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Measuring liquidity risk effects on carry trades across currencies and regimes

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ABSTRACT

We study the effects of FX liquidity risk on carry trade returns using a novel low-frequency market-wide liquidity measure. We show conclusively that the vast majority of variation in carry trade returns can be explained by two risk factors (liquidity risk and market risk). Our results are further corroborated when the mimicking liquidity risk factor is replaced with a non-tradable innovations risk factor. Safe-haven currencies (SHC) provide insurance against crash risk by having negative liquidity betas, across all time periods. SHCs provide the highest levels of protection during periods of extreme volatility. We find that liquidity risk is priced in the cross-section of carry trade returns, and estimate the liquidity risk premium in the FX market to be around 412 basis points per annum.

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1. Introduction

The issue of liquidity and its effects in equity and bond markets have been studied extensively in the finance literature[2]. This cannot be said about liquidity in the foreign exchange (FX) market. This is puzzling considering the fact that the FX market is the world's largest financial market with an estimated average daily trading volume of about US$6.6 trillion in 2019 (BIS, 2019), which corresponds to about 10 times the size of global equity markets (WFE, 2019)[3].

Market liquidity is an important feature for the well-functioning of all financial markets, yet little is known about FX liquidity and its co-movement with individual currency-pairs. A quick look into the global financial crisis of 2007–2008 sheds some light on this. Liquidity in money markets declined significantly following credit rationing in the interbank markets. This was due to the fact that banks refused to lend to each other because of funding liquidity problems relating to uncertainty over their exposure to structured products. The amount of exposure was a significant consideration because market liquidity of these structured assets had declined significantly, thereby reinforcing difficulties in valuing such structured products (Ivashina and Scharfstein, 2010). Banks are central to the activities of all markets and may hoard liquidity because of fears over liquidity risk or liquidity shocks [(Acharya and Merrouche, 2012), (Ashcraft et al., 2011)], and risk that their counterparties might not be strong enough to deliver in times of stress, even in treasury markets (Afonso et al., 2011). This study helps to fill the gap created due to the lack of depth and coverage of liquidity crisis of the FX market during the great recession of 2007–2008, and the "normal" times before and thereafter[4].

Liquidity and its converse, illiquidity, are concepts that need to be studied thoroughly. A liquid security is characterized by the ability to buy or sell large quantities of it at a low cost. A good example is U.S. Treasury bills, which can be sold in blocks of $20 million dollars instantaneously at the cost of a fraction of a basis point. On the other hand, trading an illiquid security is difficult, time-consuming, and costly. Illiquidity is observed when there is a large difference between the offered sale price and the bid (buying) price, if trading of a large quantity of a security moves its price by a lot, or when it takes a long time to liquidate a position. Liquidity risk is the risk that a security will be more illiquid when its holder needs to sell it in the future, and a liquidity crisis is a time when many securities become highly illiquid at the same time (Amihud et al., 2013). In short, liquidity risk is the uncertainty associated with the liquidity level.

Academic research on liquidity is of relatively recent vintage. The theory assumed "frictionless markets" which are perfectly liquid all of the time. This study takes the opposite view in support of Lustig et al. (2011). We argue that liquidity is a central feature of the securities and financial markets. Recent events of the global financial crisis during 2007–2008 support this study[5]. This study is also motivated by Burnside (2008), who suggests that liquidity frictions may explain the profitability of carry trades because liquidity spirals can aggravate currency crashes[6].

In studying currency crashes from the recent financial crisis, Brunnermeier et al. (2008) highlight the importance of liquidity in the FX market[7]. A decline in FX liquidity impacts carry traders and triggers liquidity spirals. Carry trades are investments where investors borrow from low interest rate capital markets and invest in high yield markets capitalizing on

[2] Chung and Chuwonganant (2014) show that stock market uncertainty as measured by VIX exerts a large market-wide impact on liquidity. Amihud and Mendelson (1986); Chordia et al. (2001), among others, use trading activity and transaction costs to study daily liquidity in equity markets. Hasbrouck (2009) estimates the effective cost of trades by relying on the spread model of Roll (1984). Pastor and Stambaugh (2003) measure stock market liquidity using return reversal, and show that liquidity risk is priced in the cross-section of stock returns. Goyenko et al. (2009) compare various proxies of liquidity against high-frequency benchmarks. Chordia et al. (2005); Fleming and Remolona (1999), among others, provide related studies for U.S. government bond markets. Green et al. (2010) study municipal bond markets, Bao et al. (2011) and Dick-Nielsen et al. (2012) study liquidity effects in corporate bond markets.

[3] Liquidity has several components at the global level, national level (central banks as providers) and at the individual national market level. The Bank of International Settlements (BIS) and the International Monetary Fund (IMF) help to provide global Liquidity. At the national level, individual central banks provide guidance and liquidity to national markets, via their monetary policies. Central banks can add or drain liquidity from their national markets. The main players in the national markets have to heed the signals of the central banks (Acharya and Merrouche, 2012). Many studies have been done on central bank liquidity, this paper however, focuses on foreign exchange market liquidity.

[4] The interbank markets can be used by banks to try to relieve liquidity pressures in national markets, but even in the interbank markets, problems arose during the financial crisis (Nyborg and Ostberg, 2014). Alexius et al. (2014) find that the main determinants of the Swedish interbank premium are international variables, such as US and EURO area risk premia. International exchange rate volatility and the EURO/USD deviations from CIP also matter, while standard measures of domestic market liquidity and domestic credit risk have insignificant effects. Liquidity and credit quality are of course interrelated ((Corvitz and Downing, 2007); (Friewald et al., 2012)), but the recent evidence points more to the fact that liquidity dried up during the great recession ((Brunnermeier, 2009); (Cornett et al., 2011)). Schwartz (2019) finds that credit and liquidity are both important but that liquidity dominated during 2007–2008 crises. Many supposedly safe markets failed during the crisis all because of liquidity; debt markets (Krishnamurthy, 2010), money markets (Kacperczyk and Schnabl, 2013), commercial paper (Kacperczyk and Schnabl, 2010), and repo markets (Gorton, 2009).

[5] The importance of liquidity risk was re-emphasized by the former Chairman of the United States Federal Reserve Bank, Ben Bernanke, at the Chicago Federal Reserve Annual Conference on Bank Structure and Competition on May 15, 2008: "Some more-successful firms consistently embed market liquidity premiums in their pricing models and valuations. In contrast, less-successful firms did not develop adequate capacity to conduct independent valuations and did not take into account the greater liquidity risks posed by some classes of assets."

[6] A carry-trade is a form of arbitrage albeit a risky one. Arbitrage opportunities should exist in all markets even during periods of market breakdowns (Pasquariello, 2014), efficiency conditions (Grossman and Stiglitz, 1980), different types of market structures (Grossman and Miller, 1988), and conditions of international market segmentation (Blenman, 1991). There are different rates of returns to covered interest rate arbitrage and carry trade strategies. In good conditions for the carry trade, we would expect carry trade returns to dominate pure arbitrage strategies, like covered interest rate arbitrage. See Blenman and Wingender (QJFA, 2019) and Blenman and Wang (QJFA 2017) for a good overview of the problems of CAPM, IRPT and Law of One Price issues.

[7] Avery (2015) writes about the decision taken by the Swiss National Bank to unpeg the Swiss franc from the euro and the devastating effect on the country's private banks, leading to market liquidity drying up in the eurozone.

the interest rate differential[8] . There are two major ways of executing the carry trade strategy. First, investors may borrow from the low interest rate capital market, and invest in a high yield market, to make risky arbitrage profits from the interest rate differential. As long as the investment currency does not depreciate against the funding currency, profits are positive [(Galati et al., 2007), (Zhang et al., 2010)]. A second strategy is to exploit the forward premium, which is the difference between the forward exchange rate and the spot exchange rate of two currencies [Brunnermeier et al. (2008); Burnside et al. (2009)][9] .

This study provides a comprehensive analysis that links liquidity risk to carry trade returns, and provides an explanation of why carry trade investors should consider and manage FX liquidity risk. In our empirical analysis, we follow the seminal work of Lustig et al. (2011) and sort currencies into mimicking portfolios according to their liquidity level at the end of each month. We form five mimicking portfolios and our carry trade portfolio return, IML[10] (illiquid minus liquid), is a zero-cost return strategy that takes a long position in the 4 most illiquid currencies and short the 4 most liquid currencies in our sample currency-pairs. The other mimicking portfolios are used in the Fama-MacBeth procedure to estimate the liquidity risk premium of the FX market. Following Chan et al. (1998), the fourth mimicking portfolio is selected as the carry trade portfolio return. Chan et al. (1998) find that mimicking portfolio with the largest return volatility captures the highest amount of factor risk as measured by the volatility of the spread in returns between the long and short positions[11] .

Our study is closely related to three papers in the recent FX literature. First, as in Lustig et al. (2011), we show that carry trade excess returns can be explained by two risk factors (liquidity and market risk). Whereas Lustig et al. (2011) employed the HML_{FX}[12] factor, we investigate the empirical performance of a low-frequency liquidity risk factor (IML). Second, as in Mancini et al. (2013), we show that liquid currencies exhibit negative liquidity betas, thus offering insurance against liquidity risk. On the other hand, illiquid currencies have positive liquidity betas and tend to provide exposure to liquidity risk. Whereas Mancini et al. (2013) explain their liquidity effects with high-frequency liquidity measures during the 2007–2009 financial crisis, our results rely on low-frequency liquidity measures spanning over 15 years and capturing both “turbulent” and “normal” times of market events. Third, as in Karnaukh et al. (2015), we show that FX liquidity can be accurately measured using daily and readily available data. Whereas Karnaukh et al. (2015) focused on the commonality and other dynamics of the low-frequency FX liquidity measure, we performed a comprehensive analysis of the effects of the low-frequency liquidity measure on carry trade returns in an asset pricing framework.

We analyze the sensitivity of the liquidity level of our currency-pairs following Pastor and Stambaugh (2003) by regressing individual currency-pair liquidity level on the low-frequency market-wide liquidity measure. The sensitivity (liquidity beta) output of this regression is used to rank the liquidity of our currencies. The ranking is then used to construct our mimicking liquidity portfolios. We then show that liquidity risk constructed using mimicking portfolios explains carry trade returns across exchange rate sub-periods. This is done by utilizing a two-factor liquidity-adjusted asset pricing model where excess carry trade return is regressed on the mimicking liquidity portfolio and a market risk factor. This model implies that the expected carry trade return is explained by the covariance of its return with the mimicking liquidity risk factor and the market risk factor. If the two-factor model explains asset returns, the intercept should not be significantly different from zero. Our results show that the two-factor model provides a good fit to the data as shown by adjusted-R^2 ranging from 41 % to 93 %. Since all exchange rates load fairly equally on the market risk factor, the liquidity risk factor is the only plausible candidate risk factor that might explain the cross-section of portfolio excess carry trade returns.

To further substantiate our findings and contributions, we replace the low-frequency mimicking liquidity factor with an innovations risk factor, which is the residuals of an AR (1) model fitted to the liquidity risk factor. Whereas the mimicking liquidity portfolio is tradable; giving carry trade investors the flexibility to hedge liquidity risk exposures, the innovations risk factor is not. Results for the innovations risk factor are virtually in the same direction as that of the mimicking liquidity risk factor. This validates our output with the low-frequency mimicking liquidity risk factor. Whereas most of the studies use a shorter time period that includes financial crisis when liquidity issues are likely to be important, our study uses 15 years of data to investigate the role liquidity risk plays in explaining carry trade returns in both “normal” and times of stressful market conditions.

After establishing that FX mimicking liquidity portfolio and innovations risk factors explain carry trade returns, we show that liquidity risk is priced in the cross-section of carry trade portfolio returns. Our empirical asset pricing results suggest the presence of a statistically and economically significant risk premium associated with FX liquidity risk as shown in our results. This risk premium is estimated to be around 4.12 percent per annum. The market price of risk stays significant after controlling for other common risk factors in the FX market. This validates the hypothesis that liquidity risk is priced in the cross-section of carry trade returns.

[8] The low interest rate capital market currency is known as the “funding currency” and the high yield market currency is referred to as the “investment currency”.

[9] A third strategy of carry trade makes use of options and futures contracts as documented by Burnside et al. (2011a), Christiansen et al. (2011), Andersen et al. (2007), and (Jorion, 1995).

[10] As all FX rates use USD as their base currency, to construct IML, an investor pays USD 4 to buy the four most illiquid currencies and receives USD 4 for selling the four most liquid currencies.

[11] Specification in Eq. (8) and liquidity beta output in Table 3 are used to construct the mimicking portfolios.

[12] HML_{FX} strategy is going long in the most high interest rate currency and shorting the most low interest rate currency.

To summarize, our study contributes to the international finance and empirical asset pricing literature with a unique construction of a low-frequency market-wide liquidity risk factor. The process of constructing this factor captures the most important dimensions of liquidity (width, depth, immediacy, and resiliency). This is the first study, to the best of our knowledge, to investigate the effects of liquidity risk on carry trade returns across exchange rate sub-periods, using a low-frequency mimicking liquidity measure constructed from daily transaction prices. The possibility of using a low-frequency liquidity measure circumvents the restricted and costly access of intraday high-frequency data. Not only is access to high-frequency data limited and costly, but their use involves time-consuming handling, cleaning, and filtering techniques. Fong et al. (2017) find that the best liquidity proxies for global research are those constructed from low-frequency data. We also find that liquid and illiquid G10 currencies behave differently toward liquidity risk for all sub-periods in our study. Whereas liquid currencies such as the JPY and EUR are not that sensitive to liquidity risk, illiquid currencies such as the AUD and NZD are highly sensitive to liquidity risk. Liquid currencies exhibit negative liquidity betas whereas illiquid currencies show positive liquidity betas.

The remainder of this paper is organized as follows: Section 2 discusses the related literature, Section 3 describes the data set and construction of the liquidity measures. In Section 4, we run the currency-pair liquidity sensitivity regressions and rank the currencies in our sample according to their liquidity level. We also estimate the two-factor liquidity-adjusted model, which is the cornerstone of this study, and then run the Fama-MacBeth procedure to estimate the liquidity risk premium of the FX market. Section 5 concludes with recommended future work.

2. Related literature

Liquidity is an important feature of financial markets, yet little is known about its evolution over time or about its time-series determinants. A better understanding of these determinants might increase investor confidence in financial markets and thereby enhance the efficiency of corporate resource allocation.

Notwithstanding the importance of research on liquidity, existing studies have all been performed over short time-spans of three years or less. This is probably due to the tedious task of handling voluminous intraday data and the paucity of intraday data going back in years.

Studies connecting liquidity to asset pricing in the equity and bond markets have evolved over time and are currently based on a twofold proposition that the level of illiquidity and illiquidity risk are priced. One of the initial studies pioneering the former aspect of liquidity is credited to Amihud and Mendelson (1986), who documented a positive relationship between an asset's level of illiquidity and expected returns. Pastor and Stambaugh (2003) elaborated further on Amihud and Mendelson's study of the level of illiquidity and demonstrated a link between asset returns and liquidity risk. Amihud (2002) investigated systematic illiquidity risk and proposed that expected market illiquidity is priced positively, while shocks to market illiquidity lower contemporaneous returns. Amihud (2002) provided this evidence for the U.S. market, whereas Bekaert et al. (2007) tested these hypotheses for the emerging markets. Bao et al. (2011) show that the illiquidity in corporate bonds is substantial, significantly greater than what can be explained by bid-ask spreads.

In their study, Pastor and Stambaugh (2003) find that stocks whose prices decline when the market gets more illiquid receive compensation in expected returns. Dividing stocks into ten portfolios based on liquidity betas, the portfolio of high-beta stocks earned 9% more than the portfolio of low-beta stocks after accounting for market, size, and value-growth effects with the Fama-French 3-factor model. Our study follows a similar methodology using currency-pairs instead of stocks,[13] and we construct a liquidity risk factor, which helps in explaining the variation of carry trade returns across exchange rate sub-periods.

Acharya and Pedersen (2005) performed a similar but general investigative study to that of Pastor and Stambaugh (2003). They form 25 portfolios sorted on the basis of previous year's liquidity (liquidity of individual stocks). They find that in general, expected returns are higher for stocks that are illiquid on average. Documented average returns range from 0.48 % to 1.10 % per month as the illiquidity of the portfolios rises.

Currency carry trade is a trading strategy which consists of selling low interest-rate currencies (funding currencies) and investing in high interest-rate currencies (investment currencies). While the uncovered interest rate parity (UIP) hypothesizes that the carry gain due to the interest-rate differential is offset by a commensurate depreciation of the investment currency, empirically, the reverse holds, namely, the investment currency appreciates a little on average with a low predictive R^2 as documented by Fama (1984). This violation of the UIP - often referred to as the "forward premium puzzle" - is precisely the key driver of profitable carry trade investment strategy. Abankwa (2020) provided an explanation of the forward premium puzzle using FX liquidity risk measure constructed from daily transaction prices.

Koijen et al. (2017) apply the concept of "carry" to any asset. A security's expected return is decomposed into its "carry", expected price appreciation, and unexpected price appreciation. They define carry uniformly as the return on a futures position when the price stays constant over the holding period. Koijen et al. (2017) derive the carry of a currency from forward or futures prices that compares to the classic definition using interest rate differential. They apply the forward/futures

[13] Following Papell and Theodoridis (2001), our numeraire currency for the ten currency-pairs is the U.S. dollar (USD). We recognize that there might be slight differences across currency numeraires, but we make our choice based on the dominance of the U.S. dollar in world financial markets. We expect that our main results will be invariant to the choice of currency numeraire.

definition across eight diverse asset classes: currencies, equities, global bonds, commodities, US Treasuries, credit, call index options, and put index options.

Brunnermeier et al. (2008) show that carry traders are subject to crash risk. They argue that crash risk as measured by negative skewness is due to sudden unwinding of carry trades, which tend to occur in periods in which risk appetite and funding liquidity decrease. Burnside et al. (2009) and Lustig et al. (2011) show that traditional risk factors in the exchange rate market cannot explain carry trade returns. These risks are either not correlated with carry trade returns or are too small to explain the carry trade profit. Burnside et al. (2011b) confirm that traditional factor models like CAPM and Fama-French 3-factor model, are not helpful in capturing the risk factors in carry trade.

Lustig and Verdelhan (2007) sort currencies into portfolios according to their forward discount and define risk factors to price the portfolios. Lustig et al. (2011) discuss an alternative way to define risk factors. They were motivated by the stock returns literature, like Fama and French (1993), in which risk factors are derived from particular investment strategies or stock returns. Lustig et al. (2011) propose a single global risk factor that explains most of the variation in the excess return between high and low interest rate currencies. Our liquidity risk factor (IML) for the whole sample period is strongly correlated (0.84) with their global risk factor. Menkhoff et al. (2012) establish that global foreign exchange volatility risk offers the best explanation of cross-sectional excess returns of carry trade portfolios. Mancini et al. (2013) use a high-frequency (HF) market-wide liquidity measure constructed from intraday data from 2007–2009, and show that funding currencies offer insurance against liquidity risk, while investment currencies offer exposure to liquidity risk. This is consistent with our finding of liquid and illiquid currencies, respectively exhibiting low and high exposure to liquidity risk. Whereas the studies above use a shorter time period that includes financial crisis when liquidity issues are likely to be important, our study uses 15 years of data to investigate the role liquidity risk plays in explaining carry trade returns in both “normal” and times of stressful market conditions.

Karnaukh et al. (2015) show that FX liquidity can be accurately measured with readily available daily data. They provide a study of FX liquidity and its commonality over a wide range of exchange rates. They also investigate the supply-side and demand-side sources of FX liquidity. Our study focuses on how low-frequency liquidity risk helps in explaining the cross-sectional variation in carry trade returns.

3. Data & methodology

We collect daily nominal exchange rates to the U.S. dollar (USD) and 1-month deposit interest rates from

Bloomberg and Thomson Reuters from December 1998[14] to July 2015 for ten major developed markets[15] : Eurozone (EUR), Great Britain (GBP), Canada (CAD), Japan (JPY), Switzerland (CHF), Australia (AUD), New Zealand (NZD), Norway (NOK), Sweden (SEK), and Denmark (DKK).

For each trading day, the midpoint of the bid and ask quotes, low and high transaction prices, and close prices are used to construct the liquidity measures and carry trade returns. Following Mancini et al. (2013) and Brunnermeier et al. (2008), daily 1-month country deposit rates are used to construct the carry trade returns as shown in Eq. (9). Carry trade returns calculations are validated using forward rates. We also collect data from Bloomberg on the Invesco’s PowerShares DB G10 Currency Harvest (DBV) Carry Index Fund. This is used for a robustness check to ascertain that our liquidity risk factor constructed using principal components analysis, can explain the variation of index fund returns or portfolio carry trade returns across exchange rate sub-periods.

Following Bullard (2012), we divide our sample into exchange rate sub-periods using Lehman Brother’s collapse on September 15, 2008 as a reference point of gauging how liquidity measures respond to market dislocations. The rationale for using different sample periods is to test whether carry trade returns are driven by financial crisis or economic events across exchange rate sub-periods. Although the major events of the global financial crisis occurred during 2007–2009, the post-crisis period in our study still captures some of the market crisis’ spill-overs. For instance, on November 22, 2010, the EU/IMF authorities unanimously agreed to a three year joint financial assistance programme for Ireland. Fannie Mae (The Federal National Mortgage Association) on May 10, 2010, reports a net loss of $11.5 billion in the first quarter of 2010. The U.S. Treasury Department announced on March 21, 2011, to sell about $142 billion of the agency guaranteed mortgage-backed securities (MBS). The effects of all these events on the market were considered in the construction of the crisis and post-crisis periods.

3.1. Constructing liquidity measures

Liquidity measures were selected after careful and intensive review of the liquidity literature. Because our major contribution of this study is to show that easily accessible low-frequency liquidity measures can be constructed, and a systematic

[14] Our data start from December 1998 because of euro’s inception on January 1, 1999. With a higher trading volume behind the U.S. dollar (BIS, 2019), the euro’s market share was a key driver of our decision not to rely on historical spliced time series, which could bias our results because of the potential noise associated with the splicing process. We therefore relied on the actual euro time series since its inception.

[15] Emerging countries’ currencies were not considered in our study for two reasons. First, most of these currencies are not candidates for active carry trade investment strategy as their markets are not deep enough for serious carry trade players. Second, each currency’s liquidity is evaluated using the five liquidity measures, and the G10 currencies are representative of the entire FX market.

market-wide liquidity measure gleaned from these measures, we selected liquidity measures that capture low frequency liquidity dimensions of the data set.

3.1.1. Bid-ask bounce (Roll, 1984)

The first liquidity measure investigated in this study is Roll (1984) bid-ask bounce estimation of transaction costs. Roll (1984) argues that trades hit either bid or ask prices and this bid-ask bounce induce a first-order negative serial dependence in successive observed market price changes. Given market efficiency, Roll (1984) deduced the effective bid-ask spread as:

$$Spread = 2\sqrt{-Cov(\Delta S_t, \Delta S_{t-1})_t} \tag{1}$$

where "Cov" is the first-order serial covariance of price changes and S_t is the transaction price at time t.

This measure is directly linked to liquidity, and the higher the Roll spread, the lower the liquidity[16] .

$$V_t = V_{t-1} + e_t \tag{1.1}$$

where e_t is the mean-zero, serially uncorrelated public information shock on day t. Next, let S_t be the last observed trade price on day t. Assume that S_t is determined by

$$S_t = V_t + \frac{1}{2} CQ_t \tag{1.2}$$

where C is the effective spread or cost and Q_t is a buy/sell indicator for the last trade that equals +1 for a buy or -1 for a sell. Q_t is equally likely to be +1 or -1, and is serially uncorrelated, and independent of e_t. Taking the first difference of Eq. (1.2) and combining it with Eq. (1.1) yields

$$\Delta S_t = \frac{1}{2} C\Delta Q_t + e_t \tag{1.3}$$

where Δ is the change operator. Given this setup, Roll (1984) shows that the serial covariance is:

$$Cov(\Delta S_t, \Delta S_{t-1}) = \frac{1}{4} C^2 \tag{1.4}$$

Solving Eq. (1.4) for C gives Roll's estimator in Eq. (1).

3.1.2. Liquidity measure (Goyenko et al., 2009)

Goyenko et al. (2009) argue that daily price changes exhibit positive serial dependence some times and hence modified the Roll (1984) measure. Harris (1990) first documented the ill-behavior of the Roll (1984) spread estimator. He finds that the serial covariance estimator yields poor empirical results when used to estimate individual security spreads. Estimated first-order serial covariances are positive for about half of all securities so that the square root in the estimator is not properly defined. Harris (1990) concludes that the serial covariance estimator is very noisy in daily data and is biased downward in small samples.

Goyenko et al. (2009) modified the Roll (1984) measure so that if first-order serial covariance is positive, it will still be defined.

$$Modified\ Roll = \begin{cases} 2\sqrt{-Cov(\Delta S_t, \Delta S_{t-1})_t} & \text{when } Cov\ (\Delta St, \Delta St-1)\ < 0 \\ 0 & \text{when } Cov\ (\Delta St, \Delta St-1)\ \geq 0 \end{cases} \tag{2}$$

Goyenko et al. (2009) modified Roll (1984) measure is therefore used as our modified spread measure. The higher the spread measure, the lower the liquidity.

3.1.3. Hasbrouck's Gibbs measure

Hasbrouck (2009) advocates a Bayesian estimation of Roll (1984) model using Markov chain Monte Carlo (MCMC) estimator, the Gibbs sampler. Bayesian analyses are often motivated as a means for incorporating prior beliefs, and are often criticized for the sensitivity to choice of prior distributions. In Hasbrouck (2009), the posterior density of the parameters in Roll's model is obtained by random draws based on their prior distribution and these random draws are generated using the Gibbs sampler. Hasbrouck (2009) restates Roll's model as:

$$\begin{aligned} m_t &= m_{t-1} + u_t \\ u_t &\sim N\left(0, \sigma_u^2\right) \\ S_t &= m_t + cq_t \end{aligned} \tag{3}$$

[16] In deriving Eq. (1), Roll (1984) denotes V_t as the unobservable fundamental value of the stock on day t. Assume that this fundamental value evolves as a random walk.

where m_t is the efficient price (price in a frictionless market) following a Gaussian random walk, u_t is the public information shock and is assumed to be normally distributed with a mean of zero and a variance of σ_u^2, and independent of q_t. S_t is the log trade price, c is the effective cost to be estimated, and q_t is the trade direction indicator, which equals +1 for a buy and -1 for a sell with equal probability.

The transaction price (S_t) is observed. The trade direction (q_t) and efficient price (m_t) are not. By taking first differences of the transaction price equation:

$$\Delta S_t = c\Delta q_t + u_t \tag{4}$$

Eq. (4) is important for the Bayesian estimation approach because if Δq_t was known, this would have been a simple regression specification and the Bayesian approach would not have been warranted. The transaction price data sample is $S \equiv \{S_1, S_2, \ldots, S_T\}$, where T is the number of months in the time period. The model parameters $\{c, \sigma_u^2\}$, the latent buy/sell indicator, $q \equiv \{q_1, q_2, \ldots, q_T\}$, and the latent efficient prices, $m \equiv \{m_1, m_2, \ldots, m_T\}$ are to be numerically estimated.

The approach of the Gibbs sampler is an iterative process in which one sweep consists of three steps[17] . Each sampler is run for 1000 sweeps, of which the first 200 are discarded to remove the effect of starting values (burn-in values), and the mean value of c in the remaining 800 sweeps serves as the estimate of the effective cost.[18]

3.1.4. *Liquidity measure (Menkhoff et al., 2012)*

Menkhoff et al. (2012) propose a relative bid-ask spread and volatility measures to capture transaction cost. The bid-ask spread is the difference between the bid and ask (offer) prices quoted by a dealer who makes a market in FX market, and bridges the time gap between asynchronous public buy and sell orders. The ask (offer) price quoted for a security includes a premium for immediate buying, and the bid price reflects a price concession for immediate sale. The bid-ask spread may thus be viewed as the price the dealer (or market-maker) demands for providing liquidity services and immediacy of execution.

$$\text{Bid} - \text{Ask Spread} = \frac{A_t - B_t}{M_t} \tag{5}$$

$$\text{Volatility} = \left|(\Delta S_\tau)\right| \tag{6}$$

where A_t, B_t, and τ are the ask quote, bid quote, and return period respectively. M_t is the mid-quote price at time t.

The volatility measure has similarities to measures of realized volatility used by Andersen et al. (2001), although we use absolute returns following Menkhoff et al. (2012), and not squared returns to minimize the impact of outlier returns.

3.1.5. *Corwin-Schultz liquidity measure*

Corwin and Schultz (2012) develop a spread estimator from daily high and low transaction prices. Daily high (low) prices are almost always buy (sell) orders. Hence the high-low ratio reflects both the asset's variance and its bid-ask spread. While the variance component of the high-low ratio is proportional to the return interval, the spread component is not. This allows for a closed form derivation of the spread estimator as a function of high-low ratios over one-day and two-day intervals. The spread estimator is given by:

$$\begin{aligned} &\text{Corwin Schultz} = \frac{2\left(e^{\alpha} - 1\right)}{1 + e^{\alpha}} \\ &\alpha = \left(1 + \sqrt{2}\right)\left(\sqrt{\beta} - \sqrt{\gamma}\right) \\ &\beta = \sum_{j=0}^{1}\left[\ln\left(\frac{H_{t+j}}{L_{t+j}}\right)\right]^2 \\ &\gamma = \left[\ln\left(\frac{H_{t,t+1}}{L_{t,t+1}}\right)\right]^2 \end{aligned} \tag{7}$$

where H and L are the high and low daily close prices respectively. Being a spread estimator, a lower value indicates high liquidity and vice versa.

Daily liquidity measures are constructed for the ten currency-pairs using Eqs. (1)–(7). Taken together, the liquidity measures capture width, depth, immediacy, and resiliency dimensions of liquidity (Harris, 1990)[19] . EBA (2013) documented the

[17] First, a Bayesian regression is used to estimate the effective cost, c, based on the sample of prices, the starting values of q, and the priors for $c, {\sigma_u}^2$. Second, a new draw of ${\sigma_u}^2$ is made from an inverted gamma distribution based on S, q, the prior for ${\sigma_u}^2$, and the updated estimate of c. Third, new draws of q and m are made based on the updated estimate of c and the new draw of ${\sigma_u}^2$.

[18] We use the program code provided on Hasbrouck's website to estimate the Gibbs measure empirically. Hasbrouck corrects for possible negative transaction cost estimates in the Roll (1984) model by restricting them to be positive in the Bayesian approach. For each currency, the standard deviation of the transaction cost prior is set to be equal to $\sqrt{a - b}$, where a and b are the daily averages of ask and bid prices respectively.

[19] Width is typically captured by the size of the bid-ask spread, which measures the cost of consuming liquidity immediately, but does not capture the quantity that can be traded at that spread; Depth is the quantity of liquidity supplied, typically measured by the volume offered at the bid-ask spread;

need to assess liquidity across different dimensions simultaneously. Since each spread measure captures different dimension of liquidity, a principal component analysis (PCA) is used to extract the common liquidity information among the constructed measures across the ten currency-pairs. This is consistent with Hasbrouck and Seppi (2001) and Korajczyk and Sadka (2008) in the equity literature. The first principal component represents the market-wide liquidity measure[20] . Currency pair liquidity measures are also constructed across the liquidity measures for the ten currency-pairs. Fig. 1 shows the profile of the constructed five liquidity measures. The profiles of the currency-pair liquidity measures and the five liquidity measures for all currencies are shown in the Internet Appendix. It is evident that constructed liquidity measures capture the drop in market liquidity during the Lehman Brothers collapse in September 2008.

Table 1 shows the summary statistics of constructed liquidity measures for the whole sample and the three sub-periods (Pre-Crisis, Crisis, and Post-Crisis). For the whole sample, JPY and EUR appear to be the most liquid currencies as they have the least spreads across all the five liquidity measures. In contrast, NZD, AUD, and NOK appear to be the most illiquid currencies as indicated by their wide spreads. Table 2 shows the co-movement of the constructed liquidity measures. Chordia et al. (2000) analyzed commonality in the stock and bond markets and found that individual liquidity measures co-move with each other. Studying such co-movement can help to facilitate the understanding of macro views of market- and industry-wide liquidity. The correlation matrix of the currency-pair liquidity measures and the systematic market-wide liquidity measure is shown in the Internet Appendix.

Overall, summary statistics show that JPY, EUR, DKK and CHF are the most liquid currencies in the sample. In contrast, NZD, AUD, NOK and SEK are the most illiquid. Estimating the specification of Eq. (8) in the next section, liquidity betas indicate that JPY is the most liquid currency in the whole sample period followed by EUR. This is in line with the perception of market participants and the fact that the Euro and Japanese yen have by far dominated the FX market in terms of market share and turnover (BIS, 2019). Following Pastor and Stambaugh (2003), liquidity beta is the loading on the market-wide liquidity measure when individual currencies are regressed on the market-wide liquidity measure. Highly liquid currencies are expected to have smaller loading because they are not that sensitive to the market-wide liquidity measure. In contrast, illiquid currencies are expected to have higher loadings because they are sensitive to the market-wide liquidity measure.

4. Currency-pair liquidity sensitivity to systematic FX liquidity

Following Pastor and Stambaugh (2003) and Mancini et al. (2013), we analyze the sensitivity of the liquidity of exchange rate j to a change in the systematic or market-wide liquidity measure. We run a time-series regression of individual currency-pair liquidity, $L_{j,t}$, on market-wide liquidity measure, MKT_t, by estimating the following equation:

$$L_{j,t} = \alpha_{\mathrm{j}} + \beta_{\mathrm{j}}\mathrm{MKT}_{\mathrm{t}} + \varepsilon_{\mathrm{j,t}} \tag{8}$$

where $\varepsilon_{j,t}$ represents an idiosyncratic liquidity shock. The sensitivity is captured by the slope coefficient β_j. To prevent potentially upward-biased sensitivities, we reconstruct MKT_t excluding exchange rate j. Estimation results in Table 3 indicate that specification of Eq. (8) provides a good fit to the data with an R^2 ranging from 54.2%–85.6%. All estimated slope coefficients are positive and statistically significant at conventional levels. This provides the evidence that the liquidity of every FX rate depends positively on the market-wide liquidity measure. The most liquid currencies (JPY, EUR, DKK, and CHF) have the lowest liquidity sensitivities to market-wide FX liquidity. The least liquid currencies (SEK, NOK, AUD, and NZD) have the highest liquidity sensitivities.

These findings suggest that illiquid currencies are very sensitive to changes in market-wide liquidity. In contrast, the most liquid currencies are less sensitive to changes in market-wide liquidity and as a result, may offer a “liquidity hedge” as they tend to remain relatively liquid, even when the market-wide liquidity drops. These findings are consistent with Mancini et al. (2013) and Brunnermeier et al. (2008). Liquidity betas of Eq. (8) are then used to rank all the ten currencies in our sample in order of decreasing market liquidity (JPY, EUR, DKK, CHF, CAD, GBP, NZD, AUD, NOK, SEK).

4.1. Carry trade returns

Following Mancini et al. (2013), Christiansen et al. (2011) and Brunnermeier et al. (2008), we denote the carry trade return in the foreign currency investment financed by borrowing in the domestic currency (USD$) by:

Immediacy is how quickly a large trade can be accomplished; and Resiliency is how long it takes for the price to return to the pre-trade equilibrium after a large trade consumes liquidity (Harris, 1990).

[20] We extract the common systematic components of liquidity across ten currency-pairs and from a set of five measures of liquidity. With ten currency-pairs (n=10), five measures of liquidity, and a sample size of T (T=4326), we extract latent factors from a cross-sectional sample of T x M (M=10 x 5 = 50). The first principal component represents the market-wide liquidity measure. Following Korajczyk and Sadka (2008), we demean, standardize, and collect all five liquidity measures in a 5 x T matrix, L_j, for each currency-pair, j. T is the number of days in our sample. We use the eigenvector decomposition of the covariance matrix, $L_j {L^T}_j E_j = E_j D_j$, where E_j is the 5 x 5 eigenvector matrix and D_j is the 5 x 5 diagonal matrix of eigenvalues, and ^{T} is the transpose operator. The first principal component of currency-pair, j, is given by ${E_j}^T L_j$ corresponding to the largest eigenvalue, where E_j is chosen so that the variance of ${E_j}^T L_j$ is maximized over all vectors of E_j. PCA assumes that principal components with large variances have important dynamics and lower variances correspond to noise.

$$r^e_{j,t+1} = \left(i^*_{j,t} - i_t\right) - \Delta s_{j,t+1} \tag{9}$$

where $r^e_{j,t+1}$ is the excess carry trade returns over UIP, s_t = log(nominal exchange rate), $i^*_{j,t}$ and i_t are the logarithm of foreign interest rate for currency j and domestic (U.S.) interest rate respectively, and $\Delta s_{t+1} \equiv s_{t+1} - s_t$, is the depreciation of the foreign currency. Under UIP, $r_t{}^e{}_{+1}$ should not be forecastable, that is, $E\left[r^e_{j,t+1}\right] = 0$. Hence, r^e_{t+1} can be interpreted as the abnormal return to a carry trade strategy where the foreign currency is the investment currency and the U.S. dollar is the funding currency.

Summary statistics of carry trade returns in Table 4 indicate that financial crisis period exhibit higher negative returns. This could be due to carry traders unwinding their positions when liquidity dries up during financial crisis. This finding is consistent with Brunnermeier et al. (2008). Post-crisis period is marked by high carry trade returns as indicated by their Sharpe ratios. This may imply that carry trade investors engage in this risky speculative trade with the expectation that the high interest rate currency will continue to appreciate in "calmer periods" where liquidity picks up.

4.2. Two-factor liquidity-adjusted model

Breeden (1979) shows that mimicking portfolios can replace the state variables in the intertemporal asset pricing model of Merton (1973). A number of studies use mimicking portfolios for economic factors. Chen et al. (1986) construct mimicking portfolios for several macroeconomic factors. Breeden et al. (1989) adopt mimicking factors for aggregate consumption growth, and Fama and French (1996) construct their SMB and HML mimicking portfolios in an attempt to capture distress risk. The construction of our mimicking liquidity factor, IML, is discussed in the next section.

Both the arbitrage pricing theory (APT) and equilibrium models show that asset pricing models have the following form:[21]

$$E(r_j) = \lambda_0 + \beta_{j1}\lambda_1 + \beta_{j2}\lambda_2 + \ldots + \beta_{jK}\lambda_K \tag{10}$$

where $E(r_j)$ is the expected return of asset j, β_{jk} is the beta of asset j relative to the kth risk factor, λ_k is the risk premium of the kth factor (k = 1, 2, ..., K), and λ_0 is the expected zero-beta rate. We construct our two-factor model based on the CAPM plus the IML factor that captures liquidity risk. The expected excess return of security/portfolio j from the two-factor model is:

$$E(r_j) - r_f = \beta_{m,j}[E(r_m) - r_f] + \beta_{l,j}\mathrm{E}(IML) \tag{11}$$

where $E(r_m)$ is the expected return of the market portfolio, $E(IML)$ is the expected return of the mimicking liquidity portfolio, and the factor loadings $\beta_{m,j}$ and $\beta_{l,j}$ are the slope coefficients for the expected excess market return and the mimicking liquidity portfolio respectively.

The two-factor model implies that the expected excess carry trade return of a currency is explained by the covariance of its return with the market factor and the liquidity factor. Eq. (11) is valid only if the liquidity factor is a priced state variable.

4.3. Liquidity risk factor

We formally test whether liquidity risk affects carry trade returns. To do this, we assume that the variation in the cross-section of returns is caused by different exposures of risk factors as documented by Ross (1976) in his APT model.

The liquidity risk factor is tested in two ways. First, we construct a tradable low-frequency mimicking portfolio and show that this risk factor is priced in the cross section of carry trade returns. Second, we construct an innovations risk factor using residuals from an AR (1) model fitted to the market-wide liquidity risk factor. We corroborate the results of the first construction by showing that the innovations risk factor explains the variation of carry trade returns across exchange rate sub-periods.

In the construction of the mimicking portfolios, we introduce a liquidity risk factor given by a currency portfolio that is long in the most illiquid and short in the most liquid FX rate on each day. We repeat this portfolio formation for a total of five mimicking portfolios using Eq. (8) and results in Table 3. For example, in the four-currency portfolio formation, we utilize the regression loadings in Eq. (8) to go long in NZD, AUD, NOK, and SEK, and short in JPY, EUR, DKK, and CHF. Following Chan et al. (1998), the portfolio that goes long in the 4 most illiquid currencies and short in the 4 most liquid currencies has the largest return volatility. This implies that the portfolio captures the highest amount of factor risk as measured by the volatility of the spread in returns between the long and short positions. We label this mimicking liquidity portfolio as IML, which stands for illiquid minus liquid portfolio. IML is interpreted as the return in dollars on a zero-cost trading strategy that goes long in the 4 most illiquid currencies and short in the 4 most liquid currencies. As IML is a tradable risk factor, currency investors can easily hedge associated liquidity risk exposures.

Lustig et al. (2011) introduce HML as a carry trade risk factor. HML is given by a currency portfolio that is long in high interest rate currencies and short in low interest rate currencies. Lustig et al. (2011) find that HML explains the common

[21] The arbitrage pricing theory is developed by Ross (1976) and the multiple-beta equilibrium model by Merton (1973); Breeden (1979), and Cox et al. (1985). Fama and French (1996) explore the relation between expected return and multiple risk factors.

variation in carry trade returns and suggest that this risk factor captures “global risk” for which carry traders earn a risk premium. Following Lustig et al. (2011) in the spirit of arbitrage pricing theory and equilibrium models, we run a two-factor model with IML as the liquidity risk factor (mimicking portfolio) and AER (average excess return) as the market risk factor. The “market risk” factor or AER is computed as the first principal component of all the ten currency-pairs carry trade returns. AER is interpreted as the average return for a U.S. currency investor who goes long in all the ten exchange rates available in the sample. The following factor model from Eq. (11) is then estimated:

$$r^{e}_{\mathrm{j,t}}=\alpha_{\mathrm{j}}+\beta_{\mathrm{AER,j}}\mathrm{AER_t}+\beta_{\mathrm{IML,j}}\mathrm{IML_t}+\varepsilon_{\mathrm{j,t}} \tag{12}$$

where $\beta_{AER,j}$ and $\beta_{IML,j}$ represent the exposure of carry trade return j to the market risk factor (AER) and liquidity risk factor (IML) respectively. As dictated by econometric modeling, any unusual or abnormal return that is not explained by the FX risk factor is captured by the constant α_j.

As shown in Table 5, Eq. (12) provides a good fit to the data with adjusted-R^2 for regressions ranging from 41 % to 93 %. This implies that the vast majority of variation in carry trade returns during any exchange rate sub-period can be explained by two risk factors (the market risk factor and the liquidity risk factor). Liquidity betas, β_{IMLj}, are economically and statistically significant at conventional levels. As depicted in Table 6, economic significance of liquidity betas implies that when liquidity factor (IML) decreases by one standard deviation, AUD depreciates by 0.39 standard deviations, whereas JPY appreciates by 0.62 standard deviations for the whole sample. The consistency of results across sub-periods implies that carry trade returns are not driven by financial crisis or disaster events in the economy.

When we run a univariate regression with IML as the only explanatory factor, R^2 as high as 61.3% is obtained as shown in the Internet Appendix. This underscores the crucial role of liquidity risk in explaining the variation of carry trade returns across exchange rate sub-periods. As noted by Lustig et al. (2011), all exchange rates load fairly equally on the market risk factor (AER), which helps in explaining the average level of carry trade returns. Liquidity betas, β_{IMLj}, however, vary significantly across currencies and exchange rate sub-periods.

An interesting pattern emerges from the results. Typical high interest rate currencies, such as AUD and NZD, exhibit the largest positive liquidity betas and typical low interest rate currencies, such as JPY and CHF, exhibit the largest negative liquidity betas. Fig. 2 shows the liquidity betas (from Table 5, Panel A) corresponding to low and high interest rate currencies. This implies that high interest rate currencies are sensitive to liquidity risk and provide a higher exposure to liquidity risk. In contrast, low interest bearing currencies are less sensitive to liquidity risk and thus offer insurance against liquidity risk or exhibit a “liquidity hedge” against liquidity risk. The high interest rate currencies correspond to the illiquid FX rates whereas the low interest rate currencies correspond to the liquid FX rates in our sample. These findings indicate that when FX liquidity improves, illiquid currencies appreciate further because of the positive liquidity betas. In contrast, liquid currencies depreciate when liquidity improves because of the negative liquidity betas[22] . This observation is consistent with the findings of Mancini et al. (2013), and increases the deviation of FX rates from UIP (Forward Premium Puzzle).

The results also show that Japanese yen (JPY) exhibits a liquidity hedge against liquidity risk. This implies that JPY appreciates when liquidity drops, as evident with its persistent negative liquidity beta in our regression results. This lends support to the global usage of JPY as funding currency for the carry trade strategy, and the fact that JPY is a safe haven currency consistent with Fatum and Yamamoto (2016) and Lee (2016). Fatum and Yamamoto (2016) find that the JPY is the safest” of safe haven currencies and that only the JPY appreciates as market uncertainty increases. Lee (2016) uses Markov regime-switching vector autoregressive models to test whether six haven currencies are negatively related to risky assets and whether the negative relation is stronger in times of crisis than in times of growth. Lee (2016) finds that Swiss franc and Japanese yen qualify as strong safe havens.

In this study, FX liquidity is analyzed in two phases. First, the level of liquidity is the systematic market-wide liquidity measure constructed using principal components analysis. Our mimicking liquidity risk factor (IML) is then obtained using regression results of the systematic market-wide liquidity measure. Second, following Pastor and Stambaugh (2003) and Acharya and Pedersen (2005), liquidity shock is defined as the residuals from an AR(1) model fitted to the systematic market-wide liquidity measure as shown in Fig. 3. Pastor and Stambaugh (2003) and Acharya and Pedersen (2005) show that correlations between liquidity shocks and returns are closer to twice the correlations between liquidity levels and returns. Correlation results in the Internet Appendix show that this is consistent with carry trade returns. Such strong co-movements between carry trade returns and shocks in liquidity are consistent with liquidity risk being a risk factor for carry trade returns. When the hedged liquidity factor, IML, is replaced with the innovations risk factor (liquidity shocks), the results in Table 7 are virtually in the same direction as that in Table 5. Also, Fig. 4 with the innovations risk factor exhibits similar characteristics as Fig. 2. The implication of this finding is that, irrespective of the method used to construct the FX liquidity risk factor, both liquid and illiquid currencies will retain their characteristics and dynamics toward the risk factor. This demonstrates the importance of liquidity risk as a determinant of carry trade returns.

[22] Results are consistent across all exchange rate sub-periods (pre-crisis, crisis and post-crisis).

4.4. FX liquidity risk premium

After showing that FX mimicking liquidity portfolios explain carry trade returns, we investigate whether our liquidity risk factor is priced in the cross-section of excess carry trade returns of the sorted portfolios.

The question that we ask is, how much liquidity premium does carry trade investors require to hold portfolios made up of the G10 currencies?

We answer the above question by quantifying the FX liquidity risk premium in the FX market. We do this by conducting a standard Fama and MacBeth (1973) regression analysis. In the first step, we run a time-series regression of portfolios' returns on the risk factors. In the second step, we run a cross-sectional regression of the portfolios' returns on the estimated betas in the first step. Following Lustig et al. (2011), we do not include a constant in the second step ($\lambda_0 = 0$). Taking the perspective of a U.S. investor, we test whether our liquidity risk factor prices the excess returns of the liquidity-sorted portfolios. We do this by testing the significance of the liquidity risk factor conditioning on other factors such as the global carry trade risk factor proposed by Lustig et al. (2011).

The liquidity-sorted portfolios are mimicking portfolios constructed by taking a long position in the most illiquid currency-pair and shorting the most liquid currency-pair. Four liquidity-sorted return portfolios are used for the estimation of the liquidity risk premium. The first portfolio takes a long position in the most illiquid currency-pair and short the most liquid currency-pair. The second portfolio uses the two most illiquid and liquid currency-pairs. The third portfolio employs the three most illiquid and liquid currency-pairs, and the fourth portfolio will long the 5 most illiquid currency-pairs and short the 5 most liquid currency-pairs[23] .

We apply the standard Fama-MacBeth procedure by estimating the sensitivities of the portfolios to the mimicking liquidity risk factor (IML) and some common currency risk factors through a time-series regression of the form shown in Eq. (13):

$$r^e_{j,t} = \alpha_j + \beta_j^{LIQ} IML_t^{LIQ} + \beta_j^{Other} f_t^{Other} + \varepsilon_{j,t} \quad \textit{for} \;\; j = 1, \ldots, 4 \tag{13}$$

where $r^e_{j,t}$ is the return of mimicking portfolio j (4 in total) at time t, IML_t^{LIQ} is our liquidity risk factor at time t, β_j are the factor exposures or loadings that describe how portfolio returns are exposed to the risk factors, and t goes from 1 through T. The choice of our common currency risk factor is the carry risk factor (HML) or the average excess carry returns (AER) proposed by Lustig et al. (2011).

In the second-stage of the Fama-MacBeth procedure, we determine the cross-sectional impact of the sensitivities on the mimicking portfolios by running a cross-sectional regression of the excess returns of the mimicking portfolios on the sensitivities of the risk factors at each point in time as shown in Eq. (14).

$$r^e_{j,t} = \hat{\beta}_j^{LIQ} \lambda_t^{LIQ} + \hat{\beta}_j^{Other} \lambda_t^{Other} + \epsilon_{j,t} \quad \text{for t} = 1, \ldots, \text{T} \tag{14}$$

where λ_t is the market price of a specific risk factor at time t and the $\beta^0 s$ are estimated from the first-stage regression in Eq. (13). The market price of risk and pricing errors are then estimated by averaging the cross-sectional regression estimates as shown in Eqs. (15)–(17).

$$\hat{\lambda}^{LIQ} = \frac{1}{T}\sum_{t=1}^{T} \lambda_t^{LIQ} \tag{15}$$

$$\hat{\lambda}^{Other} = \frac{1}{T}\sum_{t=1}^{T} \lambda_t^{Other} \tag{16}$$

$$\hat{\epsilon}_j = \frac{1}{T}\sum_{t=1}^{T} \epsilon_{j,t} \tag{17}$$

To show that liquidity risk is priced in the cross-section of excess carry trade portfolio returns in the FX market, the market price must be positive and statistically significant. In addition, the market price must stay significant after controlling for other common currency factors (Lustig et al., 2011). Table 8 shows the results of the Fama-MacBeth procedure with different regression specifications. Panel A reports the analysis where we test whether our liquidity risk factor is priced in the cross-section of carry trade portfolio returns.

The market price of risk (λ) associated with the liquidity risk factor is positive and statistically significant. We estimate an annualized liquidity risk premium of about 4.12 percent. Controlling for other common risk factors, Panels B, C, and D of Table 8 show the pricing of risk results when the carry risk and average excess returns factors are included in our specification. In all the panels, the λ associated with the liquidity risk factor remains statistically significant at conventional levels. We therefore validate the hypothesis that liquidity risk is a priced factor in the FX market.

[23] Note that the 4 most illiquid and liquid currency-pairs are used in the construction of IML following Chan et al. (1998).

Mancini et al. (2013) suggest that currency investors demand a liquidity risk premium by examining the persistence of the shocks to market-wide liquidity, and showing that the shocks are correlated with carry trade returns. We validate this observation in Table 7. Banti et al. (2012) estimate a liquidity risk premium of about 4.7 % per annum. Lustig et al. (2011) estimate a risk premium of 5.5 % per annum. Our low estimate of the liquidity risk premium could be due to our sample of G10 currencies, as compared with a blend of emerging market currencies with the other studies.

4.5. Robustness checks

As a robustness check, we use Eq. (12) to explain the variation of carry trade portfolios using the Invesco PowerShares DB G10 Currency Harvest (DBV) Index Fund. The goal of this robustness test is to show how liquidity risk explains the variation in carry trade portfolios. The fund is designed to exploit the trend that currencies associated with relatively high interest rates, on average, tend to rise in value relative to currencies associated with relatively low interest rates. The Index is rebalanced annually, and at any time, made up of long futures contracts on the three G10 Currencies associated with the highest interest rates and short futures contracts on the three G10 Currencies associated with the lowest interest rates. The rebalanced portfolio as of the date of data collection was made up of long futures contracts in NZD, AUD, NOK and short futures contracts in JPY, EUR and CHF. Table 9 shows the results of how our liquidity risk factors explain carry trade portfolio returns. Eq. (12) is estimated replacing excess carry trade returns with the PowerShares DBV Index returns. The liquidity beta for DBV is significant at conventional levels. This supports the finding that liquidity risk is an important risk factor for carry trade returns across all exchange rate sub-periods.

Following Lustig et al. (2011) and Mancini et al. (2013), we regress FX returns ($-\Delta S_{j,t+1}$) on the market and liquidity risk factors. All liquidity betas are virtually the same as shown in the Internet Appendix. This implies that liquid currencies act as a liquidity hedge because they appreciate when market-wide FX liquidity drops, not because the interest rates on these currencies increase. In contrast, illiquid currencies have high exposure to liquidity risk because they depreciate when FX liquidity drops, not because the interest rates associated with these currencies decline. The support of the robustness checks to the findings of this study, confirms that liquidity risk is an important risk factor for carry trade returns.

5. Conclusion

Using low-frequency liquidity measures, we provide a comprehensive investigation into FX liquidity risk and carry trade returns. The study's main contribution is the identification and construction of new low-frequency liquidity risk measures that significantly and economically explain the cross-sectional variation of carry trade returns. Our low-frequency liquidity measures are extracted via principal component analysis of commonly used volatility and liquidity measures, that are available in all currency markets. We therefore provide an economically feasible approach that will enable researchers to work even with thinly traded currencies and measure liquidity risks in such currencies. We also show that FX liquidity is an important issue in the global FX market. Our model prices liquidity risks in carry trades, with leveraged or unlevered portfolios, that involve spot and forward or currency futures markets positions.

Liquidity betas are used to construct mimicking liquidity risk factors, which help in explaining the variation of carry trade returns across exchange rate sub-periods. The explanatory power of the liquidity risk measure is further corroborated using residuals of an AR (1) model fitted to the systematic market-wide liquidity measure. We infer from our analysis that carry trade investors demand premiums for holding illiquid currencies in their portfolios, implying that liquidity risk is priced. We employ a liquidity-adjusted asset pricing approach and introduce a measure of mimicking FX liquidity portfolio as a liquidity risk factor. We estimate the liquidity risk premium to be around 4.12 percent per annum, which is both statistically and economically significant.

The implication of this finding is three fold. Firstly, the monitoring of FX liquidity will enable central banks and regulatory authorities to evaluate the effectiveness of their policies. The role of liquidity risk will help currency investors to adequately assess the risk of their international portfolios and carry trade investors would be able to assess currency crashes better due to liquidity spirals. The exhibited individual currency-pair liquidity dynamics would enable carry traders to take hedged positions with their portfolios. In the area of portfolio selection and diversification, our finding may guide investors in balancing expected liquidity risk against expected carry trade returns. In sum, we demonstrate the importance of liquidity risk as a determinant of carry trade returns.

We also show that our liquidity risk measures also explain the variation in leveraged carry trade portfolios. We demonstrate this by doing a robustness check of carry trade returns, involving the Invesco's PowerShares DB G10 Currency Harvest (DBV) Index Fund. This carry trade fund is based on leveraged currency futures positions. We further demonstrate that truly liquid currencies have negative liquidity betas across all sub-periods, that include normal periods, crisis and post crisis period. Such currencies are deemed safe-haven currencies. They provide good insurance against surprises especially in times of currency market crises and other episodes of flights to safety. We find that the Euro, JPY (Yen), DKK and CHF display strong safe-haven currency features. They have their highest negative loading during periods of crisis. We show that GBP does not have strong safe haven characteristics. Our liquidity risk measure would therefore be useful to market participants interested in portfolio carry trades, to balance their expected liquidity risk with expected returns.

Future research work should focus on how our liquidity risk factor construction would be leveraged in stress testing and comprehensive capital analysis and review (CCAR) of the big banks. Currently, most of the internal models of the big banks do not adequately capture liquidity risk. We also should be able to show how to optimally lift carry trade positions, by analyzing the joint history of carry trade returns and liquidity measures. Our work also holds promise for predicting the onset of currency crashes.

Appendix A.

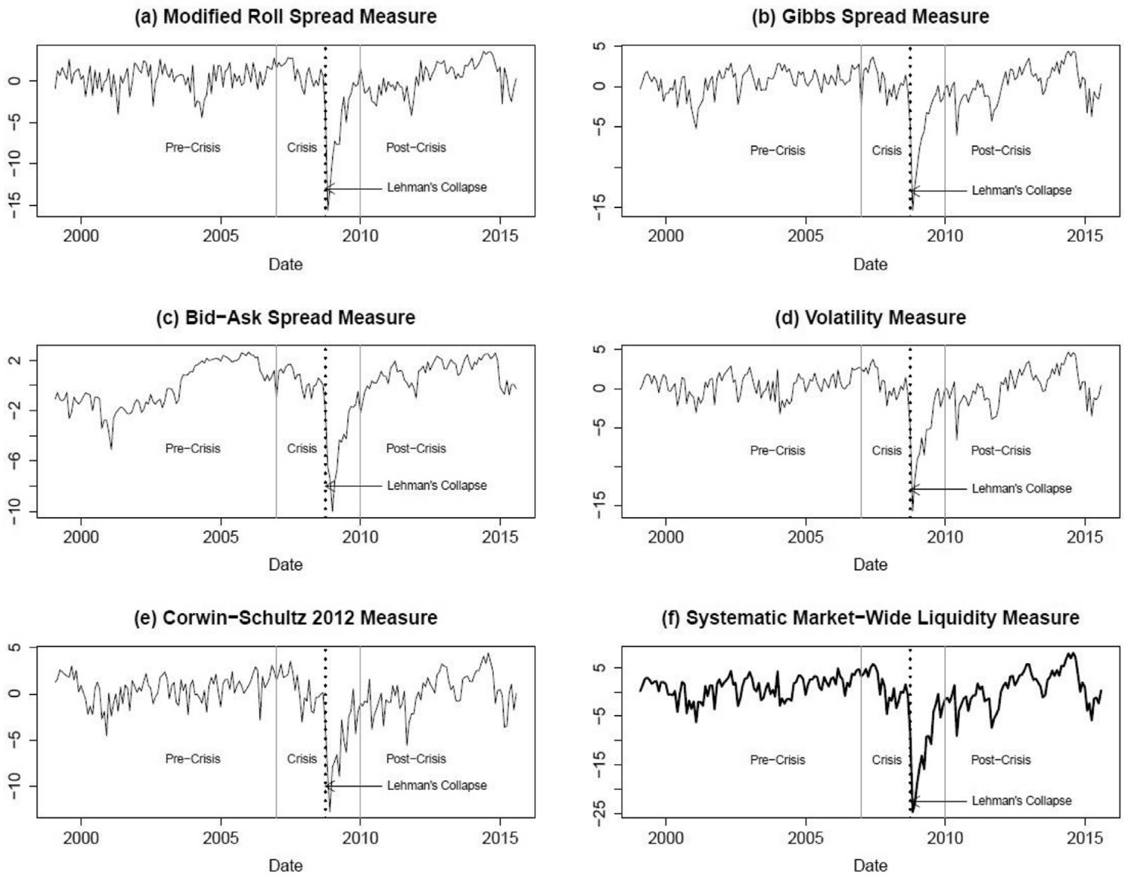

Fig. 1 Individual Liquidity Measures and Systematic Market-Wide Liquidity Measure: Modified Roll, Gibbs, Bid-Ask Spread, Volatility, Corwin-Schultz 2012, and Systematic Market-Wide Liquidity.

Panels (a) to (e) depict monthly standardized liquidity measures across all ten currencies. Each measure is the first principal component across all currencies. The sign of each liquidity measure is adjusted to represent liquidity instead of illiquidity. Panel (f) shows the profile of the systematic market-wide liquidity measure. The systematic market-wide liquidity measure is the first principal component obtained by running a PCA of the five liquidity measures across the ten currency-pairs. Sample period is from January 1999 to July 2015. Grey dotted line represents Lehman Brothers collapse in September 2008.

Table 1
Summary Statistics of Liquidity Measures.

	EUR	GBP	JPY	CAD	CHF	AUD	NZD	NOK	SEK	DKK
	Panel A: Whole Sample (Jan 1999 - Jul 2015)									
	Modified Roll - Goyenko et al., 2009 (%)									
Mean	0.39	0.34	0.33	0.32	0.42	0.46	0.50	0.45	0.47	0.39
Std. Dev	0.18	0.16	0.18	0.24	0.20	0.28	0.22	0.22	0.24	0.18
	Gibbs Spread - Hasbrouck, 2009 (%)									
Mean	0.85	0.74	0.72	1.06	0.95	1.03	1.10	1.02	1.03	0.86
Std. Dev	0.29	0.27	0.35	0.33	0.54	0.55	0.43	0.39	0.39	0.29
	Volatility - Menkhoff et al., 2012 (%)									
Mean	1.66	1.43	1.42	1.65	1.78	2.00	2.14	1.98	2.00	1.66
Std. Dev	0.56	0.53	0.69	0.72	0.65	1.05	0.87	0.75	0.78	0.57

	Corwin and Schultz 2012 (bps)									
Mean	24.86	21.82	21.93	25.10	27.94	29.80	32.96	30.24	30.60	23.90
Std. Dev	9.26	9.55	10.13	11.99	11.40	13.71	13.59	14.80	14.93	10.92
	Bid-Ask Spread – Menkhoff et al., 2012 (bps)									
Mean	2.78	2.81	12.64	3.83	4.58	5.71	10.39	10.70	8.80	4.67
Std. Dev	2.07	1.54	23.64	2.27	2.33	2.59	4.02	6.34	4.43	9.76
	Panel B: Pre-Crisis Period (Jan 1999 – Dec 2006)									
	Modified Roll - Goyenko et al., 2009 (%)									
Mean	0.40	0.32	0.27	0.32	0.42	0.42	0.46	0.41	0.42	0.40
Std. Dev	0.14	0.12	0.10	0.25	0.14	0.15	0.16	0.14	0.14	0.15
	Gibbs Spread (%)									
Mean	0.87	0.70	0.60	1.07	0.93	0.91	1.00	0.91	0.94	0.88
Std. Dev	0.22	0.17	0.19	0.28	0.23	0.26	0.27	0.22	0.22	0.23
	Volatility - Menkhoff et al., 2012 (%)									
Mean	1.67	1.37	1.17	1.62	1.78	1.77	1.94	1.77	1.81	1.68
Std. Dev	0.42	0.33	0.34	0.64	0.41	0.48	0.49	0.41	0.42	0.44
	Corwin and Schultz 2012 (bps)									
Mean	24.31	20.16	18.36	25.30	27.96	27.25	30.70	25.26	26.02	22.98
Std. Dev	7.06	5.65	5.98	12.42	12.06	7.87	8.58	11.63	12.89	11.30
	Bid-Ask Spread – Menkhoff et al., 2012 (bps)									
Mean	3.90	3.33	5.41	3.98	3.60	6.86	11.37	5.82	6.33	7.19
Std. Dev	2.34	1.54	8.12	1.88	1.42	2.38	3.55	1.84	2.57	13.55
	Panel C: Crisis Period (Jan 2007 – Dec 2009)									
	Modified Roll - Goyenko et al., 2009 (%)									
Mean	0.44	0.43	0.50	0.39	0.45	0.65	0.67	0.59	0.61	0.44
Std. Dev	0.29	0.27	0.27	0.26	0.22	0.54	0.35	0.34	0.43	0.29
	Gibbs Spread (%)									
Mean	0.90	0.96	1.09	1.24	0.98	1.47	1.50	1.32	1.29	0.90
Std. Dev	0.42	0.46	0.50	0.46	0.39	1.02	0.68	0.64	0.68	0.42
	Volatility - Menkhoff et al., 2012 (%)									
Mean	1.75	1.85	2.17	2.05	1.89	2.90	2.98	2.54	2.54	1.75
Std. Dev	0.82	0.90	1.05	1.00	0.73	1.94	1.40	1.22	1.32	0.81
	Corwin and Schultz 2012 (bps)									
Mean	27.26	29.07	32.93	31.97	31.29	42.29	45.50	39.74	36.93	26.64
Std. Dev	13.22	15.34	14.31	13.80	12.37	23.11	20.16	21.97	19.63	12.61
	Bid-Ask Spread – Menkhoff et al., 2012 (bps)									
Mean	2.48	3.27	6.19	5.19	6.71	5.94	10.09	15.52	13.37	3.68
Std. Dev	1.22	1.48	2.43	3.21	3.58	3.02	4.96	6.71	6.48	1.61
	Panel D: Post-Crisis Period (Jan 2010 – Jul 2015)									
	Modified Roll - Goyenko et al., 2009 (%)									
Mean	0.36	0.31	0.32	0.29	0.39	0.43	0.46	0.44	0.46	0.36
Std. Dev	0.15	0.11	0.16	0.23	0.25	0.17	0.17	0.19	0.16	0.15
	Gibbs Spread (%)									
Mean	0.81	0.67	0.70	0.94	0.95	0.96	1.02	1.02	1.02	0.81
Std. Dev	0.28	0.19	0.27	0.26	0.86	0.35	0.33	0.33	0.32	0.28
	Volatility - Menkhoff et al. 2012 (%)									
Mean	1.58	1.30	1.39	1.48	1.71	1.86	1.99	1.97	1.97	1.58
Std. Dev	0.57	0.39	0.54	0.55	0.85	0.68	0.64	0.65	0.64	0.57
	Corwin-Schultz 2012 (bps)									
Mean	24.36	20.29	21.14	21.13	26.09	26.75	29.46	32.26	33.77	23.74
Std. Dev	9.44	8.24	7.93	8.16	9.49	9.35	11.26	10.82	12.75	9.16
	Bid-Ask Spread – Menkhoff et al. 2012 (bps)									
Mean										
Std. Dev	0.50	1.02	1.40	0.62	1.64	1.41	3.77	4.99	2.34	1.11

Table 2
Correlation of Liquidity Measures.

	GHT	Gibbs	Vol	CS	BAS	MKT
GHT	1					
Gibbs	0.82	1				
Vol	0.91	0.91	1			
CS	0.77	0.84	0.87	1		

BAS	0.59	0.70	0.62	0.64	1	
MKT	**0.91**	**0.95**	**0.97**	**0.92**	**0.75**	**1**

GHT, Gibbs, Vol, BAS, CS, and MKT denote modified Roll (1984) by Goyenko et al. (2009), Gibbs by Hasbrouck (2009), Volatility by Menkhoff et al. (2012), Bid-Ask Spread by Menkhoff et al. (2012), CS Spread by Corwin and Schultz (2012), and Systematic Market-Wide Liquidity Measure respectively.

Table 3

Liquidity Sensitivity to Changes in Market-Wide FX Liquidity (Whole Sample: Jan 1999 – Jul 2015). This table reports liquidity sensitivities to changes in the market-wide liquidity measure for individual currency-pairs as shown in Eq. (8):

$$L_{j,t} = \alpha_{\mathrm{j}} + \beta_{\mathrm{j}} \mathrm{MKT_t} + \varepsilon_{\mathrm{j,t}}$$

Liquidity of FX rate j is excluded before computing MKT_t. Heteroskedasticity and autocorrelation consistent (HAC) robust standard errors are shown in parentheses. N is the number of observations. The sample is from January 1999 to July 2015.

	Dependent variable:				
	EUR.PC1	GBP.PC1	CAD.PC1	JPY.PC1	CHF.PC1
	(1)	(2)	(3)	(4)	(5)
MKT	0.314***	0.341***	0.327***	0.239***	0.321***
	(0.037)	(0.016)	(0.020)	(0.033)	(0.036)
Constant	0.028	−0.015	−0.053	−0.023	0.045
	(0.139)	(0.065)	(0.084)	(0.170)	(0.091)
N	199	199	199	199	199
R^2	0.751	0.856	0.705	0.542	0.585
Note:	*p < 0.1; **p < 0.05; ***p < 0.01				

	Dependent variable:				
	AUD.PC1	NZD.PC1	NOK.PC1	SEK.PC1	DKK.PC1
	(1)	(2)	(3)	(4)	(5)
MKT	0.435***	0.434***	0.437***	0.450***	0.315***
	(0.037)	(0.018)	(0.012)	(0.022)	(0.038)
Constant	−0.025	0.033	−0.024	−0.038	−0.055
	(0.067)	(0.055)	(0.086)	(0.073)	(0.121)
N	199	199	199	199	199
R^2	0.828	0.834	0.802	0.854	0.755

Note: *p < 0.1; **p < 0.05; ***p < 0.01

Table 4

Summary Statistics of Carry Trade Returns.

	EUR	GBP	CAD	JPY	CHF	AUD	NZD	NOK	SEK	DKK
Panel A: Whole Sample (Jan 1999 - Jul 2015, N = 199)										
FX return: $\Delta S_{j,t+1}$										
Mean	−0.40	−0.37	−0.12	−0.51	2.13	1.09	1.32	−0.48	−0.38	−0.40
Std. Dev.	10.52	8.57	8.29	9.61	10.85	13.14	13.55	11.54	11.74	10.48
Interest rate differential: $i^f - i^d$										
Mean	−0.15	0.89	0.29	−2.11	−1.36	2.47	2.78	1.39	0.10	−0.01
Std. Dev.	1.28	1.09	0.81	2.09	1.42	1.59	1.51	1.85	1.68	1.36
Carry trade returns: $r^e_{j,t+1}$										
Mean	0.24	1.26	0.41	−1.63	−3.50	1.37	1.44	1.89	0.47	0.39
Std. Dev.	10.49	8.59	8.30	9.65	10.83	13.14	13.56	11.55	11.71	10.45
SR	0.02	0.15	0.05	−0.17	−0.32	0.10	0.11	0.16	0.04	0.04
Panel B: Pre-Crisis Period (Jan 1999 - Dec 2006, N = 96)										
FX return: $\Delta S_{j,t+1}$										
Mean	1.47	2.07	3.47	−0.55	1.50	3.20	3.56	2.40	2.10	1.48
Std. Dev.	9.36	7.63	6.90	9.35	9.64	10.44	11.18	10.01	10.35	9.36
Interest rate differential: $i^f - i^d$										
Mean	−0.52	1.21	0.10	−3.43	−2.18	1.70	2.43	1.25	−0.42	−0.27
Std. Dev.	1.59	1.31	0.97	1.82	1.41	1.65	1.87	2.45	2.02	1.57
Carry trade returns: $r^e_{j,t+1}$										
Mean	−1.99	−0.85	−3.36	−2.88	−3.68	−1.51	−1.16	−1.09	−2.51	−1.74
Std. Dev.	9.26	7.60	6.87	9.30	9.56	10.37	11.06	9.95	10.25	9.27
SR	−0.21	−0.11	−0.49	−0.31	−0.39	−0.15	−0.11	−0.11	−0.24	−0.19

Panel C: Crisis Period (Jan 2007 - Dec 2009, N = 36)										
FX return: $\Delta S_{j,t+1}$										
Mean	2.72	−6.39	3.42	8.24	5.53	4.32	0.88	2.44	−1.47	2.78
Std. Dev.	12.95	11.22	14.20	11.28	12.61	18.68	18.65	13.24	15.14	12.93
Interest rate differential: i^f-i^d										
Mean	0.26	1.12	−0.06	−2.23	−1.21	2.80	3.63	1.36	0.08	0.67
Std. Dev.	1.18	1.03	0.64	1.90	1.26	1.33	1.40	1.60	1.44	1.57
Carry trade returns: $r^e_{j,t+1}$										
Mean	−2.52	7.50	−3.51	−10.59	−6.83	−1.60	2.74	−1.17	1.49	−2.17
Std. Dev.	13.02	11.33	14.21	11.37	12.66	18.81	18.84	13.42	15.21	12.94
SR	−0.19	0.66	−0.25	−0.93	−0.54	−0.09	0.15	−0.09	0.10	−0.17

Panel D: Post-Crisis Period (Jan 2010 - Jul 2015, N = 67)										
FX return: $\Delta S_{j,t+1}$										
Mean	−4.75	−0.62	−3.91	−5.13	1.21	−3.68	−1.65	−6.17	−3.34	−4.80
Std. Dev.	10.69	8.22	8.98	8.88	11.59	13.16	13.61	12.57	11.65	10.59
Interest rate differential: i^f-i^d										
Mean	0.15	0.32	0.75	−0.16	−0.27	3.38	2.83	1.62	0.85	−0.01
Std. Dev.	0.39	0.08	0.25	0.09	0.34	0.98	0.42	0.43	0.78	0.58
Carry trade returns: $r^e_{j,t+1}$										
Mean	4.91	0.93	4.66	4.98	−1.46	7.09	4.47	7.80	4.20	4.81
Std. Dev.	10.69	8.22	8.98	8.87	11.59	13.11	13.63	12.56	11.63	10.60
SR	0.46	0.11	0.52	0.56	−0.13	0.54	0.33	0.62	0.36	0.45

Table 5
Regressions of Carry Trade Returns.

$$r^e_{j,t} = \alpha_j + \beta_{AER,j} AER_t + \beta_{IML,j} IML_t + \varepsilon_{j,t}$$

$\beta_{AER,j}$ is the factor loading of the market risk factor defined as the first principal component of all the ten currencies. The market risk factor is interpreted as the average excess FX rate of return for a U.S. investor who goes long in all the currencies. $\beta_{IML,j}$ is the factor loading of the liquidity risk factor, IML. IML is interpreted as the excess return of a portfolio that is long in the most four illiquid and short in the most four liquid exchange rates. Heteroskedasticity and autocorrelation consistent (HAC) robust standard errors are shown in parentheses. R^2 is the adjusted-R^2 and N is the number of observations.

Panel A: Whole Sample (Jan 1999 - Jul 2015)										
	Dependent variable:									
	EUR (1)	**GBP** (2)	**CAD** (3)	**JPY** (4)	**CHF** (5)	**AUD** (6)	**NZD** (7)	**NOK** (8)	**SEK** (9)	**DKK** (10)
AER	1.233***	0.723***	0.576***	0.650***	1.238***	1.032***	1.034***	1.096***	1.188***	1.229***
	(0.037)	(0.093)	(0.055)	(0.075)	(0.057)	(0.064)	(0.072)	(0.077)	(0.046)	(0.037)
IML	−0.089***	0.002	0.123***	−0.215***	−0.169***	0.186***	0.180***	0.040**	0.032**	−0.089***
	(0.013)	(0.034)	(0.016)	(0.024)	(0.018)	(0.023)	(0.022)	(0.019)	(0.015)	(0.012)
Constant	0.945	1.152	−1.946	0.372	−1.019	−0.560	−0.428	1.366	0.018	1.099
	(0.818)	(1.228)	(1.270)	(1.772)	(1.043)	(0.982)	(1.501)	(1.346)	(1.132)	(0.814)
N	199	199	199	199	199	199	199	199	199	199
R^2	0.891	0.542	0.599	0.407	0.800	0.858	0.791	0.762	0.844	0.892
Panel B: Pre-Crisis Period (Jan 1999 - Dec 2006)										
AER	1.208***	0.803***	0.451***	0.748***	1.207***	0.951***	1.019***	1.145***	1.258***	1.211***
	(0.046)	(0.059)	(0.077)	(0.120)	(0.049)	(0.069)	(0.087)	(0.078)	(0.063)	(0.044)
IML	−0.108***	−0.052*	0.099***	−0.153***	−0.155***	0.250***	0.239***	0.028	0.015	−0.107***
	(0.014)	(0.029)	(0.022)	(0.031)	(0.014)	(0.021)	(0.027)	(0.021)	(0.027)	(0.013)
Constant	0.958	1.030	−2.818	−0.712	−0.551	−0.540	−0.005	1.398	0.042	1.200
	(0.955)	(1.547)	(1.909)	(2.551)	(1.055)	(1.601)	(2.034)	(2.008)	(1.652)	(0.949)
N	96	96	96	96	96	96	96	96	96	96
R^2	0.911	0.588	0.663	0.419	0.893	0.809	0.748	0.697	0.811	0.913
Panel C: Crisis Period (Jan 2007 - Dec 2009)										
AER	1.253***	0.478**	0.674***	0.666***	1.255***	1.295***	1.212***	0.759***	1.159***	1.250***
	(0.092)	(0.233)	(0.128)	(0.175)	(0.132)	(0.133)	(0.183)	(0.159)	(0.105)	(0.092)
IML	−0.087***	0.090*	0.119***	−0.252***	−0.176***	0.117***	0.119***	0.116***	0.043*	−0.090***
	(0.021)	(0.049)	(0.034)	(0.042)	(0.030)	(0.037)	(0.041)	(0.037)	(0.025)	(0.020)

Constant	1.628	6.179	−5.198	−3.552	−0.591	−2.211	1.950	−2.631	2.402	2.025
	(2.191)	(4.539)	(4.089)	(4.330)	(2.309)	(2.066)	(4.836)	(3.565)	(2.663)	(2.166)
N	36	36	36	36	36	36	36	36	36	36
R^2	0.926	0.534	0.642	0.652	0.875	0.924	0.834	0.821	0.885	0.927
Panel D: Post-Crisis Period (Jan 2010 - Jul 2015)										
AER	1.213***	0.854***	0.580***	0.539***	1.328***	0.981***	0.992***	1.207***	1.103***	1.203***
	(0.074)	(0.086)	(0.075)	(0.131)	(0.153)	(0.068)	(0.106)	(0.090)	(0.072)	(0.073)
IML	−0.069**	0.064*	0.139***	−0.203***	−0.196***	0.185***	0.182***	0.045	0.051*	−0.069**
	(0.034)	(0.035)	(0.034)	(0.046)	(0.069)	(0.032)	(0.036)	(0.031)	(0.029)	(0.033)
Constant	0.482	−2.022	0.767	2.788	−1.066	1.025	−1.615	2.227	−1.009	0.424
	(1.818)	(2.046)	(1.761)	(3.612)	(2.091)	(1.857)	(2.656)	(1.964)	(2.076)	(1.823)
N	67	67	67	67	67	67	67	67	67	67
R^2	0.845	0.667	0.771	0.522	0.672	0.876	0.815	0.845	0.852	0.844
Note:	*p < 0.1; **p < 0.05; ***p < 0.01									

Table 6
Economic Significance of Liquidity Betas, β_{IML}.

EUR	GBP	CAD	JPY	CHF	AUD	NZD	NOK	SEK	DKK
Panel A: Whole Sample (Jan 1999 - Jul 2015									
−0.235	0.006	0.367	−0.618	−0.433	0.393	0.368	0.096	0.076	−0.236
Panel B: Pre-Crisis Period (Jan 1999 - Dec 2006)									
−0.252	0.148	0.312	−0.356	−0.351	0.522	0.467	0.061	0.032	−0.250
Panel C: Crisis Period (Jan 2007 - Dec 2009)									
−0.290	0.345	0.364	−0.962	−0.604	0.670	0.574	0.375	0.123	−0.302
Panel D: Post-Crisis Period (Jan 2010 - Jul 2015)									
−0.069	0.064	0.139	−0.203	−0.196	0.185	0.182	0.045	0.051	−0.069

Economic significance shows the change in carry trade returns (in number of standard deviations) in response to an increase of one standard deviation in the tradable liquidity risk factor, IML. For example, when IML decreases by one standard deviation, AUD depreciates by 0.39 standard deviations, whereas JPY appreciates by 0.62 standard deviations for the whole sample. Following Chan et al. (1998), IML has the largest return volatility, implying that it captures the highest amount of factor risk as measured by the volatility of the spread in returns between the long and short positions.

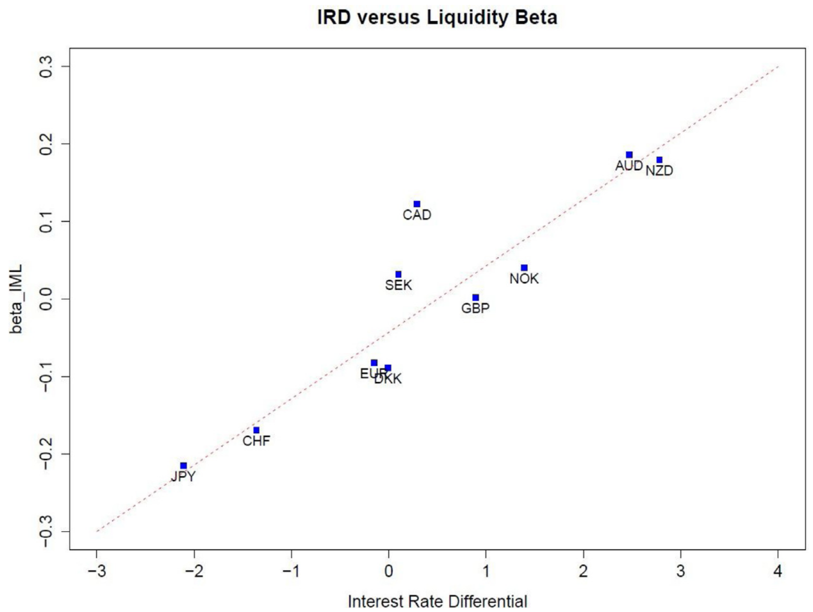

Fig. 2 Interest Rate Differential (IRD) and Liquidity Risk Sensitivity.

This graph shows interest rate differential on the horizontal axis $i^f - i^d$, and liquidity beta on the vertical axis, β_{IML}. Liquidity betas are for the whole sample from Table 5, Panel A. IML is a currency portfolio that is long in the most four illiquid currencies and short in the most four liquid currencies. Sample is from January 1999 to July 2015. JPY and CHF are low interest rate currencies with the lowest liquidity betas. AUD and NZD are high interest rate currencies with the highest liquidity betas.

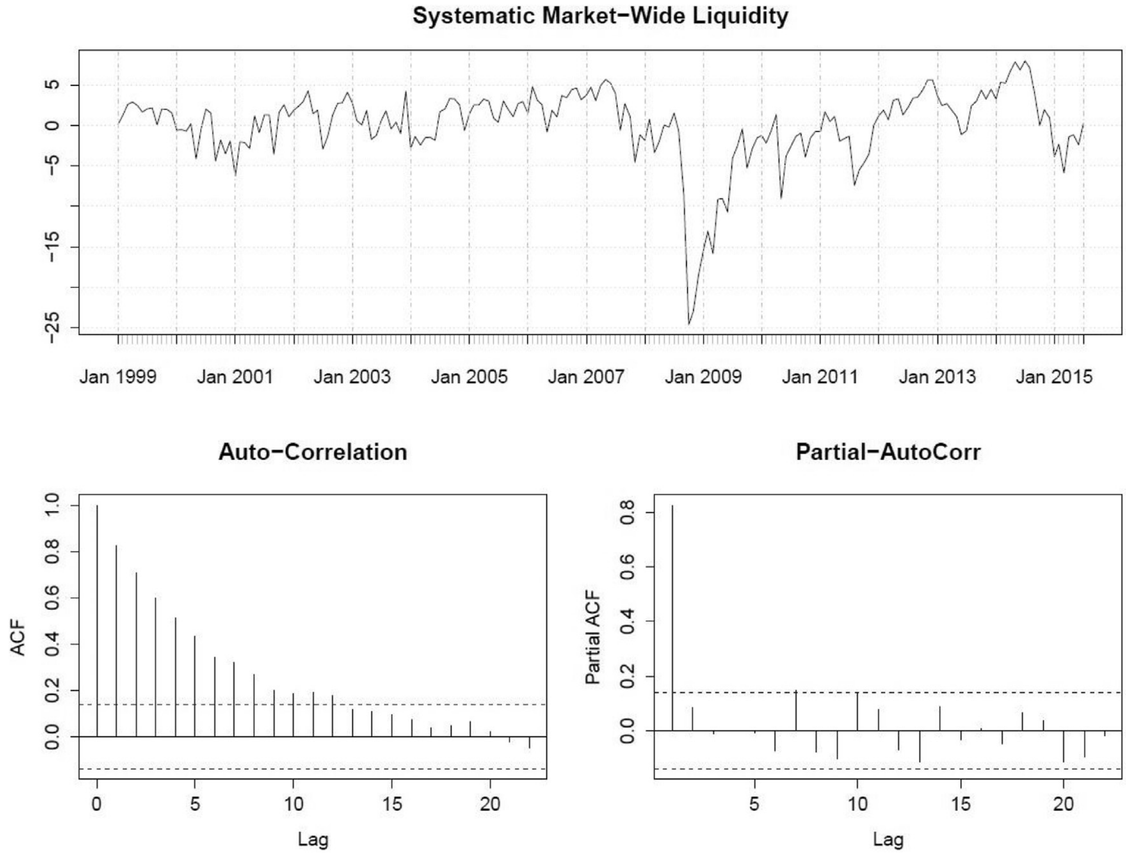

Fig. 3 Autocorrelation and Partial-Autocorrelation of Systematic Market-Wide Liquidity.

The top graph depicts the systematic market-wide liquidity measure. Bottom graphs show the autocorrelation (ACF) and partial-autocorrelation (PACF) of the systematic market-wide liquidity measure. The PACF shows that residuals of AR (1) should be used as a proxy risk factor.

Table 7
Regressions of Innovations Risk.

$$r^{e}_{\mathrm{j,t}} = \alpha_{\mathrm{j}} + \beta_{\mathrm{AER,j}}\mathrm{AER_t} + \beta_{\mathrm{Resid.MKT,j}}\mathrm{Resid.MKT_t} + \varepsilon_{\mathrm{j,t}}$$

$\beta_{AER,j}$ is the factor loading of the market risk factor defined as the first principal component of all the ten currencies. The market risk factor is interpreted as the average excess FX rate of return for a U.S. investor who goes long in all the currencies. $\beta_{Resid.MKT,j}$ is the factor loading of the proxy liquidity risk factor, Resid.MKT. Liquidity risk factor, Resid.MKT, is the residuals of AR (1) model fitted to MKT.PC1. Heteroskedasticity and autocorrelation consistent (HAC) robust standard errors are shown in parentheses. R^2 is the adjusted-R^2 and N is the number of observations.

Panel A: Whole Sample (Jan 1999 - Jul 2015)										
	Dependent variable:									
	EUR (1)	**GBP** (2)	**CAD** (3)	**JPY** (4)	**CHF** (5)	**AUD** (6)	**NZD** (7)	**NOK** (8)	**SEK** (9)	**DKK** (10)
AER	1.136***	0.711***	0.690***	0.427***	1.057***	1.237***	1.258***	1.117***	1.234***	1.132***
	(0.042)	(0.067)	(0.060)	(0.087)	(0.072)	(0.052)	(0.070)	(0.068)	(0.046)	(0.044)
Resid_MKT	−1.142***	0.596	0.458***	−3.302**	−2.386***	2.358***	1.183	1.465**	0.032	−1.199***
	(0.390)	(0.660)	(0.136)	(1.336)	(0.839)	(0.683)	(0.861)	(0.584)	(0.452)	(0.369)
Constant	−0.080	1.122	−0.662	−1.791	−1.406	1.427	1.397	1.759	0.556	0.079
	(0.987)	(1.358)	(1.479)	(2.224)	(1.305)	(1.593)	(1.971)	(1.196)	(1.128)	(0.989)
N	198	198	198	198	198	198	198	198	198	198
R^2	0.857	0.545	0.529	0.461	0.676	0.754	0.687	0.763	0.845	0.857

Panel B: Pre-Crisis Period (Jan 1999 - Dec 2006)										
AER	1.165***	0.783***	0.489***	0.690***	1.148***	1.046***	1.109***	1.135***	1.266***	1.169***
	(0.050)	(0.061)	(0.083)	(0.128)	(0.058)	(0.089)	(0.093)	(0.079)	(0.062)	(0.048)
Resid_MKT	−1.495**	0.776	0.345	−0.242	−1.578*	1.903	2.925*	1.169	0.144	−1.541**
	(0.657)	(1.089)	(0.945)	(1.109)	(0.948)	(1.461)	(1.745)	(1.093)	(0.694)	(0.640)
Constant	−0.213	0.521	−2.070	−1.624	−1.922	1.447	1.917	1.247	0.638	0.057
	(1.222)	(1.531)	(2.112)	(2.833)	(1.484)	(2.371)	(2.882)	(2.097)	(1.556)	(1.206)
N	95	95	95	95	95	95	95	95	95	95
R^2	0.869	0.571	0.472	0.495	0.788	0.561	0.561	0.694	0.826	0.871
Panel C: Crisis Period (Jan 2007 - Dec 2009)										
AER	1.149***	0.621**	0.651***	0.448***	1.090***	1.405***	1.493***	0.758***	1.238***	1.147***
	(0.120)	(0.256)	(0.171)	(0.153)	(0.205)	(0.086)	(0.176)	(0.149)	(0.151)	(0.124)
Resid_MKT	−1.505*	0.899	1.078***	−5.842***	−3.857***	2.586***	1.501	4.539***	0.230	−1.627**
	(0.833)	(1.648)	(0.242)	(1.829)	(1.299)	(0.959)	(1.504)	(1.040)	(1.269)	(0.783)
Constant	0.595	1.820	−1.468	−2.197	−1.947	−1.317	2.627	−1.521	3.370	1.038
	(2.362)	(2.626)	(1.622)	(2.686)	(2.829)	(1.303)	(2.047)	(3.061)	(2.920)	(2.201)
N	36	36	36	36	36	36	36	36	36	36
R^2	0.881	0.658	0.676	0.575	0.715	0.892	0.783	0.837	0.874	0.880
Panel D: Post-Crisis Period (Jan 2010 - Jul 2015)										
AER	1.090***	0.697***	0.813***	0.220	0.997***	1.288***	1.334***	1.265***	1.217***	1.079***
	(0.066)	(0.052)	(0.065)	(0.138)	(0.133)	(0.072)	(0.085)	(0.058)	(0.062)	(0.065)
Resid_MKT	−0.077	1.841***	0.788	−2.055	−0.978	1.147	0.664	1.001	0.945	−0.057
	(0.926)	(0.622)	(1.553)	(1.610)	(2.184)	(0.827)	(1.137)	(1.011)	(0.708)	(0.913)
Constant	0.276	−1.722	1.345	3.711	−2.848	1.819	−1.295	2.605	−1.114	0.222
	(1.910)	(2.031)	(2.149)	(4.074)	(3.328)	(2.579)	(3.126)	(2.211)	(2.077)	(1.907)
N	67	67	67	67	67	67	67	67	67	67
R^2	0.830	0.665	0.687	0.352	0.570	0.806	0.750	0.842	0.848	0.828
Note:	*p < 0.1; **p < 0.05; ***p < 0.01									

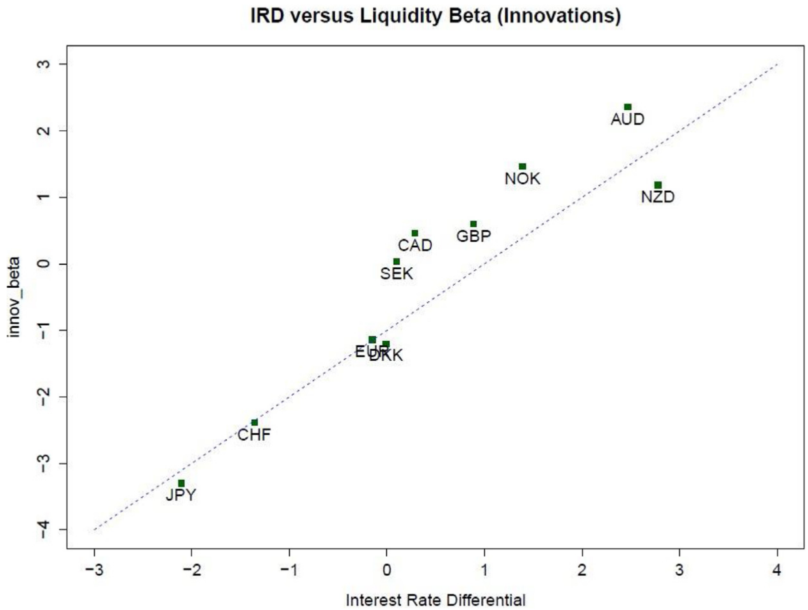

Fig. 4 Interest Rate Differential (IRD) and Innovations Risk Sensitivity.

This graph shows interest rate differential on the horizontal axis $i^f - i^d$, and innovations beta on the vertical axis, β_{IML}. Innovations liquidity betas are for the whole sample from Table 7, Panel A. IML is a currency portfolio that is long the most four illiquid currencies and short the most four liquid currencies. Sample is from January 1999 to July 2015. JPY and CHF are low interest rate currencies with the lowest liquidity betas. AUD and NZD are high interest rate currencies with the highest liquidity betas.

Table 8
Cross-sectional pricing analysis (Fama-MacBeth procedure).

Estimations are done using the Fama-MacBeth procedure with 60-months of rolling betas. λ is the market price of risk. LIQ is the liquidity risk factor. AER is the market risk factor (Average Excess Returns) and is calculated as the average of the cross-sectional portfolios' monthly excess returns. HML is the Lustig et al. (2011) carry risk factor, which is the return of a strategy that is long in the high-interest rate portfolio and short in the low-interest rate portfolio. The estimated coefficients reported are annualized and the t-statistics are corrected with the Shanken (1992) adjustment. The t-statistics are reported in parenthesis. The p-values of the χ^2 test for the null hypothesis of zero pricing errors are adjusted according to Shanken (1992). R^2 is adjusted-R^2. Following Lustig et al. (2011), a constant is included in the cross-sectional regressions, but it is only reported when it is statistically significant.

$$r^e_{j,t} = \hat{\beta}^{LIQ}_j \lambda^{LIQ}_t + \hat{\beta}^{Other}_j \lambda^{Other}_t + \in_{j,t} \quad \text{for t} = 1, \ldots, \text{T}$$

Panel A: Liquidity Risk Factor			
	LIQ	R^2	χ^2
λ	0.0412	65.87	0.6428
t-statistic (SH)	(3.0584)		

Panel B: Liquidity Risk Factor & Market Risk Factor				
	LIQ	AER	$R2$	χ2
λ	0.0385	0.0401	68.54	0.2129
t-statistic (SH)	(3.0967)	(1.8596)		

Panel C: Liquidity Risk Factor & Carry Risk Factor				
	LIQ	HML	$R2$	χ2
λ	0.0393	0.0322	77.35	0.3034
t-statistic (SH)	(3.2362)	(0.8236)		

Panel D: Liquidity Risk Factor, Market Risk Factor & Carry Risk Factor					
	LIQ	AER	HML	$R2$	χ2
λ	0.0375	0.0382	0.0301	78.57	0.2953
t-statistic (SH)	(3.0783)	(1.7894)	(0.7974)		

Table 9
Invesco's PowerShares DB G10 Currency Harvest Fund (Whole Sample & Crisis Period).

This table reports regression results for portfolio trades using Invesco's PowerShares DB G10 Currency Harvest Fund (DBV) in the place of carry trade returns in Eq. (12). Models (1) to (3) represent the whole sample, and (4) to (6) for the crisis sub-period. The PowerShares DB G10 Currency Harvest Index is rebalanced annually, and at any time, made up of long futures contracts on the 3 G10 Currencies associated with the highest interest rates, and short futures contracts on the 3 G10 Currencies associated with the lowest interest rates. The rebalanced portfolio as of data collection was made up of long futures contracts in NZD, AUD, NOK and short futures contracts in JPY, EUR and CHF. The G10 currency universe from which the Index selects its longs and shorts currently includes USD, EUR, JPY, CAD, CHF, GBP, AUD, NZD, NOK, and SKK.

$$DBV_t{}^{\mathrm{e}} = \alpha_{\mathrm{t}} + \beta_{\mathrm{AER}}\mathrm{AER}_{\mathrm{t}} + \beta_{\mathrm{F,i}}\mathrm{F}_{\mathrm{t,i}} + \varepsilon_{\mathrm{t}}$$

where $DBV_t{}^e$ is the excess PowerShares portfolio returns, β_{AER} is the factor loading of the market risk factor (AER), and $\beta_{F,i}$ is the factor loading of the liquidity risk factor (IML), the innovations risk factor (*Resid.MKT*), and the systematic market-wide liquidity risk measure (MKT).

	Dependent variable:					
	DBV					
	(1)	(2)	(3)	(4)	(5)	(6)
AER	0.015***	0.042***	0.039***	0.021*	0.060***	0.043***
	(0.005)	(0.008)	(0.006)	(0.011)	(0.017)	(0.015)
IML	0.022***			0.022***		
	(0.001)			(0.003)		
MKT		0.138**			0.120	
		(0.066)			(0.083)	
Resid.MKT			0.322***			0.455**
			(0.104)			(0.178)
Constant	0.563	0.328	0.327	0.218	0.117	0.036
	(0.788)	(0.461)	(0.453)	(0.267)	(0.457)	(0.410)

N	198	198	198	36	36	36
R^2	0.770	0.334	0.370	0.860	0.473	0.570
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$					

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