy sub-categories, the liquidity timing coefficient is larger in the period since August 2007, compared to those prior to the recent financial crisis.

These findings also imply that liquidity timing skills exist prior to the financial crisis for some funds and it was further shown to be also present during the post crisis period. This is true for the currency hedge funds, but strong evidence of timing ability only exists in the post crisis period for the systematic future hedge funds.

Finally, we offer some further comments on liquidity timing. The liquidity of the FX market, in relation to its operational function such as the 4 pm fix, presents good opportunities for timing the market profitably. For example, FX traders/brokers may break down large orders into smaller chunks to control for trading volume subject to the market liquidity and then to time it appropriately so that the effects on price and profitability would not be huge as the time drew nearer to 4 pm. This is more so if currency is treated as an asset class and applicable to the currency hedge funds. In the case of the systematic future hedge funds, we observe a weaker evidence of timing prior to the financial crisis period. As the assets underlying the systematic futures hedge funds are those consisting of global options and futures markets, there may be joint timing strategies targeting at both the FX and the underlying derivative markets<sup>8</sup>. This may have resulted in the concentration and the degree of involvement in the FX market to be different to that of the currency hedge funds, resulting in weaker evidence prior to the recent financial crisis.

As for the post crisis period, following the several episodes of QE from various countries and in different periods, this provided opportunities to observe liquidity in the FX market to time for entry and exit points for profit making opportunities. In the post financial period, both the U.S. and the U.K. implemented their respective QE programmes. The QE is a form of credit creation that inject liquidity to the financial market, aiming at putting downward pressure on the interest rate moving forward;

<sup>&</sup>lt;sup>8</sup> Li, et al (2017), for example, has found evidence supporting joint liquidity timing across the equity and bond markets for the debt-oriented hedge funds

hence it caused predictable changes in the interest rate differentials among the many currency pairs in trading, particularly those that were U.S.- and U.K.-based currency pairs. This explains the importance of timing the QE programmes as an appropriate strategy since such programs include not only one-off plan to purchase securities, but also regular ones to make securities purchases in subsequent periods<sup>9</sup>. This may provide good profit opportunities by appropriately timing the liquidity condition and reveal relatively stronger results even for the systematic futures hedge funds in the post crisis period. This shows that the implementation of the QE programmes might have an effect on their involvements and the execution of liquidity timing strategies in the FX market.

#### [Table 4]

#### 3.5 *Effects on return timing and volatility timing*

Hedge fund managers may use a sophisticated set of timing strategies to hedge risks in financial markets (see, e.g. Chen and Liang, 2007; Li et al. 2017). In this section, we extend model (5) to test if the hedge fund managers in the 'Currency' and 'Systematic Futures' sub-categories also use other timing skills such as return and volatility timings. This analysis also serves a robustness check to investigate if the liquidity timing ability revealed in the previous section can be attributed to the return timing and volatility timing.

In the literature, there is some evidence that the FX market liquidity has positive relation with FX market returns and negative relation with FX market volatility (Berger, Chaboud and Hjalmarsson, 2009; Melvin and Taylor, 2009; Bubak, Kocenda and Zikes, 2011; Danielsson and Payne, 2012;

<sup>&</sup>lt;sup>9</sup> The U.S. QE3 in 2012 led to some market speculations in 2013 following further plans to purchase securities later the year as announced in June 2013. This occurred as the market started to speculate the timing of the "tapering" of the asset purchased to be made by the U.S. Fed. Market sources such as those reported in the FT (Strauss, D. "Forex trading shrinks sharply in dismal end to 2013". Financial Times. 7 January 2014) revealed that the wrong interpretation of the timing had led to suffering of losses arising from wrongly betting the direction of the FX market. Both the systematic currency and discretionary hedge funds were affected, and had even led to the collapse of "FX concept" in the last quarter of 2013. Furthermore, the trading volume in the FX market was also affected by the continued probe into the suspected cases of manipulation of the benchmark rates in the U.K. It was also noted that the average daily trading volumes at ICAP, the world's biggest interdealer broker, fell to \$71bn in December 2013, a 23 percent drop from the same month in 2012 and the lowest level since ICAP bought its currency trading business EBS in 2006.

Menkhoff et al., 2012; Mancini et al., 2013). Hedge fund managers may have the skills to time the FX market returns or volatility. Thus, managers' liquidity timing skills could partially reflect their ability of timing returns or volatility. To investigate this possibility, we control for the FX market returns and volatility timing skills and extend Eq. (5) as follows:

$$r_{p,t+1} = \alpha_p + \beta_p F X F_{t+1} + \lambda_p F X F_{t+1} \left( L_{FX,t+1} - \overline{L}_{FX} \right) + \varphi_p F X F_{t+1}^2$$
$$+ \theta_p F X F_{t+1} \left( Vol_{FX,t+1} - \overline{Vol}_{FX} \right) + \int_{j=1}^J \gamma_j f_{j,t+1} + \varepsilon_{p,t+1}, \qquad (6)$$

where  $Vol_{FX,t+1}$  is the realized FX market volatility in time period t+1, which is calculated as the standard deviation of daily market returns in period t+1, and  $\overline{Vol}_{FX}$  is the mean value of the FX market volatility.  $\varphi_p$  and  $\theta_p$  denote the return timing coefficient and volatility timing coefficient respectively.

Table 5 reports the results on liquidity timing skills in the FX market after controlling for the FX market return timing and volatility timing. All the estimates of the liquidity timing coefficient  $\lambda_p$  are statistically significant at the 1% level and thus it strongly supports that these hedge fund managers have liquidity timing skills in the FX market. Therefore, the managers' liquidity timing ability cannot be fully attributed to the positive link between the FX market liquidity and returns or the negative connection between FX market liquidity and volatility. The results of successful liquidity timing skills in Table 5 emphasize that timing FX market liquidity is important for hedge funds' professional portfolio management.

#### [Table 5]

Interestingly, the results in Table 5 also show some evidence that the managers in the 'Systematic Futures' style have volatility timing ability; the volatility timing coefficient  $\theta_p$  is significant at the

5% level. However, this is not the case for the 'Currency' style. This could be due to the reason that the former trades in diversified global markets where volatility differs in different markets (e.g. commodities, bonds, equity indexes, etc.), whereas the latter focuses on money market only. In this case, the 'Systematic Futures' hedge funds may time volatility of the FX market to cushion against volatility exposure underlying the foreign derivative assets.

#### 4. Robustness checks and alternative explanation

This section consolidates the main findings by undertaking various robustness checks. Specifically we will: (a) check robustness against data bias and funds' size; (b) explore an important alternative explanation and investigate if the market liquidity revealed in the previous sections can be attributed to other factors such as funding constraints; and (c) investigate statistical robustness.

#### 4.1 Robustness against data bias and funds' size

Hedge fund data sold by database vendors may potentially contain biases which must be carefully examined. This section discusses and addresses the impact of two important types of data bias, i.e. survivorship and backfilling biases, and also examines the size effect.

First, we follow the literature and include both live and defunct funds in all the analyses throughout this study. It is clear that, if funds exit the database mainly due to poor performances, the inclusion of defunct funds is necessary to mitigate this survivorship bias.

The backfill bias<sup>10</sup> arises because a hedge fund could backfill its historical performance when it is added to a database. To address this bias, we follow Avramov, Kosowski, Naik and Teo (2011), Fung and Hsieh (2000, 2011), and Cao et al. (2013), and discard hedge funds' first 12 months of returns considering backfill effects. We re-analyse the problem and display the obtained results in Table 6.

<sup>&</sup>lt;sup>10</sup>Other biases such as selection bias are difficult to examine because we do not observe funds that choose not to report to any database. Nevertheless, the literature (e.g. Fung and Hsieh, 1997; Agarwal, *et al* 2013) shows evidence that the selection bias could be limited.

It can be seen from Table 6 that for hedge fund managers in both 'Currency' and 'Systematic Futures', as well as for the whole 'Global Derivatives' category, the liquidity timing coefficient is significant at the 1% level. This indicates that fund managers in these sub-categories have liquidity timing ability in the FX market. Hence, after controlling for the backfill bias, the findings are consistent with those obtained in Table 2.

Care must be taken, however, when reading the results in Table 6. Because the analysis here requires all funds to have at least 24 monthly returns after their backfill periods, it tilts the sample towards funds with longer histories. This leads to excluding younger funds and funds with short histories from the analysis.

#### [Table 6]

We now test the effect of hedge funds' size on market liquidity. There is a concern that the liquidity timing discovered in the previous sections is mainly driven by the impact of large funds' trading in the market. In order to reduce the effect of large trades on the FX market liquidity timing, we investigate two smaller hedge fund subgroups, one with AUM less than \$150 million and the other with AUM less than \$50 million respectively, where according to the regulation of the Dodd-Frank Wall Street Reform and the Consumer Protection Act of 2010, hedge funds with AUM of at least \$150 million are considered to be large. We use this criterion to differentiate large size and small size hedge funds.

#### [Table 7]

Panels A and B of Table 7 display the liquidity timing coefficient for hedge funds with AUM less than \$150 million and \$50 million respectively. It can be seen that hedge funds under investigation show successful liquidity timing skills in the FX market in both cases where all the liquidity timing

coefficients are significant at the 1% significance level. This indicates that hedge fund managers' successful liquidity timing ability in the FX market is not driven by the funds' size.

#### 4.2. Funding constraints: an alternative interpretation

In this sub-section, we explore whether the liquidity timing ability revealed in the previous sections has an alternative interpretation.

Our main concern is about the effect of market financing condition on the operation, performance and the timing ability of the hedge funds. In this case, funding liquidity may drive hedge fund managers' liquidity timing ability in the FX market. The prime brokers normally use short-term funding to provide leverage to hedge funds. However, hedge funds can be forced to liquidate their assets' positions by sudden margin calls. During a liquidity crisis period, these forced liquidations could happen to many hedge funds simultaneously. Due to the destabilization of margins, funding liquidity and market liquidity of the assets can be mutually reinforcing during market liquidity shocks, leading to liquidity spirals (Brunnermeier and Pedersen, 2009). It is possible that the hedge funds' reduction of FX market exposure during liquidity crisis periods is caused by the increase of borrowing costs or cutting of funding by prime brokers, which potentially leads to the reduction in the foreign derivative assets' investments, in the case of the global derivatives hedge funds, and may impact upon the timing ability.

Now, we investigate the impact of market funding constraints on hedge fund investors. To control for the impact of market funding constraints, we use the TED measure, which is the difference between the three-month London Interbank Offered Rate (LIBOR) and the three-month Treasury bill rate (Brunnermeier et al., 2008; Banti and Phylaktis, 2012; Menkhoff et al., 2012; Nucera and Valente, 2013). The TED spread reflects the market perceived counterparty default risk and a wider TED spread indicates an increase of counterparty default risk. This may impact upon the cost that the prime

broker would charge when providing higher borrowing leverages to the hedge funds. To take into consideration the impact of TED spread, we modify Eq. (5) as:

$$r_{p,t+1} = \alpha_p + \beta_p FXF_{t+1} + \lambda_p FXF_{t+1} \left( L_{FX,t+1} - \overline{L}_{FX} \right)$$
$$+ \varphi_p FXF_{t+1}TED_{t+1} + \sum_{j=1}^7 \beta_j f_{j,t+1} + \varepsilon_{p,t+1},$$

where  $TED_{t+1}$  is the TED spread in month t+1.

Table 8 reports the estimated liquidity timing coefficients considering the effect of funding constraints. We find that all the estimates of the liquidity timing coefficient are statistically significant at the 1% significance level, which is consistent with the findings in Table 2. Hence, the evidence of successful liquidity timing ability does not change after controlling for the effect of TED spread.

#### [Table 8]

#### 4.3. Statistical robustness: bootstrap analysis

This subsection conducts bootstrap<sup>11</sup> analysis for the main findings reported in Sections 3.2 and 3.3. The results obtained in Sections 3.2 and 3.3 depend on the normality assumption which may not be valid for some hedge returns. To address this issue, we carry out bootstrap analysis where the normality assumption is removed.

More specifically, we test whether the *t*-statistic of the estimated liquidity timing coefficient for the actual hedge funds is statistically different from that bootstrapped hedge funds without liquidity

<sup>&</sup>lt;sup>11</sup> See Efron (1979) and Davidson and Hinkley (1997) for an overview of bootstrap methods.

timing skills. We bootstrap the *t*-statistic rather than the liquidity timing coefficient *per se* because the *t*-statistic is pivotal (Chen and Liang, 2007).

We first consider bootstrap analysis at the category level. The bootstrap analysis includes four steps. First, for hedge fund category p, we run Eq. (5) and save the estimated coefficients  $\{\hat{\alpha}_{p}, \hat{\beta}_{p}, \hat{\lambda}_{p}, ...\}$  and the time series of regression residuals  $\{\hat{\varepsilon}_{p,t+1}, t = 0, ..., T_{p} - 1\}$ , where  $T_{p}$  stands for the number of monthly returns for p. Second, we randomly resample the hedge fund's residuals with replacements and generate time series of residual  $\{\hat{\varepsilon}_{p,t+1}^{b}\}$ . We resample B times, and thus b = 1, 2, ..., B. Then, we obtain a hypothetical hedge fund's monthly excess returns by setting the liquidity timing coefficient to zero in Eq. (5) as follows:

$$r_{p,t+1}^{b} = \hat{\alpha}_{p} + \hat{\beta}_{p} F X F_{t+1} + \int_{j=1}^{t} \hat{\gamma}_{j} f_{j,t+1} + \hat{\varepsilon}_{p,t+1}^{b}.$$
(8)

Third, we estimate Eq. (5) by employing the hypothetical hedge fund's monthly excess returns  $r_{p,t+1}^{b}$ in Eq. (8) and save the estimated liquidity timing coefficient and t-statistic. Note that because the hypothetical hedge fund has no liquidity timing ability, any nonzero liquidity timing coefficient and tstatistic are contributed to sampling variation. Fourth, we repeat the first three steps for *B* times to generate distributions of the above t-statistics. We set *B* to be 5,000 in the bootstrap analysis and calculated the corresponding p-value defined as the frequency that the statistical values of hypothetical hedge funds from *B* time simulations exceed the statistical value for actual hedge funds.

Table 9 displays the bootstrap analysis results of hedge fund managers' liquidity timing coefficient and the corresponding p-value for testing the null hypothesis  $\lambda_p = 0$  without imposing the normality assumption. It can be seen that the p-values in Table 9 are all small, providing strong evidence of liquidity timing at the category level. This indicates that, without the normality assumption, the main results obtained in Section 3.2 are still valid.

#### [Table 9]

Next, we perform bootstrap analysis at the individual fund level. Because the number of the funds under investigation is huge, we only show the results for top and bottom funds. More specifically, for each hedge fund p within a fund category (sample), bootstrap analysis is carried out in the same way as outlined for the category level. We repeat the first three steps for all actual hedge funds in the sample, and hence we can obtain the cross-sectional statistics, such as the top 5 percentile, of estimated liquidity timing coefficients and t-statistics for all sample hedge funds. Finally, we repeat these steps for B = 5,000 times to generate hedge funds' empirical distribution of the t-statistic, such as the top 5 percentile. For a given cross-sectional statistic, we calculate its empirical p-value as the frequency that the values of the bootstrapped cross-sectional statistic (e.g., the top 5 percentile) for the pseudo-funds from B simulations exceed the actual value of the cross-sectional statistic. See Cao et al. (2013) for further detailed description for the bootstrap analysis.

Table 10 reports the t-statistics and the corresponding p-values at different extreme percentiles obtained in the bootstrap analysis at the individual fund level. The extreme percentiles we choose include the bottom 1%, 3%, 5% and 10% and the top 1%, 3%, 5% and 10%. Based on the p-values in Table 10, we find that hedge funds with top t-statistics of the liquidity timing coefficient have liquidity timing skills, which do not come from pure luck. For example, the t-statistic of the top 3% percentile hedge funds within the 'Global Derivatives' category is 3.732 and its corresponding p-value is 0; this indicates that the top 3% 'Global Derivatives' hedge funds have liquidity timing ability in the FX market. In general, the evidence in Table 10 reveals that the top-ranked hedge fund managers have successful liquidity timing skills in the FX market. This indicates that, at the individual fund level, the main results in Section 3.3 are still valid for the top-ranked funds without requiring the normality assumption.

#### [Table 10]

#### 5. Discussion and conclusions

This paper investigates hedge funds' liquidity timing ability in the FX market. Most studies in this area, however, have been focused on the equity and bond markets. The FX market is the world's largest financial market and regarded as extremely liquid (Mancini et al., 2013), with an average daily trading volume that was reported to be an estimated 5.1 trillion US Dollars in April 2016 based on a recent survey (Bank for International Settlements, 2016). In a market with trading volume of such an enormous scale, what is the additional implication of liquidity condition for hedge funds, especially in relation to their style of trading? To provide better insight into this issue, this paper also relates liquidity in the FX market to the recent QE programmes implemented by the various countries in which huge liquidity is injected into the financial markets. Did these liquidity injections motivate hedge funds to time the liquidity in the FX market following the likely impact on the FX market? This is also a question this paper aims to address.

To do this, we begin by investigating whether hedge funds implement timing strategies in the FX market, particularly those with investment styles that have a greater focus in the FX market, such as the global derivative hedge funds which are known to operate in a less restrictive market environment that allows the exploitation of more opportunities underlying investment and exposure managements. Our findings reveal evidence of liquidity timing ability of the global derivatives hedge funds in the FX market, especially the timing ability underlying the systematic and discretionary styles of trading which are known to be followed by the 'Currency' and 'Systematic Futures' hedge funds.

The findings also show differences in the liquidity timing skills between the 'Systematic Futures' hedge funds and the 'Currency' hedge funds. These differences could be explained by the types of markets transacted by these two types of hedge funds. The 'Systematic Futures' hedge funds trade liquid global futures, options and FX contracts, unlike the currency hedge funds which invest mainly

in currency portfolios through short-term money market instruments, derivative instruments and cash deposits. This implies the 'Systematic Futures' hedge funds face two main exposures in their investments that consist of the sources from the FX and the foreign assets markets. This may lead to a difference in the use or perception of the FX market for profit making or for managing exposure purpose. Unlike the 'Currency' hedge funds, the 'Systematic Futures' hedge funds possess volatility timing ability alongside liquidity timings ability. This could be explained by the needs to manage exposure underlying the foreign derivative assets via timing the volatility in the FX market. This contributes to cushioning exposure against volatility in the foreign derivative assets' markets.

We have also investigated the liquidity timing ability before and during/after the recent financial crisis periods. Our findings reveal both the 'Currency' and 'Systematic Futures' hedge funds exhibit evidence on timing the liquidity of the FX markets in these two periods. Particularly for the period since August 2007, in which a few episodes of the QE implementations were known to have taken place in the US, UK, Japan and some European countries. News sources<sup>12</sup> reported the currency hedge funds to have attempted to use the dates of the QE programs as important point(s) of entering/exiting the FX market. This provides good support for our findings.

Finally, existing findings in Kazemi and Li (2009) shows that the systematic and discretionary Commodity Trading Advisor (CTAs) that invest extensively in the futures and options markets are able to time the market returns and volatility in the futures and commodity markets they claimed to have specialized. In support of Kazemi and Li (2009), our findings imply that, when similar systematic and discretionary styles of trading are implemented by the global derivatives hedge funds, we show that timing skills are possible to extend to timing the liquidity condition of the FX market, further contributing to the planning and implementation of successful investment strategy.

<sup>&</sup>lt;sup>12</sup> See footnote 9

#### Bibliography

- Ackermann, C., McEnally, R., and Ravenscraft, D. (1999). The performance of hedge funds: risk, return, and incentives. The Journal of Finance, 54, 833–74.
- Admati, A.R., Bhattacharya, S., Pfleiderer, P., Ross, S.A. (1986). On timing and selectivity. The Journal of Finance, 41(3), 715-730.
- Agarwal, V., Naik, N.Y. (2004). Risks and portfolio decisions involving hedge funds. Review of Financial Studies, 17(1), 63-98.
- Ait-Sahalia, Y., Mykland, P.A., Zhang, L. (2005). How often to sample a continuous-time process in the presence of market microstructure noise. Review of Financial Studies, 18(2), 351-416.
- Ates, A., Wang, G.H.K. (2005). Liquidity and the evolution of price discovery on floor versus screenbased trading system: an analysis of the foreign exchange futures market. Working paper. Akdeniz University.
- Avramov, D., Kosowski, R., Naik, N. Y. and Teo, M. (2011). Hedge fund, managerial skill, and macroeconomic variables. Journal of Financial Economics, 99, 672–92.
- Bangassa, K., Su, C. and Joseph, N.L. (2012). Selectivity and Timing Performance of UK Investment Trusts. Journal of International Financial Markets, Institutions and Money, 22, 1149-1175.
- Bank for International Settlements. (2016). Foreign exchange turnover in April 2016. Triennial Central Bank Survey.
- Banti, C., Phylaktis, K. (2012). FX market illiquidity and funding liquidity constraints. Working paper. Cass Business School.
- Banti, C., Phylaktis, K., Sarno, L. (2012). Global liquidity risk in the foreign exchange market. Journal of International Money and Finance, 31(2), 267-291.

30

- Ben-David, I., Franzoni, F., Moussawi, R. (2012). Hedge fund stock trading in the financial crisis of 2007-2009. Review of Financial Studies, 25, 1–54.
- Berger, D., Chaboud, A., Hjalmarsson, E. (2009). What drive volatility persistence in the foreign exchange market? Journal of Financial Economics, 94(2), 192-213.
- Boyson, N.M., Stahel, C.W., Stulz, R.M. (2010). Hedge fund contagion and liquidity shocks. The Journal of Finance, 65(5), 1789-1816.
- Brown, S.J., Goetzmann, W.N., Ibbotson, R.G. (1999). Offshore hedge funds: survival and performance, 1989-95. Journal of Business, 72(1), 91-117.
- Bubak, V., Kocenda, E., Zikes, F. (2011). Volatility transmission in emerging European foreign exchange markets. Journal of Financial Economics, 35(11), 2829-2841.
- Busse, J. (1999). Volatility timing in mutual funds: evidence from daily returns. Review of Financial Studies, 12, 1009–41.
- Campbell, J.Y., Grossman, S.J., Wang, J. (1993). Trading volume and serial correlation in stock returns. Quarterly Journal of Economics, 108(4), 905-939.
- Cao, C., Chen, Y., Liang, B., Lo, A.W. (2013). Can hedge funds time market liquidity? Journal of Financial Economics, 109, 493–516.
- Chen, Y., Liang, B. (2007). Do market timing hedge funds time the market? Journal of Financial and Quantitative Analysis, 42, 827–56.
- Chen, Y. (2007). Timing ability in the focus market of hedge funds. Journal of Investment Management, 5, 66–98.
- Chen, Y. (2011). Derivatives use and risk taking: evidence from the hedge fund industry. Journal of Financial and Quantitative Analysis, 46(4), 1073-1106.
- Cheung, Y.-W., Chinn, M. D. (2001). Currency traders and exchange rate dynamics: A survey of the US market. Journal of International Money and Finance, 20: 439-471.

- Chordia, T., Roll, R., Subrahmanyam, A. (2000). Commonality in liquidity. Journal of Financial Economics, 56(1), 3-28.
- Danielsson, J., Payne, R. (2012). Liquidity determination in an order-driven market. European Journal of Finance, 18(9), 799-821.
- Ding, L., Hiltrop, J. (2010). The electronic trading systems and bid-ask spreads in the foreign exchange market. Journal of International Financial Markets, Institutions and Money, 20, 323-345.
- Eling, M., Faust, R. (2010). The performance of hedge funds and mutual funds in emerging markets. Journal of Banking and Finance, 34, 1993–2009.
- Frankel, J. A., Froot, K. A. (1990). Chartists, fundamentalists, and trading in the foreign exchange market. American Economic Review, Papers and Proceedings 80, 181-185.
- Fahlenbrach, R., Prilmeier, R., Stulz, R.M. (2012). This time is the same: Using bank performance in 1998 to explain bank performance during the recent financial crisis. The Journal of Finance, 67(6), 2139-2185.
- Farhi, E., Fraiberger, S.P., Gabaix, X., Ranciere, R. and Verdelhan, A., 2009. Crash risk in currency markets. Working paper (No. w15062). National Bureau of Economic Research.
- Fidelity Investment. (2015). Bond market: Resetting expectations in a post-QE world 2014. Last accessed May 2015, <u>http://www.fidelityecompendium.com/archive/2014/q4/</u> <u>articles/2014/q4/financial-markets/bond-market-post-qe-world/index.shtml</u>.
- French, C. W., Ko, D. B. (2007). How hedge funds beat the market. Journal of Investment Management, 5 (2), 112–25.
- Froot, K.A., Ramadorai, T. (2005). Currency returns, intrinsic value, and institutional-investor flows. The Journal of Finance, 60(3), 1535-1566.
- Fung, W., Hsieh, D. A. (1997). Empirical characteristics of dynamic trading strategies: the case of hedge funds. Review of Financial Studies, 10, 275–302.

- Fung, W., Hsieh, D. A. (2001). The risk in hedge fund strategies: theory and evidence from trend followers. Review of Financial Studies, 14 (2), 313–41.
- Fung, W., Hsieh, D. A. (2004). Hedge fund benchmarks: a risk-based approach. Financial Analyst Journal, 60, 65–80.
- Fung, W., Hsieh, D.A., Naik, N.Y., Ramadorai, T. (2008). Hedge funds: performance, risk, and capital formation. The Journal of Finance, 63(4), 1777-1803.
- Goyenko, R.Y., Holden, C.W., Trzcinka, C.A. (2009). Do liquidity measures measure liquidity? Journal of financial Economics, 92(2), 153-181.
- Hsu, P.-H., Taylor, M. P., Wang, Z. (2016). Technical trading: Is it still beating the foreign exchange market? Journal of International Economics 102, 188–208.
- Jagannathan, R., Malakhov, A., Novikov, D. (2010). Do hot hands exist among hedge funds manager? An empirical evaluation. The Journal of Finance, 65(1), 217-255.
- Joenväärä, J., Kosowski, R., Tolonen, P. (2013). Hedge fund performance: what do we know? Working Paper (Social Science Research Network), available at **Error! Hyperlink reference not valid.**
- Jurek, J.W. (2008). Crash-neutral currency carry trades. Working paper. Princeton University.
- Karnaukh, N., Ranaldo, A., Söderlind, P. (2015). Understanding FX liquidity. Review of Financial Studies, 28(11), 3073-3108.
- Kaul, A., Stefanescu, C. (2011). Liquidity comovement in the foreign exchange market. Working paper. University of Alberta, ESSES Business School.
- Kazemi, H., Li, Y. (2009). Market timing of CTAs: An examination of systematic CTAs vs. discretionary CTAs. Journal of Futures Markets, 29(11), 1067–1099.
- Kessler, S., Scherer, B. (2011). Hedge funds return sensitivity to global liquidity. Journal of Financial Markets, 14 (2), 301–22.
- Kyle, A.S. (1985). Continuous auctions and insider trading. Econometrics, 53(6), 1315-1335.

- Li, B, Luo, J, Tee, K (2017). The market liquidity timing skills of debt-oriented hedge funds. European Financial Management, 23(1), 32-54.
- Lou, X., Sadka, R. (2011). Liquidity level or liquidity risk? Evidence from the financial crisis. Financial Analysts Journal, 67(3), 51-62.
- Mancini, L., Ranaldo, A., Wrampelmeyer, J. (2013). Liquidity in the foreign exchange market: measurement, commonality, and risk premiums. The Journal of Finance, 68(5), 1805-1841.
- Melvin, M., Taylor, M.P. (2009). The crisis in the foreign exchange market. Journal of International Money and Finance, 28(8), 1317-1330.
- Menkhoff, L., Sarno, L., Schmeling, M., Schrimpf, A. (2012). Carry trades and global foreign exchange volatility. The Journal of Finance, 67(2), 681-718.
- Mitchell, M., Pulvino, T. (2001). Characteristics of risk and return in risk arbitrage. The Journal of Finance, 56(6), 2135-2175.
- Morningstar. (2014). The Morningstar category classifications for hedge funds. Last accessed March 2015, <u>http://corporate.morningstar.com/uk/documents/MethodologyDocuments/</u> <u>MethodologyPapers/MorningstarHedgeFundCategories\_Methodology.pdf</u>.
- Pastor, L., Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. Journal of Political Economy, 111, 642–85.
- Patton, A. J., Ramadorai, T. (2013). On the high-frequency dynamics of hedge fund risk exposures. The Journal of Finance, 68(2), 597–635.
- Stefanova, D., Siegmann, A. (2012). Market liquidity and exposure of hedge funds. Working Paper. VU University Amsterdam.
- Stoll, H. R. (1978). The supply of dealer services in securities markets. The Journal of Finance, 33(4), 1133-1151.
- Taylor, M. P., H. L. Allen. (1992). The use of technical analysis in the foreign exchange market. Journal of International Money and Finance, 11: 304-314.

- Treynor, J., Mazuy, K. (1966). Can mutual funds outguess the market? Harvard Business Review, 44, 131–36.
- Wrampelmeyer, J. (2012). The joint dynamics of hedge fund returns, illiquidity, and volatility. Journal of Alternative Investments, 15(1), 43-67.
- Zhang, L., Mykland, P.A., Ait-Sahalia, Y. (2005). A tale of two time scales: determining integrated volatility with noisy high-frequency data. Journal of the American Statistical Association, 100(472), 1394-1411.

#### Table 1

|--|

| Variables                              | Ν               | Mean   | Median | Standard Deviation | 25%     | 75%    |
|--|-----------------|--------|--------|--------------------|---------|--------|
| Panel A: Summary of h                  | edge fund retur | ms     |        |                    |         | ~      |
| Global Derivatives                     | 1323            | 0.758  | 0.641  | 1.993              | -0.590  | 2.046  |
| Currency                               | 70              | 0.595  | 0.483  | 1.539              | -0.291  | 1.345  |
| Global Macro                           | 498             | 0.730  | 0.663  | 1.253              | -0.112  | 1.424  |
| Systematic Futures                     | 707             | 0.802  | 0.631  | 2.969              | -1.302  | 2.902  |
| Volatility                             | 48              | 1.063  | 0.861  | 2.155              | -0.075  | 2.047  |
| Panel B: Summary of fa                 | actor data      |        |        |                    |         |        |
| MKT                                    |                 | 0.155  | 0.768  | 4.568              | -2.161  | 3.134  |
| SMB                                    |                 | 0.368  | 0.253  | 3.477              | -1.536  | 2.520  |
| BMF                                    |                 | -0.017 | -0.010 | 0.278              | -0.213  | 0.143  |
| CSF                                    |                 | 0.002  | 0.000  | 0.249              | -0.120  | 0.093  |
| PTFSBD                                 |                 | -2.539 | -5.025 | 14.695             | -13.405 | 3.350  |
| PTFSFX                                 |                 | -0.430 | -4.860 | 18.729             | -13.628 | 8.340  |
| PTFSCOM                                |                 | -0.710 | -4.180 | 14.235             | -9.788  | 5.910  |
| FXF                                    |                 | 0.127  | 0.101  | 2.146              | -1.044  | 1.491  |
| Panel C: Summary of liquidity measures |                 |        |        |                    |         |        |
| Liquidity(10)                          |                 | -0.054 | -0.049 | 0.013              | -0.057  | -0.046 |
| Liquidity(G10)                         |                 | -0.056 | -0.051 | 0.014              | -0.060  | -0.048 |
| Liquidity(6)                           |                 | -0.044 | -0.041 | 0.011              | -0.046  | -0.038 |

Note: This table provides a statistical summary of the data used in the empirical analysis. Panel A summarizes average monthly returns on the global derivative hedge funds and its four sub-categories. The monthly returns are in percentage per month. N denotes the number of hedge funds that exist during the sample period. The study includes both live and dead hedge funds in our sample. Panel B summarizes the Fund-Hsieh seven factors and the foreign exchange market factor (FXF). These eight factors are used to benchmark hedge funds' performances. Specifically, the Fund-Hsieh seven factors include the market excess return (MKT), a size factor (SMB), monthly change in the ten-year treasury constant maturity yield (BMF), monthly change in the Moody's Baa yield less ten-year treasury constant maturity yield (CSF), and three trend-following factors that are PFTSBD (bond), PFTSFX (currency), and PFTSCOM (commodity). The foreign exchange market factor (FXF) is the change in the trade-weighted U.S. dollar exchange rate index. Panel C summarizes the liquidity measures in the foreign exchange market, i.e., Liquidity(10), Liquidity(G10), and Liquidity(6). The measure of Liquidity(10) is calculated using negative illiquidity in equation (2) with a basket of 10 currencies against U.S. dollar, including Australian dollar (AUD), British pound (GBP), Canadian dollar (CAD), Danish krone (DKK), Euro (EUR), Japanese yen (JPY), New Zealand dollar (NZD), Norwegian krone (NOK), Swedish krona (SEK) and Swiss franc (CHF). The measure of Liquidity(G10) is calculated using negative illiquidity in equation (2) with a basket of G10 currencies comprising AUD, CAD, CHF, EUR, GBP, JPY, NOK, NZD, SEK, and the U.S. dollar (USD). The measure of Liquidity(6) is calculated using negative illiquidity in equation (2) with a basket

of 6 major currencies including AUD, CAD, CHF, EUR, GBP and JPY. The sample period is from January 1999 to December 2012.

#### Table 2

The results for liquidity timing analysis for the global derivative hedge funds and the different hedge fund sub-categories

|                    | Global<br>Derivatives | Currency  | Global<br>Macro  | Systematic<br>Futures | Volatility |
|--------------------|-----------------------|-----------|------------------|-----------------------|------------|
|                    |                       |           |                  |                       |            |
|                    |                       | F         | anel A: Liquidit | y(10)                 |            |
| 2                  | 15.765                | 15.512    | 4.796            | 24.262                | 6.430      |
| - E                | (3.32***)             | (4.02***) | (1.66*)          | (3.40***)             | (1.08)     |
| PTFSBD             | 0.021                 | -0.008    | 0.008            | 0.033                 | 0.031      |
|                    | (2.25**)              | (-1.08)   | (1.36)           | (2.31**)              | (2.60***)  |
| PTFSFX             | 0.029                 | 0.035     | 0.009            | 0.040                 | -0.001     |
|                    | (3.55***)             | (5.39***) | (1.92*)          | (3.34***)             | (-0.10)    |
| PTFSCOM            | 0.023                 | -0.003    | 0.009            | 0.035                 | 0.006      |
|                    | (2.30**)              | (-0.33)   | (1.52)           | (2.39**)              | (0.51)     |
| EMF                | 0.001                 | 0.002     | 0.095            | -0.052                | -0.057     |
|                    | (0.01)                | (0.08)    | (4.28***)        | (-0.95)               | (-1.23)    |
| SSF                | 0.113                 | 0.020     | 0.120            | 0.124                 | 0.103      |
|                    | (2.99***)             | (0.66)    | (5.27***)        | (2.19**)              | (2.18**)   |
| BMF                | -1.029                | -1.171    | -0.791           | -1.110                | 0.113      |
|                    | (-1.69*)              | (-2.37**) | (-2.14**)        | (-1.21)               | (0.15)     |
| CSF                | -0.388                | -1.231    | -0.547           | -0.156                | 0.678      |
|                    | (-0.53)               | (-2.07**) | (-1.23)          | (-0.14)               | (0.74)     |
| FXF                | 0.251                 | 0.122     | 0.113            | 0.383                 | -0.051     |
|                    | (3.43***)             | (2.06**)  | (2.54**)         | (3.49***)             | (-0.55)    |
| Constant           | 0.520                 | 0.316     | 0.471            | 0.572                 | 0.950      |
|                    | (4.04***)             | (3.02***) | (6.04***)        | (2.96***)             | (5.87***)  |
| Adj R <sup>2</sup> | 0.332                 | 0.261     | 0.368            | 0.326                 | 0.080      |

|          |           | Pa        | inel B: Liquidity | (G10)     |           |
|----------|-----------|-----------|-------------------|-----------|-----------|
| 2        | 14.833    | 14.693    | 4.587             | 22.766    | 5.838     |
| ~~p      | (3.31***) | (4.05***) | (1.69*)           | (3.38***) | (1.04)    |
| PTFSBD   | 0.0217    | -0.008    | 0.008             | 0.0333    | 0.0311    |
|          | (2.27**)  | (-1.05)   | (1.37)            | (2.32**)  | (2.59***) |
| PTFSFX   | 0.0285    | 0.035     | 0.009             | 0.040     | -0.001    |
|          | (3.54***) | (5.37***) | (1.91*)           | (3.32***) | (-0.10)   |
| PTFSCOM  | 0.023     | -0.002    | 0.009             | 0.036     | 0.006     |
|          | (2.32**)  | (-0.30)   | (1.53)            | (2.41**)  | (0.50)    |
| EMF      | 0.001     | 0.003     | 0.096             | -0.051    | -0.057    |
|          | (0.04)    | (0.11)    | (4.29***)         | (-0.93)   | (-1.23)   |
| SSF      | 0.112     | 0.020     | 0.120             | 0.123     | 0.103     |
|          | (2.99***) | (0.65)    | (5.27***)         | (2.18**)  | (2.18**)  |
| BMF      | -1.039    | -1.184    | -0.797            | -1.124    | 0.111     |
|          | (-1.70*)  | (-2.40**) | (-2.15**)         | (-1.23)   | (0.15)    |
| CSF      | -0.403    | -1.249    | -0.554            | -0.177    | 0.677     |
|          | (-0.55)   | (-2.10**) | (-1.24)           | (-0.16)   | (0.73)    |
| FXF      | 0.252     | 0.123     | 0.113             | 0.384     | -0.051    |
|          | (3.44***) | (2.08**)  | (2.55**)          | (3.50***) | (-0.56)   |
| Constant | 0.517     | 0.312     | 0.470             | 0.567     | 0.950     |

# Panel B: Liquidity(G10)

|                    | (4.01***) | (2.99***) | (6.02***)         | (2.93***) | (5.87***) |
|--------------------|-----------|-----------|-------------------|-----------|-----------|
| Adj R <sup>2</sup> | 0.332     | 0.262     | 0.369             | 0.326     | 0.079     |
|                    |           | I         | Panel C: Liquidit | y(6)      |           |
| 2                  | 19.13     | 24.447    | 5.463             | 28.593    | 4.861     |
| , m                | (3.10***) | (5.04***) | (1.46)            | (3.08***) | (0.63)    |
| PTFSBD             | 0.0208    | -0.008    | 0.008             | 0.032     | 0.032     |
|                    | (2.17**)  | (-1.04)   | (1.31)            | (2.21**)  | (2.68***) |
| PTFSFX             | 0.027     | 0.032     | 0.009             | 0.037     | -0.001    |
|                    | (3.26***) | (4.98***) | (1.79*)           | (3.05***) | (-0.08)   |
| PTFSCOM            | 0.0248    | 0.001     | 0.010             | 0.039     | 0.006     |
|                    | (2.50**)  | (0.08)    | (1.61)            | (2.59**)  | (0.47)    |
| EMF                | 0.007     | 0.013     | 0.097             | -0.0423   | -0.057    |
|                    | (0.20)    | (0.46)    | (4.33***)         | (-0.76)   | (-1.23)   |
| SSF                | 0.105     | 0.014     | 0.118             | 0.112     | 0.106     |
|                    | (2.80***) | (0.48)    | (5.18***)         | (1.99**)  | (2.26**)  |
| BMF                | -0.749    | -0.935    | -0.704            | -0.674    | -0.021    |
|                    | (-1.25)   | (-1.98**) | (-1.94*)          | (-0.75)   | (-0.03)   |
| CSF                | -0.016    | -0.898    | -0.432            | 0.422     | 0.509     |
|                    | (-0.02)   | (-1.58)   | (-0.99)           | (0.39)    | (0.56)    |
| FXF                | 0.244     | 0.115     | 0.111             | 0.373     | -0.049    |
|                    | (3.33***) | (1.99**)  | (2.49**)          | (3.38***) | (-0.53)   |
| Constant           | 0.513     | 0.295     | 0.470             | 0.563     | 0.946     |
|                    | (3.96***) | (2.89***) | (5.99***)         | (2.89***) | (5.82***) |
| Adj R <sup>2</sup> | 0.326     | 0.298     | 0.366             | 0.318     | 0.075     |
|                    | •         | •         |                   |           |           |

This table reports the coefficients and t-statistics of the liquidity timing model (5). Column (2) contains the results combining all funds in the 'Global Derivatives' category that include the "Currency", "Systematic Futures", "Global Macro", and "Volatility" strategy sub-categories. Columns (3)-(6) display the results for each of these four sub-categories. The coefficient  $\lambda_p$  measures foreign exchange market liquidity timing ability. The measures of foreign exchange market liquidity, i.e. Liquidity(10), Liquidity(G10), and Liquidity(6), are used in each of the three panels respectively, where the measure of Liquidity(10) is calculated using negative illiquidity in equation (2) with a basket of 10 currencies against U.S. dollar, including Australian dollar (AUD), British pound (GBP), Canadian dollar (CAD), Danish krone (DKK), Euro (EUR), Japanese yen (JPY), New Zealand dollar (NZD), Norwegian krone (NOK), Swedish krona (SEK) and Swiss franc (CHF). The measure of Liquidity(G10) is calculated using negative illiquidity in equation (2) with a basket of G10 currencies comprising AUD, CAD, CHF, EUR, GBP, JPY, NOK, NZD, SEK, and the U.S. dollar (USD). The measure of Liquidity(6) is calculated using negative illiquidity in equation (2) with a basket of 6 major currencies including AUD, CAD, CHF, EUR, GBP and JPY. The numbers in parentheses are t-statistics. \*, \*\* and \*\*\* indicate that the coefficient is significantly different from zero at the 10%, 5%, and 1% levels, respectively.

| Table | 3 |
|-------|---|
|-------|---|

#### Distributions of t-statistics for the individual hedge funds' liquidity timing coefficient

|  | t <b>≤</b> -2.326 | t <b>≤</b> -1.960 | t <b>≤</b> -1.645 | t <b>≤</b> -1.282 | t ≥1.282 | t ≥1.645 | t ≥1.960 | t <b>≥</b> 2.326 |
|--|-------------------|-------------------|-------------------|-------------------|----------|----------|----------|------------------|
| Panel A: Distribution                                | of t-statistic    | s (Liquidity      | (10))             |                   |          | ٠        | .0       |                  |
| Global Derivatives                                   | 0.026             | 0.037             | 0.059             | 0.098             | 0.364    | 0.280    | 0.215    | 0.160            |
| Currency   | 0.014             | 0.029             | 0.057             | 0.071             | 0.400    | 0.371    | 0.286    | 0.214            |
| Systematic Futures                                   | 0.007             | 0.011             | 0.024             | 0.058             | 0.434    | 0.349    | 0.270    | 0.215            |
|  |                   |                   |                   |                   |          |          |          |                  |
| Panel B: Distribution                                | of t-statistic    | s (Liquidity      | (G10))            |                   |          |          |          |                  |
| Global Derivatives                                   | 0.027             | 0.039             | 0.060             | 0.096             | 0.364    | 0.277    | 0.212    | 0.160            |
| Currency   | 0.014             | 0.014             | 0.057             | 0.071             | 0.386    | 0.371    | 0.286    | 0.214            |
| Systematic Futures                                   | 0.007             | 0.014             | 0.024             | 0.058             | 0.433    | 0.342    | 0.272    | 0.215            |
|  |                   |                   |                   |                   |          |          |          |                  |
| Panel C: Distribution of t-statistics (Liquidity(6)) |                   |                   |                   |                   |          |          |          |                  |
| Global Derivatives                                   | 0.024             | 0.039             | 0.060             | 0.086             | 0.335    | 0.246    | 0.194    | 0.138            |
| Currency   | 0.014             | 0.029             | 0.057             | 0.057             | 0.429    | 0.286    | 0.271    | 0.171            |
| Systematic Futures                                   | 0.004             | 0.016             | 0.031             | 0.054             | 0.375    | 0.290    | 0.228    | 0.170            |

Note: This table summarizes the distributions of the t-statistics for cross-sectional individual hedge funds' liquidity timing coefficient  $\mathbf{1}_{\mathbf{p}}$  in the equation (5). The numbers in the table are the percentage of hedge funds with the t-statistics of the estimated liquidity timing coefficients that exceed the indicated values. The measures of foreign exchange market liquidity, i.e. Liquidity(10), Liquidity(G10), and Liquidity(6), are used in each of the three panels respectively, where the measure of Liquidity(10) is calculated using negative illiquidity in equation (2) with a basket of 10 currencies against U.S. dollar, including Australian dollar (AUD), British pound (GBP), Canadian dollar (CAD), Danish krone (DKK), Euro (EUR), Japanese yen (JPY), New Zealand dollar (NZD), Norwegian krone (NOK), Swedish krona (SEK) and Swiss franc (CHF). The measure of Liquidity(G10) is calculated using negative illiquidity in equation (2) with a basket of G10 currencies comprising AUD, CAD, CHF, EUR, GBP, JPY, NOK, NZD, SEK, and the U.S. dollar (USD). The measure of Liquidity(6) is calculated using negative illiquidity in equation (2) with a basket of 6 major currencies including AUD, CAD, CHF, EUR, GBP and JPY.

#### Table 4

#### The liquidity timing coefficient during the financial crisis period

|                    | Time period: January 1999 – July 2007 |                |                |  |  |
|--------------------|---------------------------------------|----------------|----------------|--|--|
|                    | Liquidity(10)                         | Liquidity(G10) | Liquidity(6)   |  |  |
|                    | A <sub>pp</sub>                       | A <sub>p</sub> | A <sub>p</sub> |  |  |
| Global Derivatives | 9.159                                 | 8.686          | 11.421         |  |  |
|                    | (1.62)                                | (1.63)         | (1.69*)        |  |  |
| Currency           | 14.673                                | 14.033         | 21.463         |  |  |
|                    | (2.97***)                             | (3.01***)      | (3.70***)      |  |  |
| Systematic Futures | 14.815                                | 13.924         | 17.728         |  |  |
|                    | (1.73*)                               | (1.72*)        | (1.73*)        |  |  |

Time period: August 2007 - December 2012\*\*\*\*

|                    | Liquidity(10)<br>A <sub>p</sub> | Liquidity(G10) | Liquidity(6)<br>A <sub>pp</sub> |
|--------------------|---------------------------------|----------------|---------------------------------|
| Global Derivatives | 30.996                          | 28.833         | 52.768                          |
|                    | (2.93***)                       | (2.92***)      | (2.54**)                        |
| Currency           | 20.287                          | 18.595         | 36.178                          |
|                    | (2.77***)                       | (2.72***)      | (2.53**)                        |
| Systematic Futures | 45.991                          | 42.906         | 74.625                          |
|                    | (2.92***)                       | (2.92***)      | (2.40**)                        |

This table reports the estimated liquidity timing coefficients and their t-statistics in the liquidity timing model (5) in different time periods, respectively. The coefficient  $\lambda_p$  measures foreign exchange market liquidity timing ability. The measures of foreign exchange market liquidity, i.e. Liquidity(10), Liquidity(G10), and Liquidity(6), are used in each of the empirical analyses respectively, where the measure of Liquidity(10) is calculated using negative illiquidity in equation (2) with a basket of 10 currencies against U.S. dollar, including Australian dollar (AUD), British pound (GBP), Canadian dollar (CAD), Danish krone (DKK), Euro (EUR), Japanese yen (JPY), New Zealand dollar (NZD), Norwegian krone (NOK), Swedish krona (SEK) and Swiss franc (CHF). The measure of Liquidity(G10) is calculated using negative illiquidity in equation (2) with a basket of G10 currencies comprising AUD, CAD, CHF, EUR, GBP, JPY, NOK, NZD, SEK, and the U.S. dollar (USD). The measure of Liquidity(6) is calculated using negative illiquidity in equation (2) with a basket of 6 major currencies including AUD, CAD, CHF, EUR, GBP and JPY. The numbers in parentheses are t-statistics. \*, \*\* and \*\*\* indicate that the coefficient is significantly different from zero at the 10%, 5%, and 1% levels, respectively.

\*\*\*\* This period covers those during and after the financial crises, following those in Ben-David, et al (2012).

#### Table 5

The liquidity timing coefficient after controlling for foreign exchange market return and volatility timings

|                    | Panel A: Liquidity(10)           |                             |                            |   |  |
|--------------------|----------------------------------|-----------------------------|----------------------------|---|--|
|                    | $\lambda_{\gamma p}$             | $\varphi_p$                 | $\theta_p$                 |   |  |
|                    |                                  |                             |                            |   |  |
|                    |                                  |                             |                            |   |  |
| Global Derivatives | 15.649<br>(3.28***)              | -0.0202                     | 0.758<br>(2.53**)          |   |  |
| Currency           | 15.380                           | -0.004                      | 0.211                      |   |  |
| Systematic Futures | (3.91***)<br>24.081<br>(3.34***) | -0.023<br>(-0.75)           | (0.83)<br>0.890<br>(1.96*) |   |  |
|                    |                                  | Panel B: Liquidity(G1       | 0)                         |   |  |
|                    | $\lambda_{p}$                    | $\varphi_p$                 | $\theta_p$                 |   |  |
|                    |                                  |                             |                            |   |  |
| Global Derivatives | 14.687                           | -0.020<br>(3.26***) (-1.01) | 0.754<br>(2.52**)          |   |  |
| Currency           | 14.566<br>(3.93***)              | -0.004<br>(-0.22)           | 0.207<br>(0.84)            |   |  |
| Systematic Futures | 22.550<br>(3.31***)              | -0.023                      | 0.884<br>(1.95*)           |   |  |
|                    |                                  | Panel C: Liquidity(6)       | )                          |   |  |
|                    |                                  |                             |                            |   |  |
|                    | λ.,,                             | φ <sub>p</sub>              | θ                          | , |  |
| Global Derivatives | 20.234<br>(3.31***)              | -0.019<br>(-0.95)           | 0.841<br>(2.80***)         |   |  |
| Currency           | 24.751<br>(5.05***)              | -0.004<br>(-0.28)           | 0.310<br>(1.28)            |   |  |
| Systematic Futures | 29.814<br>(3.21***)              | -0.020<br>(-0.67)           | 1.012<br>(2.22**)          |   |  |

This table reports the estimated coefficients of liquidity timing, volatility timing and return timing, and their tstatistics in the timing model (6). The coefficient  $\mathbf{A}_{\mathbf{p}}$  measures foreign exchange market liquidity timing ability. The coefficients  $\boldsymbol{\varphi}_{\mathbf{p}}$  and  $\boldsymbol{\theta}_{\mathbf{p}}$  measure the foreign exchange market return-timing and volatility-timing abilities. The measures of foreign exchange market liquidity, i.e. Liquidity(10), Liquidity(G10), and Liquidity(6), are used in each of the three panels respectively, where the measure of Liquidity(10) is calculated using negative illiquidity in equation (2) with a basket of 10 currencies against U.S. dollar, including Australian dollar (AUD), British pound (GBP), Canadian dollar (CAD), Danish krone (DKK), Euro (EUR), Japanese yen (JPY), New Zealand dollar (NZD), Norwegian krone (NOK), Swedish krona (SEK) and Swiss franc (CHF). The measure of Liquidity(G10) is calculated using negative illiquidity in equation (2) with a basket of G10 currencies comprising AUD, CAD, CHF, EUR, GBP, JPY, NOK, NZD, SEK, and the U.S. dollar (USD). The measure of

Liquidity(6) is calculated using negative illiquidity in equation (2) with a basket of 6 major currencies including AUD, CAD, CHF, EUR, GBP and JPY. The numbers in parentheses are t-statistics. \*, \*\* and \*\*\* indicate that the coefficient is significantly different from zero at the 10%, 5%, and 1% levels, respectively.

#### Table 6

|                    | Liquidity(10)  | Liquidity(G10) | Liquidity(6)    |
|--------------------|----------------|----------------|-----------------|
|                    | $\lambda_{np}$ | λ <sub>γ</sub> | λ <sub>γρ</sub> |
| Global Derivatives | 16.621         | 15.638         | 20.305          |
|                    | (3.36***)      | (3.36***)      | (3.17***)       |
| Currency           | 16.272         | 15.453         | 25.257          |
|                    | (4.01***)      | (4.04***)      | (4.93***)       |
| Systematic Futures | 25.481         | 23.887         | 30.078          |
|                    | (3.47***)      | (3.45***)      | (3.15***)       |

#### The liquidity timing coefficient after controlling for backfill bias

This table reports the estimated liquidity timing coefficients and their t-statistics in the liquidity timing model (5), controlling for backfill bias. The coefficient  $\mathbf{1}_{\mathbf{p}}$  measures foreign exchange market liquidity timing ability. The measures of foreign exchange market liquidity, i.e. Liquidity(10), Liquidity(G10), and Liquidity(6), are used in each of the empirical analyses respectively, where the measure of Liquidity(10) is calculated using negative illiquidity in equation (2) with a basket of 10 currencies against U.S. dollar, including Australian dollar (AUD), British pound (GBP), Canadian dollar (CAD), Danish krone (DKK), Euro (EUR), Japanese yen (JPY), New Zealand dollar (NZD), Norwegian krone (NOK), Swedish krona (SEK) and Swiss franc (CHF). The measure of Liquidity(G10) is calculated using negative illiquidity in equation (2) with a basket of G10 currencies comprising AUD, CAD, CHF, EUR, GBP, JPY, NOK, NZD, SEK, and the U.S. dollar (USD). The measure of Liquidity(6) is calculated using negative illiquidity in equation (2) with a basket of 6 major currencies including AUD, CAD, CHF, EUR, GBP and JPY. The numbers in parentheses are t-statistics. \*, \*\* and \*\*\* indicate that the coefficient is significantly different from zero at the 10%, 5%, and 1% levels, respectively.

#### Table 7

|                    | Liquidity(10)       | Liquidity(G10) | Liquidity(6)   |
|--------------------|---------------------|----------------|----------------|
|                    | $\lambda_p$         | $\lambda_{p}$  | λ <sub>φ</sub> |
| Panel A:           | AUM less than \$150 | million        | .0             |
| Global Derivatives | 21.152              | 20.007         | 25.652         |
|                    | (3.50***)           | (3.51***)      | (3.27***)      |
| Currency           | 19.613              | 18.744         | 30.417         |
|                    | (4.08***)           | (4.15***)      | (5.02***)      |
| Systematic Futures | 28.909              | 27.203         | 34.201         |
|                    | (3.54***)           | (3.54***)      | (3.23***)      |
| Panel B:           | AUM less than \$50  | million        |                |
| Global Derivatives | 19.661              | 18.637         | 24.380         |
|                    | (3.39***)           | (3.41***)      | (3.25***)      |
| Currency           | 20.089              | 19.215         | 30.885         |
|                    | (4.01***)           | (4.08***)      | (4.88***)      |
| Systematic Futures | 26.324              | 24.790         | 31.075         |
|                    | (3.24***)           | (3.24***)      | (2.95***)      |

## The liquidity timing coefficient for hedge funds with different sizes: AUM less than \$150 million (Panel A) and AUM less than \$50 million (Panel B)

This table reports the estimated liquidity timing coefficients and their t-statistics in the liquidity timing model (5) for hedge funds with AUM less than \$150 million and with AUM less than \$50 million, respectively. The coefficient  $\lambda_{p}$  measures foreign exchange market liquidity timing ability. The measures of foreign exchange market liquidity, i.e. Liquidity(10), Liquidity(G10), and Liquidity(6), are used in each of the empirical analyses respectively, where the measure of Liquidity(10) is calculated using negative illiquidity in equation (2) with a basket of 10 currencies against U.S. dollar, including Australian dollar (AUD), British pound (GBP), Canadian dollar (CAD), Danish krone (DKK), Euro (EUR), Japanese yen (JPY), New Zealand dollar (NZD), Norwegian krone (NOK), Swedish krona (SEK) and Swiss franc (CHF). The measure of Liquidity(G10) is calculated using negative illiquidity in equation (2) with a basket of G10 currencies comprising AUD, CAD, CHF, EUR, GBP, JPY, NOK, NZD, SEK, and the U.S. dollar (USD). The measure of Liquidity(6) is calculated using negative illiquidity in equation (2) with a basket of 6 major currencies including AUD, CAD, CHF, EUR, GBP and JPY. The numbers in parentheses are t-statistics. \*, \*\* and \*\*\* indicate that the coefficient is significantly different from zero at the 10%, 5%, and 1% levels, respectively.

#### Table 8

|                    | Liquidity(10)        | Liquidity(G10) | Liquidity(6)   |
|--------------------|----------------------|----------------|----------------|
|                    | <b>A<sub>p</sub></b> | A <sub>p</sub> | A <sub>p</sub> |
| Global Derivatives | 15.834               | 14.897         | 20.532         |
|                    | (3.32***)            | (3.31***)      | (3.23***)      |
| Currency           | 15.140               | 14.346         | 23.226         |
|                    | (3.96***)            | (3.98***)      | (4.64***)      |
| Systematic Futures | 24.418               | 22.910         | 31.030         |
|                    | (3.41***)            | (3.39***)      | (3.25***)      |

The liquidity timing coefficient after controlling for the impact of funding constraints

This table reports the estimated liquidity timing coefficients and their t-statistics in the liquidity timing model (5) for controlling for the funding constraints. The coefficient  $\mathbf{A}_{\mathbf{p}}$  measures foreign exchange market liquidity timing ability. The measures of foreign exchange market liquidity, i.e. Liquidity(10), Liquidity(G10), and Liquidity(6), are used in each of the empirical analyses respectively, where the measure of Liquidity(10) is calculated using negative illiquidity in equation (2) with a basket of 10 currencies against U.S. dollar, including Australian dollar (AUD), British pound (GBP), Canadian dollar (CAD), Danish krone (DKK), Euro (EUR), Japanese yen (JPY), New Zealand dollar (NZD), Norwegian krone (NOK), Swedish krona (SEK) and Swiss franc (CHF). The measure of Liquidity(G10) is calculated using negative illiquidity in equation (2) with a basket of G10 currencies comprising AUD, CAD, CHF, EUR, GBP, JPY, NOK, NZD, SEK, and the U.S. dollar (USD). The measure of Liquidity(6) is calculated using negative illiquidity in equation (2) with a basket of 6 major currencies including AUD, CAD, CHF, EUR, GBP and JPY. The numbers in parentheses are t-statistics. \*, \*\* and \*\*\* indicate that the coefficient is significantly different from zero at the 10%, 5%, and 1% levels, respectively.

60

#### Table 9

## Bootstrap analysis for liquidity timing at the category level: t-statistics with the corresponding p-values in parentheses

|                    | Liquidity(10)   | Liquidity(G10)  | Liquidity(6) |  |  |
|--------------------|-----------------|-----------------|--------------|--|--|
|                    | $\lambda_{p}$   | $\lambda_p$     | $\lambda_p$  |  |  |
|                    |                 |                 |              |  |  |
| Global Derivatives | 15.765          | 14.833          | 19.131       |  |  |
|                    | $(0.011^{**})$  | $(0.008^{***})$ | (0.026**)    |  |  |
| Currency           | 15.512          | 14.693          | 24.447       |  |  |
|                    | $(0.007^{***})$ | $(0.005^{***})$ | (0.003***)   |  |  |
| Systematic Futures | 25.262          | 22.766          | 28.593       |  |  |
|                    | (0.002***)      | (0.005***)      | (0.014**)    |  |  |

This table reports the bootstrap analysis results at the category level, including the estimated liquidity timing coefficient  $\lambda_{\mathbf{y}}$  and the corresponding p-values. The number of bootstrap simulations is set as 5,000. The measures of foreign exchange market liquidity, i.e. Liquidity(10), Liquidity(G10), and Liquidity(6), are used in each of the empirical analyses respectively, where the measure of Liquidity(10) is calculated using negative illiquidity in equation (2) with a basket of 10 currencies against U.S. dollar, including Australian dollar (AUD), British pound (GBP), Canadian dollar (CAD), Danish krone (DKK), Euro (EUR), Japanese yen (JPY), New Zealand dollar (NZD), Norwegian krone (NOK), Swedish krona (SEK) and Swiss franc (CHF). The measure of Liquidity(G10) is calculated using negative illiquidity in equation (2) with a basket of G10 currencies comprising AUD, CAD, CHF, EUR, GBP, JPY, NOK, NZD, SEK, and the U.S. dollar (USD). The measure of Liquidity(6) is calculated using negative illiquidity in equation (2) with a basket of 6 major currencies including AUD, CAD, CHF, EUR, GBP and JPY. The numbers in parentheses are t-statistics. \*, \*\* and \*\*\* indicate that the coefficient is significantly different from zero at the 10%, 5%, and 1% levels, respectively.

|              |              |                | 1 0                   | 1            | 1       |                                  |         |         |
|--------------|--------------|----------------|-----------------------|--------------|---------|----------------------------------|---------|---------|
|              | Bo           | ottom t-stati  | stics for $\lambda_p$ |              |         | Top t-statistics for $\lambda_p$ |         |         |
|              |              |                |                       |              |         |                                  |         |         |
|              | 1%           | 3%             | 5%                    | 10%          | 10%     | 5%                               | 3%      | 1%      |
|              |              |                |                       |              |         |                                  |         |         |
| Panel A: Boo | tstrap anal  | ysis of liquio | dity timing (         | (Liquidity(1 | 0))     |                                  |         |         |
| Global       | -3.101       | -2.115         | -1.742                | -1.245       | 2.794   | 3.274                            | 3.732   | 4.307   |
| Derivatives  | (0.106)      | (0.000)        | (0.000)               | (0.000)      | (0.000) | (0.000)                          | (0.000) | (0.001) |
| Currency     | -2.388       | -1.837         | -1.667                | -1.122       | 3.523   | 3.980                            | 4.356   | 4.505   |
|              | (0.118)      | (0.136)        | (0.145)               | (0.040)      | (0.000) | (0.000)                          | (0.000) | (0.125) |
| Systematic   | -2.007       | -1.449         | -1.344                | -0.868       | 2.968   | 3.590                            | 3.809   | 4.411   |
| Futures      | (0.000)      | (0.000)        | (0.000)               | (0.000)      | (0.000) | (0.000)                          | (0.000) | (0.003) |
|              |              |                |                       |              |         |                                  |         |         |
| Panel B: Boo | tstrap analy | ysis of liquid | lity timing (         | (Liquidity(C | 510))   |                                  |         |         |
| Global       | -3.065       | -2.119         | -1.768                | -1.259       | 2.744   | 3.256                            | 3.715   | 4.364   |
| Derivatives  | (0.068)      | (0.000)        | (0.000)               | (0.000)      | (0.000) | (0.000)                          | (0.000) | (0.001) |
| Currency     | -2.358       | -1.784         | -1.768                | -1.192       | 3.571   | 4.002                            | 4.350   | 4.515   |
|              | (0.108)      | (0.110)        | (0.237)               | (0.074)      | (0.000) | (0.000)                          | (0.000) | (0.127) |
| Systematic   | -2.090       | -1.502         | -1.357                | -0.918       | 2.948   | 3.563                            | 3.780   | 4.400   |
| Futures      | (0.000)      | (0.000)        | (0.000)               | (0.000)      | (0.000) | (0.000)                          | (0.000) | (0.005) |
|              |              |                |                       |              |         |                                  |         |         |
| Panel C: Boo | tstrap analy | ysis of liquid | lity timing (         | (Liquidity(6 | ))      |                                  |         |         |
| Global       | -3.074       | -2.174         | -1.769                | -1.140       | 2.620   | 3.163                            | 3.4890  | 4.175   |
| Derivatives  | (0.149)      | (0.005)        | (0.000)               | (0.000)      | (0.000) | (0.000)                          | (0.000) | (0.001) |
| Currency     | -2.572       | -1.800         | -1.730                | -1.222       | 3.280   | 3.798                            | 3.953   | 4.951   |
|              | (0.195)      | (0.111)        | (0.170)               | (0.068)      | (0.000) | (0.000)                          | (0.001) | (0.075) |
| Systematic   | -2.048       | -1.723         | -1.322                | -0.862       | 2.869   | 3.233                            | 3.478   | 4.160   |
| Futures      | (0.000)      | (0.000)        | (0.000)               | (0.000)      | (0.000) | (0.000)                          | (0.000) | (0.004) |

| Table 10   |
|--|
| Bootstrap analysis for liquidity timing at the individual level: t-statistics with the |
| corresponding p-values in parentheses  |

This table reports the bootstrap analysis results at the individual fund level, including the t-statistics and the corresponding p-values in the various top percentile levels. The number of bootstrap simulations is set as 5,000. The coefficient  $\mathbf{A}_{\mathbf{p}}$  measures foreign exchange market liquidity timing ability. The measures of foreign exchange market liquidity, i.e. Liquidity(10), Liquidity(G10), and Liquidity(6), are used in each of the three panels respectively, where the measure of Liquidity(10) is calculated using negative illiquidity in equation (2) with a basket of 10 currencies against U.S. dollar, including Australian dollar (AUD), British pound (GBP), Canadian dollar (CAD), Danish krone (DKK), Euro (EUR), Japanese yen (JPY), New Zealand dollar (NZD), Norwegian krone (NOK), Swedish krona (SEK) and Swiss franc (CHF). The measure of Liquidity(G10) is calculated using negative illiquidity in equation (2) with a basket of G10 currencies comprising AUD, CAD, CHF, EUR, GBP,

JPY, NOK, NZD, SEK, and the U.S. dollar (USD). The measure of Liquidity(6) is calculated using negative illiquidity in equation (2) with a basket of 6 major currencies including AUD, CAD, CHF, EUR, GBP and JPY.