Currency Crash Risk in the Carry Trade

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M.Sc. in High Performance Computing

B.Sc. in Information System

Submitted in fulfilment of the requirements for the

Degree of Doctor in Philosophy

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College of Social Sciences
University of Glasgow

August 2017

Abstract

This thesis provides a systematic study of currency crash risk and funding liquidity risk in carry trade strategy in the foreign exchange (FX) market. Carry trade, which involves longing currencies with high interest rate and shorting currencies with low interest rate, is a popular currency trading strategy in the FX market for obtaining annualized excess return as high as 12%.

This thesis studies exchange rates of 9 currencies over 13 years from a microstructure perspective. We identify a global skewness factor and use it to measure the currency crash risk. Applying a portfolio approach in cross-sectional asset pricing, we find that global skewness factor explains more than 80% of carry trade excess returns. On the other hand, funding liquidity is effective in predicting the future currency crash risk. Funding liquidity explains more than 70% of carry trade excess returns. We also use the coefficient of price impact from customer order flows to measure the liquidity, which reveals heterogeneous information content possessed by different types of customers. We find that the order flow implied liquidity risk factor can explain a fraction of carry trade excess returns but with small risk premium on quarterly basis.

We provide empirical evidence to show that the excess return and crash risk in carry trade is endogenous; *i.e.*, the crash risk premium is inherent in carry trade process. As the natural condition widely affects all investors, we argue that funding constraints are effective in explaining the excess returns of carry trade. When capital moves smoothly in a liquid condition and investor have sufficient funding supply, carry trade is prosperous in the FX market. When investors hit their funding constraints, market-wide liquidity drop, which force the carry trade positions diminishing. The exchange rates respond as that the low interest rate currencies appreciate and high interest rate currencies depreciate, which exacerbates currency crash risk and induces large loss to carry traders. Our cross-sectional analysis provides empirical evidence to show that funding constraints helps to explain the forward premium puzzle and push the exchange rate shift back to the direction the UIP expects.

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Acknowledgement

I would like to thank my supervisor Prof. Mario Cerrato for his patient guidance and enormous support during my Ph.D. study; and my second supervisor Prof. Christian Ewald for his valuable advice and mentoring. I would also like to thank Professor Craig Burnside for stimulating discussions about some questions relating to this thesis. I must also thank the University of Glasgow for providing funding to participate in conferences, summer schools and workshops, which strengthened my research skills and enriched my professional experiences. Thanks to UBS for kindly agreeing to supply me with data for research purposes, most this work would not have been possible without that.

My special thanks go to my parents for their continuous encouragement and unconditional care. I also need to thank my friends Dr Yingru Li and Dr Minmin Du, I would not have made it this far without their support. My thanks also go to my office mates Cristina Isabel Ibarra Armenta, Yan Long and all my friends at Adam Smith Business School who have made this journey more enjoyable and colourful.

Author’s declaration

I declare that, except where explicit reference is made to the contribution of others, that this dissertation is the result of my own work and has not been submitted for any other degree at the University of Glasgow or any other institution.”

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1. Introduction

Carry trade is a widely applied currency trading strategy in the FX market which involves selling currencies with low interest rate and buying currencies with high interest rate. Carry trade is profitable when the gains from interest rate differentials of two currencies are not overwhelmed by their exchange rate movements, which is theoretically considered as a violation of UIP. UIP states a parity condition that the interest rate differential should equal the expected change of exchange rate between the two countries' currencies, which means the gains from the interest rate differential should be offset by the depreciation of the currency with high interest rate or the appreciation of currency with low interest rate. Recent empirical study shows that currency with high interest rate appreciates and currency with low interest rate further depreciates on average. This violation phenomenon of UIP, referred to as the 'forward premium puzzle', has been extensively documented in empirical studies since Fama (1984). Although exchange rate is ultimately expected to converge to long-term equilibrium, determinants proposed in macroeconomic models have difficulty in providing theoretical support to explain the exchange rate movement in the short-term. Theoretical model settings proposed in macro inspired models do not match the feature of short-term actual trading process in the FX market. Different equilibrium conditions that models of short-term and long-term are built on imply that the corresponding determinants of risk premium in short-term and long-term can be different.

The failure of UIP not holding in short-term motivates researchers to seek for explanations for the excess return of carry trade. Recent microstructure studies attribute the excess return of carry trade to crash risk premium which is inherent in carry trade process. Burnside *et al.* (2006) argue that conventional models of risk, which used to price the stock market, do not price currency returns. However, risk factors derived from excess returns are more successful in explaining the excess return of carry trade. Galati *et al.* (2007) find that the excess returns of carry trade portfolios tend to reverse abruptly under stressful condition of the financial market. Currency crash happens when exchange rate of funding currency has a sharp and quick appreciation or that of investment currency has a sudden depreciation.[1]

[1] Currency with high interest rate is referred as investment currency; currency with low interest rate is referred to as funding currency.

However, it is difficult to accurately predict the exact timing when exchange rate reverts against direction favoured in carry trade. Hence the risk associated with these abrupt losses requires compensation and should be reflected in final excess returns.

Brunnermeier and Pedersen (2007a) propose a theoretical liquidity spiral model and use it along with the empirical evidence from Brunnermeier *et al.* (2008) to explain the negative skewness of the carry trade excess returns. A large number of carry trade investors drives the exchange rate to deviate from UIP, which generates profits for carry traders in short term. As more participants are attracted into trading, the exchange rate is pushed further in a favourable direction until an unexpected event wipes out the profit. Brunnermeier *et al.* (2008) argue that liquidity crisis is a significant market events which rebalances the setup of market condition. When currency crashes and moves against the favoured direction of carry trade, loss of profit forces investors to liquidate their position, investment currency depreciates more and funding currency appreciates more. Then liquidity in the market is further worsened. As liquidity in the market quickly dries out, the exchange rate of investment currencies further depreciates, as documented by Abreu and Brunnermeier (2003) “the exchange rates go up by the stairs and down by the elevator”. The exchange rate of funding currencies further appreciates. We witnessed the liquidity spiral in 2008, when currencies with high interest rate, such as Australian dollar and New Zealand dollar, depreciated sharply after long period of appreciation against the currencies with low interest rate, such as Japanese Yen, US dollar and Swiss Franc.

The explanation of funding liquidity constraints to the negative skewness of carry trade excess return is due to investors reacting differently to shocks leading to gain and those leading to loss in exchange rate. The shocks leading to gains of carry trade are not amplified but, when they hit funding constraints, shocks that lead to loss are amplified. The skewness is endogenous and can be directly affected by other aspects within the carry trade process. If this assumption holds, then the abrupt and large amount of loss in carry trade can happen.

The contribution of our study is that our empirical evidence not only supports the impact of market liquidity on carry trade excess return but also demonstrates that the assumption of the endogeneity of carry trade excess return holds regardless of the crisis period or the normal conditions. Using a dataset consisting of 9 major currencies in the FX market, we derive a global skewness factor from the excess return to capture the currency crash risk and find that its positive premium is capable of explaining 81% of excess return of carry trade.

We then link the global skewness factor to funding liquidity via the global VIX index and TED spread that are widely traded in the FX market. We find that the funding liquidity risk factor has a negative risk premium and explains 70% of excess return of carry trade.

Following Rafferty (2010) and Burnside (2011), our empirical study starts by arguing that the excess return of carry trade can be attributed to currency crash risk. We construct a global skewness factor from daily data within one month. On both cross-section and time series dimensions, it is shown that the global skewness factor is an effective measurement of crash risk in the G10 currency market and has a significant positive risk premium in explaining time variation in carry trade excess returns. This shows that large interest rate differential attracts investors and drives excess return, however, excess return of carry trade is subject to currency crash risk. We find that currencies with different interest rate differentials have heterogeneous loading on currency crash risk: currencies with high interest rate demand high excess return for investors bearing the crash risk; whereas currencies with low interest rate offer a hedge to investors for losing out when currency crash risk is high.

Following Brunnermeier *et al.* (2008) and Farhi *et al.* (2009), the second part of our empirical study focus on how currency crash risk relates to other essential aspects in carry trade, including the price of currency options, recent payoff and carry trade positions. We use risk reversal to measure the price of currency crash risk, because the price of risk reversal reflects the cost that investors would pay to protect carry trade positions to hedge the risk caused by currency crash. We use future positions to measure carry trade activities. We provide empirical evidence to show that excess return and crash risk in carry trade are both endogenous. Firstly, prosperous carry trade activity, measured by future position, helps to build up currency crash risk. Equivalently, unwinding carry trade inventories in funding currency helps to ease crash risk. Secondly, we find a skewness premium that varies negatively with recent payoff of carry trade. Thirdly, the risk reversal does not predict future negative skewness after controlling other relevant variables. This means that the currency options do not contain advanced information compared to other macro variables in predicting the evolvement of exchange rates in the FX market.

In the third part, we follow Banti *et al.* (2012) and Menkhoff *et al.* (2012b) and propose a market liquidity factor extracted from order data to explain the excess return of carry trade. The order flow data set are disaggregated by 4 customer types which represent heterogeneous information content that market players have. The data set covers the 8 most liquid currencies in the FX market over 7 years, which allows us conduct a study in liquidity risk under FX microstructure framework. We argue that customer order flow captures time-varying liquidity risk premium in the FX market. Different customer groups play different roles of being informed trader and non-informed trader, where financial customers (asset managers and hedge funds) are more advanced in possessing high quality of information content and play the role of informed traders in the FX market.

In the fourth part, we follow Menkhoff *et al.* (2012a) and Mancini *et al.* (2013) to use VIX index and TED spread to measure the funding liquidity in FX market. We argue that funding liquidity risk is capable to explain the negative skewness of carry trade excess return. We find a negative funding liquidity premium through a cross-sectional analysis. Our results suggest that currencies with high interest rates co-move negatively to funding liquidity risk, and therefore demand high excess returns when liquidity condition is tight in the FX market. Currencies with low interest rate are a hedge against loss when the market is illiquid.

This thesis is related to a large amount of literature that finds the importance of asymmetries of excess returns in asset pricing. This finding could be traced back to Kraus and Litzenberger (1976) which develops an asset pricing model based on the coskewness of an asset with market return to reflect that investors have a preference for positive skewness of returns. Harvey and Siddique (2000) extend this model to a conditional three moment asset pricing model and show that conditional skewness is effective in explaining cross-sectional difference in risk premiums. Merton (1976) propose an intertemporal capital asset pricing model (ICAPM) model and consider skewness as a state variable that characterizes the investment opportunity set. The skewness approach is widely studied in the stock market, such as in Conrad *et al.* (2013) and Chang *et al.* (2013), and also applied in the FX market, such as Farhi *et al.* (2009) and Burnside *et al.* (2011)

The outline of this thesis is as follows: a general review of relevant literature is presented in chapter 2. Literature review regarding specific topics is in each chapter. In chapter 3 we report the stylized facts of our two data sets: the currency data set and the order flow data set. In chapter 4, we introduce the construction of portfolios. In chapter 5, we address currency crash risk in carry trade. We present the model of predicting realized crash risk and perceived crash risk in chapter 6. We propose an innovative method to measure market liquidity with order flows in chapter 7, and present empirical evidence of funding liquidity premium in carry trade in chapter 8. Chapter 9 concludes.

2. Literature review of carry trade

2.1 Forward premium puzzle

In this section, we present the forward premium puzzles associated with the drift in the exchange rate. We also discuss the implications and explanations for the forward risk premium. The focus will be the risk-based explanations to the forward premium, which is the research category this thesis falls into.

2.1.1 Deviation of UIP

Interest rate parity is the non-arbitrage condition under which investors will be indifferent to interest rates of two countries. UIP is the non-arbitrage condition that is satisfied without using the forward rate and it can be parameterized as follows:

$$(1 + i_t^*) = (1 + i_t)\frac{E(S_{t+k})}{S_t} \tag{1}$$

where $E(S_{t+k})$ is the expected exchange rate at time $t + k$, S_t is the spot exchange rate and is measured as units of foreign currency per USD. i_t^* and i_t is the interest rate for the foreign country and domestic country respectively. UIP implies that the changes in exchange rate is determined by the interest rates of both foreign country and domestic country with assumption of market efficiency.

When trying to use forward rate to hedge the exposure to the exchange rate risk, we have Covered Interest rate Parity (CIP) to represent the non-arbitrage condition under which the investors are indifferent to the interest rate of two countries. Burnside *et al.* (2006) argues that, CIP expects the assets return measured in domestic currency equals to the that measured by foreign currency:

$$(1 + i_t^*) = (1 + i_t)\frac{F_t}{S_t} \tag{2}$$

where F_t is the forward rate at t and quoted as units of foreign currency per USD. $(1 + i_t^*)$ is the foreign currency interest rate return, while $(1 + i_t)\frac{F_t}{S_t}$ is the domestic interest rate return converted into units of foreign currency.

Dividing the equation (1) by equation (2) yield:

$$F_t = E(S_{t+k}). \tag{3}$$

Equation (3) is the unbiasedness hypothesis, which means that the forward rate is an unbiased estimator of the future spot exchange rate. To test if UIP holds, equation (3) can be tested in the following econometrics model:

$$S_{t+k} - S_t = \alpha_1 + \beta_1 \times (F_t - S_t) + e_{t+k} \tag{4}$$

Where $e_{t+k}$is a zero-mean random disturbance, which is orthogonal to time t information. Notice that the unbiasedness hypothesis (3) is based on the joint assumption of both efficient market and the rational expectation. If these two assumptions jointly hold with UIP, it is expected to have $\alpha = 0, \beta = 1$, which means that forward rate at time t unbiasedly predict the future spot rate at time $t + k$.

Extensive literatures documented the rejection of the hypothesis in equation (4), which means that equation (3) does not hold and the forward rate is not the unbiased estimator of future estimator. The rejection of UIP have been widely documented in decades of empirical studies such asK.A. Froot and Thaler (1990), Hodrick and Srivastava (1987), Lewis (1995) and Engel and Kim (1996) These early studies find that, the coefficient between the expected exchange rate movement and the forward premium is found to be negative with an absolute value larger than one which comes with the wrong sign and wrong magnitude, in terms of those that the original UIP predicts. The negative β means that the country with lower interest rate was supposed to be compensated by the expected appreciation of its currency, however in the real FX market, the currency with lower interest rate depreciates. Whereas currency with higher interest rate, which is expected to depreciate, appreciates in the reality. This deviation of UIP is referred to as the forward discount bias, which is a pervasive phenomenon not yet fully understood in FX market.[2]

2.1.2 Explanations of UIP deviation

There is a large literature aimed at explaining the failure of equation (3) and try to resolve the forward premium puzzle in the theoretical model. Contributions from both theoretical and empirical study can be classified into two general categories: the non-risk based approach and the risk-based approach.

Fama (1984) decompose the *ex ante* forward premium into the expected change in exchange rate $E_t(\Delta s_{t+1})$ and the deviation from the expectation p_t. Equation (3) means that the forward premium is consists of the expected exchange movement plus a risk premium. Hodrick and Srivastava (1987) prove that time-varying forward premium is negatively correlated with p_t, and p_t is more volatile than rationally expected, suggesting that it is potentially large. Mark and Wu (1998) further derive the *ex post* exchange movement and prove through a noise trade model that the risk premium can be theoretically both positive and negative and that p_t is negatively correlated to $E(\Delta s_{t+1})$. The noise traders which play an essential role in their model refers to those investors with distorted beliefs on the future return from their portfolio investments. Domowitz and Hakkio (1985) decompose the deviation from the expectation p_t with a constant component and a time-varying component, which is the conditional standard deviation. Bacchetta and Van Wincoop (2006) examines to what extent the forward premium puzzle cane be explained by two types of incomplete information process: the infrequent processing and partial information processing. They find that the incomplete information is optimal which results in the uncertainty in exchange rate movements.

In terms of the studies relating to the carry trade, Meese and Rogoff (1983) find that the exchange rate follows a random walk rule which offers speculators a chance to gain profit

[2] Another puzzling feature is that the exchange rate does not move with news announcement. DeBondt and Thaler (1987) reports evidence of investors and financial analysts overreacting to news.

from interest rate differential without suffering exchange rate depreciation. In the short run, a high interest rate currency tends to appreciate in the short run. Whereas in the long run, the exchange rate still goes back to the theoretical track in that it converges to the purchasing power parity, although the degree of this tendency is weak. K.A. Froot and Thaler (1990) argue that the forward premium puzzle is not a pre-condition of having carry trade activity, instead, it is the consequence of the predominance of carry trade activity in the market. K.A. Froot and Thaler (1990) claims that the mismatch between interest rate and exchange rate movement is caused by the slow response of market participants to interest rate differential changes. Burnside *et al.* (2006) argues that the currency strategies with high sharp ratios are not the compensation for risk but the result of price pressure, which points to that the exchange rates are an increasing function of net order flow.

The risk-based approach refers to the time-varying risk premium from a macroeconomics perspective and a market micro-structure. Cutler *et al.* (1991) and Fair (2001) estimate asset pricing models with risk factor derived from a macro or long-term basis. Lewis (1995) proposes a model that addresses a boarder range of potential determinants of risk premium. The model incorporates risk aversion, portfolio holding of domestic and foreign assets at home and abroad, the conditional variance of the exchange rate and the covariances between exchange rate and domestic and foreign inflation. Unfortunately, it turns out that fundamental analysis with macroeconomic risk factors may not be a good way to understand the short-term movement of asset price. Bansal and Dahlquist (2000) show the possibility of having positive slope β in a forward premium puzzle test by separating the positive and negative observations; this yields a slope with mean-reverting property. Some recent empirical studies search for an explanation with short term risk factors which are primarily related to agents operating in short horizons. A theoretical model with focus on flow equilibrium, proposed by Carlson *et al.* (1995), shows that the time varying risk premium depends mainly on interest rate differentials and is endogenous in the Forex trading strategy.

2.2 Carry trade return

The excess return of carry trade results in the violation of UIP. In this section, we present the studies which focus on explaining the excess return of carry trade. This thesis falls to this category.

2.2.1 Asymmetries of excess return

Documented in IMF (1998a), Béranger *et al.* (1999) and Cairns *et al.* (2007) carry trade has significant impact on short-term exchange rate movement which deviates from the macro exchange rate model predicted by UIP. A series of previous studies document that UIP does not hold on the short term and the exchange change rate is pushed to the opposite direction as UIP expected. The failure of the joint hypothesis of UIP and rationale expectation infers that there exists non-zero excess return to currency speculation.

Although the annualized return of carry trade comes with sharp ratio larger than 1, the loss of carry trade can be enormous when the market performs poorly. Abreu and Brunnermeier (2003) report the slow boom and sudden crash in the financial market. Carry trade lost approximate 20% return in the 2008 credit risk period. Plantin and Shin (2006) is the first to describe the abrupt reverse of the exchange rate movement as “going up by stairs and down by the elevator”.

Empirical studies show that the realized carry trade return is skewed. Harvey and Siddique (2000) show that investors naturally prefer positive skewness, which contracts with the fact that carry trade return is negatively skewed. Researchers in the field are interested to know the underlying economic mechanism reflected by this asymmetric distribution. Theories to explain the negative asymmetries in market returns can be generally categorized into a representative-investor group and models with market heterogeneity belief approaches.

In the representative-investor approach, theory to explain the negative asymmetries can be further classified into stands of leverage effect, volatility feedback and stochastic bubble models. Initially proposed by Black (1976) and Christie (1982), leverage effect is the most venerable theory which states a negative correlation between return and volatility. In most cases, a drop in prices raises operating and financial leverage, and the volatility of return is increased as a consequence. G. W. Schwert (1990) and Bekaert and Wu (2000) argue that high frequency data cannot be explained by this theory, as the leverage effect is not quantitatively important enough to explain the feature of return. Volatility feedback theory, developed by French *et al.* (1987) and J.Y. Campbell and Hentschel (1992), focuses on the different impact of good news and bad news on stock price volatilities. The criticism, proposed mainly by Poterba and Summers (1986), on the volatility feedback mechanism is that the impact magnitude can be too small because of the short-lived volatility shocks. The stochastic bubble models, developed by Blanchard and Watson (1982), attribute the large negative returns to those events with low probabilities.

The representative-investor approach ignores the heterogeneous market participants and is challenged by market heterogeneity belief approach. Veldkamp (2006) argues that this unconditional asymmetry in exchanges rate movements can be explained by the endogenous flow of information, which can be gauged by the time-irreversibility and the skewness. Chen *et al.* (2001) place investor heterogeneity at the centre of the asymmetric return phenomenon. They argue that negative skewness in asset trading is formed by different opinions among investors and arbitrageurs regarding the fundamental value of the market form. The heterogeneity belief approach is more close to the real market structure and therefore attribute the skewed return in a promising way.

2.2.2 Risk-based explanation to the excess return of carry trade

Burnside *et al.* (2006) derived a risk based explanation to currency speculation, where the forward rate consists of two components: the expected value of the future spot and a risk premium. The presence of risk premium results from the non-zero marginal utility of foreign currency. Literatures pursuing this risk premium approach seek different risk resources to explain the excess return of carry trade.

The first group of papers attempts to explain the excess return by the market liquidity in the Forex market. Brunnermeier *et al.* (2008) proposed a generic crash model that outlines that the speculators’ position is leveraged and subject to margin calls. These authors argue that tight funding liquidity causes a rapid unwinding of carry trade position and thus leads to abrupt change in exchange rate movement. The currency crash risk is the major concern which prevents speculators entering the trading position. Galati *et al.* (2007) provide evidence that foreign exchange trade volumes are positively correlated with higher domestic interest rates. The authors asserts that carry trade strategy works well during times of low exchange rate volatility and regimes of stable interest rate policies. Abreu and Brunnermeier (2003) demonstrate that, given the dispersed information pattern in the foreign exchange market, unfortunately, traders cannot simultaneously and immediately liquidate positions to avoid crash and bubbles in equilibrium. Therefore, under real market conditions, market participants should protect their positions by using conditional trading strategies.

Another group of researchers study the downside risk when disasters happen in the market. These papers examine whether crash premium is a valid explanation for the high return of carry trade. Plantin and Shin (2006) explain carry trade speculation by the existence of a bubble in the Forex market. Burnside *et al.* (2011) refer to the Peso problem as an explanation for the high excess return of carry trade. They find that the standard deviation of payoffs to the hedged carry trade portfolios is substantially lower than those of the non-hedged carry trade portfolios. Farhi *et al.* (2009) decompose the excess return of carry trade into a component generated as a Gaussian risk premium and another component generated as a disaster risk premium. By using options to hedge carry trade portfolio, they find their disaster risk premium can explain the average excess return. The approach of Burnside *et al.* (2011) and that of Farhi *et al.* (2009) link the disaster risk to the Peso problem. Jurek (2008) investigates whether the excess return of carry trade is due to the portfolio's exposure to crash risk. He adopts implied options to proxy the dynamics of the moment in risk-neutral distribution. Jurek (2008) finds that the crash risk premium explains 30%-40% of the total return in carry trade. Bhansali (2007) finds that the volatility of such an option is proportional to the currencies' interest rate differential. They find a positive relationship between carry trade return and volatility. Clarida *et al.* (2009) find further empirical support to the volatility approach by extending the implementation of strategy with forward contact and options.

Some researchers look at carry trade excess return by other approaches. Bacchetta and Van Wincoop (2006) attributes the failure of UIP to infrequent revision of portfolio allocations. Jylhä and Suominen (2011) documents higher inflation risk in high interest rate currencies; they find a positive relationship between carry trade returns and hedge fund indices. Lustig and Verdelhan (2007) uses a consumption-based model to explain the excess return of carry trade. They adopt the habit preferences proposed in J.Y. Campbell and Cochrane (2000). Following Barro (2006), Farhi and Gabaix (2008) extend the standard consumption-based model with disaster risk factors and find that the risky countries command high risk premium and therefore their interest rate appreciates.

2.3 Review of key papers

This thesis follows the risk premium approach and try to explain the excess returns of carry trade with disaster type risk factor and market liquidity. We not only study the risk factors proposed in the first two research groups, but also find a link between these two sources of risk premiums.

Next, we proceed to review five key papers in this field in this section.

2.3.1 Peso problem

Burnside (2011) finds out that the excess return of carry trade cannot be explained by those traditional risk factors. Instead, they refer to the Peso problem as an explanation of the high excess return of carry trade. The Peso problem is defined as a generic term for the effects of large events with small probabilities in the real trading world.

This paper begins with a comprehensive investigation on whether traditional risk factors are effective in explaining the payoff of carry trade. These traditional risk factors include: consumption growth, returns on the stock market, the Fama and French (1993) factors, various kinds of per-capita growth rate proposed by J.Y. Campbell and Yogo (2006), luxury sales growth proposed by J.Y. Campbell and Yogo (2006). Thus, these conventional measures of risks turn out to be uncorrelated with the excess return of carry trade.

Burnside (2011) implement a carry trade strategy that does not yield high negative return in a Peso state. This Peso-immune strategy is developed as follows: the investor sells the foreign currency forward and simultaneously buys a call option on that currency. If the foreign currency appreciates beyond the strike price, then the forward contract is exercised to fulfil the obligation. Under this construction, this hedged carry trade portfolio does not generate large negative return in the Peso state. To estimate the average payoffs of the hedged carry trade, Burnside et al. use at-the-money options with one-month maturity to pay off in all Peso states and non-Peso states. A linear stochastic discount factor is built based on the Peso event probability framework to address the pricing power of the Peso problem.

The dataset contains daily spot and daily 1-month forward exchange rates that cover 20 countries. One put and call option data set ranges from January 1987 to April 2009. Another at the money option data set ranges from February 1995 to July 2009. The observations in the model are built on monthly frequency which is converted by daily observations. All data spans are from January 1976 to July 2009.

Burnside (2011) find that the option hedged and non-option hedged carry trade portfolios generate similar returns. The standard deviation of payoffs to the hedge carry trade is substantially lower than that of the non-hedged carry trade portfolios. The payoff of the non-hedged carry trade portfolio in the Peso state is only moderately negative. The standard deviation of carry trade payoff is over one hundred times larger in the Peso state than in the non-Peso state.

Burnside (2011) defines the Peso event as a large value of stochastic discount factor rather than a large carry trade loss. This claim roots from their empirical finding that SDF is much larger in Peso state than that in non-Peso state. However, the empirical results show that the loss of hedged and unhedged carry trade in Peso state is not very different, which indicates that carry trade loss is not an effective pricing factor in the excess return.

2.3.2 Option implied crash risk

Jurek (2008) proposes a currency crash premium to explain the excess return in carry trade. The fraction of the excess return that can be explained by this crash risk factor is obtained by comparing returns from crash-hedged and unhedged portfolios. The crash risk factor is claimed to explain around 35% excess return in carry trade; while the explained fraction in Jurek (2014) is smaller, less than 10%.

Under the crash risk hypothesis, excess return in high interest rate currencies is the compensation for the exposure to the risk of rapid and large devaluation. The crash risk in Jurek (2008) is defined as the exchange rate shocks that exceed some pre-specified threshold value or a multiple of the option-implied volatility. This paper uses options, which represent an *ex ante* perception of crash, to hedge volatility. The crash risk is measured as a volatility-implied risk premium. In Jurek (2014), the crash risk premium is further decomposed into diffusive and jump risk premium. The diffusive premium estimates the average return of the crash-neutral portfolio, while the jump risk premium explains the difference in return between the hedged and unhedged portfolios.

Jurek (2008) uses daily LIBOR on G10 currencies spanning from January 1999 to December 2008, as well as nominal exchange rate quoted as US dollars per foreign currency. The options of daily implied volatility quote on five different strikes with four standard maturities are used in the study. The method used to derive risk neutral moments of exchange rates, implied volatility, implied skewness and implied kurtosis is adopted from techniques in Bakshi *et al.* (2003). The model is built with tests carried out on a monthly basis. Jurek (2014) uses a similar model with an extended dataset, which ranges from 1990 to 2012.

Jurek (2014) has several findings: firstly, after hedging off the crash risk, portfolios without dollar risk exposures show negligible returns, while portfolios with dollar exposures are weakly significant. Secondly, hedging with quarterly options has better performance. Thirdly, the option is considered to be mispriced. The price of options should have been 4 times more expensive than their observed value. Lastly and also importantly, inspired by the variance premium in Della Corte *et al.* (2011), Jurek (2014) finds evidence of the existence of skewness premium, which is negatively related to interest rate differentials. To answer the question whether options are priced too cheaply, the author argues that the option is not priced cheaply, as evidence shows that implied skewness does not forecast return, compared with realized skewness. The existence of skewness premium between realized and perceived skewness plays the role of a wedge to deviate the forecasting power of options.

Some criticism arises on Jurek (2008) and Jurek (2014). Firstly, this option-implied crash risk does not explain all the excess return in carry trade. As shown in the performance of non-dollar-neutral portfolio, the hedged excess return is still marginally significant. This means that there could be a common risk factor underlying dollar denominated portfolios. Secondly, in terms of the pricing power, the disaster risk premium measured in Jurek (2014) is much smaller than the disaster premium estimated in Farhi *et al.* (2009). The reason could be that, when the investment horizon approaches to zero, hedged excess return with out-of-money bears only 90% disaster risk at 10 delta and 75% dollar exposure risk. Hence there is an estimation bias in the process. Thirdly, Jurek (2014)'s method is not presented in an structured model. It does not formalize the risk factor into an asset pricing model.

2.3.3 Disaster risk premium

Farhi *et al.* (2009) postulates that the excess return can be explained by the existence of rare but large adverse aggregate shocks to stochastic discount factors. They propose a parsimonious exchange rate model using currency options to estimate world disaster risk premium. They claim that the disaster risk factor could explain more than a third of excess return in carry trade.

This class of disaster-based structured models is pioneered by Rietz (1988) and Barro (2006). Due to the lack of disaster in the samples, Farhi *et al.* (2009) use options to develop the measure of disaster. This option implied model is inspired by the fact that option smiles on high and low interest rate currencies have an asymmetric pattern since the credit crisis in 2008. That is, the price of out-of-money put option is more expensive than out-of-money call options for high interest rate currencies, while the former is cheaper than the latter for low interest rate currencies.

The stochastic discount factor in this model incorporates two components: a traditional log-normal component and a disaster component. The log-normal component represents observed random shocks or Gaussian shocks. The disaster component represents a global disaster shock with heterogeneous impact on different countries. The volatility premium is abstracted from daily variation of exchange rate and allowed to vary monthly. The model delivers a closed form solution for call and put option prices and the expected currency excess returns.

Farhi *et al.* (2009) uses spot rate, forward and option data from January 1996 to December 2011 for 10 developed currency markets. The spot rate and forward rate data come monthly, and the options are with 1-month maturity. Following Lustig and Verdelhan (2007) and Farhi *et al.* (2009), we sort currencies by the interest rate when construction currency portfolios.

Through the analysis, Farhi *et al.* (2009) assure the importance of disaster risk in explaining carry trade return by the following facts: firstly, although the volatility goes back to the level before crisis, the disaster risk is still an order of magnitude higher than before, which means that the investors have large compensation for the disaster risk. Secondly, the model suggests a strong positive relationship between the interest rates and disaster premium. Thirdly, the model shows that during the crisis of 2008, the change in exchange rate negatively related to disaster premium. Thus, currencies with small exposures to global disaster risk appreciate in times of disaster, while currencies with large exposures to global disaster risk appreciate.

Compared with peers' work, this option-implied model is a very specific model, which cannot be widely applied on other assets. There is no support for the view that this disaster risk factor also prices other cross section assets returns, such as currency momentum portfolios, stock return momentum portfolios, corporate and international bonds and individual currency returns. Moreover, similarly to the other option-implied risk factor proposed in Jurek (2008), the disaster risk hedged portfolios show that there is still unexplained excess return, which means that hedging off disaster risk with a put option only offers a biased estimation of disaster risk premium.

Lastly, in the assumptions of the model, the independence of two component factors, Gaussian shock and disaster shock, is difficult to test. Hence these two component factors are not guaranteed to be orthogonal, which could bias the estimation of the model.

2.3.4 Common risk factor

Lustig *et al.* (2011) proposes that cross sectional currency excess returns can be explained by covariance between returns and return-based slope factor. Lustig *et al.* (2011) find that high interest rate currencies load more of this slope factor than low interest rate currencies particularly when the market is volatile. By building up a linear factor model with factor mimicking portfolios, these authors claim that their carry trade risk premium accounts for most of the cross-sectional variations in the excess return.

Lustig *et al.* (2011) provide a data driven approach under the framework of the Arbitrage Pricing Theory of Ross (1976). The non-arbitrage model of interest rate proposed by this paper includes two factors: a country-specific factor and a global factor. This structural model is built up on the empirical findings from the Principle Component Analysis (PCA). These two factors in the asset pricing model map the two components obtained from PCA. The currency risk premium in the model consists of dollar risk premium, which resembles the level factor *RX* in PCA, and carry trade risk premium, which refers to slope factor *HML* in PCA. The carry trade risk premium is determined by its loading spread between the common component of high and low interest rate currencies and that of the price of global risk.

The slope factor is identified by building carry trade portfolios, in which currencies are sorted on the forward rate. If UIP holds, sorting on forward exchange rate is equivalent to sorting on interest rates. The paper shows evidence to prove that sorting currencies by interest rate is sorting by the exposure to the risk factor situated in exchange rate.

Lustig *et al.* (2011) uses daily spot and exchange rate, quoted as US dollars per foreign currency. The data ranges from November 1983 to March 2008. These come in two sets of data, a smaller data set with 15 developed countries and a larger data set with 37 countries.

Their model suggests that high interest rate currencies depreciate more in cases of global shocks. Implied from the PCA, currencies with high interest rate depreciate more with larger loading on global risk factor. Since the carry trade risk premium depends on the loading spread in the model, in times of global shock, carry trade risk premium goes up as the loading spread increases. Lustig *et al.* (2011) also find that carry trade return co-moves more intensely with stock returns in times of global volatility. Specifically, the correlation between return of carry trade and that of the stock market increases sharply during times of high volatility.

Lustig *et al.* (2011) contributes a theoretical method for building portfolio and extracting risk factor with PCA. It clarifies the rationale of sorting currencies. We claim that sorting currencies by interest rate does not hinder the study on the effect of risk factor. The return of carry trade is due to its covariance with the risk factor. The downside of adopting PCA is that it is difficult to interpret the extracted risk factors. Furthermore, as shown by other research, carry trade excess return is affected by the stock market; while the volatility factor extracted in Lustig *et al.* (2011) is purely from currency market return, which ignores the impact from the stock market.

2.3.5 Volatility risk premium

Following previous studies such as Adrian and Rosenberg (2008) and Da and Schaumburg (2011) on volatility, Menkhoff *et al.* (2012a) proposes a negative currency market volatility premium that accounts for more than 90% of cross sectional carry trade return. In terms of different currencies, they find that high interest rate currencies are negatively related to volatility and hence deliver low return in times of high volatility. Low interest rate currencies have positive return. By running a series of tests for comparison, Menkhoff *et al.* (2012a) claim that liquidity risk plays a less important role than volatility risk in explaining carry trade excess return.

Menkhoff *et al.* (2012a) rationalizes global Forex volatility risk into a standard linear asset pricing framework to test the explanatory ability of volatility risk in excess return of carry trade. Similar to Lustig *et al.* (2011), Menkhoff *et al.* (2012a) also considers two types of factors: dollar risk factor and a global Forex volatility factor. They show that global Forex volatility is a key driver of risk premium in explaining cross-sectional carry trade return. The results are examined through robustness test with different proxies of volatility and comparative test also run against other proposed risk factors. The results are also robust to the extreme value, which infers that the Peso problem is unlikely to be the reason driving the pricing power of volatility risk factor.

They use data for spot exchange rate and 1-month forward exchange rate quoted as foreign currency per dollar. The empirical analysis is carried out on a monthly basis. Menkhoff *et al.* (2012a) use two sets of data, a smaller data set with 15 developed countries and a larger data set with 48 countries. Considering the transaction cost in trading, currencies are sorted on the forward exchange rate and 5 portfolios are constructed.

Menkhoff *et al.* (2012a) argue that excess return of carry trade is a compensation of time-varying volatility risk. Carry trade performs poorly during a market turmoil period. Interestingly, investment and funding currencies react differently in times of high volatility, high interest rate currencies deliver low return while low interest rate currencies provide a hedge by yielding positive return. Menkhoff *et al.* (2012a) also show that the pricing power of volatility risk factor can be widely applied on other assets, including Forex momentum strategy, individual currency return, domestic US corporate bonds, US equity momentum, Forex option portfolios and international bond portfolios.

The main criticisms on the volatility factor extracted from the currency market are that it is difficult to disentangle volatility from other risk factors. Firstly, as pointed out by Menkhoff *et al.* (2012a), it is difficult to separate the effect of volatility from liquidity risk in the currency market. The liquidity dries out when volatility is high in the market. Thus, the effect of each risk factor could be covered by the other. Secondly, it is difficult to disentangle volatility with downside disaster risk. As tested by Farhi *et al.* (2009), the loading pattern on global currency volatility reveals a similar pattern on disaster proxies by risk reversal. Lettau *et al.* (2014) proposes a structural model on option prices to disentangle time-varying volatility from disaster risk premium.

2.4 Conclusion

The forward premium puzzle, which states that exchange rate changes do not compensate interest rate differential, offers carry trade a considerate amount of profit. Extensive literatures have been studying the forward premium puzzle for decades. Early in the research stage, the theoretical origin and form of forward premium was derived. However, the empirical risk factor that drives this risk premium and further explains the carry trade excess return has not been identified and agreed on by researchers.

The research approaches to explaining carry trade excess return can be generally categorised into risk-based and non-risk-based. The literature shows that asset pricing models with risk factor derived on macro or long term basis tend to contribute little to answer the general question of what affects the movement of exchange rate in the short term. Innovatively, those models incorporating non-conventional crisis risk factors are more successful in explaining currency returns than the conventional risk factors. Our thesis focuses on the risk-based strand with risk factors derived under the market microstructure framework.

The literature suggests that non-conventional risk factors can be effective in pricing currency returns at a certain level. The risk based literature find that: Firstly, some stock market risk factors are also effective in explaining excess returns in FX market, such as the return asymmetries, the option prices and the implied volatility index. Secondly, studying excess return from the perspective of portfolios is a successful approach when studying cross-sectional returns, because it filters that the idiosyncratic features that does not explain the general feature of cross-sectional assets. Nevertheless, most of the literatures suffer the problem that those proposed risk factors cannot explain all excess returns and the pricing risk factors are not applicable to a wider range of assets.

We follow those successful approaches when seeking the effective risk factors in the following chapters. Moreover, we try to find risk factors that explain large portion of excess returns and are generally priced in all foreign currencies.

3. Data

3.1 Currency data set variables

Our data set consists of 9 most liquid currencies with largest trading volume from the G10 currency group. We have the price quotes of spot, future and option markets from Bloomberg. These currencies in the G10 group join the General Arrangements to Borrow (GAB) and can be bought and sold in an open market with minimal impact on their international exchange rates. These 9 currencies are: US dollar (USD), Euro (EUR), Great Britain pound (GBP), Japanese Yen (JPY), Swiss franc (CHF), Canadian dollar (CAD), Australian dollar (AUD), Norwegian kroner (NOK) and New Zealand dollar (NZD).

We follow Farhi *et al.* (2009) Lustig *et al.* (2011) and Burnside (2011) to conduct empirical studies of currency trading at monthly frequency. We conduct a monthly analysis in chapter 5, chapter 6 and chapter 8. We start from daily data and use the end-of-month LIBOR quote, end-of-month spot exchange rate, end-of-month risk reversal quote, end-of-month future position quote, end-of-month VIX index and end-of-month TED index. Additionally, the monthly skewness of exchange rate movements is generated by daily exchange rate within one month.

3.1.1 Excess return of carry trade

Burnside *et al.* (2006), Burnside (2011) and Caballero and Doyle (2012) define the excess return of carry trade by describing the actual currency trading process: taking the perspective of a US investor borrowing 1 USD at month t at the interest rate $(1 + i_t)$ and spontaneously investing on an asset dominated by foreign currency j at interest rate $(1 + i^*_{j,t})$. We quote exchange rate S_t as the units of foreign currency per USD. From month t to month $t + 1$, both USD and foreign currency grow by their interest rate. On month $t + 1$, the exchange rate is updated to S_{t+1}. Ignoring the transaction cost, the dollar value excess return to borrow 1 USD and buy in foreign currency is:

$$(1+i_{j,t}^{*})\frac{S_t^j}{S_{t+1}^j}-(1+i_t) \tag{5}$$

On the other hand, carry trade between two currencies can happen in the opposite trading direction, where the US investor borrows foreign currency and buy in 1 USD: at month t, in order to buy in 1 USD the investor borrows S_t units of FCU. After 1-month growth at interest rates $(1+i_t)$ for USD and at $(1+i_{j,t}^{*})$ for the foreign currency, the dollar value excess return to buy 1 USD and borrow foreign currency is:

$$(1+i_t)-(1+i_{j,t}^{*})\frac{S_t^j}{S_{t+1}^j} \tag{6}$$

Equation (5) and (6) above indicate a generalized definition form of carry trade excess return which accommodates the trading direction of buying or selling foreign currencies as:

$$Z_{t+1}^j = sign(i_{j,t}^{*}-i_t)[\big(1+i_{j,t}^{*}\big)\frac{S_t^j}{S_{t+1}^j}-(1+i_t)] \tag{7}$$

where

$$sign\big(i_{j,t}^{*}-i_t\big)=\begin{Bmatrix}+1 & if\ i_{j,t}^{*}>i_t\\ -1 & if\ i_{j,t}^{*}<i_t\end{Bmatrix}$$

we have the interest rate differential $IRD_t^j=(i_{j,t}^{*}-i_t)$, where $i_{j,t}^{*}$ and i_t are the foreign and domestic interest rates at month t. We use LIBOR rates to compute the interest rate differentials for each currency. [3] We use end-of-month spot exchange rate and end-of-month LIBOR quote with 1-month maturity to calculate monthly excess return for individual currency j. $i_{j,t}^{*}>i_t$ indicates that excess return of carry trade is obtained by buying foreign currency and selling USD, while $i_{j,t}^{*}<i_t$ indicates that excess return of carry trade is obtained by selling foreign currency and buying USD. We note that the excess return is

[3] LIBOR is the average interbank interest rate at which a selection of banks on London money market lend to one another.

signed by the interest rate differential of month t because the trading direction is initiated at month t, whereas the excess return is obtained one month after the change in exchange movement is realized.

We do not consider the transaction cost measured by bid-ask spread. Mancini *et al.* (2013) argue that the excess return net of bid-ask spreads overestimate the true cost of trading, Gilmore and Hayashi (2011Oct) provide the empirical evidence to support.

3.1.2 Skewness of changes in exchange rates and crash risk

As an important variable in this thesis, we use the realized skewness of the changes in exchange rate to measure the currency crash risk and denote it $skew_t^j$. Chen *et al.* (2001) propose using the skewness to measure the crash risk in stock market. Brunnermeier *et al.* (2008) borrow this idea from the stock market and apply it in carry trade in the FX market. Burnside (2011) studies the excess return of carry trade with a factor derived from the skewness of exchange rate on a one-month basis. We follow Chen *et al.* (2001), Brunnermeier and Pedersen (2007a) and Burnside (2011) and compute monthly realized skewness for currency j at month t using daily exchange rate changes within month t The skewness coefficient is defined as a function of the third moment of the change in exchange rates.

$$skew_t^j = \frac{\frac{1}{n}\sum_{\tau_i}^{n}(\Delta S_\tau^j - \Delta \bar{S}_t^j)^3}{(\frac{1}{n}\sum_{\tau_i}^{n}(\Delta S_\tau^j - \Delta \bar{S}_t^j)^2)^{3/2}} \quad (8)$$

where n is the total number of trading days within month t. We have trading days $\tau_i, i = 1,2 \ldots n$. ΔS_τ^j is the log difference of exchange rate for currency j on day τ over last day: $\Delta S_\tau^j = logS_\tau^j - logS_{\tau-1}^j$, and $\Delta \bar{S}_t^j$ is the mean of exchange rate changes for currency j at month t. n is the number of observations at month t.[4]. A positive skewness ($skew_t^j > 0$) means large ΔS is likely to appear and indicates foreign currency depreciates, USD

[4] We use daily exchange rate movement of one currency pair within one month to generate monthly skewness, then take this generated monthly skewness as one respective observation for that currency pair in the data set.

appreciates. A negative skewness ($skew_t^j < 0$) indicates foreign currency is likely to appreciate; USD depreciates.

Brunnermeier and Pedersen (2007a) develop a liquidity spiral model to support the idea of using skewness to measure currency crash risk. They show that securities with positive excess returns are accompanied by negative skewness. The positive return is a premium for providing liquidity, and the negative skewness is caused by asymmetric responses to fundamental shocks: shocks that lead to speculators loss are amplified. When speculators hit funding constraints, positions are unwound leading to further depressing prices and deteriorating market liquidity condition. However, shocks that lead to speculator gains are not amplified.

Chen *et al.* (2001) address that the log difference of exchange rate is essential in the calculation of exchange rate. Because, if the exchange rate were lognormally distributed, then the change of exchange rate based on log changes should have a zero mean. This leads to the fact that negative skewness based on log changes should also have a zero mean, which is a preferred statistical feature in distribution research.

3.1.3 Risk reversal and price of crash risk

Recent studies find that risk reversal represents investors' view on the direction of exchange rate movement and contains information in forecasting future currency crash. Following Jurek (2008), Farhi *et al.* (2009) and Hutchison and Sushko (2013), we use end-of-month 25Δ out-of-money risk reversal to measure the perceived crash risk by investors in the FX market. Risk reversal is the implied volatility spread between an out-of-money call option and an out-of-money put option of the same moneyness and maturity, Wystup (2006):

$$RR_t^j = \sigma_{j,t}^{call} - \sigma_{j,t}^{put} \tag{9}$$

where $\sigma_{j,t}^{call}$ is the implied volatility of 25ΔOTM call option for currency j at month t and $\sigma_{j,t}^{put}$ is the implied volatility of 25ΔOTM put option for currency j at month t. The Δ represents the sensitivity of the option to the changes in the exercise prices. 25Δ risk reversals are with 25% sensitivity to changes in its strike price. Implied volatilities $\sigma_{j,t}^{call}$ and $\sigma_{j,t}^{put}$ are computed from Black and Scholes (1973).

Risk reversal is a directional bet against large price swings. The sign of risk reversal reflects market view regarding the future exchange rates. Our risk reversal quotes are in line with the exchange rate pairs. A positive risk reversal ($RR_t^j > 0$) indicates more investors betting on higher probability of USD being worth more in foreign currencies. In other words, a positive risk reversal represents a market hedge against the depreciation in foreign currency j in case a crash happens. Purchasing a risk reversal represents the price of insurance that investors would like to pay to protect against the depreciation in foreign currency. On the contrary, a negative risk reversal ($RR_t^j < 0$) means more betting on higher probability of USD being worth less in foreign currencies. Thus, a negative risk reversal represents a hedge against the appreciation in foreign currency j.

Our study of risk reversal provides empirical evidence in investigating the information content of option in forecasting market crash. We do not assume option price contains absolute information content about the state of market and so do not extract information from the option prices. Instead, we investigate whether option price still can effectively forecast exchange rate movements when controlling other informative variables, because option price is not the only source of information which carry both macro news or micro news. Our monthly risk reversal quotes for currency EUR, GBP, JPY, CAD, AUD and NZD spans from October 2003 to February 2013. Monthly risk reversal quotes for CHF and NOK come with shorter sample period, which spans from March 2005 to February 2013.

3.1.4 Future position and carry trade activity

Previous studies find that carry trade activity needs to be measured with indirect measures, due to lack of direct evidence on investor positions of carry trade. We follow Klitgaard and Weir (2004) and Brunnermeier *et al.* (2008) by using the ratio of end-of-month net non-commercial positions with regard to open interests to measure carry trade activity, which are both published by Chicago Mercantile Exchange (CME).

Net positions are defined as long future contracts in the foreign currency minus short future contracts in the foreign currency.[5] The CFTC defines open interest as the sum of all futures contracts not yet offset by transaction, delivery or exercise. Non-commercial traders are described as speculators who are profit driven and act on their views of market short-term direction, and include commodity trading advisors. A positive future position means more long future contracts in foreign currency and indicates buying the foreign currency. One taking a long position gains if foreign currency appreciates. A negative future position means more short contracts and indicates selling the foreign currency. One taking a short position gains if foreign currency depreciates.

We are aware that CFTC future position data suffers some problems in measuring carry trade activity: future contracts is not capable of distinguishing futures for carry trade from other investment activities purposes. They cannot capture the over-the-counter trading in forward market or in the derivatives market.[6] Additionally, future position ignores the leverage effect in carry trade. However, the carry trade strategy we study in this thesis does not focus on leverage effect.

The monthly net future position quotes of 7 currencies are obtained from Bloomberg, including EUR, JPY, GBP, CHF, AUD, CAD and NZD. Future position data of NOK is not available. The sample period of future position data is from November 2001to February 2013. NZD has a later start and ranges from July 2004 to February 2013.

3.1.5 VIX, TED and funding liquidity

In this thesis, we use two measurements VIX and TED as the proxies for the funding liquidity level in FX market. VIX is an index of the implied volatility of S&P 500 options, which is published by CBOE. It measures speculators' willingness and ability to put capital at risk. TED spread is the difference between the LIBOR rates and T-Bill rates, which measures the

[5] Future position information is issued via the Commitments of Traders report (COT) from CME, which is the largest exchange for foreign exchange futures by volume. This report states the position held at the end of the preceding Tuesday and is released every Friday. Future contracts can be used for hedging or speculation, which can be further categorized into investor and speculator respectively. Accordingly, CFTC reports data on firms as 'commercial' and 'non-commercial'. Commercial traders are generally described as hedgers or firms using a future contract to hedge business risk, typically made up of banks, hedge funds, other nonfinancial corporations and market makers.

[6] For example, hedge funds, which are consider to be prominent in the carry trade, apply this strategy a lot in the forward market rather than the future market, which falls out of the reporting scope of the future position data.

level of credit risk and funding liquidity in the interbank market. The LIBOR rates is the uncollateralized lending rate in the interbank market, which is subject to the default risk. While T-Bill is a widely accepted risk free interest rate since it is guaranteed by the US government.

Previous research has shown that VIX and TED are two useful proxies in the FX market to measure investor's fear and uncertainty level to the financial market. Brunnermeier *et al.* (2008) find that the funding constraint is the reason for investors to unwind carry trade positions in the FX market, by using weekly VIX and TED from 1992 to 2006 to measure funding liquidity. Menkhoff *et al.* (2012a) use innovations of monthly VIX and TED from 1986 to 2009 to measure the market volatility in the FX market. They argue that VIX and TED are effective to measure to volatility of the common component across various assets in the FX market. Mancini *et al.* (2013) use daily VIX and TED from 2007 to 2009 and find a negative relationship between market liquidity and VIX and TED, which suggests that low FX market liquidity can be explained by the increase in investors' uncertainty to the market or the reduction of funding liquidity.

We follow previous studies by using VIX and TED to measure the funding liquidity in FX market. We have end-of-month VIX and TED quoted monthly from Bloomberg spanning from October 2001 to February 2013. We consider that VIX and TED are equivalent in representing the following three concepts: investors' fear of market uncertainty, funding liquidity or funding constraints that investors face and the risk adversity level of investors. The reason is that higher risk adversity level can be caused either by higher funding constraints or lower funding liquidity level, both of which may reflect investors' fear of the market future uncertainty. This points to the same interpretation the higher the VIX and TED quote, the lower the market funding liquidity.

To sum up, in this section, we introduce all variables involved in the study of this thesis with theoretical support from previous studies. Our investment horizon is one month. We use end of month data of each variables described above. In the next section, we present the stylized factor of each variable and provide preliminary data analysis of the results.

3.2 Stylized facts of currency data set

In the setup of empirical analysis, the properties of the variables affect the choice of models. In order to choose an empirical model that responds correctly to the real data generation process, we start by investigating the property of variables. The choice of empirical model is based on these stylized facts and pre-estimation tests.

3.2.1 Changes in exchange rate

We follow Lustig *et al.* (2011) and Brunnermeier *et al.* (2008) by defining the changes in exchange rate as the log difference of exchange rate over last period. Table 3-1 presents the descriptive statistics of the change in exchange rate across 8 currencies. As the exchange rate is quoted as units of foreign currency per US dollar, the first row of Table 3-1 shows that all 8 foreign currencies have a tendency of appreciation during the full sample period, with similar level of standard deviation. CHF and JPY are the currencies which appreciate the least, while AUD and NZD are currencies which appreciate the most. We run a CH test Cumby and Huizinga (1992) to test the auto correlation with the null hypothesis of no auto correlation under the assumption of heteroscedasticity. The results show that all CH test statistics are rejected at 1% significance level, meaning none of the foreign currencies exchange rate series is auto correlated. We next run a LM test for heteroscedasticity of ARCH effect. The LM statistics of CHF, AUD and NOK are rejected at 5% significance level, meaning these currencies' exchange rate series are heteroscedastic and other foreign currencies' exchange rate series are not. In order to test the stationarity, we run a ZA test Zivot and Andrews (1992) which accounts for one structural break in the series, assuming that the financial crisis may cause a potential structural break in the series. The null hypothesis of containing unit root in ZA test are all rejected at 1% significance level. This means that all series of changes in exchange rates of foreign currencies are stationary from December 2001 to February 2013.

In Panel B and Panel C in Table 3-1, we also report the mean and standard deviations of currencies before and after the big currency crash in 2008. We refer to the period of this crisis specified by Farhi *et al.* (2009). We find that before the crisis, CHF and JPY appreciate the least among all currencies, and after the crisis, they maintain this appreciation level. Currencies such as EUR, GBP, CAD and NOK turn from appreciation before the crisis to depreciation afterwards. AUD and NZD keep appreciating, but the magnitude of appreciation is smaller than CHF and JPY. The analysis from panel A to panel C suggests that the movement of exchange rates for currencies changes before and after the crisis. This reflects that the market condition of currency trading changes after the crash happened.

Next, Table 3-2 presents the correlation between exchange rate movements across currencies for the full sample period. We see that all currencies are positively correlated, meaning the exchange rate movement of one currency pushes other currencies to make a move in the same direction. This is consistent with the finding that all currencies appreciate during the full sample period. Particularly, all European currencies have strong correlations, meaning currencies such as the EUR, GBP, CHF and NOK strongly co-move with each other. The correlation between EUR and CHF is as high as 0.84, that between EUR and NOK is as high as 0.82, while the correlations between the European countries and Non-European countries are relatively weaker: EUR is 0.21 correlated to JPY. CAD is 0.07 correlated to JPY.

3.2.2 Interest rate differential

We present the statistics of interest rate differentials (IRD_t^j) for foreign currencies j in Table 3-3. The descriptive analysis serves to detect sub-periods in IRD_t^j endogenous structure breaks. We plot time series IRD_t^j for between foreign currencies and the US in Figure 3-1 and 1-month LIBOR rate of 9 countries in Figure 3-2.Table 3-3 presents the descriptive statistics of IRD_t^j across 8 foreign currencies. We see that only the IRD of JPY and CHF is negative, meaning the interest rate of JPY and CHF is generally lower than that of the US. Other currencies' interest rate is higher than that of the US. This suggests that JPY and CHF potentially serve as funding currencies in carry trade since they have low interest rates. Other currencies, especially AUD, NOK and NZD potentially serve as investment currencies in carry trade since they have high interest rates. Actually, AUD, NOK and NZD are well known as commodity currency in FX market for the constant high interest rates. Next, the AR(1) regression coefficients of all foreign currencies are significant at 1%, meaning there the IRD of these foreign currencies are highly autocorrelated. This autocorrelation can also be detected by running a CH test. The null hypothesis of the CH test, that the series has no serial correlation under an assumption of heteroscedasticity, is rejected at 1% significance level in all foreign currencies. The LM statistics of the ARCH effect test shows that the null hypothesis of no heteroscedasticity is rejected at 1% significance level in all foreign currencies. Regarding the stationarity test, we run several stationarity tests including the

Dickey Fuller-GLS (DF-GLS) test, the (PP) test and (ZA) test. The DF-GLS test performs an Adjusted Dickey Fuller test in which the series are transformed by a generalized least-square regression to improve the test power. The PP test use Newey-west standard errors to account for serial correlation and the heteroscedasticity in the Dickey Fuller test regression. The ZA test accounts for the potential one structural break that happened in the financial crisis in 2008. All these three stationarity tests show that the null hypothesis of containing unit root cannot be rejected at 10% significance level in all foreign currencies, except NZD in the DF-GLS test. This means that all IRDs of foreign currencies are non-stationarity in sample period from December 2001 to February 2013.

We see in Figure 3-1 that all foreign countries' IRDs have a significant fall, which starts from July 2004 and lasts till August 2006. Then IRDs start to increase back to around 0.2% on July 2008. After going through some volatility, the IRDs plunge again from 0.2% to less than 0.1% during October 2008 and September 2009. Afterwards, the IRDs maintain at around 0.1% from July 2009.

Turning to Figure 3-2, we find that the sharp IRDs decrease between May 2004 and August 2006, shown in Figure 3-1, is mainly caused by the leading raise of USD LIBOR rate, which starts before July 2004. Other LIBOR rates catch up with the increasing trend after July 2004 and reach their peaks around September 2007. Given that the IRD is taken as the difference between the foreign currency and USD, this slow increase in foreign countries LIBOR rates with respect to US LIBOR causes the IRDs to decrease sharply between July 2004 and August 2006. The second decreasing trend corresponds to the financial crisis in 2008. We see in Figure 3-2 that all countries' LIBOR rate starts to decrease from September 2008 and these low LIBOR rates last until September 2009. The decreasing level in IRDs for the period from July 2008 and September 2009 is smaller than that for the period from July 2004 to August 2006. This is because LIBOR rates of all countries synchronize better in the latter period than in the first period, which leaves a smaller gap in IRDs.

Our results of time series IRDs are in line with Gubler and Bank (2014), which documents two sharp decline trends in IRD between US and Swiss 3-month interbank interest rate. We find the two sharp decline trends in IRDs for 9 developed currency markets on a longer time span. Moreover, since the IRD is based on 9 currencies, it reflects the impact of interest rate changes to the major currencies markets on a global level. The results in Figure 3-1 and Figure 3-2 imply a structural change and the existence of unit root in IRDs.

3.2.3 Excess return of carry trade

We next report statistics of annualized excess return defined in equation (7). We annualize the monthly excess return by following method in Lustig *et al.* (2011).[7] The first row of Table 3-4 shows that all currency has positive excess returns. This implies, firstly, that the violation of UIP on the monthly horizon is apparent. The average the carry trade strategy implemented by individual G10 currency has excess return of 2.22% per annum, with a standard deviation of 0.11 and a sharp ratio of 0.20. Secondly, currencies with lower interest rate, such as JPY, CHF and EUR have lower excess returns. Currencies normally with high interest rates, such as AUD NZD have higher excess returns.[8] This is consistent with Brunnermeier *et al.* (2008), who find a positive relationship between the interest rate differential and the excess returns. Later we provide evidence that different excess return of currency is due to different exposure to currency crash risk.

The third row of skewness shows that currencies with positive excess returns have negative skewness with fat tail on the loss side, currencies with negative excess returns have positive skewness with fat tail on the gain side. This means that even though excess returns of carry trade have a higher mean, the most negative results are likely to occur. Contrarily, extremely positive excess returns are most likely to occur when the general excess return is low. This cross sectional heterogeneous negative skewness in return distribution has been widely documented in FX literature, and our finding is consistent with previous studies, such as Brunnermeier *et al.* (2008), Burnside (2011) and Caballero and Doyle (2012). This can be interpreted as the largest movement of return in FX market being usually against the direction of profit and the loss happening large and fast, which complies with the practitioner's saying "the exchange rates go up by stairs but down by elevator". Moreover, the negative skewness pattern in return supports the idea that, from the speculators' perspective, it is highly necessary to buy options as insurance to protect against potential

[7] Lustig et al (2011) suggests to multiply the mean of monthly excess return mean by 12 and the standard deviation by $\sqrt{12}$.

[8] Galati and Melvin (2004) identify Switzerland and Japan as the main low interest countries and the United Kingdom, Australia, and New Zealand as the main high interest rate countries based on the historical data till 2004.

loss. This implies that foreign exchange options contain information regarding the negative skewed excess returns in carry trade.

The fourth row shows that most individual currencies' distribution is leptokurtic. Lastly, we calculate sharp ratio and present the results in the fifth row. We use US LIBOR as risk free return calculated as excess return gained per unit of volatility. The sharp ratio across currencies varies from -0.63 in CHF to 0.60 as in AUD. Next, none of the AC(1) coefficients and CH test statistics are significant at 10% level, which means that none of these individual excess returns are autocorrelated. For the LM statistics of ARCH effect, only the LM statistics of CHF are significant at 5% level. This means that none of the currencies' excess returns is heteroscedastic. The results of all stationarity tests show that all series are stationary in the sample period from December 2001 to February 2013.

3.2.4 Skewness of changes in exchange rates and currency crash risk

As elaborated in section 3.1.2, we calculate the monthly skewness $skew_t^j$ for currency j by daily exchange rate changes within month t. We present the statistics of individual currencies' monthly skewness in Table 3-5.

We find that the skewness of EUR, JPY, CHF and CAD are negative. Other currencies, including GBP, AUD, NOK and NZD have positive skewness. The mean values of individual currencies' skewness show cross-sectional heterogeneous skewness. CHF has the most negative skewness, whereas AUD and NZD have the most positive skewness. CHF has a very leptokurtic distribution. None of the AC(1) coefficients and CH test statistics are significant at 10% level, which means that none of these individual skewness are autocorrelated. None of the LM statistics of ARCH effect is significant at 10% level, meaning none of the currencies' skewness is heteroscedastic. The results of all stationarity tests show that all series are stationary even take structural break into account for the financial crisis in 2008.

3.2.5 Risk reversal and price of crash risk

Table 3-6 presents the stylized facts of monthly 25Δ risk reversals RR_t^j from October 2001 to February 2013. We see that only JPY and CHF, which are typically low interest rate currencies, have negative risk reversals. Other currencies with relatively high interest rate differential have positive risk reversals. As stated in section 3.1.3, a positive risk reversal quoted in USD/FCU represents the market view on the deprecation of the foreign currency, hence we consider a positive risk reversal ($RR_t^j > 0$) to represent purchasing an insurance against risk of depreciation in high interest rate currencies. The statistics of positive risk reversal in high interest rate currencies such as AUD, NOK and NZD support this interpretation. On the contrary, the negative risk reversal in JPY and CHF supports the interpretation that a negative risk reversal ($RR_t^j < 0$) quoted in USD/FCU represents an insurance against risk of appreciation in low interest rate currencies.

The distribution of JPY and AUD is very peaked which indicates there are more outliers in the risk reversal of JPY and AUD than in other currencies. The autocorrelation coefficients from AC(1) coefficient suggest that all risk reversal series are highly autocorrelated with coefficients bigger than 0.70 and statistically significant at 1% level. This strong auto correlation is also detected from the CH test, which accounts for the heteroscedasticity in the series. LM statistics of ARCH effect test show that all risk reversal series are heterogeneous at 1% significance level. In terms of the stationarity, 3 unit root tests yield different results, however, they are consistent about the fact that CAD, AUD and NZD reject the null hypothesis of non-stationarity at 1% significance level regardless of the different assumptions on the series distribution. The rest of series, such as EUR, GBP, JPY, CHF and NOK is likely to contain unit roots which depends on the assumptions in the unit-root tests. Thus, we consider that 3 out of 8 currencies are not stationary in the sample period from December 2001 to February 2013.

3.2.6. Future position and carry trade activity

Table 3-7 presents the stylized facts of monthly future positions FP_t^j of 7 currencies spanning from October 2001 to February 2013[9]. We see that only JPY and CHF, which are typically low interest rate currencies, have negative future positions. Other currencies, including commercial currencies with high interest rate differential such as AUD and NZD have positive future positions.

[9] Future position date of NOK is not available. NZD data has a late start, which ranges from July 2004 to February 2013.

All currencies' future positions look reasonably peaked which indicates few outliers in the raw data. The AC(1) coefficients are all above 0.68 and statistically significant at 1% level, and CH test accounting for heteroscedasticity in the series generate the same results. We also applied LM test for ARCH effect in monthly future position data, and find that all of them have significant ARCH effect at 5% significance level. The ZA test accounting for a single structure break and find that future positions data of all currencies can reject the null of containing unit root at least 5% significant level, except that EUR and NZD. However, the DF-GLS test which applies a GLS de-trending technique and the non-parametric PP test, which is robust to serial correlation and heteroscedasticities, both have the test statistics of EUR and NZD rejected at 5% significance level. Thus, we consider that all currencies' future position series are stationary in the sample period from October 2001 to February 2013.

3.2.7 VIX, TED and funding liquidity

Following Brunnermeier *et al.* (2008), Menkhoff *et al.* (2012a) and Mancini *et al.* (2013), we use implied volatility VIX index and interbank interest rate TED spread to measure the funding liquidity level in FX market.

We present the stylized facts of monthly VIX and TED from October 2001 to February 2013 in Table 3-8 and plot VIX and TED with NBER published recession period in Figure 3-3. The Figure 3-3 shows that VIX and TED are both very volatile during recession period from 2007 to May 2009. Financial crisis on 2008 summer were accompanied with strong increases in VIX and TED, especially that TED is highly peaked.

Table 3-8 shows that the autocorrelation coefficients of VIX and TED are both over 0.8 and both statistically significant at 1% level, which is the same results from the CH test and account for the heteroscedasticity. We find that both of VIX and TED have significant ARCH effect at 1% significance level. The ZA stationarity test, accounting for a single structure breaks, shows that VIX cannot reject the null of containing unit root at 5% significant level, while TED rejects the null of containing unit root at 5% significant level. Our empirical features of VIX and TED is consistent with Ang *et al.* (2006) and Menkhoff *et al.* (2012a), who find that VIX and TED are highly autocorrelated on daily and monthly basis during different historical periods.

3.3 Order flow data set

In this thesis, we use a unique dataset from UBS containing weekly customer order flows for 9 currencies from November 2001 to November 2007. These 9 currencies are developed countries according to the classification of the International Monetary Fund IMF (2010), and are US dollar (USD), Euro (EUR), Japanese Yen (JPY), Great Britain pound (GBP), Swiss franc (CHF), Australian dollar (AUD), Canadian dollar (CAD), Norwegian kroner (NOK), Swedish krona (SEK) and New Zealand dollar (NZD).

This data set is unique in that it is a proprietary dataset from one of the largest markets in the FX market, which is aggregated across clients of 4 groups: asset manager (AM), corporate clients (CO), hedge funds (HF) and private clients (PR). Aggregate order flow sums up disaggregate order flows across four segments and generates a general landscape of market view net demand/supply situation of USD; while disaggregate order flows show the characteristics of market view of one type of market player. The empirical results presented in chapter 7 are produced with currency data defined in this section.

We believe that the order flows collected by UBS are representative of the end-user currency demands in the FX market. The reason is the following: firstly, UBS is one the largest dealers in the FX market with significant daily market share as much as more than 10%.[10] Secondly, Menkhoff *et al.* (2012b) argue that a handful of top dealers with more than 50% of total market share have access to the same set of large customers. As one of these large dealers, UBS's dataset is likely to correlate with order flows observed by other big market dealers, such as Deutsche Bank, Barclays, Citigroup and JP Morgan. Thus, the UBS order flow data represents the top end of customer trading in the FX market.

We consider this data set to have advantages in studying the order flow implied liquidity problem for the following reasons:

Firstly, this data set contains reliable information of trading volumes as well as trading direction, which is crucial for an accurate estimation of liquidity. Because it avoids using

[10] By the end of 2011, UBS had a market share over 15% in FX market, documented by Euromoney survey.

just the direction information, such as Rime *et al.* (2010) and Evans and Lyons (2002a), neither volume only information with the method, proposed by Charles. Lee and Ready (1991), to infer the trade directions. All quotes in this USB data set is transactable with low counter party risk because all dealers are screened for credit. Secondly, the heterogeneous information of different client groups offers us an opportunity to discover client-specific pricing factors, which is a limitation in some other studies, such as Banti *et al.* (2012), and Mancini *et al.* (2013). Disaggregate data helps us to investigate the role of informed trader and non-informed trader, which further suggests the role of liquidity provider in FX market. Thirdly, the information in our dataset provides fuller information coverage rather than filtered data, which are used in some FX studies under microstructure framework, such as Sager and Taylor (2008).

3.3.1 Aggregate order flow and stylized facts

Order flow differentiates from the trading volume in that order flow shows the buying pressure or selling pressure indicated by a sign.[11] Our aggregate order flow data quotes as foreign currency per US dollars, which is in line with the exchange rates. A positive order flow coefficient means buying pressure with unit of billions in US dollars (foreign currency selling) and indicates there are more buyer-initiated than seller-initiated orders. A negative order flow means a net selling pressure of USD (foreign currency buying).

In this thesis, we refer to these order flows as "aggregate order flows" because they are aggregated across all UBS customers attached to one currency pair. Panel A in Table 3-9 shows the descriptive statistics for weekly aggregate order flows for 9 currencies, in units of billion US dollars[12]. We see that EUR, JPY and CHF are generally more heavily traded than other currencies. The USD/EUR pair is the most demanded currency while USD/JPY is the most borrowed currency in the developed country market. On the other hand, order flows of EUR, JPY, GBP and CHF also have much larger variance than other currencies. The weekly aggregate order flow series display a high kurtosis, meaning that there are many extreme large or small order flows in all currencies. The statistics of standard deviation suggest that it is necessary to standardize the raw order flow data when comparing the order flows of different volatility scale. Otherwise the results of regressions are more driven by the order flows with large absolute size. We will take this into account when doing empirical analysis

[11] The distinction between order flow and trading volume is defined in Evans and Lyons (2007).

[12] Stats of order flow here is the raw order flows without standardization.

in Chapter 7. The AC(1) coefficients shows that the weekly order flows of GBP and SEK are positively autocorrelated. The results of the Cumby-Huizinga test, which accounts for heteroscedasticity, also show that the null hypothesis of non-autocorrelation is rejected at 1% significance level in GBP and SEK. The results of ZA test for stationarity show that all order flow series are stationary over the sample period from November 2001 to November 2007.

Panel B in Table 3-9 shows some patterns of the correlations of aggregate order flows. JPY and CHF, which are low interest rate currencies, move inversely with most other order flows, except with GBP. Those commodity currencies AUD, CAD, NOK and NZD, which are low interest rate currencies, tend to positively move together. These correlation patterns display the general investment themes in currency markets over the sample period.

3.3.2 Disaggregate order flow and stylized facts

Apart from the aggregate order flow data, we also have the option to conduct the research based on disaggregate order flow data of different customers. Similarly to aggregate order flows, the positive (negative) disaggregate order flows measure the amount of buying (selling) USD against foreign currencies. Aggregate order flow is measured as the sum of disaggregate order flows across the four types of customers in each week.

These four types of customers are: asset manager (AM), corporate clients (CO), hedge funds (HF) and private clients (PR). Asset managers represent long-term real money investors, such as mutual funds and pensions funds. Corporates are non-financial corporations, which import and export products and services around the world or conduct business within a worldwide scope. Hedge fund customers are marked as performing trading with highly leveraged short-term positions. The private clients segment represents orders from wealthy clients with higher than US$3 million investible liquid assets. These four types of customers are likely to differ considerably in the degree of information.

The disaggregate order flow data is generated in the following way: each trading transaction booked with the UBS execution system at any of its worldwide offices is tagged with a client type according to the customer category described above. For an order initiated by a customer at time *t*, the transaction is marked as positive if UBS fills a purchase of foreign currency or marked as negative if it is a sale order of foreign currency. The weekly order flows are the sum of all transactions recorded around the world within one week, from the market opening in Singapore on Monday to market close in New York on Friday. Over a week, the UBS system synthesizes the cumulative flow of buyer-initiated and seller-initiated orders.

Our order flow data set is informative as it provides information about how the exchange rate's movement is viewed by either the general market or by a type of customer segmentation. For brevity, Panel A in Table 3-10 shows the statistics of total disaggregate order flows across 9 currencies of a client type instead of disaggregate order flow of each currency. We see that asset managers and private customers have more selling pressure in USD while corporates and hedge funds have more buying pressure. Asset managers have the largest average weekly flow. The private customer has the smallest amount of flow, which is about only one fifth that of the asset manager. Asset managers and hedge funds have larger variance than corporates and private customers, which suggests that it is necessary to standardize the disaggregate order flows before entering the models. Asset managers has the largest kurtosis, meaning the order flow of asset managers is driven by the extreme numbers and is very volatile in general. Corporates are least driven by extreme numbers and the least volatile in the groups. Next, the AC(1) coefficients and the CH test accounting for heteroscedasticity show that the weekly order flows of asset managers and corporates are positively autocorrelated. The results of ZA test for stationarity show that order flow series of all customer groups are stationary over the sample period from November 2001 to November 2007.

Panel B in Table 3-10 shows that order flows of different customer groups are uncorrelated. The most negative correlation is between the hedge funds and private customers for -0.32. We note that asset manager is positively correlated with hedge funds. Asset manager and hedge funds are negatively correlated to corporates and private customers. This low correlation across customer groups means that flows of one customer group do not forecast flows of other customer groups.

3.4 Conclusion

In this section, we introduce the currency data set and order flow data set. The currency data set contains monthly data of 9 largest and most liquid currencies from G10 currency group. The order flow data set contains weekly aggregate and disaggregate order flows of 9 currencies of developed countries, which is collected by one of the largest dealer in FX market.

We define the variables involved in our empirical study and explore the stylized facts of both currency dataset and order flow dataset. Regarding the order flow data set, we find that EUR, JPY, GBP and CHF are the most frequently traded currencies in the market, with largest volatility at the same time. Moreover, the unique disaggregate order flow source implies that different types of customer are playing different roles as informed or non-informed trader in the market: asset managers, corporates and hedge funds are more involved in currency trading than private customers are. Hedge funds have capital allocated the closest to the general FX market trading rule, which is financing commodity currencies by shorting funding currencies. Corporate customers deviate the most from the general speculation rule in the FX market.

Table 3-1: Descriptive statistics of changes in exchange rate Δs_t^j

	EUR	GBP	JPY	CHF	CAD	AUD	NOK	NZD
				Panel A: Period 2001m12-2013m2				
Mean	-0.0028	-0.0034	-0.0022	-0.0020	-0.0031	-0.0050	-0.0033	-0.0047
Sd dev	0.03	0.03	0.03	0.03	0.03	0.04	0.04	0.04
CH test	0.03	1.89	1.03	1.89	1.08	0.21	0.15	0.09
LM test	0.67	0.27	0.26	4.74**	1.13	4.02**	3.86**	0.52
ZA test	-11.90***	-10.72***	-11.38***	-13.30***	-13.09***	-11.87***	-11.36***	-5.89***
				Panel B: Period 2001m12-2008m8				
Mean	-0.0071	-0.0042	-0.0019	-0.0006	-0.0055	-0.0077	-0.0071	-0.0076
Sd dev	0.02	0.02	0.02	0.03	0.02	0.03	0.03	0.03
				Panel C: Period 2008m9-2013m12				
Mean	0.0033	0.0048	-0.0025	-0.0016	0.0002	-0.0012	0.0021	-0.0015
Sd dev	0.04	0.03	0.03	0.04	0.04	0.05	0.04	0.05

Note: This table reports the statistics of the monthly change in exchange rate for EUR, GBP, JPY, CHF, CAD, AUD, NOK and NZD ranging from December 2001 to February 2013. The monthly change in exchange rate is calculated as the log change of exchange rate over previous month. We report statistics of full sample in Panel A, statistics of before and after crisis period in Panel B and Panel C respectively. The separating point of crisis time is referred to Farhi *et al.* (2009). We report mean and standard deviations for each currency. To test auto correlation, we report the statistics of the CH test Cumby and Huizinga (1992). The H_0 of the CH test: the series has no serial correlation under assumption of heteroscedasticity. The highest lags order tested for the CH test are selected by the G.W Schwert (1989) standard. To test heteroscedasticity, we report the LM statistics of the ARCH effect. To test stationarity, we report the statistic of the ZA test Zivot and Andrews (1992) which has the null of non-stationarity tested under the assumption of one structural break. The optimal lags used in the ZA test are selected by the standard of minimal BIC, proposed in Ng and Perron (2001). We mark the significant statistics at 1%, 5%, 10% level by asterisk ***, ** and *.

Table 3-2: Correlation between the changes in exchange rate across currencies

	EUR	GBP	JPY	CHF	CAD	AUD	NOK	NZD
EUR	1.00							
GBP	0.66	1.00						
JPY	0.21	0.10	1.00					
CHF	0.84	0.55	0.35	1.00				
CAD	0.54	0.51	0.04	0.42	1.00			
AUD	0.74	0.60	0.07	0.62	0.73	1.00		
NOK	0.82	0.66	0.11	0.70	0.59	0.69	1.00	
NZD	0.70	0.56	0.06	0.65	0.60	0.85	0.59	1.00

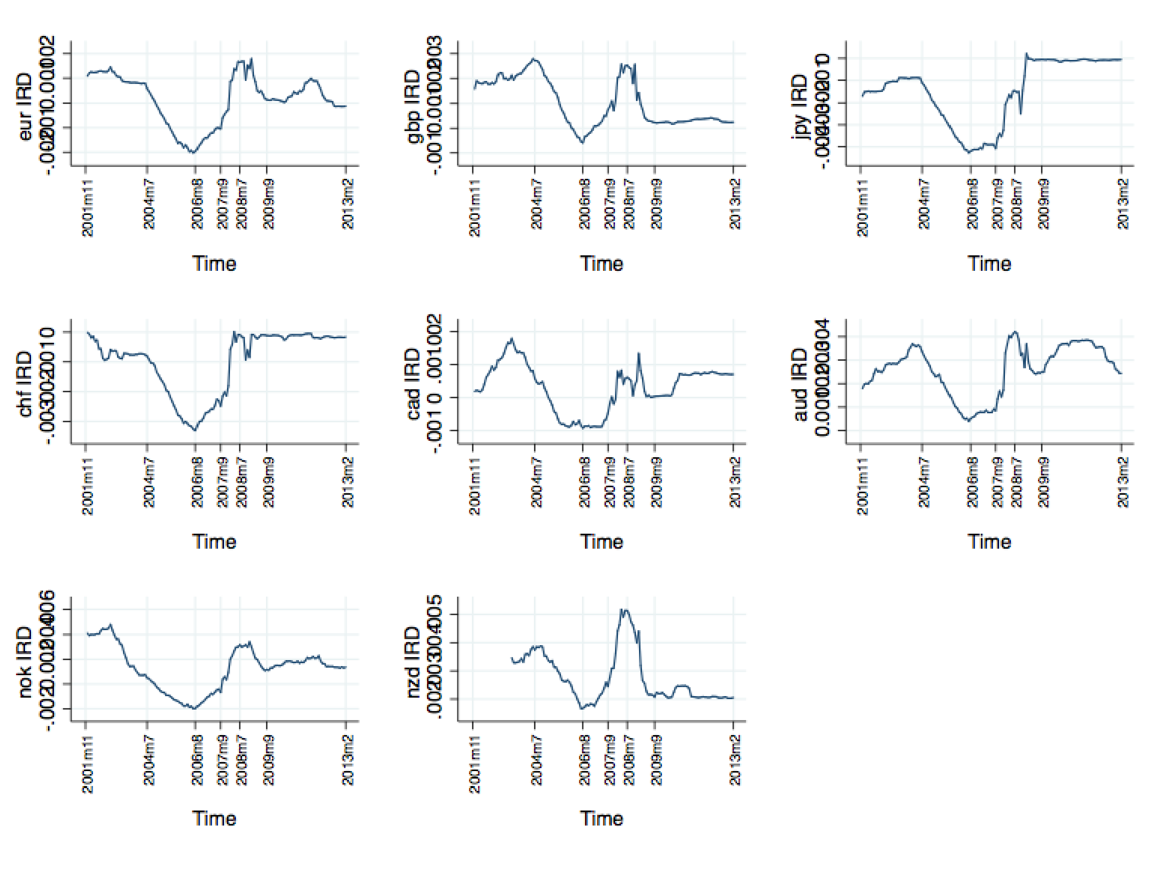
Note: This table reports the correlation of the monthly changes in exchange rates across currencies EUR, GBP, JPY, CHF, CAD, AUD, NOK and NZD ranging from December 2001 to February 2013.

Table 3-3: Stats of interest rate differentials IRD_t^j for individual currencies

	EUR	GBP	JPY	CHF	CAD	AUD	NOK	NZD
Mean	0.0002	0.0010	-0.0015	-0.0010	0.0003	0.0026	0.0013	0.0028
Sd dev	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Skew	-0.62	0.34	-0.70	-0.98	-0.28	-0.60	-0.09	1.04
Kurt	2.38	1.62	2.12	2.47	2.27	2.25	2.26	3.14
Auto correlation test								
AC(1)	0.98***	0.97***	0.99***	0.98***	0.97***	0.97***	0.98***	0.97***
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)
CH test	129.44**	129.37***	131.87***	129.96***	128.09***	127.85***	130.25***	110.09***
Heteroscedasticity test								
LM test	121.93**	98.67***	127.40***	128.92***	120.13***	124.63***	127.92***	97.28***
Stationarity test								
DF-GLS test	-1.94	-2.54	-2.38	-1.59	-3.11**	-2.39	-1.94	-3.26**
PP test	-1.36	-2.11	-1.11	-1.76	-1.50	-1.48	-1.56	-1.85
ZA test	-3.86	-3.47	-3.98	-4.31	-3.44	-3.40	-3.96	-4.77

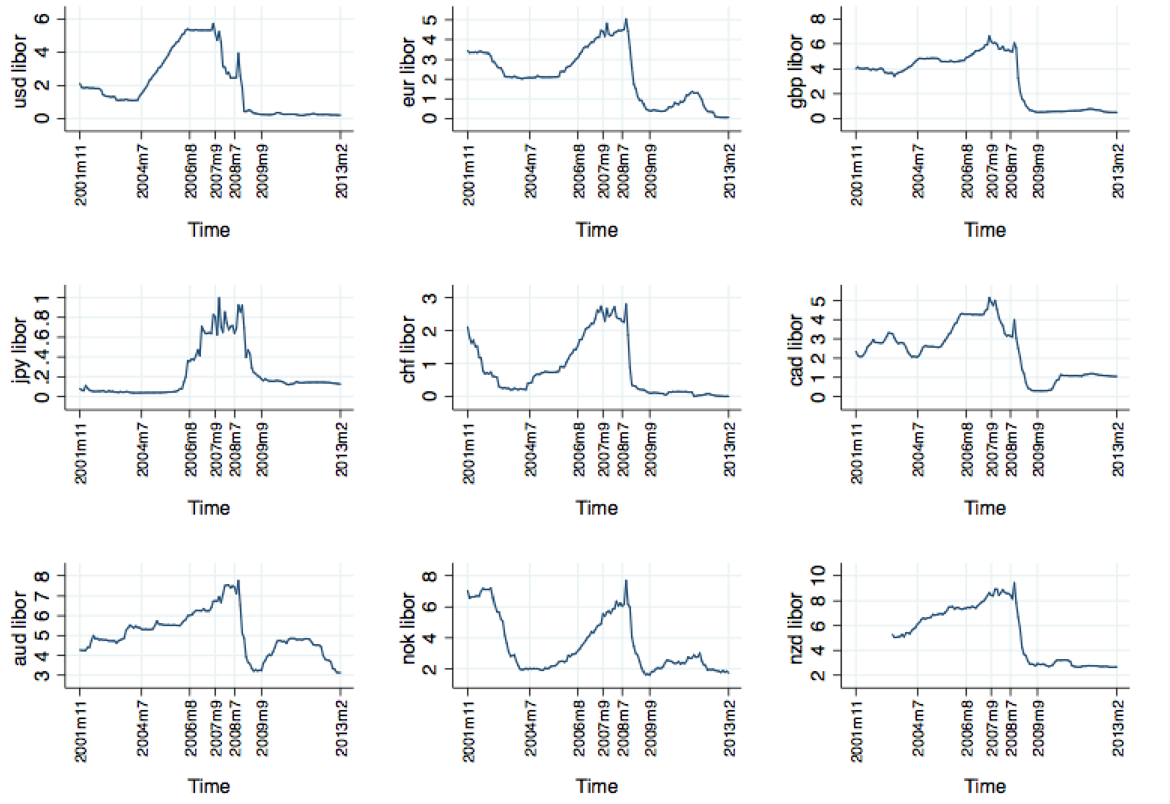
Note: Monthly interest rate differential data is available for EUR, GBP, JPY, CHF, CAD, AUD, NOK and NZD, ranging from October 2001 to January 2013. We report mean, standard deviations, skewness, kurtosis. To test auto correlation, we report the first order autocorrelation coefficient AC(1) from the AR(1) process and the statistics of the CH test Cumby and Huizinga (1992). The standard errors of AC(1) are reported in brackets. The H_0 of CH test: the series has no serial correlation under assumption of heteroscedasticity. The highest lags order tested for the CH test are selected by the G.W Schwert (1989) standard. To test heteroscedasticity, we report the LM statistics of the ARCH effect. To test stationarity, we report the statistics of Dickey-Fuller GLS (DF-GLS) test, Phillips and Perron (1988) (PP) test and the ZA test Zivot and Andrews (1992). DF-GLS test has a null of non-stationarity and perform an ADF test with GLS detrending. PP test has a null of non-stationarity and deal with the serial correlation in a nonparametric way by using Newey and West (1987) standard errors. ZA test has the null of non-stationarity tested under the assumption of one structural break in the series. Optimal lags used in all stationarity tests are selected by the standard of minimal BIC, proposed in Ng and Perron (2001). We mark the significant statistics at 1%, 5%, 10% level by asterisk ***, ** and *.

Figure 3-1: Interest rate differentials IRD_t^j of each foreign country



Note: Time series plot of $IRD_{j,t}$ for GBP, EUR, JPY, CHF, CAD, AUD, NOK, SEK, NZD respectively. $IRD_{j,t}$ is calculated as the difference of monthly LIBOR rate for 1 month maturity between the foreign country j and the US. Date involved are monthly LIBOR rate ranging from November 2001 to February 2013.

Figure 3-2: End-of-month $LIBOR_t^j$ rate for all countries



Note: Time series plot of end-of-month LIBOR rate for 1-month maturity for GBP, EUR, JPY, CHF, CAD, AUD, NOK, SEK, NZD respectively. Date involved are monthly LIBOR rate ranging from November 2001 to February 2013.

Table 3-4: Stats of annualized excess returns of carry trade z_t^j for individual currencies

	EUR	GBP	JPY	CHF	CAD	AUD	NOK	NZD	AVG
Mean	0.0173	0.0102	-0.0111	-0.0536	0.0033	0.1007	0.0372	0.0798	0.0222
Sd dev	0.11	0.09	0.09	0.12	0.10	0.14	0.12	0.15	0.11
Skew	-0.05	-0.25	0.28	0.15	-0.45	-0.67	-0.49	-0.34	
Kurt	3.88	4.37	3.18	4.89	5.57	5.28	3.66	4.70	
Sharp ratio	0.20	0.03	-0.32	-0.63	0.27	0.60	0.35	0.40	0.20
Auto correlation test									
AC(1)	-0.02	0.11	0.10	-0.10	-0.02	0.03	0.01	-0.07	
	(0.09)	(0.09)	(0.08)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	
CH test	0.03	1.74	1.30	1.27	0.06	0.22	0.01	0.77	
Heteroscedasticity test									
LM test	0.42	0.08	0.30	5.09**	2.26	4.28*	2.09	0.19	
Stationarity test									
DF-GLS	-5.37***	-4.40***	-4.54***	-3.51**	-3.98***	-2.89**	-4.29***	-4.07***	
PP test	-12.11***	-10.29***	-10.60***	-12.61***	-11.70***	-11.19***	-11.97***	-11.26***	
ZA test	-12.67***	-11.11***	-11.26***	-12.96***	-13.19***	-12.09***	-12.30***	-5.35**	

Note: This table contains statistics of annualized excess returns for EUR, GBP, JPY, CHF, CAD, AUD, NOK and NZD from December 2001 to January 2013. We report mean, standard deviations, skewness, kurtosis. Annualized excess return is calculated as multiplying monthly means by 12 and multiplying monthly standard deviations by $\sqrt{12}$. To test auto correlation, we report the first order autocorrelation coefficient AC(1) from the AR(1) process and the statistics of the CH test Cumby and Huizinga (1992). The standard errors of AC(1) are reported in brackets. The H_0 of CH test: the series has no serial correlation under assumption of heteroscedasticity. The highest lags order tested for the CH test are selected by G.W Schwert (1989) standard. To test heteroscedasticity, we report the LM statistics of the ARCH effect. To test stationarity, we report the statistics of Dickey-Fuller GLS (DF-GLS) test, Phillips and Perron (1988) test and the ZA test Zivot and Andrews (1992). DF-GLS test has a null of non-stationarity and perform an ADF test with GLS detrending. PP test has a null of non-stationarity and deal with the serial correlation in a nonparametric way by using Newey and West (1987) standard errors. ZA test has the null of non-stationarity tested under the assumption of one structural break in the series. Optimal lags used in all stationarity tests are selected by the standard of minimal BIC, proposed in Ng and Perron (2001). We mark the significant statistics at 1%, 5%, 10% level by asterisk ***, ** and *.

Table 3-5: Stats of skewness $skew_t^j$ for individual currencies

	EUR	GBP	JPY	CHF	CAD	AUD	NOK	NZD
Mean	-0.0114	0.0703	-0.0370	-0.0441	-0.0211	0.1667	0.0737	0.1337
Sd dev	0.50	0.53	0.70	0.60	0.51	0.57	0.53	0.62
Skew	-0.32	-0.08	0.30	1.29	-0.59	0.93	0.31	0.93
Kurt	3.14	4.50	5.77	8.81	4.60	5.68	4.73	4.39
Auto correlation test								
AC(1)	0.09	0.13	-0.02	0.00	0.05	0.05	0.03	0.11
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
CH test	1.03	2.40	0.05	0.87	0.39	0.39	0.09	1.63
Heteroscedasticity test								
LM test	0.11	0.47	0.21	0.78	0.17	8.28	0.17	0.23
Stationarity test								
DF-GLS test	-4.16***	-3.86***	-3.02**	-2.96**	-4.24***	-3.39**	-3.20**	-4.00***
PP test	-10.60***	-10.06***	-11.92***	-11.58***	-11.01***	-10.93***	-11.07***	-10.21***
ZA test	-11.10***	-10.52***	-12.78***	-12.32***	-11.68***	-11.69***	-12.05***	-11.19***

Note: This table contains statistics of monthly skewness of exchange rate changes for EUR, GBP, JPY, CHF, CAD, AUD, NOK and NZD, ranging from November 2001 to January 2013. The monthly skewness for each currency is calculated as the skewness of daily exchange rate changes quoted as (USD/FCU) within one month. We report mean, standard deviations, skewness, kurtosis. To test auto correlation, we report the first order autocorrelation coefficient AC(1) from the AR(1) process and the statistics of the CH test Cumby and Huizinga (1992). The standard errors of AC(1) are reported in brackets. The H_0 of CH test: the series has no serial correlation under assumption of heteroscedasticity. The highest lags order tested for the CH test are selected by G.W Schwert (1989) standard. To test heteroscedasticity, we report the LM statistics of the ARCH effect. To test stationarity, we report the statistics of Dickey-Fuller GLS (DF-GLS) test, Phillips and Perron (1988) test and the ZA test Zivot and Andrews (1992). DF-GLS test has a null of non-stationarity and perform an ADF test with GLS detrending. PP test has a null of non-stationarity and deal with the serial correlation in a nonparametric way by using Newey and West (1987) standard errors. ZA test has the null of non-stationarity tested under the assumption of one structural break in the series. Optimal lags used in all stationarity tests are selected by the standard of minimal BIC, proposed in Ng and Perron (2001). We mark the significant statistics at 1%, 5%, 10% level by asterisk ***, ** and *.

Table 3-6: Stats of 25Δ risk reversals RR_t^j for individual currencies

	EUR	GBP	JPY	CHF	CAD	AUD	NOK	NZD
Mean	0.4951	0.6489	-1.3232	-0.0978	0.4689	1.3683	0.7106	1.4523
Sd dev	0.92	0.79	1.62	0.77	0.78	1.34	0.93	1.23
Skew	1.06	0.95	-2.34	0.52	1.55	2.14	0.78	2.10
Kurt	3.60	3.74	10.60	3.37	5.83	8.56	2.95	8.31
Auto correlation test								
AC(1)	0.85	0.80	0.85	0.78	0.80	0.75	0.84	0.71
	(0.05)	(0.06)	(0.05)	(0.07)	(0.06)	(0.06)	(0.05)	(0.07)
CH test	80.41***	72.37***	80.46***	57.57***	71.34***	62.89***	68.28***	57.28***
Heteroscedasticity test								
LM test	47.42***	20.02***	60.12***	34.07***	21.32***	29.42***	46.34***	27.27***
Stationarity test								
DF-GLS test	-3.42**	-1.52	-2.71	-2.84	-3.32**	-4.63***	-2.72	-4.20***
PP test	-4.07***	-4.09***	-3.00	-3.66**	-4.79***	-4.83***	-4.01***	-5.02***
ZA test	-5.90*	-5.57***	-4.90*	-5.81***	-5.87***	-6.02***	-4.98*	-5.84***

Note: Monthly 25Δ risk reversal data is available for EUR, GBP, JPY, CHF, CAD, AUD, NOK and NZD, ranging from October 2001 to January 2013. We report mean, standard deviations, skewness, kurtosis. To test auto correlation, we report the first order autocorrelation coefficient AC(1) from the AR(1) process and the statistics of Cumby and Huizinga (1992) (CH) test. The standard errors of AC(1) are reported in brackets. The H_0 of CH test: the series has no serial correlation under assumption of heteroscedasticity. The highest lags order tested for CH test are selected by G.W Schwert (1989) standard. To test heteroscedasticity, we report the LM statistics of the ARCH effect. To test stationarity, we report the statistics of Dickey-Fuller GLS (DF-GLS) test, Phillips and Perron (1988) (PP) test and Zivot and Andrews (1992) (ZA) test. DF-GLS test has a null of non-stationarity and perform an ADF test with GLS detrending. PP test has a null of non-stationarity and deal with the serial correlation in a nonparametric way by using Newey and West (1987) standard errors. ZA test has the null of non-stationarity tested under the assumption of one structural break in the series. Optimal lags used in all stationarity tests are selected by the standard of minimal BIC, proposed in Ng and Perron (2001). We mark the significant statistics at 1%, 5%, 10% level by asterisk ***, ** and *

Table 3-7: Stats of future position FP_t^j for individual currencies

	EUR	GBP	JPY	CHF	CAD	AUD	NOK	NZD
Mean	0.0662	0.0240	-0.0036	-0.0585	0.1369	0.3091	n/a	0.3948
Sd dev	0.25	0.27	0.25	0.29	0.24	0.21	n/a	0.27
Skew	-0.57	-0.02	-0.17	0.01	-0.60	-0.62	n/a	-0.91
Kurt	2.61	2.27	1.93	1.93	2.42	2.77	n/a	3.47
Auto correlation test								
AC(1)	0.90	0.82	0.77	0.68	0.72	0.74	n/a	0.70
	(0.04)	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)		(0.07)
CH test	110.95***	91.27***	80.01***	62.80***	69.22***	73.85***	n/a	44.93***
Heteroscedasticity test								
LM test	81.21***	56.30***	35.61***	17.04***	57.37***	20.13***	n/a	13.27***
Stationarity test								
DF-GLS test	-3.27**	-1.65	-1.88	-1.96	-3.45**	-4.44***	n/a	-3.15**
PP test	-3.42**	-3.85***	-4.65***	-4.69***	-5.07***	-5.15***	n/a	-3.61**
ZA test	-4.27	-5.79***	-6.22***	-5.64***	-5.48**	-5.54**	n/a	-4.68

Note: Monthly future position data is available for EUR, GBP, JPY, CHF, CAD, AUD and NZD, ranging from October 2001 to January 2013[13]. We report mean, standard deviations, skewness, kurtosis. To test auto correlation, we report the first order autocorrelation coefficient AC(1) from the AR(1) process and the statistics of Cumby and Huizinga (1992) (CH) test. The standard errors of AC(1) are reported in brackets. The H_0 of CH test: the series has no serial correlation under assumption of heteroscedasticity. To test heteroscedasticity, we report the LM statistics of the ARCH effect. To test stationarity, we report the statistics of Dickey-Fuller GLS (DF-GLS) test, Phillips and Perron (1988) (PP) test and Zivot and Andrews (1992) (ZA) test. DF-GLS test has a null of non-stationarity and perform an ADF test with GLS detrending. PP test has a null of non-stationarity and deal with the serial correlation in a nonparametric way by using Newey and West (1987) standard errors. ZA test has the null of non-stationarity tested under the assumption of one structural break in the series. Optimal lags used in all stationarity tests are selected by the standard of minimal BIC, proposed in Ng and Perron (2001). We mark the significant statistics at 1%, 5%, 10% level by asterisk ***, ** and *.

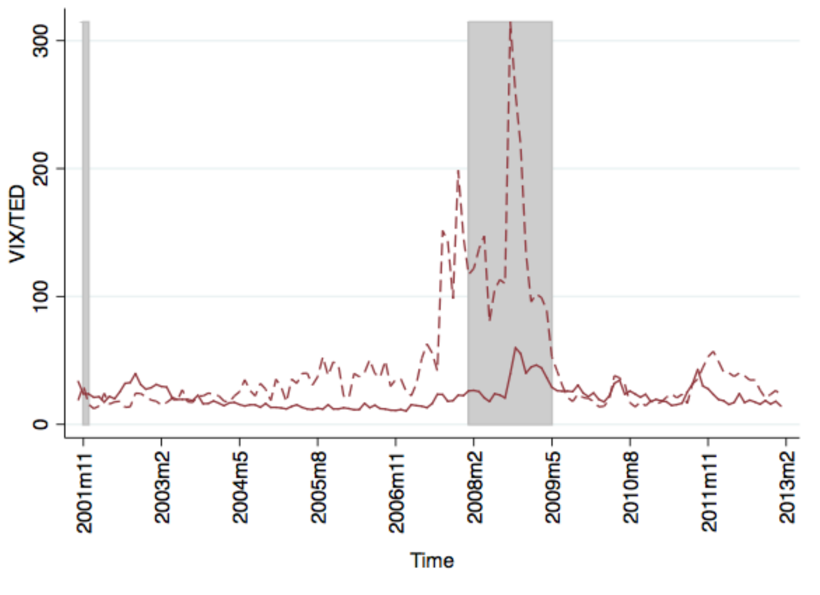
[13] Future position of NZD is from July 2004 to January 2013.

Table 3-8: Stats of VIX index and TED spread

	VIX	*TED*
Mean	21.49	46.07
Sd dev	9.01	48.34
Skew	1.57	2.91
Kurt	6.10	12.86
AC(1)	0.86***	0.84***
	(0.04)	(0.05)
CH test	99.33***	96.92***
LM test	62.43***	47.90***
ZA test	-4.831*	-5.286**

Note: This table contains statistics of mean S&P500 VIX index and TED spread, ranging from October 2001 to February 2013. We report mean, standard deviations, skewness, kurtosis. To test serial correlation, we report first order autocorrelation coefficients AC(1) and statistics of Cumby and Huizinga (1992) (CH) test. AC(1) coefficients are the residuals from the AR(1) regression. The H_0 of CH test: the series has no serial correlation under assumption of heteroscedasticity. Highest lag order used in CH test are selected by the G.W Schwert (1989) standard. To test heteroscedasticity, we test the ARCH effect of series and report the LM statistics. To test stationarity, we report the statistics of Zivot and Andrews (1992) (ZA) test which accounts for one structural break in the series. The H_0 of ZA test is: the series contains unit root under assumption of one structural break. Optimal lags used in ZA test are selected by the standard of minimal BIC, proposed in Ng and Perron (2001). We mark the statistics that are statistically significant at 1%, 5%, 10% by asterisk ***, ** and *.

Figure 3-3: VIX and TED with crisis periods



Note: Time series of global VIX (solid line) and TED (dash line) with recession periods published by NBER in shaded area. The sample period is from October 2001 to February 2013.

Table 3-9: Descriptive stats of aggregate order flows for individual currencies

Panel A: Statistics

	EUR	GBP	JPY	CHF	CAD	AUD	NOK	SEK	NZD
Mean	0.2776	-0.0050	-0.2398	-0.1291	-0.0158	-0.0007	0.0097	-0.0072	0.0138
Std	1.47	0.81	0.83	0.75	0.25	0.30	0.11	0.15	0.11
Skew	0.94	-3.96	0.80	-0.36	0.91	0.87	0.89	1.58	1.31
Kurt	13.95	36.95	13.64	5.77	12.24	8.94	10.09	11.28	16.08
AC(1)	0.04	0.33	-0.003	0.04	-0.03	0.03	-0.03	0.21	0.05
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
CH test	0.50	33.50***	0.00	0.44	0.29	0.32	0.30	14.18***	0.72
ZA test	-18.29***	-13.24***	-18.82***	-10.89***	-18.46***	-17.44***	-19.36***	-14.73***	-17.07***

Panel B: Correlations

	EUR	GBP	JPY	CHF	CAD	AUD	NOK	SEK	NZD
EUR	1								
GBP	-0.33	1							
JPY	-0.21	0.23	1						
CHF	-0.30	0.10	0.14	1					
CAD	0.08	-0.03	-0.08	-0.08	1				
AUD	-0.01	-0.18	-0.07	-0.10	0.03	1			
NOK	0.08	0.03	-0.11	-0.13	0.14	0.13	1		
SEK	0.12	-0.33	-0.07	-0.15	0.05	0.14	0.06	1	
NZD	-0.11	0.06	-0.04	-0.02	-0.05	0.06	-0.06	0.04	1

Note: Panel A contains statistics for aggregate order flows of 9 currencies pairs: EUR, GBP, JPY, CHF, CAD, AUD, NOK, SEK and NZD. Order flows are measured in net transaction of buying or selling USD against foreign currencies. A positive (negative) order flow means a net buying (selling) pressure for USD. We report mean, standard deviations, skewness, kurtosis. To test serial correlation, we report first order autocorrelation coefficients AC(1) and statistics of Cumby and Huizinga (1992) (CH) test. AC(1) coefficients are the residuals from the AR(1) regression. The H_0 of CH test: the series has no serial correlation under assumption of heteroscedasticity. Highest lag order used in CH test are selected by the G.W Schwert (1989) standard. To test heteroscedasticity, we test the ARCH effect of series and report the LM statistics. To test stationarity, we report the statistics of Zivot and Andrews (1992) (ZA) test which accounts for one structural break in the series. The H_0 of ZA test is: the series contains unit root under assumption of one structural break. Optimal lags used in ZA test are selected by the standard of minimal BIC, proposed in Ng and Perron (2001). We mark the statistics that are statistically significant at 1%, 5%, 10% by asterisk ***, ** and *. Panel B reports the correlation stats of order flows across the 9 currencies. Data frequency is weekly and ranges from November 2001 to November 2007.

Table 3-10: Descriptive statistics of disaggregate order flows

Panel A: Statistics

	AM	CO	HF	PR	Avg
Mean	-0.2469	0.1006	0.0976	-0.0478	-0.0241
Std	1.25	0.49	1.30	0.86	0.97
Skew	-1.3	0.46	-0.29	-0.09	-0.31
Kurt	8.25	4.88	4.81	6.36	6.08
AC(1)	0.14	0.14	-0.05	-0.004	
	(0.06)	(0.06)	(0.06)	(0.06)	
CH test	6.07***	6.21***	0.89	0.01	
ZA test	-15.93***	-16.80***	-18.76***	-18.03***	

Panel B: Correlations

	AM	CO	HF	PR
AM	1			
CO	-0.15	1		
HF	0.09	-0.14	1	
PR	-0.21	0.10	-0.32	1

Note: Panel A contains statistics for disaggregate order flows across currencies of different customer groups: AM denotes asset manager, CO denotes corporate clients, HF denotes hedge funds PR denotes private clients. Order flows are measured in net transaction of buying or selling USD against foreign currencies. A positive (negative) order flow means a net buying (selling) pressure for USD. We report mean, standard deviations, skewness, kurtosis. To test serial correlation, we report first order autocorrelation coefficients AC(1) and statistics of Cumby and Huizinga (1992) (CH) test. AC(1) coefficients are the residuals from the AR(1) regression. The H_0 of CH test: the series has no serial correlation under assumption of heteroscedasticity. Highest lag order used in CH test are selected by the G.W Schwert (1989) standard. To test heteroscedasticity, we test the ARCH effect of series and report the LM statistics. To test stationarity, we report the statistics of Zivot and Andrews (1992) (ZA) test which accounts for one structural break in the series. The H_0 of ZA test is: the series contains unit root under assumption of one structural break. Optimal lags used in ZA test are selected by the standard of minimal BIC, proposed in Ng and Perron (2001). We mark the statistics that are statistically significant at 1%, 5%, 10% by asterisk ***, ** and *. Panel B reports the correlation stats of disaggregate order flows across the 4 groups of customers. Data frequency is weekly and ranges from November 2001 to November 2007.

4. Portfolios of currency trading

In this thesis, we follow the technique of Lustig and Verdelhan (2007) to study the risk-return trade-off for a US investor investing in foreign currency markets from the perspective of portfolios. The reasons to construct currency portfolios when studying the predictability of excess return are: firstly, sorting currencies into portfolios helps to eliminate the idiosyncratic characteristics in individual currency and enable us to extract the characteristics that systematically affect average excess returns. Constructing portfolios shift the focus from individual currencies to high versus low interest rate currencies, which is analogous to the Fama and French portfolio construction technique of sorting stocks on size and book-to-market ratios. Secondly, building portfolios filter out currency changes that are orthogonal to changes in interest rates, which leaves the changes in exchange rate mainly reflecting the risk premium component. Thirdly, sorting time-series individual currencies into portfolios better captures the time-varying features of excess return rather than studying the average excess returns across individual currencies in the time-series direction. Because when calculating the average excess returns across individual currencies, the excess return of high interest rate currencies and low interest rate currencies cancel out each other. This leads to that the average excess returns shrink size and lost the information to study the time-series variation of excess return.

4.1 Portfolio construction

In this thesis, we construct 3 types of currency portfolios: carry trade portfolio, HML portfolio and SL portfolios. In this section, we introduce the method to construct these currency portfolios.

4.1.1 Carry trade portfolios

The first group of portfolios are carry trade portfolios. There are two techniques to sort currencies: by interest rate differential or by forward discount. Lustig and Verdelhan (2007) are the first to propose to sort currencies on the interest rate differentials $IRD_t^j = i_{j,t}^* - i_t$ between the foreign currency j and US dollar, followed by Brunnermeier *et al.* (2008), Farhi *et al.* (2009) and Mancini *et al.* (2013). The interest rate differentials motivate the carry trade implemented with two currencies and illustrates the failure of UIP generically. Another group of researchers, such as Lustig *et al.* (2011) and Menkhoff *et al.* (2012a), sort currencies on the forward discount $F_{j,t} - S_{j,t}$, where $F_{j,t}$ is the forward exchange rate, $S_{j,t}$ is the spot exchange rate.

Regarding these two sorting techniques, Menkhoff *et al.* (2012a) argues that sorting currencies by the interest rate differentials is equivalent to sorting currencies by the forward discount. Because the CIP stated in equation (2) can be re-arranged as:

$$\frac{F_j - S_j}{S_{j,t}} = \frac{i^*_{j,t} - i_t}{1 + i_t} \tag{10}$$

Akram *et al.* (2008 Dec) find that CIP hold at daily or lower frequencies. Specifically, Burnside *et al.* (2006) and Burnside (2011) prove that CIP hold on 1-month investment horizon, which is the investment horizon in this thesis. Therefore, equation (10) shows that sorting by forward discount is equivalent to sorting by interest rate differentials in our study.

We follow Lustig and Verdelhan (2007) to sort currencies on the interest rate differentials and construct 3 carry trade portfolios, C_1 C_2 and C_3 due to the limit of the available currencies in our data set. At the end of each period t, we allocate currencies into 3 portfolios on their interest rate differentials IRD_t. We then compute the excess return Z_t^i for portfolio i by taking the average excess return of individual currencies that are sorted into portfolio i. The individual currency excess return Z_t^j, which is defined in (7), contributes equally to the portfolio excess return Z_t^i. The carry trade portfolios are rebalanced at the end of every month. The allocation of carry trade portfolio is: portfolio C_1 contains 3 currencies with the lowest interest rate differential, portfolio C_3 contains 3 currencies with the highest interest rate differentials. The rest of 2 currencies with mid-level interest rate are sorted into portfolio C_2.[14]

[14] We tried to vary the number of currencies sorted to 3 portfolios in other allocation scenario, given 8 currencies cannot be evenly distributed into 3 portfolios. We also sort 3 currencies for C_1, 2 currencies for C_2 and 3 currencies for C_3. The empirical results show that our analysis does not biased because of the differences of allocation of currencies.

We take the perspective of US investors and carry trade portfolios are exposed to the US dollar risk, because all carry trade portfolios consist of a short position of USD and a long position of a basket of foreign currencies.

4.1.2 HML portfolio

The second group of portfolio is HML portfolio, which is proposed by Lustig and Verdelhan (2007). HML portfolio is constructed as the difference between C_1 and C_3, as $C_3 - C_1$. It mimics the technique of Fama and French (1993) designed for the stock market for taking the value difference between high minus small. A HML portfolio involves borrowing 1 USD in C_1 and lending 1USD in C_3. It is practically a carry trade in which the investor borrows low interest rate currencies in C_1 and invests in high interest rate currencies in C_3. Following Lustig and Verdelhan (2007), we refer to this portfolio as HML portfolio in this thesis.

4.1.3 Short Long portfolios

The third group of portfolio is short long portfolios, proposed by Brunnermeier *et al.* (2008). In each month, we take long positions of k currencies with highest interest rate, and at the same time, we take short positions of k currencies with lowest interest rate. We construct portfolios with k =1,2,3,4 and refer them as SL_1 SL_2 $SL_3$and SL_4. For example, in SL_2 we long 2 currencies with highest interest rate and short 2 currencies with lowest interest rate.

Constructing an SL portfolio is equivalent to implement carry trade in which the investors borrows currencies in the basket of low interest rate and buys currencies in the basket of high interest rate. We consider short and long portfolios as an extension of HML portfolio. SL portfolios are different from HML portfolio for that, SL portfolios explicitly specify the number of currencies to be operated on the short and long positions, while HML portfolio operates on a basket of currencies on short and long positions without controlling the specific number of currencies in each basket.

The HML portfolio and SL portfolios are neutral to dollar risk because the USD is cancelled when shorting the basket of foreign currencies and longing the basket of foreign currencies by construction.

4.2 Stylized facts of currency portfolios

We now report stylized facts of excess returns of currency portfolios, which are constructed by sorting currencies on interest rate differentials.

There are two pairs of correlations in the results of carry trade portfolios in Table 4-1.[15] Firstly, the excess return is positively correlated to the standard deviation. The mean of excess return increases from -0.0169 in low interest rate portfolio to 0.0923 in high interest portfolio, while the standard deviation increases from 0.06 to 0.13. Besides, the sharp ratio also increases from -0.21 to 0.15. The same trend of sharp ratio and standard deviation indicates that the high sharp ratio comes at the cost of high volatility.

Secondly, there is a negative correlation between the excess return and the skewness. While the excess return increases from low interest rate portfolio to high interest portfolio, the skewness becomes more negative, decreasing from -0.35 in portfolio C_1 to -0.67 in portfolio C_3. The distribution of excess return in high interest rate currencies has higher mean positive, but also has strong negative skewness with a long tail on the left. This means that the most negative returns are likely to occur in this case. On the other hand, although currencies with low interest rates have negative mean in the excess return distribution, the largest positive returns are most likely to occur. The negative skewness in the excess return has been widely documented in previous carry trade studies. Our finding of G10 currencies in the last 13 years are consistent with these studies. We contribute to the literature by showing that the negative relationship between excess return and skewness holds on a monthly basis. It is then reasonable to infer that the skewness contains information regarding the currency crash and further has a price impact on the excess returns. This hypothesis is tested in chapter 5.

Next, we construct HML portfolio and present the statistics in the last column in Table 4-1. HML has sharp ratio at 0.35 and the most negative skewness at -1.15. The sharp ratio and skewness of HML is consistent with the facts that HML portfolio is constructed as the difference of C_3 and C_1. None of the AC(1) coefficient is significant at 10% significance

[15] We considered another currency allocations: having 3,2,3 currencies for Portfolio C_1, C_2, C_3.We report the results of this allocation variation in Table 10-1 in Appendix. We do not find the different allocation of currencies in portfolios bias the statistics results or the cross-sectional results.

level. This means that none of these portfolio excess returns is autocorrelated. To test the stationarity, we run the ZA test; the test statistics are all significant at 1% significance level, meaning all of these portfolio excess returns are I(0).

In Table 4-2, we present results of SL portfolios. We find that the excess returns of 4 SL portfolios do not change greatly and neither do the sharp ratios. There is no a clear pattern of skewness when more currencies are involved. All SL portfolios have large negative skewness which is more negative than -0.9. We see that the negative skewness cannot be diversified by adding more currencies into the portfolio. The constant negative skewness across SL portfolios suggests that SL portfolios have large positive excess return but also have large probability to lose.

Next, in order to illustrate the crash risk visually, we plot the distribution of excess return conditional on the interest rate differentials. Figure 4-1 plots the kernel-smoothed density distribution of different currency portfolios: the top panel plots the distribution of carry trade portfolios' excess returns, with observations split into IRD_t^j< -0.001, -0.001 < IRD_t^j< 0.001 and $IRD_t^j > 0.001$. The bottom panel plots the distribution of short and long portfolios' excess returns. The top panel shows that when the interest rates are highly positive (solid line), the distribution of carry trade excess returns have a larger mean but also strong negative skewness with a long tail to the left. This means that the positive mean of excess return is accompanied by most negative outcomes, where the loss of carry trade is likely to happen. On the contrary, when the interest rates are highly negative (dotted line), the distribution of carry trade excess returns have a smaller mean and are less negatively skewed without the fat tail to the left. This implies that although low interest rate currencies have smaller carry trade profit, they are also less likely to suffer loss. The bottom panel in Figure 4-1 plots the kernel-smoothed density for the short and long portfolios. Table 4-2 shows that all SL portfolio have high positive excess return and very negative skewness. Bottom panel in Figure 4-1 is visualized in this finding by showing the long fat left tail on the distribution of taking long positions in high interest rate currencies and short positions in low interest rate currencies.

To sum up, the stylized facts of excess return show that the negative skewness in carry trade portfolios' excess return distribution can be linked to the currency crash, because it implies potentially very negative outcomes even when carry trade seems to be profitable.

4.3 Conclusion

In this section, we introduce the technique to form currency portfolios. Following Lustig and Verdelhan (2007), we sort currencies into 3 portfolios on the interest rate differentials with respect to the US interest rate and construct the 3 kinds of currency portfolios, including currency portfolios, HML portfolios and SL portfolios. We explore the stylized facts of these the currency portfolios and find several patterns across different variables: the excess return of carry trade portfolio reveals an increase trend from low interest rate portfolio to high interest rate portfolio, while the skewness of exchange rate movements reveals a decline trend from low interest rate portfolio to high interest rate portfolio. The negative skewness can be interpreted as a measure of crash risk or downside risk inherent in carry trade strategy, as it means that large negative excess return is likely to occur and induce the loss of profit.

We build portfolios of currencies for investigating the cross-sectional risk premium. By building portfolios, we filter out the currency changes that are orthogonal to changes in interest rates. Instead, the changes in the average exchange rates should reflect mainly the risk premium component, which is the part we are interested in. Moreover, building portfolios shift the focus from the individual currencies to currencies with interest rates from high to low, which is the same way that the Fama and French portfolios of stocks are sorted; sorting on size and book-to-market ratios shift the focus from individual stock to stocks of either small or large value.

The portfolio empirical results reveal a systematic variation in the average excess returns and a connection to the negative skewness. We expect a risk-based explanation for the average excess return with different exposures to this risk factor. We study the currency crash risk by extracting information from the skewness of exchange rates in the next chapter.

Table 4-1: Currency portfolios sorted on IRD_t^j

Portfolio	C_1	C_2	C_3	DOL	HML
Mean	-0.0169	0.0192	0.0923	0.0222	0.1092
st dev	0.06	0.09	0.13	0.06	0.16
Skew	-0.35	-0.52	-0.67	-0.55	-1.15
kurt	3.57	5.64	5.22	9.26	3.49
Sharp Ratio	-0.21	0.01	0.15	0.02	0.35
CH test	0.00	0.48	0.30	2.49	5.30
LM test	0.09	0.06	3.97*	1.66	2.01
ZA test	-12.00***	-12.12***	-12.23***	-11.41***	-12.36***

Note: This table contains statistics of annualized excess return for carry trade portfolios, DOL and HML portfolio, which are constructed based on the rank of interest rate differentials IRD_t^j relative to USD. Portfolio C_1 contains 3 currencies with smallest interest rate differentials, C_2 contains 3 currencies with second smallest interest rate differentials, C_3 contains 2 currencies with largest interest rate differentials. DOL is the average of portfolio C_1 to C_3. HML is the difference between C_1 and C_3. Portfolios are re-balanced at the end of every month. Annualized excess return is calculated as multiplying monthly means by 12 and multiplying monthly standard deviations by $\sqrt{12}$. Sharp ratio is computed as ratios of annualized excess returns means to annualized standard deviations, considering US interest rate as the risk-free asset. We also report statistics of Cumby and Huizinga (1992) (CH) test for auto correlation; the LM statistics of the ARCH effect for the heteroscedasticity and the statistic of Zivot and Andrews (1992) (ZA) test for stationarity. Data involved here is monthly data ranging from December 2001 to February 2013. Data involved here is monthly data ranging from December 2001 to February 2013.

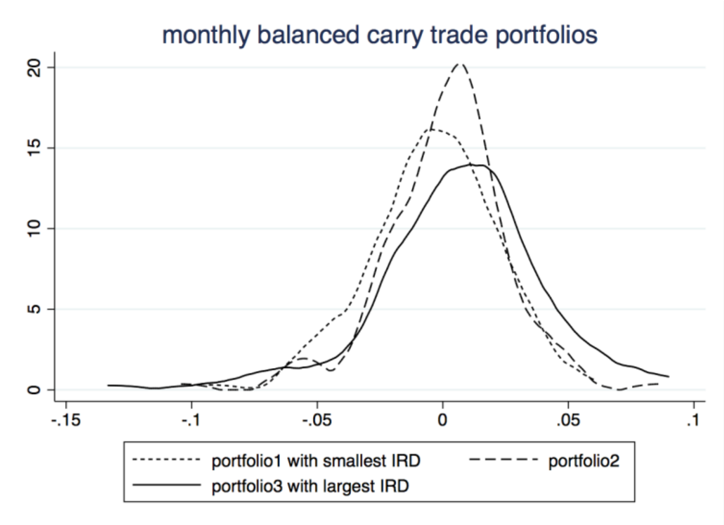
Table 4-2: Short and long portfolios sorted on IRD_t^j

Portfolio	SL_1	SL_2	SL_3	SL_4
Mean	0.0672	0.0502	0.0585	0.0480
st dev	0.13	0.12	0.12	0.12
Skew	-1.23	-0.92	-1.36	-1.22
kurt	8.45	7.14	10.01	9.06
Sharp Ratio	0.32	0.30	0.22	0.29
CH test	4.56**	1.70	1.34	1.87
LM test	5.58**	1.63	2.10	1.87
ZA test	-10.26***	-11.21***	-11.57***	-11.61***

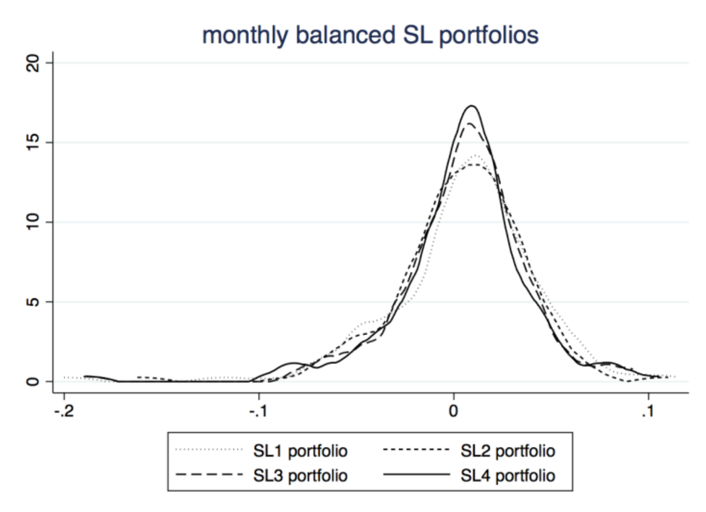
Note: This table contains statistics of annualized excess return for short and long portfolios, constructed based on interest rate differentials IRD_t^j between the foreign country and the US. In a SL_k portfolio, we short k currencies with lowest interest rate differential and long k currencies with highest interest rate differential, where k=1,2,3,4. The excess return of portfolio SL_k is the mean across currencies allocated on short and long positions with equal weights. Annualized excess return is calculated as multiplying monthly means by 12 and multiplying monthly standard deviations by $\sqrt{12}$. Sharp ratio is computed as ratios of annualized excess returns means to annualized standard deviations, considering US interest rate as the risk-free asset. To test auto correlation, we report the statistics of Cumby and Huizinga (1992) (CH) test. The H_0 of CH test: the series has no serial correlation under assumption of heteroscedasticity. The highest lags order tested for CH test are selected by G.W Schwert (1989) standard. To test heteroscedasticity, we report the LM statistics of the ARCH effect. To test stationarity, we report the statistic of Zivot and Andrews (1992) (ZA) test which has the null of non-stationarity tested under the assumption of one structural break. The optimal lags used in the ZA test are selected by the standard of minimal BIC, proposed in Ng and Perron (2001). We mark the significant statistics at 1%, 5%, 10% level by asterisk ***, ** and *. Data involved here is monthly data ranging from December 2001 to February 2013.

Figure 4-1: Kernel density of monthly excess return distribution for currency portfolios

(a): carry trade portfolios



(b) SL portfolios



Note: Panel (a) shows the kernel density of distribution of carry trade portfolios constructed by interest rate differentials IRD_t^j: where IRD_t^j< -0.001 (portfolio 1 in dotted line), -0.001 < IRD_t^j< 0.001 (portfolio 2 in dashed line), IRD_t^j > 0.001 (portfolio 3 in solid line). Panel (b) shows the kernel density of distribution of SL portfolios, which are constructed by shorting k currencies with lowest IRD_t^j and long k currencies with highest IRD_t^j, where k=1 (in dotted line), 2 (in short dashed line), 3 (in long dashed line), 4 (in solid line). Data involved here is monthly data ranging from December 2001 to February 2013.

5. Currency crash risk in carry trade

5.1 Introduction

Recent studies find that the high excess return of carry trade is subject to currency crash risk. The crash risk of the carry trade can be viewed as an abrupt depreciation of high interest rate currencies with respect to low interest currencies. In this chapter, we identify currency crash risk by constructing a global skewness factor then investigate whether this factor can explain the excess return in carry trade. Our objective is to measure the economic significance of the failure of UIP by the amount of money that can be made by exploiting this violation.

We use the skewness of changes in exchange rate to measure the individual currency crash risk. Chen *et al.* (2001) are the first to use the stock price asymmetries to measure the crash risk in stock returns. Brunnermeier *et al.* (2008) borrow the idea of skewness from the stock market and propose to use skewness to measure the currency crash risk in FX market. They find that currencies with high interest rate differential are subject to currency crash risk. We follow the approach of Burnside *et al.* (2011), Burnside (2011) and Rafferty (2010) and construct a global skewness factor that measures aggregate currency skewness in the G10 currency market. And we find that this global skewness factor is effective in explaining the excess returns of carry trade on a monthly analysis and individual currencies that have heterogeneous loadings of global skewness risk factor.

We conduct an empirical study using a monthly currency data set consisting of 8 foreign currencies spanning 13 years. We employ two sets of models to study the global skewness risk factor: a generalized method of moments (GMM) procedure firstly proposed by Hansen (1982) with the linear factor framework proposed by Lustig and Verdelhan (2007), and the Fama-MacBeth procedure (FMB) proposed by Fama and MacBeth (1973). 2 risk factors are used in our asset pricing model: dollar risk factor (DOL) and global skewness risk factor ($signSKW$). Proposed by Lustig *et al.* (2011), DOL risk factor measures the underlying risk in the base currency and is widely applied in carry trade literature. Proposed by Rafferty (2010) and Burnside (2011), $signSKW$ risk factor measures the currency crash risk and is computed as the average of realized individual skewness signed by individual currencies' interest rate with respect to USD. The test assets are carry trade portfolios, which are formed by sorting individual currencies based on the interest rate differential as proposed in Lustig and Verdelhan (2007).

We have several contributions to the existing literature: firstly, the global skewness factor focuses on aggregate crash risk in the FX market rather than crash risk at the individual currency level. It is an effective measure for global crash risk and has proved to be priced in the excess return of carry trade. Secondly, we conduct a cross-sectional analysis which is an extension to the panel analysis of Brunnermeier *et al.* (2008) and quantify a global skewness premium that is capable of explaining 81% of the excess return of carry trade. The high interest rate currencies have large currency crash risk loading, which demands a risk premium for bearing the currency crash risk to hold a foreign currency. Low interest rate currencies have negative crash risk loading, and they provide a hedge when the currency market is likely to crash. Differently from Burnside (2011) and Rafferty (2010), we focus on the G10 currency market, which is the most liquid currency market and involves the least government intervention in the global currency market. Thirdly, we apply the portfolio approach, which has been proven useful in recent cross-sectional FX asset pricing studies, and provide a simple and intuitive way to gauge the economic significance of the violation of UIP.

We organize this chapter in the following way: we introduce related background literature and motivation in section 5.2. In section 5.3, we construct risk factors for the asset pricing model. We elaborate the empirical model and estimation method in section 5.4. We discuss empirical results in section 5.5. In Section 5.6, we present a robustness test with a variation of testing assets. Section 5.7 concludes.

5.2 Background and motivation

The global skewness factor studied in this chapter is derived from currency returns. The construction of factors of this kind started from Lustig *et al.* (2011) who borrowed the idea from stock market literature where is common to use risk factors that are the returns of particular investment strategies. Fama and French (1993) construct risk factors with return differentials between small and large firms (SMB), and high and low value firms (HML). In the field of momentum strategy research, Jegadeesh and Titman (1993) use a momentum risk factor to identify anomalies to explain stock returns.

Chen *et al.* (2001) propose measuring stock market crash by negative skewness, which is a function of the third moment of daily stock return. They argue that it is the different opinions among investors and arbitrageurs regarding the fundamental value of the market that cause the negative skewness in the entire trading period. Their model predicts that negative skewness in returns will be most pronounced after periods of heavy trading volume. The model of Chen *et al.* (2001) places heterogeneity in investors in the centre of the asymmetric return phenomenon.

In the context of measuring downside risk, this thesis is related to a significant amount of literature Brunnermeier *et al.* (2008) proposing to explain carry trade excess return by currency crash risk. Brunnermeier *et al.* (2008) look at realized skewness at individual currency level and propose measuring currency crash risk by skewness of changes in exchange rates. They also propose using funding liquidity to explain currency crash risk. The presence of liquidity acts as friction in capital moving and causes high interest rate currencies to appreciate gradually. Currency crash happens when funding liquidity is dry in the market, which causes high interest rate currency to deprecate relative to low interest rate currencies. Plantin and Shin (2006) argue that carry trade strategy applied in a dynamic global games framework leads to destabilizing carry trade behaviour. Abreu and Brunnermeier (2003) argue that currency crash can be price correcting and close to the deviation of UIP in the FX market.

5.3 Risk factors

We seek risk-based explanations of the excess return of carry trade. We look for risk factors with economically significant betas which correlate to the movement of the payoffs. In this section, we introduce the risk factors that will be employed in our asset pricing model.

5.3.1 DOL risk factor

The first risk factor used in our empirical models is the DOL factor, proposed by Lustig *et al.* (2011). It is the most applied risk factor which explains the cross sectional excess return at levels, such as in Menkhoff *et al.* (2012a), Burnside (2011). Lustig *et al.* (2011) refer to DOL risk factor as ‘dollar risk factor’ and propose to compute it as the average excess returns of all carry trade portfolios:

$$DOL_t = \frac{1}{n}\sum_{i}^{n} Z_t^i \tag{11}$$

Z_t^i is the excess return of carry trade portfolio i at month t, which is the average excess return of individual currencies *j* allocated into portfolio i. The individual currency excess return Z_t^j for currency *j* is defined in equation (7). n is the number of portfolios, and we have 3 carry trade portfolios in the main text, as described in section 4.1.1.

DOL risk factor is designed to capture the underlying risk in the base currency, which is USD in this thesis. It can also be considered as a strategy that borrows US dollars and invests in global money markets outside of the US. It measures the aggregate FX market excess return in the G10 countries, since mathematically averaging the excess return across portfolios equals averaging the excess return across all currencies involved in the model. In this respect, DOL is analogous to the excess return of the market portfolio in the CAPM model, which is proposed in Fama and French (1993). In cross-sectional asset pricing, DOL risk factor explains the average level of excess returns while allowing other risk factors to explain the excess return variations in a portfolio.

5.3.2 SKW risk factor

The second risk factor is global skewness factor, denoted as $signSKW$, proposed by Rafferty (2010) and Burnside (2011). To construct $signSKW$ on a monthly basis, the foreign currencies are divided into two groups on the $IRD_t^j = i_{j,t-1}^* - i_{t-1}$ the end of month t: currencies with higher interest rate than US ($IRD_t^j > 0$) are considered as investment currencies; currencies with lower interest rate than US ($IRD_t^j < 0$) are considered as funding currencies. Equation (10) is derived from CIP, this is equivalent to defining currencies with a positive forward discount ($F_{j,t} - S_{j,t} > 0$) as investment currencies; and currencies with a negative forward discount ($F_{j,t} - S_{j,t} < 0$) as funding currencies. We follow Rafferty (2010) and Burnside (2011) and construct the monthly $signSKW$ factor as:

$$signSKW_t = \frac{1}{K_t}\sum_{j}^{K_t} sign\left(i_{j,t-1}^* - i_{t-1}\right) \times skew_t^j \tag{12}$$

where

$$sign\left(i_{j,t-1}^* - i_{t-1}\right) = \begin{Bmatrix} +1 & if\ i_{j.t-1}^* > i_{t-1} \\ -1 & if\ i_{j,t-1}^* < i_{t-1} \end{Bmatrix}$$

$sign\left(i_{j,t-1}^* - i_{t-1}\right) \times skew_t^j$ is the signed skewness for currency j at month t. K is the number of available currencies available at month t. $i_{j,t-1}^*$ is the interest rate of foreign country currency j at month $t-1$, i_{t-1} is the domestic interest rate for US at month $t-1$. $skew_t^j$ is the individual skewness defined in equation (8). This $signSKW$ factor combines the skewness of both investment currencies and funding currencies in a way to avoid them cancelling each other, that is it takes the realized skewness of the investment currencies and the negative of the skewness of the funding currencies. The average, across all available currencies, of these skewness statistics is the global skewness factor. $signSKW$ factor can be thought of as a measure of the depreciation of a group of target investment currencies relative to a group of funding currencies, in which the depreciation coordinates to the crashing of currencies.

The skewness factor $signSKW$ is designed to capture the risk that relates to the downside risk in exchange rate movement. We follow Burnside (2011) and Rafferty (2010) to construct the global skewness factor by interacting the realized skewness of individual currency with the sign of the interest rate differential. We explain the reason as the following: the realized skewness for an individual currency does not mean the same thing to all currencies involved in carry trade. When the exchange rate is measured as units of foreign currency per USD, a positive skewness ($skew(\Delta S) > 0$) means that the most positive value of ΔS is likely to occur. This translates into the foreign currency being likely to depreciate in the next moment, which is not the favoured direction of exchange rate movement for investment currencies but is for funding currencies. In other words, positive skewness represents currency crash risk for investment currencies, but not for funding currencies. Similarly, a negative skewness ($skew(\Delta S) < 0$) represents the crash risk for funding currencies, not for investment currencies. Thus, the unsigned realized skewness is not capable of accurately measuring the currency crash risk in all circumstances. By signing the individual realized skewness, the global skewness risk factor accommodates the trading directions and unifyies the measurements of currency crash risk for both investment currencies and funding currencies.

We show that $signSKW$ factor as a proxy for global currency crash risk effectively captures more than 80% of the cross-sectional excess returns in carry trade portfolios. We provide the empirical evidence in section 5.5.

5.4 Methodology

Taking the perspective of US investors, we now proceed to investigate whether currency crash risk is priced in the cross-sectional excess returns of the carry trade portfolios via GMM procedure and FMB procedure.

We follow Burnside (2011) and Lustig *et al.* (2011) to provide a risk-based explanation of carry trade excess returns which relies on a standard stochastic discount factor (SDF) approach Cochrane (2005). We consider the global skewness factor as included in the framework of the linear factor model. Since carry trade is a zero-cost investment strategy, the risk-adjusted excess returns should satisfy the non-arbitrage condition by having:

$$\mathbb{E}\left[m_{t+1} Z_{t+1}^{i}\right] = 0 \tag{13}$$

where Z_t^i is the monthly excess return for carry trade portfolio i, m_t is the SDF that prices excess returns. Following Cochrane (2005), we consider the vectors of linear SDF factors of the form:

$$m_{t+1} = 1 - b'(f_{t+1} - \mu) \tag{14}$$

where f_{t+1} is a $t \times k$ vector of risk factors DOL_{t+1} and $signSKW_{t+1}$. $\mu = E(f_{t+1})$ and b is the vector parameters. Burnside (2011) and Menkhoff *et al.* (2012a) argue that the expected excess return for portfolio i can be determined by the beta pricing of risk factor prices λ and risk factor loading β^i.

$$\mathbb{E}\left[Z_{t+1}^{i}\right] = \lambda' \beta^{i} \tag{15}$$

where the factor price λ is determined by vector parameters b as $\lambda = \Sigma_f b$. Σ_f is the sample covariance matrix of risk factors f_{t+1}. We estimate parameters of Eq (13) via the GMM. Following Burnside (2011), we pre-specify the weighting matrix as 1. We estimate the risk factor prices λ, the covariance matric of risk factors Σ_f along with other SDF parameters simultaneously with the moment condition:

$$\mathbb{E}\left[Z_{t+1}^{i}\left(1 - b'(f_{t+1} - \mu)\right)\right] = 0 \tag{16}$$

and k moment conditions $E(f_{t+1}) = \mu$. We report estimates of factor price λ and b from the first stage GMM. Burnside (2010a) proves that the first stage GMM, second stage GMM and iterated GMM estimators have similar size properties when calibrated linear factor models are used in the data generating process. We also report the cross-sectional R^2, the J-statistics and P value of Hansen-Jagannathan (HJ) distance measure, which test the over-identifying restrictions. The standard errors are adjusted by Newey and West (1987) with optimal lag selection.

In terms of the FMB, we follow the traditional two-pass OLS procedure to estimate betas and risk factor prices. We first obtain portfolio betas β_{DOL}^{i} and $\beta_{signSKW}^{i}$ from the parsimonious two factor model:

$$Z_{t+1}^{i} = \alpha_i + \beta_{DOL}^{i} f_{t+1}^{\mathrm{DOL}} + \beta_{signSKW}^{i} f_{t+1}^{signSKW} + \varepsilon_{i,t+1} \tag{17}$$

Where f_{t+1}^{DOL} is the DOL_{t+1} at dollar risk factor at month t. $f_{t+1}^{signSKW}$ is the global crash risk factor at month $t+1$. The test assets are portfolios excess returns Z_{t+1}^{i} formed based on the interest rate differentials and rebalanced on monthly basis. β_{DOL}^{i} and $\beta_{signSKW}^{i}$ in regression (17) represent the sensitivities of the portfolios excess returns Z_{t+1}^{i} to the risk factor DOL and $signSKW$. Regression (17) tests if the global skewness risk factor remains priced when accounting for other sources of systematic risk.

In the second step of FMB procedure, we use estimate β^i_{DOL} and $\beta^i_{signSKW}$for risk factors DOL_{t+1} and $signSKW_{t+1}$ in the first step and regress cross-sectional excess returns Z^i_{t+1} of portfolios on β^i_{DOL} and $\beta^i_{signSKW}$ as:

$$Z^i_{t+1} = \beta^i_{DOL}\lambda^{\mathrm{DOL}}_{t+1} + \beta^i_{signSKW}\lambda^{signSKW}_{t+1} + \varepsilon_{i,t+1} \tag{18}$$

$\lambda^{\mathrm{DOL}}_{t+1}$ and $\lambda^{signSKW}_{t+1}$ are the risk premium of the dollar risk factor DOL and global skewness factor $signSKW$ at month $t+1$ respectively. Following Lustig *et al.* (2011), we do not include a constant in the second stage of FMB in regression (18), because factor DOL_{t+1} already accounts for cross-sectional invariant values. We report the standard error with Newey and West (1987) standard with optimal lag selection.

Follow Lustig *et al.* (2011), we use annualized excess return for all carry trade portfolios Z^i_{t+1} in GMM and FMB procedure and report the annualized estimated risk premium. More details about the GMM estimator and FMB estimator of risk price λ are provided in the Appendix.

In previous studies, Brunnermeier *et al.* (2008) conduct a time series analysis and find that currency crash risk is priced in excess return of carry trade. In our cross-sectional analysis, we expect this global skewness risk premium $\lambda^{signSKW}$ to be significant along with dollar risk factors DOL in the asset pricing model.

A positive risk premium λ ($\lambda^{\widehat{signSKW}} > 0$) means that portfolios which co-move positively with the skewness factor yield high excess return. A negative risk premium λ ($\lambda^{\widehat{signSKW}} < 0$) means that portfolios which co-move positively with the skewness factor yield low excess return.

5.5 Empirical results

In this section, we investigate the feature of the global skewness risk factor $signSKW$, which is constructed in the way described in section 5.3.2. Then we follow the approach of Rafferty (2010) and Burnside (2011) and report the asset pricing results of factor models.

5.5.1 Stylized facts of global skewness risk factor

The results of individual currencies skewness are presented in Table 3-5 in section 3.2.4. In this section, we compute the global skewness factor $signSKW$ based on the individual currency skewness and present the stylized facts in Table 5-1.

The first column of Table 5-1 show that, the first order coefficient of AR(1) process of $signSKW$ factor is significant at 1% level. The null hypothesis of no serial correlation for CH test is rejected at 1% level. The LM test for ARCH effect in $signSKW$ factor series is also significant at 5% level. Accounting for one structural break, the test statistics of ZA test is significant at 1% level. These results mean that $signSKW$ factor series is stationary, but is auto correlated and has heteroscedasticity.

Following Menkhoff *et al.* (2012a), we deal with the autocorrelation problem by estimating a simple AR(1) process for the $signSKW$ series and take the AR(1) residual as our proxy for innovations. The reason to take the AR(1) residual instead of the first difference form is that it maintains the most information in the original series since the AR(1) model is close to the data generation process in a highly correlated raw series, and the AR(1) residual is uncorrelated with its own lags. The weakness of taking AR(1) residual is that, as a regression outcome, it introduces the errors-in-variable problem. We deal with this problem by adjusting our standard errors to the Newey-West standard and do not find a significant difference. We test the skewness factor innovation $signSKW^e$ again and present the stylized facts in the second column of Table 5-1. We find that both the AC(1) coefficient and the CH test statistics are not significant at 10% level. LM test statistics shows that the $signSKW^e$ series does not suffer heteroscedasticity. The ZA test statistics is significant at 1% level. Therefore, the skewness factor innovation $signSKW^e$ is not auto-correlated, not heteroscedastic and is stationary.

We then plot skewness factor innovation $signSKW^e$ with NBER recession periods in Figure 5-1 panel B. We find that $signSKW^e$ factor is close to the shape of white noise. The upside spikes appear before the crisis in 2008. Whereas, during the financial crisis period from December 2007 to July 2009, the skewness factor innovation had negative spikes, which suggests that no crisis risk during that period. This is consistent with disaster model explanations in Brunnermeier *et al.* (2008) and Farhi *et al.* (2009), where the crisis risk is reduced after the crisis is realized and the disaster risk premium is accordingly lower in the post-crisis period.

In Figure 5-1 panel A, we plot the cumulative excess returns for the HML portfolio and DOL portfolio, which are constructed by sorting currencies on the IRD. We see that the excess returns of HML portfolio and DOL portfolio increase steadily before August 2004. Then there is a graduate decline period between 2004 to 2006, which correspondents to the decline in IRD at the same period shown in Figure 3-1. This is consistent with Lustig and Verdelhan (2007) who argue that excess return of carry trade synchronizes the fluctuation of interest rates of foreign countries. Both HML portfolio and DOL portfolio suffers loss during the financial crisis period in the shaded area. Then HML portfolio has a sharp increase trend since mid 2009. The excess return of DOL portfolio remains on a stable level over the sample period after mid 2009.

5.5.2 Heterogeneous exposures to crash risk

After obtaining the innovation of global skewness factor, we are interested in investigating the country exposures to the global skewness innovation. In Figure 5-2, we plot two pairs of relationships during the full sample period in panel A and during the crisis period in panel B: the relationship between the interest rate differential IRD^j and currency crash risk betas, the relationship between the changes in exchange rate Δs^j and currency crash risk betas. The crisis period ranging from September 2008 to January 2009 is referred from Mancini *et al.* (2013).

We find that there is strong link between interest rates, exchange rates and currency crash risk. Firstly, Figure 5-2 shows a positive relationship between the interest rate differential and the currency crash risk betas regardless of the periods of time. This means that countries more exposed to the crash risk have higher interest rates. Currencies with large global skewness betas, such as AUD and NZD, also have high interest rates. Currencies with small global skewness betas, such as JPY and CHF, have constant low interest rates.[16] This finding is consistent with Brunnermeier *et al.* (2008), who were the first to document that the skewness exposure increases with interest rates. Our work builds on their findings and shows that a large part of the cross-sectional differences in interest rates correspond to different exposures to global currency crash risk, which is measured by the global skewness risk factor.

Secondly, Figure 5-2 shows that countries with small (large) exposure to global crash risk depreciates (appreciates) when crash risk happens. We show this point via the contrast relationship between the exchange rate and skewness betas in non-crisis and crisis periods. The change in exchange rate is negatively related to currency crash risk betas in the full sample period. However, the change in exchange rate turns to positively relate to crash risk betas in the crisis period from September 2008 to January 2009. This means that when crash risk is low, countries with high large exposure to crash risk have high interest rate and appreciate, and countries with low large exposure to crash risk have low interest rate and depreciate. This is the situation when carry trade performs well and gains profit. However, when crash risk occurs or the probability of having crash risk increases, currencies with high interest rate depreciate and currencies with low interest rate appreciate. This is exactly what happened during the crisis in 2008.

Our finding with global skewness beta is consistent with Farhi and Gabaix (2008) and Farhi *et al.* (2009), who explain the contemporaneous events of currency crash, increasing interest rates and currency depreciation with a disaster model. Our global skewness risk factor captures patterns of these events and accounts for the aggregate downside risk of the FX market in general. Our graphic empirical results show that currency crash risk is an important risk factor in explaining the cross-sectional and time-series variation of exchange rates and interest rates. We examine the links and come back to this point in the following sections.

[16] Galati and Melvin (2004) identify Switzerland and Japan as the main low interest countries and the United Kingdom, Australia, and New Zealand as the main high interest rate countries based on the historical data till 2004.

5.5.3 Asset pricing results

In this section, we use GMM and FMB procedures to conduct cross-sectional analysis for portfolio excess returns on dollar risk factor DOL and the global skewness factor innovation $signSKW^e$, constructed as in section 5.5.1. The pricing kernel is:

$$m_{t+1} = 1 - b_{DOL}(DOL_{t+1} - \mu_{DOL}) - b_{SKW}(signSKW^e_{t+1} - \mu_{signSKW^e}) \qquad (19)$$

Panel A in Table 5-2 presents the asset pricing results using 3 carry trade portfolios as the test assets. Both GMM and FMB show estimates of positive premium for DOL and $signSKW^e$. We note that the estimate of $signSKW^e$ from GMM is insignificant whereas that from FMB is significant at 5% significance level. This may be due to the reason that GMM accommodates more variation in the variances of the underlying data, the standard deviation is inflated and hence the estimates turn to be insignificant. The estimated factor price $\lambda_{signSKW}$ is 4.42 from GMM procedure and 3.97 from FMB procedure for the 8 developed countries sample. It captures more than 80% of the cross-sectional excess returns in carry trade, with insignificant HJ statistics and small root mean squared error (RMSE). We interpret the positive factor prices as showing that portfolios which co-move positively with skewness innovations have higher risk premium, whereas portfolios which co-move negatively with skewness innovations have lower risk premium.

Panel B in Table 5-2 shows that there is a monotonic increase pattern in $signSKW^e$ betas when moving from portfolio C_1 to portfolio C_3. The estimate of $\beta_{signSKW^e}$is negative at 1% significance level for low interest rate currencies and positive at 5% significance level for high interest rate currencies. We see that global skewness factor has betas with respect to DOL factor. These time series results show that high interest rate currencies exhibit large positive global skewness betas, thus are more exposed to currency crash risk, while low interest rate currencies exhibit negative betas, thus providing insurance against crash risk. This means that high interest rate currencies perform poorly when crash risk is high and therefore demand a premium and low interest rate currencies offer a hedge when crash risk happens in the FX market.

The increase trend in skewness betas from low interest rate currencies to high interest rate currencies can also be explained by the model proposed in Ilut (2012). Agents are ambiguity adverse and do not know the true stochastic process underlying the interest rate differential between high interest rate currencies and low interest rate currencies. Then high interest rate currencies attach larger weight to bad statistics with more skewness beta loadings than the low interest rate currencies do. A more positive skewness can be interpreted as an increase in ambiguity adversity or an increase in uncertainty among currency investors.

Following the construction of the skewness risk factor, our positive skewness risk premium is consistent with the finding in Burnside (2011) and Rafferty (2010). This suggests that the high interest rate of foreign currency has high excess return and is also accompanied with higher currency crash risk. Our skewness risk factor has a similar amount of impact on excess return as the volatility risk factor proposed in Menkhoff *et al.* (2012a), which is constructed from the daily changes in exchange rate. However, we do not use the absolute return value to construct the risk factor. Instead, we use the direct information in the actual exchange of exchange rate, which captures more completed information in the excess return distribution and reflects better the momentum of exchange rate.

5.5.4 Portfolios sorted on beta of global skewness factor innovation

We now further explore the explanatory power of global skewness risk factor innovation. If the currency crash risk measured by global skewness innovation is a priced factor, then it is reasonable to expect that the currencies sorted on their exposure to the global skewness innovations should reveal a spread pattern in the cross-sectional excess returns. In this way, we show that sorting currencies based on interest rates does measure the currencies' exposure to currency crash risk. Given the increase trend of beta in time series regressions, we expect to see an increase trend of excess returns from the low beta portfolio to the high beta portfolio.

Beta sorting is a widely applied technique in the FX market to investigate the risk premium, as in Lustig *et al.* (2011) and Menkhoff *et al.* (2012a). We follow Lustig *et al.* (2011) by sorting currencies according to individual currencies' global skewness betas. Specifically, for each month t, we regress each currency j's log change in exchange rate ΔS_t^j on a constant and global skewness innovation $signSKW^e$ using a 36-month rolling window that ends in month $t-1$.[17] This gives us currency j's exposure to $signSKW^e$ and we denote it $\beta_t^{j,signSKW^e}$. Then we sort currencies into portfolios by the rank of betas. Portfolio P_1 contains currencies with the lowest βs, portfolio P_3 contains currencies with the highest βs. DOL is the average of portfolio P_1 to P_3. HML is the difference between P_3 and P_1. We re-balance portfolios at the end of every month. In this way, we do not use any information in the interest rates, but only skewness information available at month t.

We present the descriptive statistics for portfolios excess returns in Table 5-3. We also report the betas used for sorting. Table 5-3 show that there is a monotonic increase pattern in excess returns from portfolio P_1 to P_3. Portfolio P_1 contains 3 currencies with excess return which is least sensitive to the global skewness factor (smallest βs) and portfolio P_3 contains 2 currencies with excess return which is most sensitive to the global skewness factor (largest βs). The spread of excess returns between portfolio P_1 to P_3 reaches 6.05% per annum. The results of pre- and post-formation βs are consistent with the principle of beta sorting technique, where the βs increase from portfolio P_1 to portfolio P_3.

We find the difference between the carry trade portfolios and these skewness beta sorted portfolios to be that they have a different skewness pattern compared to the interest rate sorted portfolios. Table 4-1 shows that excess returns of high interest rate currencies have lower skewness than low interest rate currencies. This is not the case in the skewness beta sorted portfolios, where we do not find a clear pattern. This suggests that sorting on skewness betas produces portfolios related to but not identical with the carry trade portfolios. This risk factor beta sorted portfolios feature is also found by Menkhoff *et al.* (2012a) who sort currencies on the volatility betas and do not find a decrease pattern of skewness in the beta-sorted portfolios.

To sum up, the results of different sorting techniques support our hypothesis that currency crash risk is priced in carry trade excess return. Currencies with low skewness beta have lower return than currencies with large skewness beta.

[17] We also tried another window size and report the results with window size 24 in the robustness section. We do not find that different window sizes generate inconsistent funding liquidity beta nor bias the portfolio excess return results.

5.6 Robustness

We performed several additional robustness checks regarding the variation of test asset portfolios and different window sizes in constructing factor betas sorted portfolios. We document the results here and include the empirical results in the Appendix.

5.6.1 Asset pricing results of the variation of portfolio construction

Table 10-2 contains asset pricing results of portfolios constructed as 3,2,3 currencies for Portfolio C_1, C_2, C_3. It also shows a positive skewness premium, by either GMM or FMB procedure, and a monotonic increase trend in betas of skewness factor innovation from portfolio C_1 to portfolio C_3. Estimates of $\beta_{signSKW^e}$ are negative and significant at 1% level for currencies in low interest rate currencies, whereas estimates of $\beta_{signSKW^e}$ are positive for currencies and significant at 1% level in high interest rate differential currencies. Compared with asset pricing in Table 5-2, we find that the time series results are consistent with the results of portfolios constructed as 3,3,2 shown in the main contest, which suggests a positive risk premium of skewness factor.

5.6.2 Portfolios sorted by beta of skewness factor innovation with different window sizes

We next generate skewness factor betas for sorting currencies with different size of windows. When regressing the individual currencies exchange rates on skewness factor innovations, we set a smaller rolling window size as 24 months. We present the annualized excess returns of carry trade portfolios, DOL portfolio and HML portfolio along with other variables in Table 10-3. We find that there is a monotonic increase trend in excess return, and the interest rate has an incline trend. There is no apparent pattern in skewness from portfolio P_1 to portfolio P_3, which is the same as in Table 5-3. The pre- and post- formation βs are indeed increasing as the principle of factor beta sorted principle. Generally, we do not find significant difference of the skewness beta sorted portfolios generated by different window sizes. We consider that the perspective of constructing portfolios with skewness factor beta provide a robust empirical support to the presence of positive skewness risk factor premium.

5.7 Conclusion

In this chapter, we answer the question of whether the excess return of carry trade can be attributed to currency crash risk. We construct a global skewness factor and find that it is an effective measure of crash risk with a positive risk premium in explaining cross-sectional carry trade excess returns. Investors in FX market worry about the periods when investment currency depreciates abruptly, relative to funding currencies. We find that currencies with high interest rate perform poorly when crash risk is high and therefore demand a high excess return in equilibrium. Whereas, currencies with low interest rate offer a hedge to investors for losing out when currency crash risk is high.

This empirical result clearly implies that asymmetries from the distribution of currency excess returns are important when quantifying foreign exchange rate premium. Risk factor derived from the distribution of excess return is effective in explaining the risk premium in FX trading strategy. This effectiveness can also be shown when sorting currencies on the risk factor beta, where the portfolio perspective provides us a simple and straightforward way to present the effect risk factor has on currency excess returns.

Overall, our empirical results fit into the macroeconomics view on fundamentals' determination on high and low interest rates in the long-term level. Our findings complement the macroeconomics view by showing that endogenous currency crash risk is one factor to drive exchange rates away from the values determined by the fundamentals in the short-term.

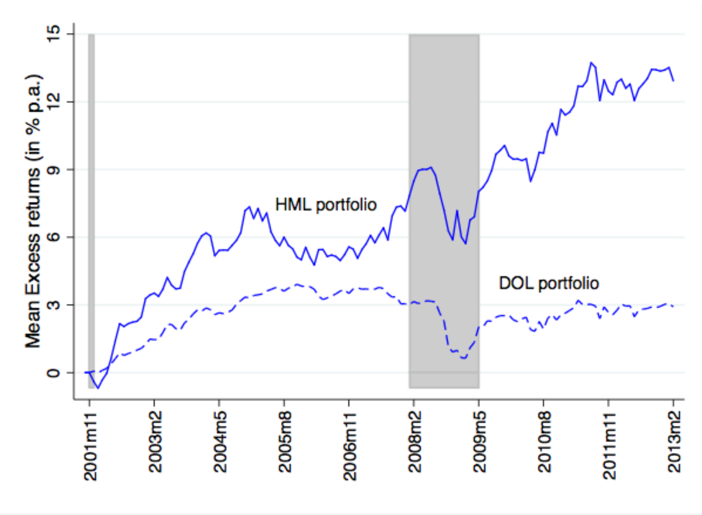
Table 5-1: Statistics of global skewness factor and its innovation

	$signSKW$	$signSKW^e$
Mean	0.074	-6.96$\times 10^{-11}$
Sd dev	0.239	0.23
Skew	-0.22	-0.22
Kurt	3.55	3.39
AC(1)	0.19**	0.00
	(0.08)	(0.09)
CH test	7.14**	0.00
LM test	4.12**	0.37
ZA test	-10.44***	-12.55***

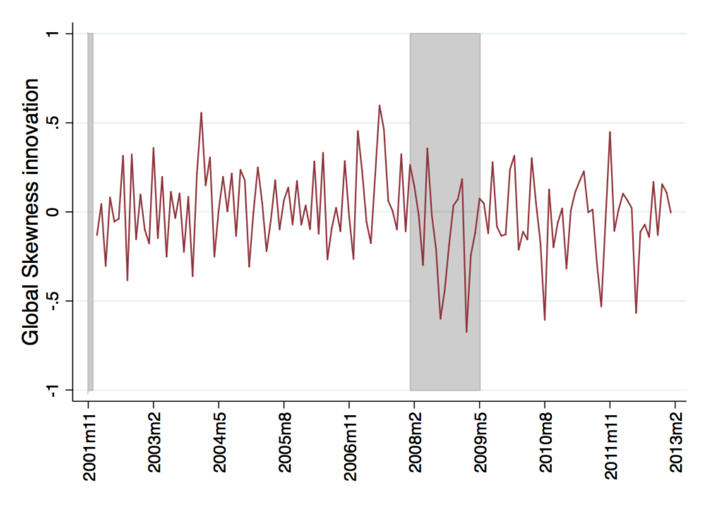
Note: This table contains statistics of global skewness factor $signSKW$ and the skewness factor innovation $signSKW^e$. $signSKW$ is calculated as the monthly cross sectional average signed skewness of individual currencies. The signed monthly skewness for each currency is calculated as the skewness of exchange rate changes within one month attached with the sign of interest rate differential between foreign currency and USD at the end of month. $signSKW^e$ is the AR(1) residual of $signSKW$. We report mean, standard deviations, skewness, kurtosis. To test auto correlation, we report the first order autocorrelation coefficient AC(1) from the AR(1) process and the statistics of Cumby and Huizinga (1992) (CH) test. The standard errors of AC(1) are reported in brackets. The H_0 of CH test: the series has no serial correlation under assumption of heteroscedasticity. The highest lag order tested for CH test is selected by G.W Schwert (1989) standard. To test heteroscedasticity, we report the LM statistics of the ARCH effect. To test stationarity, we report the statistic of Zivot and Andrews (1992) (ZA) test which has the null of non-stationarity tested under the assumption of one structural break. The optimal lags used in the ZA test are selected by the standard of minimal BIC, proposed in Ng and Perron (2001). We mark the significant statistics at 1%, 5%, 10% level by asterisk ***, ** and *. Data involved here is monthly data of 8 currencies ranging from November 2001 to January 2013.

Figure 5-1: Excess returns of carry trade and global skewness factor

(a) Cumulative carry trade excess returns



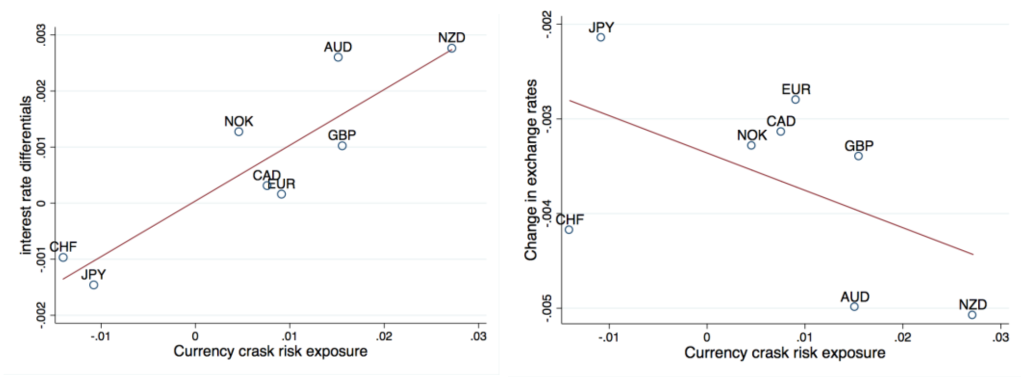
(b) Global skewness innovation



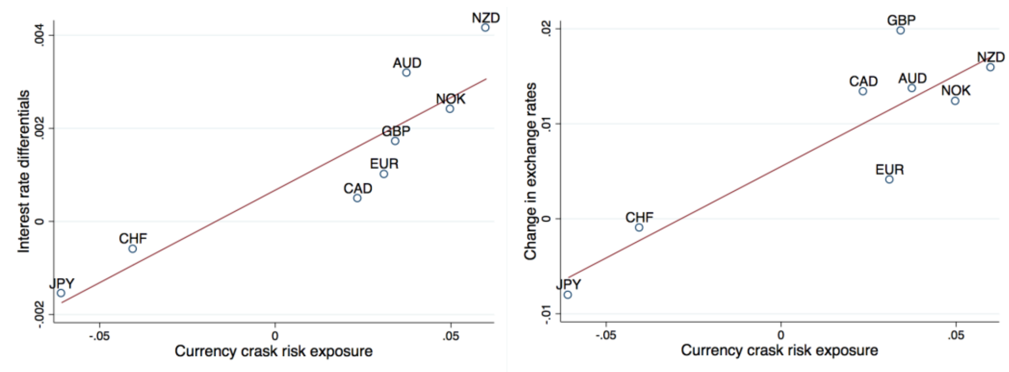
Note: The upper panel of this figure shows the percentage of annualized cumulative excess returns of the HML portfolio (in solid) and DOL portfolio (in dash). The lower panel shows the time series of global skewness factor innovation $signSKW^{e}$ with recession periods published by NBER in shaded area. In order to remove the serial correlation, we take the AR(1) residual of $signSKW$ to measure the crash risk innovation. Data involved here is monthly data of 8 currencies ranging from December 2001 to January 2013.

Figure 5-2: Heterogeneous exposures to crash risk in different periods

(a) Full sample period (December 2001 to January 2013)



(b) Crisis period (September 2008 to January 2009)



Note: This figure shows individual currency's interest rate differentials IRD^j and changes in exchange rates Δs^j with respect to the crash risk exposure β in full sample period (panel A) and in crisis period (panel B). Full sample period ranges from December 2001 to January 2013. The crisis period ranges from September 2008 to January 2009 and is referred from Mancini *et al.* (2013). Following Menkhoff *et al.* (2012a), the crash risk exposure β^j for currency j is obtained by regressing excess return Z_t^j for currency j at month t on global crash risk innovation $signSKW_t^e$ at month t, which is the AR(1) residual of $signSKW_t$. The country-specific average interest rate differentials IRD^j and average changes in exchange rates Δs^j are obtained as the time series mean within each currency j. The fitness of the lines are as following: The slope of the line in upper left is significant at 1% level and the goodness fit of the line is 80%. The slope of the line in upper right is significant at 10% level and the goodness fit of the line is 30%. The slope of the line in lower left is significant at 1% level and the goodness fit of the line is 80%. The slope of the line in lower right is significant at 1% level and the goodness fit of the line is 78%. Data involved here is monthly data of 8 currencies.

Table 5-2: Cross-sectional asset pricing results for carry trade portfolios

Panel A: Factor prices				
GMM	$\boldsymbol{DOL}$	$\boldsymbol{signSKW^e}$	$\boldsymbol{R^2}$	$\boldsymbol{HJ}$
b	-0.8887	6.9109	0.87	0.23
s.e	(1.9048)	(5.8251)		[0.63]
λ	0.0242	4.4270		
s.e	(0.0472)	(3.7201)		
FMB	$\boldsymbol{DOL}$	$\boldsymbol{signSKW^e}$	$\boldsymbol{R^2}$	$\boldsymbol{RMSE}$
λ	0.0236	3.9719**	0.81	0.0120
(NW)	(0.0183)	(2.0160)	.	.

Panel B: Factor Betas					
	$\boldsymbol{\alpha}$	$\boldsymbol{DOL}$	$\boldsymbol{signSKW^e}$	$\boldsymbol{R^2}$	$\boldsymbol{RMSE}$
C_1	-0.002**	0.222**	-0.0094***	0.05	0.0171
	(0.001)	(0.108)	(0.0025)	.	.
C_2	-0.001	1.29***	0.0051	0.77	0.0126
	(0.001)	(0.084)	(0.0033)	.	.
C_3	0.005**	1.769***	0.0052**	0.65	0.0229
	(0.002)	(0.081)	(0.0023)	.	.

Notes: This table reports the asset pricing results of the linear factor model on dollar risk factor DOL and global skewness factor innovation $signSKW^e$, which is the AR(1) residual of $signSKW$. Panel A reports the cross-sectional results from SDF parameter estimates b and risk premium λ obtained by GMM and Fama-Macbeth procedure. The test assets are portfolio excess returns C_1 C_2 C_3 sorted on interest rate differentials between foreign country and US. Portfolio C_1 contains 3 currencies with smallest interest rate differentials while Portfolio C_3 contains currencies with 2 largest interest rate differentials. Portfolios are rebalanced at the end of every month. For GMM, we report standard errors (s.e.) of coefficients estimates in the parentheses, and Hansen-Jagannathan (HJ) statistics with P-value in the square bracket. For FMB, we report market risk price λ for each factor with standard errors calculated according Newey and West (1987). Following Lustig *et al.* (2011), we do not include a constant in the second step of Fama-Macbeth procedure. Panel B reports results of time series regressions of factor betas. Standard errors reported in parentheses are adjusted to Newey-West standard and computed with the optimal lags according to BIC criteria. The adjusted R^2 and square-root of mean errors $RMSE$ are also reported. Data involved here is monthly data ranging from December 2001 to February 2013.

Table 5-3: Currency portfolios sorted on betas to the global skewness, window=36

Portfolio	P_1	P_2	P_3	DOL	HML
Mean	-0.0148	-0.0078	0.0457	0.0077	0.0605
st dev	0.0738	0.0785	0.1080	0.0689	0.1047
Skew	-0.72	-1.14	0.08	-0.96	0.47
kurt	4.85	7.78	4.83	8.06	4.70
Sharp Ratio	-0.14	-0.11	0.06	-0.06	0.21
CH test	0.12	1.01	0.01	0.64	0.64
LM test	0.20	5.17**	0.07	0.56	2.23
ZA test	-11.14***	-9.84***	-10.42***	-10.38***	-11.34***
Pre-β	-0.0247	-0.0132	0.0020	-0.0120	0.0267
Post-β	-0.0193	-0.0085	0.0042	-0.0079	0.0236

Note: This table reports statistics of annualized excess return for carry trade portfolios, DOL and HML portfolio, which are constructed by sorting currencies based on global skewness beta $\beta_t^{j,signSKW^e}$. Following Lustig *et al.* (2011), the global skewness beta is obtained by regressing currency j's log change in exchange rate ΔS_t^j on global skewness factor innovation $signSKW^e$on a 36-period moving window that ends in month $t-1$. Portfolio P_1 contains 3 currencies with the lowest βs, portfolio P_3 contains 2 currencies with the highest βs. DOL is the average of portfolio P_1 to P_3. HML is constructed by taking the difference between P_1 and P_3. The portfolios are re-balanced at the end of every month. Annualized excess return is calculated as multiplying monthly means by 12 and multiplying monthly standard deviations by $\sqrt{12}$. Sharp ratio is computed as ratios of annualized excess returns means to annualized standard deviations, considering US interest rate as the risk-free asset. We report the average pre-formation βs for each portfolio. The last panel reports the average post-formation βs, which are obtained by regressing currency j excess return Z_t^j on DOL and $signSKW^e$ on a 36-period moving window that ends in month $t-1$. We use Cumby and Huizinga (1992) (CH) test for auto correlation. The H_0 of CH test: the series has no serial correlation under assumption of heteroscedasticity. To test heteroscedasticity, we report the LM statistics of the ARCH effect. To test stationarity, we report the statistic of Zivot and Andrews (1992) (ZA) test which has the null of non-stationarity tested under the assumption of one structural break. We mark the significant statistics at 1%, 5%, 10% level by asterisk ***, ** and *. Data involved here is monthly data ranging from December 2001 to February 2013.

6. Predictors of crash risk and price of crash risk

6.1 Introduction

In this chapter, we study the information relating to currency crash in the option price. We establish a link between the perceived crash risk, measured by the option price, and the realized currency crash risk, measured by skewness of historical exchange rate movements. We study the predictors of currency crash risk and verify the idea that the currency crash risk is endogenous in carry trade. We also study the predictors of crash risk insurance, because purchasing crash insurance is widely applied in carry trade. Identifying the predictors of crash risk and crash insurance helps us to understand the FX market dynamics that link to carry trade.

Interest rate plays an essential role in carry trade and the link between interest rate and excess returns has been widely studied in carry trade literature. Burnside *et al.* (2006), Lustig and Verdelhan (2007) find that carry trade excess return strongly relates to the interest rate differentials and currencies of different interest rate levels have different risk premium loadings. Hassan and Mano (2014) develop a theoretical model through empirical findings and point out that carry trades are driven by the persistent interest rate differential. We follow these literatures and consider that interest rate differential initiates carry trade.

In this thesis, we use risk reversal to measure the price of currency crash insurance. Recent studies suggest that, although priced in a risk-neutral world, currency options contain information about the investors' view on future currency crash. The risk reversal is the implied volatility spread between two "wing" options, namely an out-of-money call option and an out-of-money put option. If the underlying exchange rate movement is symmetrically distributed, the price of the call option should be perfectly offset by that of the put option, so the price of risk reversal should equal to zero. Nevertheless, Farhi *et al.* (2009) documented that currency risk reversal is no longer symmetric since the crisis in 2008. The price of risk reversal of AUD and NZD, for example, notably increased since the beginning of crisis. For high interest rate currencies, the large depreciation risk is better prevented than the risk of large appreciations. The asymmetry of the risk reversal price implies that the underlying exchange rate movement is skewed. The skewed exchange rate distribution is linked to currency crash. Accordingly, currency options price reflects the price of insurance that investors would pay to protect against the downside risk for each lag of carry trade portfolio.[18] However, instead of using currency options to build a theoretical model as in other studies, we are interested in knowing if the option-implied disaster information synchronizes with the realized crash risk, computed as the skewness of historical changes in exchange rates. We investigate the relationship between the realized crash risk and the price of insurance while controlling the effect of interest rate and future position.

Our contribution to the literature is that we provide empirical evidence to support the presence of skewness premium from another perspective with a robust estimation framework. We find that after controlling the interest rate and the carry trade positions, there is a skewness premium which co-moves with the excess returns of carry trade. This is consistent with our finding in chapter 5, where we find a positive skewness risk premium via cross-sectional asset pricing model. Our finding on this skewness premium is in line with Brunnermeier *et al.* (2008) and Jurek (2008). Moreover, we investigate the dynamics of several aspects of carry trade in developed currency market under a robust empirical model framework. We find that the currency crash risk of carry trade is endogenously created by carry trade activity. Recent gain and large carry trade positions significantly predict future currency crash. Accordingly, recent loss of carry trade discourages carry trade activity, reduces the funding to purchase the crash risk insurance and also reduces the chance of currency crash occurring in the FX market. Nevertheless, we do not find currency options containing information to forecast currency crash risk after controlling interest rate, carry trade positions and recent payoff of carry trade.

We organize this chapter in the following way: we introduce background literature and motivation in section 6.2, followed by section 6.3 in which we specify how the variables enter our empirical models. In Section 6.4, we introduce empirical models along with the estimators we employ. We present empirical results in section 6.5 and conclude in section 6.6.

[18] We use the term risk reversal, risk-neutral skewness and the price of insurance against crash risk interchangeably in this thesis.

6.2 Background and motivation

6.2.1 Interest rate and carry trade excess return

The link between the interest rate and the exchange rate has been captured by some studies. Applying different decomposition methods, Hassan and Mano (2014) argue that the IRD is associated with the asymmetries in currency risk premium. In terms of the actual trading process, the IRD provides *ex ante* information which leads to the payoff of carry trade in the next period. Farhi *et al.* (2009) build a structural model that includes both Gaussian and disaster risk in carry trade. Their model implies strong link between interest rate, the exchange rates and the disaster risk. In their model, interest rates are high in countries whose currencies tend to depreciate when disasters occur and the model captures first-order economic links between the average compensation for disaster risk and the average interest rates.

These findings, through the theoretical models, suggest that the IRD should be included in a linear econometric model when studying the trading process of carry trade.

6.2.2 Option implied risk in carry trade

Assuming the unbiasedness of implied volatility, some literature studies disaster in currency markets from the perspective of currency options. Bhansali (2007) studies the properties of hedged carry trade strategy with a combination of options and finds that carry trade combined with options opens an arbitrage opportunity between the FX option and the interest rate market. Jurek (2008) argues that currency option contains information in forecasting currency crash and derives an option-implied crash risk factor which accounts for more than a third of excess return of carry trade. Galati *et al.* (2007) argues that risk reversal is a directional indicator of the time when depreciation of foreign currencies is likely to happen. After the crisis in 2008, the price of put options is higher than that of equivalent call options. Although the asymmetric price pattern of option smile is strengthened after 2008, currency options are still the essential tool to protect carry trade positions in trading. In other words, the arbitrage opportunity between a FX option and the interest rate market documented by Bhansali (2007) still exits. Chernov *et al.* (2014) studies daily change in exchange rates and at-the-money options. They specify the law of motion of stochastic volatility at high frequency and consider jumps in volatility. They argue that jump risk accounts for 25% of currency risk, where jumps in levels are related to macroeconomic news, while jumps in volatility are not.

A group of studies find that quoting frequency of implied volatility affects the quality of information contained in implied volatility. Particularly, high-frequency data is useful in studying option pricing with jumps. This strand of high frequency option study was pioneered by Merton (1976) with a study on equity options. Bates (1996) shows that the exchange rate jumps are necessary to explain option smiles. Carr and Wu (2007b) argue that the riskiness in Japanese Yen and British pound against the US dollar is time-varying and related to stochastic premium. Barro and Ursúa (2008) propose a model with high frequency data and test that disasters happen every 30 years.

In our study, we adopt risk reversal as a proxy of price of crash risk. We consider it conveys the market view on the evolving exchange rate movement. Our focus is on the micro-structure explanation of crash risk. Apart from the high frequency options studied in the literature, the one-month frequency quote option in our empirical study is very relevant to the practitioners as well. Farhi *et al.* (2009) uses one a month frequency option to build an effective model to quantify disaster type risk premium in crisis, which proves that a one-month frequency option is informative in reflecting the market view regarding disaster risk.

6.2.3 Measuring carry trade activity

Klitgaard and Weir (2004) find a strong contemporaneous relationship between weekly changes in speculators' net positions, published by Chicago Mercantile Exchange (CME), and exchange rate movements. Galati *et al.* (2007) use option positions data of net-commercial traders from CME and find that the growth in carry trades funded in Japanese Yen and Swiss francs contributes to the increased activity in these currencies in international banking markets, the turnover pattern in the derivatives and the FX market. Anzuini and Fornari (2012) use the monthly ratio of net position data on open interest of 6 currencies and conduct a study of the macroeconomic impact of carry trade with an extended VAR model proposed in Brunnermeier *et al.* (2008). They find that the demand shocks and confidence shocks are associated with long-term profit of carry trade activity. We follow these studies and use monthly ratio of net position of non-commercial traders regarding open interests to measure the carry trade activity.

6.3 Data cleaning

In this section, we investigate the correct form for variables to enter the empirical models. The variables involved in our empirical models are the skewness $(skew)$, interest rate differentials (IRD), trading activity (FP), carry trade return (Z) and the price of risk insurance (RR).

In section 3.2, we examine the properties of $skew_t^j$, IRD_t^j, FP_t^j, Z_t^j and RR_t^j for individual currencies j. $skew_t^j$ and Z_t^j enter the models directly since they are not auto-correlated neither nonstationary. We take the first difference of IRD_t^j, and RR_t^j to remove the non-stationarity and present the results in panel A Table 6-1. We consider there is a mix integration of I(1) and I(2) in IRD_t^j series, where IRD_t^j series of GBP, NOK and NZD are I(2), and IRD_t^j series of EUR, JPY, CHF, CAD and AUD are I(1). We deal with this mixed stationarity problem by having ΔIRD_t^j enter the models and using panel ARDL estimator to accommodate the mixed integration problem in the data. We use ΔRR_t^j for all currencies in the empirical models, since panel C in Table 6-1 shows that all ΔRR_t^j series reject the null hypothesis of non-stationarity at 1% significance level. Following Menkhoff *et al.* (2012a), we deal with the autocorrelation problem in FP_t by taking the AR(1) residual FP_t^e. Panel B in Table 6-1 shows that the serial correlation is removed, since all FP_t^e series reject the null hypothesis of non-stationarity at 1% significance level. Thus, we use FP_t^e for all currencies to enter the empirical models to measure carry trade activity.

6.4 Methodology

In this section, we set up the empirical model specification to explore the relationships between $skew$, IRD, FP, Z and RR. Following Brunnermeier *et al.* (2008), we calculate the realized $skew_t^j$ for each currency j according to formula (8) and use them in the panel regressions. We note that the realized skewness of individual currency $skew_t^j$ is different from the global skewness factor $signSKW$ we proposed in chapter 5, as the latter is the average of signed individual skewness. We focus on the individual skewness in this chapter.

6.4.1 Empirical models

Brunnermeier *et al.* (2008) proposed a series of panel regressions to predict the crash risk and the price of crash risk with a vector of predictors. We follow their approach by applying these panel regressions consisting of 8 currencies on a monthly basis.

We condition the currency crash risk and the price of crash risk on the level of interest rates. The reasons are the following: firstly, as argued by Farhi *et al.* (2009), currency market does not offer significant returns for unconditional investments in any randomly chosen currency. Thus, a study of the risks which explain carry trade returns needs to be based on interest rates. Secondly, Hassan and Mano (2014) find that carry trades are driven by persistent IRD, which is associated with the asymmetries in the currency risk premium. A rise in IRD should boost carry trade activities and a linear econometric model should include IRD. Thus, interest rate is important in predicting skewness and risk reversal. We follow Brunnermeier *et al.* (2008) by using IRD_{t-1}^j in the empirical model specified as the following:

$$skew_t^j = \alpha_j + \beta_{IRD} \times IRD_{t-1}^j + \varepsilon_{j,t} \qquad \text{model (1)}$$

We use skewness to measure currency crash risk, a large positive value of $skew_t^j$ indicates depreciation of foreign currency, meaning larger currency crash risk. A positive β_{IRD} means that higher interest rate differential predicts higher currency crash risk. A negative β_{IRD} means that higher interest rate differential predicts lower currency crash risk in the next month.

We next add future position FP_{t-1}^{j} into model (1) to examine whether the carry trade activity can predict currency crash risk after controlling IRD_{t-1}^{j}:

$$skew_t^j = \alpha_j + \beta_{IRD} \times IRD_{t-1}^j + \beta_{fp} \times FP_{t-1}^j + \varepsilon_{j,t} \qquad \text{model (2)}$$

As described in the previous section, FP_{t-1}^{j} measures the volume of carry trade activity for currency j at month $t-1$. A positive β_{fp} means that large trading positions in foreign currency predict future currency crash risk. A negative β_{fp} means that trading positions in foreign currency do not relate to the depreciation in foreign currency and then fail in predicting currency crash risk.

Then we are interested to know whether the past return of carry trade predicts currency crash. We add recent pay off Z_{t-1}^{j} into model (2), so that model (3) allows us to see the influence of recent carry trade payoff on currency crash when controlling the interest rate IRD_{t-1}^{j} and carry trade activity FP_{t-1}^{j}.

$$skew_t^j = \alpha_j + \beta_{IRD} \times IRD_{t-1}^j + \beta_{fp} \times FP_{t-1}^j + \beta_Z \times Z_{t-1}^j + \varepsilon_{j,t} \qquad \text{model (3)}$$

Z_{t-1}^{j} measures the recent payoff of carry trade for currency j at month $t-1$. A positive β_z means that gains from carry trade predicts future currency crash risk. A negative β_z means that recent loss of carry trade predicts currency crash risk.

We note the potential multi-collinearity problem in the models. We do not find large correlation between IRD_{t-1}^{j} and Z_{t-1}^{j}. We calculate the correlation for each currency and show it in panel A in Table 10-4. The correlation coefficient between IRD_{t-1}^{j} and Z_{t-1}^{j} is small. EUR, JPY, CHF, CAD, AUD, NOK have correlation smaller than 0.1. GBP, AUD have negative correlation smaller than -0.1. NZD has negative correlation at -0.14. Therefore, adding Z_{t-1}^{j} into the model does not induce the multicollinearity problem nor bias the estimation of standard error.

Most importantly, we add risk reversal RR_{t-1}^{j} to the predictive model. model (4) shows the net effect of risk reversal in predicting future currency crash risk after controlling the interest rate IRD_{t-1}^{j} and carry trade activity FP_{t-1}^{j} and past return Z_{t-1}^{j}.

$$skew_t^j = \alpha_j + \beta_{IRD} \times IRD_{t-1}^j + \beta_{fp} \times FP_{t-1}^j + \beta_Z \times Z_{t-1}^j + \beta_{rr} \times RR_{t-1}^j + \varepsilon_{j,t} \qquad \text{model (4)}$$

A positive β_{rr} means that the price of risk reversal predicts the currency crash risk. If the price of currency insurance does synchronize with the movement of downside risk in currency trading, we expect to see a positive coefficient. A negative β_{rr} means that the price of risk reversal links with negative skewness. This means that the price of insurance does not predict depreciation in foreign currency, thus failing in predicting future crash risk.

Then we turn to the predictors on the price of crash risk insurance. We focus on investigating whether the realized crash risk and the perceived crash risk are affected by the same set of market factors by regressing risk reversals on the same set of variables used in regressions of realized skewness. Running sets of comparative regressions helps to find out how the crash risk and the price of risk insurance react to the dynamics of the FX market. As with crash risk, we start by investigating the predictive power of interest rate differential IRD_{t-1}^{j} on risk reversal RR_t^j. The empirical model is specified as follows:

$$RR_t^j = \alpha_j + \beta_{IRD} \times IRD_{t-1}^j + \varepsilon_{j,t} \qquad \text{model (5)}$$

As described in the data section, RR measures the price of crash risk that investors would pay to protect carry trade positions. A positive β_{IRD} indicates that higher interest rate predicts higher price of currency crash risk. A negative β_{IRD} indicates that higher interest rate predicts lower price of currency crash risk in the next month.

Based on model (5), we next add in future position FP_{t-1}^{j} and investigate whether FP_{t-1}^{j} is effective in predicting RR_{t-1}^{j} when controlling IRD_{t-1}^{j}:

$$RR_t^j = \alpha_j + \beta_{IRD} \times IRD_{t-1}^j + \beta_{fp} \times FP_{t-1}^j + \varepsilon_{j,t} \qquad \text{model (6)}$$

A positive β_{fp} indicates that after controlling the interest rate, larger carry trade positions predict higher price of currency crash risk. A negative β_{fp} indicates that larger carry trade positions predict lower future price of currency crash risk.

Lastly, we add in the past return Z_{t-1}^j of carry trade into model (6) to examine the impact of recent payoff of carry trade on the price of crash insurance when controlling the interest rate IRD_{t-1}^j and carry trade activity FP_{t-1}^j:

$$RR_t^j = \alpha_j + \beta_{IRD} \times IRD_{t-1}^j + \beta_{fp} \times FP_{t-1}^j + \beta_z \times Z_{t-1}^j + \varepsilon_{j,t} \qquad \text{model (7)}$$

A positive β_z indicates that after controlling the effect of interest rate and trading positions, carry trade gains predict higher price of currency crash risk. A negative β_z indicates that the loss of carry trade predicts lower future price of currency crash risk.

6.4.2 Panel country fixed effect estimator and Panel ARDL estimator

We use two sets of estimators in the empirical models introduced above: the panel estimator with country fixed effect (FE) and the panel ARDL estimator. The FE estimator is used to control the cross-sectional unobservable country-specific component. Panel ARDL estimator is used to accommodate the mixed properties of I(1) and I(2) in IRD_t^j series across individual currencies, as shown in Table 6-1. The researchers who proposed this estimator M.H. Pesaran and Shin (1996) argue that it allows for independent variables being a mix of I(1) and I(0) and therefore it delivers consistent and effective estimates. Since we use the first differenced form ΔIRD_t^j to deal with the I(1) variables in the panel model, it is possible to have inconsistent estimates due to ignoring another unit root in some I(2) IRD_t^j series. M. H. Pesaran *et al.* (1999) demonstrates that the panel ARDL estimator offers consistent and efficient estimates with good small sample properties when sample sizes scales to 150 observations, which is close to our sample size in the model. We adopt critical values from M. H. Pesaran *et al.* (2001).

6.5 Empirical results

6.5.1 Portfolios sorted on interest rate differentials

In this section, we look at the characteristics of portfolios which are built to focus on the aggregate risk in carry trade and eliminate idiosyncratic variations in individual currencies. Applying the sorting technique of Lustig and Verdelhan (2007), we follow Farhi *et al.* (2009) and show the characteristics of portfolio variables in the exchange rate movement (ΔS^i), the interest rate differential (IRD^i), the negative skewness ($skew^i$), the price of risk insurance (RR^i) and the trading activity (FP^i). We sort individual currencies into 3 portfolios on the interest rate differentials at month t and rebalance the portfolios at the end of every month. Portfolio C_1 contains 3 currencies with the smallest interest rate differentials, while portfolio C_3 contains 2 currencies with the largest interest rate differentials. The portfolio variables are the sample average across the individual currencies' variables in the same portfolio with equal weights. We report the results in Table 6-2. Here we do not use the estimates of the empirical models introduced in section 6.4.1.

Firstly, the same as in Table 4-1, the excess returns in Table 6-2 increase monotonically from portfolio C_1 to portfolio C_3. The sharp ratio spread between high interest rate portfolio and low interest rate portfolio is 0.35. This is consistent with the trend in exchange rate movement and interest rate differential: high interest rate currencies tend to appreciate, where investors earn profit from both the interest rate differential and the appreciation of foreign currency. Next, we find that the perceived crash risk reflected by the implied volatility in currency options shares the same trend as the skewness from portfolio C_1 to portfolio C_3. The realized skewness increases monotonically from portfolio C_1 to portfolio C_3, which is interpreted as high interest rate currencies being more exposed to currency crash risk and that higher probabilities of depreciation of foreign currency align with higher level of risk reversals. Thirdly, if the carry trade activity is an important determinant of the cross-country variation in carry trade excess returns, a portfolio constructed by interest rate should have a spread pattern in future positions. The last panel in Table 6-2 supports this conjecture, where future position has a monotonic incline pattern from portfolio C_1 to portfolio C_3.

These results are consistent with the findings of Farhi *et al.* (2009) and Peter. Carr and Wu (2007a). We provide extensive evidence on a contemporaneous correlation between excess returns and risk reversal for 10 currencies against the US dollar. This suggests that currency crash risk matters for cross-sectional interest rates and that it is perceived by investors in the form of the price that they would pay to remain in the FX market.

We also provide a simple graphic analysis in Figure 6-1to visualize the relationship between the interest rates and other variables in carry trade. We calculate the country specific average of IRD_t^j, $skew_t^j$, Δs_t^j, FP_t^j and RR_t^j for currency j in the time series dimension and then regress the cross-sectional average of $skew_t^j$, Δs_t^j, FP_t^j and RR_t^j on the cross-sectional average IRD_t^j respectively. We see that higher interest rate currencies, such as AUD and NZD, appreciate more than lower interest rate currencies, such as JPY and CHF. However, this appreciation in high interest rate currencies is also accompanied by large skewness, meaning that there is a large chance of depreciation. Moreover, currencies with higher interest rate, such as AUD and NZD, have a higher price of risk insurance and also have a larger future position established on these currencies. These initial graphic results are consistent with the currencies sorting results in Table 6-2, which suggest that large carry trade excess returns potentially link to carry trade positions and risk reversals.

6.5.2 Panel regression results of predictors of crash risk

In this section, we present empirical results of models introduced in section 6.4.1 in Table 6-3. model (1) shows that interest rate differential positively relates to future skewness and the coefficient is significant at 1% level. The panel ARDL estimator has the same results. We then add in the other candidate predictors in model (2), model (3) and model (4) and find that the predictive power of the interest rate differential on future currency crash risk is persistent. This means that high interest rate relates to high future currency crash risk.

In terms of the relationship between future position and crash risk, results of model (2) show that future position strongly positively relates to future skewness when controlling the impact of IRD. The panel ARDL estimator also shows a significant positive future position coefficient, meaning a large position of carry trade builds up the probability of future currency crash risk. Equivalently, unwinding of carry trade position helps to ease crash risk. Next, we look at the relationship between past payoff of carry trade and currency crash risk. model (3) results show that past payoff of carry trade positively predicts future currency crash risk, albeit with marginal significant at 10% level. The panel ARDL estimator also generates results with positive past payoff coefficient with marginal significance. This means that recent gain of carry trade increases the chance of having currency crash. Equivalently, recent loss of carry trade reduces the chance of having currency crash.

Lastly, we add risk reversal into the predictor set, recalling that risk reversal is the price that investors would pay to retain their chance to gain profit in carry trade. After controlling other factors including interest rate, future position and recent payoff, we find a negative relationship between the realized skewness and the risk reversal. The panel ARDL estimator also has a negative coefficient on the risk reversal after control other variables. The negative relationship between realized skewness and risk neutral skewness in investment currency means that higher risk reversal relates to smaller future realized skewness, which indicates that a higher price of insurance does not predict future currency crash. This suggests that the moment when investors would pay more insurance against crash risk on currency positions is not the time that currency crash is likely to happen.

Putting together our findings in models of predicting realized skewness: when interest rate differential is high, carry trade looks particularly attractive. However, currencies involved in carry trade are exposed to currency crash risk. Large positions of currencies stimulated by large interest rate differential are accompanied with higher future currency crash risk. Correspondently, the chance to have currency crash is eased if carry trade loses out. Insurance that protects carry trade positions is not capable of predicting currency crash risk. Our finding regarding the predictors of currency crash risk is in line with Brunnermeier *et al.* (2008): the skewness of carry trade is endogenously created by carry trade activity. However, regarding the prediction power of insurance price, our empirical finding shows that when controlling the interest rate differential and other variables, the price of insurance fails to effectively predict future crash risk.

6.5.3 Panel regression results of the price of crash risk insurance

We next investigate the predictors of the price of currency option, which plays the roles of crash risk insurance to protect carry trade positions from downside risk. We focus on the impact of carry trade activity and recent carry trade payoff in predicting the price of crash insurance. We run models (5) (6) (7) with both country fixed estimator and panel ARDL estimator, and present the empirical results in Table 6-4. The results of model (5) in Table 6-4 show that the impact of interest rate differential on future risk neutral skewness is positive. We then add in the other candidate predictors in model (6) and model (7) and find that this positive prediction power of interest rate differential on future risk neutral skewness is persistent. This means that higher interest rate pushes up the price of risk insurance. We note that the results of ARDL estimator is superior to that of the FE estimator by showing the significant estimates, which indicates that accommodating the potential non-stationarity problem in both ΔIRD_t^j and ΔRR_t^j is necessary in the panel structure.

Comparing model (5) and model (6) in Table 6-4, we see that future position has positive impact on risk neutral skewness, although of marginal significance. Jointly with the finding shown in Table 6-3, we find that future position is positively related to both realized skewness and to risk neutral skewness. This suggests that active carry trading increases the chance of having currency crash and increases the price of crash risk insurance. After controlling the effect of interest rate and carry trade activity, recent gain in carry trade causes investors to be willing to pay more on insurance against crash risk. Recent loss in carry trade discourages investors paying for insurance. This suggests that carry trade positions are better protected by insurance against downside risk when carry trade is winning. We do not find multicollinearity problem in any empirical model which indicates our panel coefficients are stable with efficient estimated standard errors. [19]

By linking these estimation results, we find that there exists a skewness premium that wedges between realized skewness and risk neutral skewness. This is because recent payoff positively relates to realized skewness (shown in Table 6-3) and positively relates to risk neutral skewness (shown in Table 6-4). Therefore, it is natural to conjecture that there is a positive relationship between risk neutral skewness and realized skewness through the connection of recent payoff. Nevertheless, model (3) in Table 6-3 shows that risk reversal is negatively related to realized skewness. This deviation points to the existence of a skewness premium which wedges between realized skewness and risk neutral skewness. This finding is consistent with Brunnermeier *et al.* (2008) who find the skewness premium through panel regressions and Jurek (2008) who finds the skewness premium through constructing the risk factor with currency options.

[19] We test the multicollinearity by calculating the VIF for each empirical model, which stands for the variance of regressors, and present the results in Table 10-5. We do not find any empirical model have VIF value greater than 10, which is considered as an indicator of multicollinearity problem.

6.6 Conclusion

In this chapter, we verify the conjecture that crash risk premium in excess return of carry trade is created within the trade process. Chapter 5 shows that excess return of carry trade can be explained by currency crash risk. In this chapter, we further study the predictors of currency crash risk measured by skewness of exchange rate movements, and of perceived currency crash implied from currency option prices. We investigate channels through which currencies are connected to currency crash risk with robust estimators that accommodate the features of the data.

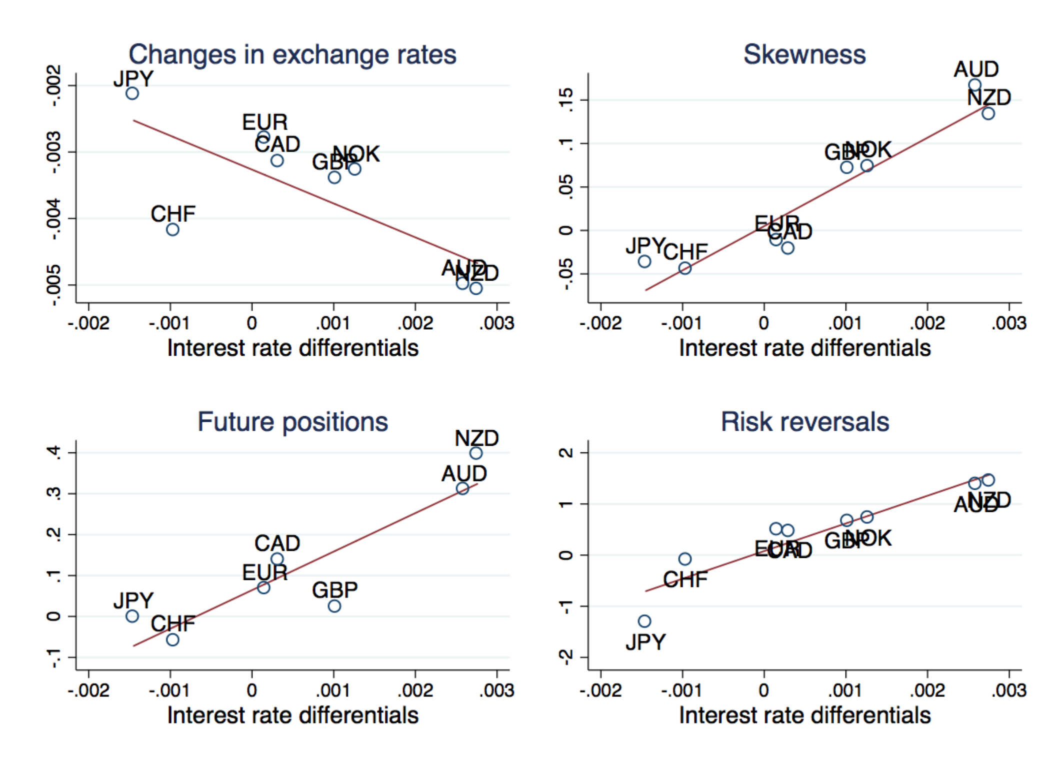
We find that the crash risk premium is endogenously created by the following empirical evidence: the carry trade positions and recent payoff both have direct impact on the profit of this strategy. Large excess return of carry trade relates to large carry trade activity and gains of carry trade attract more investors to join the game. There is a skewness premium that varies negatively with recent payoff of carry trade, which determines the formation of currency crash in both currencies with high interest rate and low interest rates. The existence of this skewness premium is not only consistent with our empirical finding in Chapter 5; we also find that the implied volatility in currency options may not help to forecast currency crash risk after controlling the impact from interest rate and recent payoff of carry trade.

Table 6-1: Test results summary for individual currency variables

	EUR	GBP	JPY	CHF	CAD	AUD	NOK	NZD
				Panel A: ΔIRD				
CH test	0.04	6.15	2.62	0.33	0.23	2.09	14.37***	5.54**
LM test	0.01	2.03	1.83	0.72	0.85	0.47	2.17	1.88
ZA test	-6.07***	-4.59	-11.19***	-6.97***	-12.09***	-6.81***	-4.58	-4.43
$\Delta^2 IRD$ ZA	-11.00***	-10.67***	-10.75***	-10.65***	-12.31***	-10.63***	-12.01***	-15.13***
				Panel B: FP^e				
CH test	0.01	0.78	0.01	0.05	0.09	0.13	n/a	0.29
LM test	0.32	0.42	0.26	0.98	8.78	0.74	n/a	0.03
ZA test	-12.03***	-13.17***	-12.57***	-11.75***	-11.92***	-11.30***	n/a	-10.70***
				Panel C: ΔRR				
CH test	0.49	0.99	0.09	0.29	0.93	1.45	5.54**	0.54
LM test	5.59	0.15	3.85	0.01***	0.07	1.18	2.42	4.94
ZA test	-10.43***	-12.83***	-12.67***	-11.70***	-12.81***	-9.55***	-11.62***	-10.02***
				Panel D: Correlation between ΔIRD_t^j and Z_t^j				
corr	0.0109	0.1904	-0.0464	-0.0511	0.0558	-0.0094	-0.0048	-0.1219

Note: Data test results of first differenced interest rate differential ΔIRD, AR(1) residual of future position FP^e and first differenced 25Δ risk reversal ΔRR. Monthly data for EUR, GBP, JPY, CHF, CAD, AUD, NOK and NZD ranging from January 2002 to January 2013. We report mean, standard deviations, skewness, kurtosis. To test auto correlation, we report the statistics of Cumby and Huizinga (1992) (CH) test. The H_0 of CH test: the series has no serial correlation under assumption of heteroscedasticity. The highest lags order tested for CH test are selected by G.W Schwert (1989) standard. To test heteroscedasticity, we report the LM statistics of the ARCH effect. To test stationarity, we report the statistics of Zivot and Andrews (1992) (ZA) test. ZA test has the null of non-stationarity tested under the assumption of one structural break in the series. Optimal lags used in all stationarity tests are selected by the standard of minimal BIC, proposed in Ng and Perron (2001). We mark the significant statistics at 1%, 5%, 10% level by asterisk ***, ** and *.

Figure 6-1: Interest rate differential and changes in exchange rates, currency skewness, future positions and risk reversals.



Note: This figure shows the negative relationship between changes in exchange rates Δs^j and interest rate differential IRD^j (top left), positive relationship between skewness $skew^j$ and IRD^j (top right), positive relationship between future positions FP^j and IRD^j (bottom left) and positive relationship between risk reversals RR^j and IRD^j (bottom right). The country-specific interest rate differential IRD^j, changes in exchange rates Δs^j, skewness $skew^j$, future positions FP^j and risk reversal RR^j are the time series average of these variables within each currency j. We then regress the Δs^j, $skew^j$, FP^j and RR^j on IRD^j respectively. The line is the fitted values of this regression. The significance and the corresponding fit of the line are as follows: slope is significant at 5% level and goodness of fit is 55% for line in top left panel, slope is significant at 1% level and goodness of fit is 90% for line in top right panel, slope is significant at 1% level and goodness of fit is 80% for line in bottom left panel, slope is significant at 1% level and goodness of fit is 87% for line in bottom left panel. Data involved here is monthly data of 8 currencies, including EUR, GBP, JPY, CHF, CAD, AUD, NOK and NZD, ranging from January 2002 to January 2013.

Table 6-2: Variables of currency portfolios sorted on IRD_t^j

	C_1	C_2	C_3	DOL	HML
			Spot exchange rate change: ΔS		
Mean	-0.0033	-0.0024	-0.0045	-0.0033	-0.0015
st dev	0.03	0.03	0.03	0.02	0.03
			Interest rate differential: IRD		
Mean	-0.0012	0.0003	0.0024	0.0005	0.0037
st dev	0.00	0.00	0.00	0.00	0.00
			Annualized excess return: Z		
Mean	-0.0169	0.0192	0.0923	0.0222	0.1092
st dev	0.06	0.09	0.13	0.06	0.16
Sharp Ratio	-0.21	0.01	0.15	0.02	0.35
			Skewness: $Skew$		
Mean	-0.0553	0.0099	0.1321	0.0289	0.1875
st dev	0.50	0.36	0.47	0.33	0.61
			Risk reversal: RR		
Mean	-0.7730	0.5027	1.1439	0.2856	1.9434
st dev	1.04	0.78	1.09	0.69	1.58
			Future position: FP		
Mean	-0.0290	0.0724	0.3075	0.1170	0.3365
st dev	0.24	0.18	0.21	0.15	0.29

Note: This table contains the mean and standard deviation of the following statistics for each portfolio C_1, C_2, C_3, DOL and HML: the log exchange rate changes ΔS, the interest rate differential IRD between the foreign country and the US, the excess return of carry trade portfolio Z, skewness of the log exchange rate changes $Skew$, 25Δ out-of-money risk reversal RR and future positions FP. For excess returns, we report the sharp ratios, computed as ratios of annualized means to annualized standard deviations, considering US interest rate as the risk-free asset. Portfolio are constructed by sorting currencies into 3 groups based on the rank of IRD_t^j for currency j at the end of month t. Portfolio C_1 contains 3 currencies with lowest IRD, portfolio C_3 contains 2 currencies with the highest IRD. Portfolios are re-balanced at the end of every month. DOL is the average of portfolio C_1 to C_3. HML is constructed by taking the difference between C_1 and C_3. Data involved here is monthly data ranging from December 2001 to February 2013.

Table 6-3: Panel regression results of predicting crash risk

	FE estimator				Panel ARDL estimator			
	model (1)	model (2)	model (3)	model (4)	model (1)	model (2)	model (3)	model (4)
	$skew_t$	$skew_t$	$skew_t$	$skew_t$	$skew_t$	$skew_t$	$skew_t$	$skew_t$
$\beta_{IRD_{t-1}}$	26.23***	30.27***	30.39***	31.19***	30.19***	30.21***	33.84***	38.61***
	(6.29)	(7.49)	(7.49)	(7.54)	(9.89)	(11.15)	(11.12)	(144.04)
$\beta_{FP_{t-1}}$		0.25***	0.21**	0.14		0.56***	0.52***	0.47**
		(0.10)	(0.11)	(0.12)		(0.17)	(0.18)	(0.21)
$\beta_{Z_{t-1}}$			1.07*	1.08			1.53*	1.90*
			(0.64)	(0.74)			(0.86)	(1.03)
$\beta_{RR_{t-1}}$				-0.05*				-0.03
				(0.03)				(0.05)
R^2	0.02	0.03	0.03	0.04	0.11	0.14	0.14	0.17
CH test	0.14	1.00	1.87	0.56	0.16	2.48	2.12	0.41
LM test					0.26	0.38	0.38	0.59

Note: This table reports panel predictive regressions results using country fixed effect estimator (left panel) and using panel ARDL estimator to account for panel non-stationarity (right panel). We regress individual currency's skewness of exchange rate changes $skew_t^j$ for currency j at month t on various predictors of month $t-1$, including interest rate differentials IRD_{t-1}^j, future positions FP_{t-1}^j, carry trade excess returns $Z_{t-1}^j$and 25Δ risk reversals RR_{t-1}^j. We use first difference form ΔIRD_{t-1}^j and $\Delta RR_{j,t}$ to enter the model to remove the non-stationarity found in the raw data series. We use AR(1) residuals ΔFP_t^e to remove the autocorrelation found in raw data series FP_{t-1}^j. Standard errors reported in parentheses are heteroscedasticity and autocorrelation robust, the optimal lags are computed according to the Newey and West (1987) standard and selected by the BIC criteria as follows: 34 lags in Model 1, 33 lags in model 2, 33 lags in model 3, 32 lags in model 4. Adjusted R square is reported as well. For the diagnostic test of residuals, we report the statistics of Cumby and Huizinga (1992) (CH) for serial correlation and of series and LM statistics for ARCH effect. The H_0 of CH test: the series has no serial correlation under assumption of heteroscedasticity. Critical values of ARDL estimator are provided in M. H. Pesaran *et al.* (2001) Table CI(iii). We mark the statistics that are statistically significant at 1%, 5%, 10% by asterisk ***, ** and *. Data involved here is monthly data for currencies EUR, GBP, JPY, CHF, CAD, AUD, NOK and NZD, ranging from January 2002 to January 2013.

Table 6-4: Panel regression results of predicting the price of crash risk

	FE estimator			Panel ARDL estimator		
	model (5)	model (6)	model (7)	model (5)	model (6)	model (7)
	RR_t	RR_t	RR_t	RR_t	RR_t	RR_t
$\beta_{IRD_{t-1}}$	6.92	9.67	9.45	18.42**	27.55***	28.78***
	(13.45)	(15.68)	(15.82)	(9.02)	(10.87)	(11.12)
$\beta_{FP_{t-1}}$		0.32*	0.25		0.49***	0.47***
		(0.17)	(0.16)		(0.18)	(0.18)
$\beta_{Z_{t-1}}$			1.65			3.11***
			(1.06)			(0.94)
R^2	0.02	0.03	0.01	0.53	0.54	0.76
CH test	82.7***	96.1***	102.4***	0.29	0.21	0.09
LM test	0.31	0.70	0.69	1.93	0.37	0.06

Note: This table reports panel predictive regressions results using country fixed effect estimator (left panel) and using panel ARDL estimator to account for panel non-stationarity (right panel). We regress individual currency's risk reversal RR_{t-1}^{j} for currency j at month t on various predictors of month $t-1$, including carry trade excess returns Z_{t-1}^{j} interest rate differentials IRD_{t-1}^{j} and future positions FP_{t-1}^{j}. We use first difference form ΔIRD_{t-1}^{j} and ΔRR_{t-1}^{j} to enter the model to remove the non-stationarity found in the raw data series. We use AR(1) residuals ΔFP_t^e to remove the autocorrelation found in raw data series FP_{t-1}^{j}. Standard errors reported in parentheses are heteroscedasticity and autocorrelation robust, the optimal lags are computed according to the Newey and West (1987) standard and selected by the BIC criteria as follows: 33 lags in Model 5, 32 lags in model 6, 32 lags in model 7. Adjusted R square is reported as well. For the diagnostic test of residuals, we report the statistics of Cumby-Huizinga test for serial correlation and of series and LM statistics for ARCH effect. The H_0 of Cumby and Huizinga (1992) test: the series has no serial correlation under assumption of heteroscedasticity. Critical values of ARDL estimator are provided in M. H. Pesaran *et al.* (2001) Table CI(iii). We mark the statistics that are statistically significant at 1%, 5%, 10% by asterisk ***, ** and *. Data involved here is monthly data for currencies EUR, GBP, JPY, CHF, CAD, AUD, NOK and NZD, ranging from January 2002 to January 2013.

7. FX market liquidity and currency order flows

7.1 Introduction

In this chapter, we explain the excess return of carry trade by the liquidity risk in the FX market. Statistics on 2010 report that the FX market is the most liquid market in the world with a total turnover as large as US$3.98 trillion. Since liquidity risk widely exists under imperfect and incomplete market conditions, market players require excess return for providing liquidity in the FX market. Liquidity risk has results in the trading process, such as latency, speed, accessibility and tradability (the ability to hit a listed price), and it is ultimately translated into cost and contributes to the excess return of trading assets.

Previous study in market liquidity has found that it is difficult to measure liquidity in a single dimension, as liquidity is a synthetic effect of trading frictions and relates to many perspectives in trading. The liquidity premium along with how it affects the price formation process has not yet been fully understood. Lately, order flow data offers an innovative angle to measure market liquidity, because it does not involve decomposing any market frictions but encapsulates the result of the synthetic effect across all market frictions to the maximum degree. In this section, we extend the traditional liquidity models and study the price impact of order flow on assets price by applying the method of Banti *et al.* (2012) under the theoretical framework proposed by Kyle (1985) and Evans and Lyons (2002b).

Using a data set comprised of weekly order flow data for 9 heavily traded currencies spanning 7 years, this chapter builds a market liquidity proxy based on the method of Pastor and Stambaugh (2001) which is widely adopted in order flow studies. Moreover, we find the presence of a large common component across the liquidity measures of individual currencies which enables us to construct a market liquidity proxy for the FX market.

Compared with other studies, our order flow data set contains advanced information regarding customer segment order flow across currencies. Customer order flow segment data is important because it provides an insight into the price impact of client-specific order flow. Thus, our study is not limited on the pricing ability of liquidity on the systematic level. We study the underlying economic link between client-specific order flow and exchange rates via constructing liquidity proxies of different customer types.

In this chapter, there are several contributions to the literature: firstly, following Banti *et al.* (2012), we construct liquidity proxy by using coefficients associating with price impact of contemporaneous order flows and find the heterogeneous cross-sectional liquidity feature of individual currency. That is, low interest rate currencies tend to have high liquidity and low sensitivity to the fluctuation of market-wide FX liquidity; while high interest rate currencies tend to have low liquidity, but have higher sensitivity to market-wide FX liquidity. Secondly, based on the various feature of individual currency's liquidity, we find the presence of commonality in individual liquidity, which can be taken as the proxy of market liquidity in the FX market. Thirdly, we find that our market liquidity risk factor has a positive liquidity premium which accounts for 84% of cross-sectional excess returns in carry trade. High interest rate currencies are more exposed to liquidity risk, and low interest rate currencies provide a hedge in times of liquidity crisis in FX market. Moreover, benefiting from the disaggregate of order flow, we find that the heterogeneous quality of information content possessed by different types of client reflects different roles that different clients play in the FX market. Financial customers, such as asset manager and hedge funds are likely to play the role of informed trader in the FX market. Non-financial customers, such as corporate clients, are likely to play the role of liquidity trader due to a lack of good quality private information about the exchange rate movement.

This chapter is organized as follows. Section 7.2 provides an overview of the relevant literature. In section 7.3, we describe the methodology of constructing the liquidity proxy in detail. The empirical results are reported and analysed in section 7.4. We provide a robustness check in section 7.5. Finally, a conclusion is drawn in section 7.6.

7.2 Background and motivation

7.2.1 Measures of liquidity

Liquidity, also known as marketability, is widely agreed to be the degree to which an asset can be traded in the market without affecting the asset's price. Lippman and McCall (1986) define liquidity as the time needed to sell an asset to the best bidder. Grossman and Miller (1988) consider liquidity as the price concession which induces a potential buyer to participate in an immediate trade. An asset is considered illiquid when it is difficult to trade in real time in the market. Liquidity premium, which relates to liquidity risk, makes investors demand higher expected return.

Liquidity comes from the trading process, rather than from any physical trading entity, such as a market maker or trader. Marker makers or dealers can be treated as carriers of liquidity. Tabb (2004) finds that liquidity in trading with individuals, institutions and brokers comes from trading decisions based upon the most profitable and advantageous trading process. Shah and Thomas (1998) argues that the market makers or traders are merely intermediaries who facilitate the market, but are not liquidity producers in the market.

In previous studies, there are several proxies proposed to measure liquidity, including: the bid-ask spread, the liquidity ratio, the volatility ratio and the auto-correlation of returns. The bid-ask spread is a widely-used proxy to capture liquidity. It was identified as early as in Demsetz (1968) then followed by a number of studies. Researchers claim that the profit for a market maker is generated by buying in via bid price and selling by ask price, so the cost of liquidity is hidden in the process of profiting and is carried by the bid-ask spread. However, a number of studies point out the limitation of this proxy. Grossman and Miller (1988) find that the bid-ask spread fails to measure the cost of immediacy, especially in the case of a simultaneous trade of buy and sell. C. M. Lee *et al.* (1993) found that the bid-ask spread can be an insufficient measure of liquidity because of the lack of consideration of the depth of trade. Next, liquidity ratio is defined as the price change per unit over an interval and was implemented by Copper *et al.* (1985). Grossman and Miller (1988) pointed out that this measure does not count in those trades larger than average or in fundamental volatility. Volatility ratio, proposed by Barnea and Denms (1975) is a ratio defined by long term return volatility and short term volatility. This concept is very difficult to measure and failed to be further developed. Auto-correlation of returns serves as the proxy for liquidity by relating the serial correlation of return with liquidity. Goldman and Beja (1979) and Grossman and Miller (1988) reported that trading frequency of security tends to be inversely related to serial correlation of returns. The auto-correlation of returns approach fails to remove the noise in serial return calculation, which weakens the accuracy of this proxy.

7.2.2 Study liquidity with currency order flows

Recently, the price impact of the transactions approach has thrived with implementation not only in the stock market but also in the FX market.

Recent studies propose a new perspective to study liquidity: the order flow along with its price impact. The price impact is the phenomenon where the incoming order (to buy or to sell) induces the price of an asset. It connects the spot price of an asset with its related trading volume, which is presented in the form of order flow. Pastor and Stambaugh (2001) propose measuring liquidity with the temporary price change which is expected to be a return reversal and links with the signed transaction volume. Amihud (2002) and Næs *et al.* (2011) apply this approach and find that lower liquidity is accompanied with a higher volume-related return reversal. Previous studies, such as Kyle (1985), Glosten and Milgrom (1985) and Gehrig and Menkhoff (2004), argue that order flow is a private information channel for dealers to gather their private and dispersed information from customers. This information channel is featured as asymmetric, because the order flow information is unknown by either the customer or the dealers who placed the order. Therefore, the presence of asymmetric information in the market influences liquidity.

Evans and Lyons (2002a) present a new model to link the environmental macroeconomic information and the order flow on a microeconomic level. Evans and Lyons (2009) argue that there is a relationship between spot rates and contemporaneous order flow. Mancini *et al.* (2013) adopt a modified version of Pastor and Stambough's method and measure liquidity with order flow data during the financial crisis. Banti *et al.* (2012) apply the same method on a dataset spanning 14 years across 20 currencies. Rime *et al.* (2010) focus on the inter-dealer market where market makers reveal their customer orders gradually to the market.

7.3 Methodology

7.3.1 Standardize order flows

The descriptive statistics in section 3.3 show that there are large differences in the absolute sizes of aggregate order flows across individual currencies (Table 3-9) and in aggregate order flows of different customer groups (Table 3-10). We make order flows comparable in the empirical analysis by applying three standardization methods proposed in Menkhoff *et al.* (2012b), where order flows are divided by the standard deviation computed on (i) a rolling scheme (ii) a recursive scheme and (iii) an in-sample scheme. We apply the standardization methods of Menkhoff *et al.* (2012b) on both aggregate and disaggregate order flows. We denote order flows $x_{j,t}$ for currency j on week t. For aggregate order flows, we define the standardized order flow $\tilde{x}_{j,t}^{R}$ on a rolling scheme by dividing weekly order flows on their lagged 12 weeks standard deviation:

$$\tilde{x}_{j,t}^{R} = \frac{x_{j,t}}{\sigma(x_{j,t-11;t})} \tag{20}$$

We define standardized order flow over a recursive window $\tilde{x}_{j,t}^{C}$ by dividing weekly order flows on their prior standard deviation up to week t:

$$\tilde{x}_{j,t}^{C} = \frac{x_{j,t}}{\sigma(x_{j,1;t})} \tag{21}$$

We define standardized order flow over in sample window $\tilde{x}_{j,t}^{s}$ by dividing weekly order flows on their full sample standard deviation:

$$\tilde{x}_{j,t}^{s} = \frac{x_{j,t}}{\sigma(x_{j,1;T})} \tag{22}$$

For disaggregate order flows, we compute the disaggregate order flows of a client type by taking the sum of 9 currencies of the same client type and then applying the standardization methods on the disaggregate order flow of each customer group. We only apply the rolling scheme approach in equation (20) to disaggregate order flows.

We note that the rolling and recursive schemes are more practical as they use up-to-date prior information in the series, while the in-sample scheme serves as a benchmark for comparison. By applying these standardization methods, all order flows in our data set are not driven by large transactions such as M&A transactions and become comparable.

7.3.2 Liquidity measure of individual currency

As an intangible and complex concept, the influence of liquidity on the exchange rate needs to be measured by an observable carrier in different dimensions: price impact, trading cost and price dispersion. Measuring liquidity in the dimension of price impact is based on the theoretical study in J. Y. Campbell *et al.* (1993) and Evans and Lyons (2002a).[20] Pastor and Stambaugh (2001) propose using trading volume to measure the price impact of market sentiment in the stock market. Banti *et al.* (2012) propose studying the liquidity in the FX market by using currency order flows. We follow the approach of Banti *et al.* (2012) by using weekly aggregate and disaggregate order flows to construct liquidity measures in the FX market.

Evans and Lyons (2002a) propose a simple regression of currency returns on contemporaneous order flow:

$$\Delta S_{j,t} = \alpha_j + \beta_j \tilde{x}_{j,t} + \varepsilon_{j,t} \tag{23}$$

$\Delta S_{j,t}$ is the exchange rate movement for currency j on week t. $\tilde{x}_{j,t}$ is the standardized order flow for currency j at week t. In our data set, exchange rate measures units of foreign currency in USD and a positive order flow measures the buying pressure in USD. Hence, the net demand (supply) in USD should induce an immediate appreciation (depreciation) of USD. We estimate regression (23) with weekly data with a non-overlapping window of size

[20] Measuring illiquidity by the trading cost can be traced back to Roll (1984); measuring liquidity by the price dispersion was proposed by Chordia, Roll and Subrahmanyam (2000) who link liquidity to the volatility level.

15 to obtain a $\hat{\beta}_{j,q}$ series on a quarterly basis. Following Banti *et al.* (2012), we construct the proxy of individual currency liquidity $L_{j,q}$ by taking the negative $\hat{\beta}_{j,q}$:

$$L_{j,q} = -\hat{\beta}_{j,q} \tag{24}$$

Where the subscript q refers to quarterly frequency of the series.[21] Corresponding to the measure of market depth in Kyle (1985), the contemporaneous price impact of order flow β on the exchange rate is the price impact of a trade which measures how much the changes in exchange rate respond to a given order flow. The higher the price impact, the more exchange rate moves after this trade, indicating illiquidity. We expect to find a positive coefficient ($\beta_j > 0$) associated with the contemporaneous order flow $\tilde{x}_{j,t}$, due to the net buying pressure. Correspondingly, our individual currency liquidity proxy constructed by (24) measures illiquidity and is expected to be negative.

Using negative β to measure liquidity is consistent with recent theoretical models. Evans and Lyons (2002a) find that dealers' quotes reflect their concerns about inventories as dealers are liquidity providers in the market. Thus, the price impact of contemporaneous order flow contains information regarding market liquidity. Rosu (2009) develops a dynamic model to prove that more liquid assets have lower price impact. Empirically, Banti *et al.* (2012) finds that a liquidity measure constructed by negative price impact coefficients does not bias the estimation of liquidity risk premium, because it compares the results with the measure of return reversal.[22]

We acknowledge the weakness of liquidity measure by the dimension of price impact under the framework of Kyle (1985). That is, it does not consider the trading cost which affects the execution of a trade, and the volatility level of the market which causes a price dispersion.

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[21] Banti et al. (2012) estimate the regression (23) with daily data within one month to generate monthly measure of liquidity.

[22] Some studies use return reversal to measure liquidity, which is the lagged order flow accompanied coefficient γ. If the effect of the lagged order flow on the returns is due to illiquidity, γ should be negative and reverses a portion of excess return from the positive impact of contemporaneous order flow.

7.3.3 Constructing market liquidity risk

Next, we construct a common component of exchange rate liquidity which is used as the measure of market liquidity risk factor. The commonality of liquidity in the stock market and bond market has been extensively documented. Despite the segmentation and the heterogeneity trading property of the FX market, the commonality of the liquidity of the FX market is also proved via theoretical models as in Brunnermeier and Pedersen (2007a) and in a series of empirical studies. Brunnermeier and Pedersen (2007a) predict the presence of a market-wide liquidity component via a liquidity spiral model which explains the market-wide crash when liquidity drops in the global market. Chordia *et al.* (2000) and Pastor and Stambaugh (2001) propose generating a systematic liquidity proxy or market liquidity proxy based on individual liquidity measures.

We compute the first difference of individual liquidity series $DL_{j,q}$ to remove the serial correlations. In order to have the proxy for market-wide liquidity less influenced by the extreme values, we follow Banti *et al.* (2012) and Mancini *et al.* (2013) and obtain the common liquidity measure DL_q by taking a trimmed mean. Specifically, we exclude the individual currency beta with the highest and lowest value of $L_{j,q}$, then we take the average of the first differential individual liquidities across the rest of currencies on quarter q:

$$DL_{j,q} = (L_{j,q} - L_{j,q-1}) \tag{25}$$

$$DL_q = \frac{I}{n}\sum_{j=1}^{n} DL_{j,q} \tag{26}$$

In order to accommodate potential autocorrelation of the liquidity measures and isolate the liquidity innovations, we obtain the unexpected component of common liquidity DL_q^c by taking the residual of an AR(1) process in the common liquidity measure DL_q: [23]

$$DL_q = \rho_0 + \rho_1 DL_{q-1} + \varepsilon_q \tag{27}$$

[23] Banti et al. (2012) argues that an AR(1) model is enough to eliminate serial correlation in the residuals. We use common, systematic and aggregate liquidity interchangeably in this thesis.

We take $DL_q^c = \hat{\varepsilon}_q$ as the proxy of systematic liquidity or market liquidity in the FX market of developed countries at quarter q. For disaggregate data, we first obtain the βs associated with disaggregate contemporaneous order flows of customer m from regression (23)(24) and then compute the common liquidity $DL_{m,q}^c$ by regression (25)(26)(27). The customer types m includes asset manager, corporate clients, hedge funds clients and private clients.

7.3.4 Currency liquidity sensitivity to the market liquidity risk

After obtaining the measure of market liquidity with a common liquidity component, we examine to what extent this common liquidity measure can explain the variation of individual currency's liquidity. Following Chordia *et al.* (2000), we run a time-series regression of the individual liquidity $DL_{j,q}$ on the market liquidity component DL_q^c to investigate the sensitivity of individual liquidity to a change in market liquidity:

$$DL_{j,q} = \delta_{0,j} + \delta_{1,j} DL_q^c + \varepsilon_{j,q} \tag{28}$$

$DL_{j,q}$ is the individual liquidity measure for currency j at quarter q obtained from regression (25). DL_q^c is the market liquidity proxy at quarter q constructed from regression (27). $\delta_{1,j}$ is the sensitivity captured by the slope coefficient. The larger the $\delta_{1,j}$ is, the more strongly individual liquidity co-moves with the market liquidity.

7.3.5 Cross-sectional asset pricing

After constructing the liquidity risk factor, we now proceed to investigate via GMM procedure whether liquidity risk is priced in the excess returns of the carry trade portfolios. Test assets are portfolios formed by sorting currencies on the interest rate differentials.

We follow Lustig *et al.* (2011) to provide risk-based explanation of the carry trade excess returns which relies on a standard stochastic discount factor (SDF) approach Cochrane (2005). We examine whether the liquidity factor is included in the framework of linear factor model. Similar in chapter 5, the risk-adjusted excess returns should satisfy the non-arbitrage condition in Equation (13). The expected excess return for portfolio i is determined by the beta pricing of risk factor prices λ and risk factor loading β^i in Equation (14).

Following Cochrane (2005), we estimate parameters of Eq (13) via the GMM. We estimate the risk factor prices λ, the covariance matric of risk factors Σ_f along with other SDF parameters simultaneously with moment condition in equation (16) and k moment conditions $E(f_{t+1}) = \mu$. Here, Z_{t+1}^i is the monthly excess return for carry trade portfolio i, m_{t+1} is the SDF that prices excess returns. f_{t+1} is a $t \times k$ vector of risk factors DOL_{t+1}, which is is defined in equation (11), and DL_t, which is defined in regression (27). $\mu = E(f_{t+1})$ and b is the vector parameters.

We report estimates of factor price λ and b from the first stage GMM. We also report the cross-sectional R^2, the J-statistics and P value of Hansen-Jagannathan (HJ) distance measure, which tests the over-identifying restrictions. The standard errors are adjusted by Newey and West (1987) with optimal lag selection. Following Burnside (2011), we pre-specify the weighting matrix as 1.

Following Lustig *et al.* (2011), we use annualized excess return for all carry trade portfolios C_i in the GMM procedure and report the annualized estimated risk premium λ^{DL}. The standard errors of the estimates are calculated with the correction of Newey and West (1987), which adjusts the covariance matrix to create an unbiased t-statistics. More details about the GMM estimator of risk price λ are provided in the Appendix.

Previous studies, including Menkhoff *et al.* (2012b) and Banti *et al.* (2012), find that the liquidity risk is priced in carry trade excess return. We conjecture that the liquidity risk constructed with quarterly order flow can also explain the excess return of carry trade, which means that we expect a positive and significant risk premium $\widehat{(\lambda^{DL}} > 0)$. This means that portfolios co-moving positively with the order flow implied liquidity risk factor yield a high excess return, whereas portfolios co-moving negatively with the factor yield low excess return. Moreover, in the disaggregate order flow analysis, if the processed superior information does drive the results, we expect to see a difference in risk premium $\hat{\lambda}_m^{DL}$ in asset pricing results of different client group m.

7.4 Empirical results

7.4.1 Liquidity measured with order flow

In this section, we compute the liquidity of the price impact dimension on a quarterly basis with accurate information about the trading volume and direction in our order flow data set.

We start from standardizing order flows by formula (20)(21)(22). We present the results of aggregate order flow in Table 7-1 and that of disaggregate order flow in Table 7-2. We see that the standardization methods of rolling, recursive and in-sample schemes deliver similar results for aggregate order flow. The standard deviations of individual order flows are now comparable. Most order flows are out of autocorrelation, expect for GBP. We only apply rolling standardization to disaggregate order flows and find that order flows of different customer groups have a similar level of standard deviations and none of them has auto correlation. We use standardized order flows to generate individual liquidity measures with both aggregate order flow and disaggregate order flows.

We then estimate regression (23) and present the results of estimated βs for each currency in Table 7-3.[24] We adopt a rolling window scheme to standardize order flows when estimating the series of βs in the main text, since it uses real time information and is useful for out-of-sample purposes. We report the results of using standardized order flow of recursive scheme and in-sample scheme in the Appendix. We do not find significant difference in generating β in different standardization methods. We follow the approach of Banti *et al.* (2012) and use negative β to construct liquidity measure according to formula (24).

We surprisingly find that SEK has a negative β coefficient, which indicates that SEK is the most liquid currency in the sample of developed market. This means that buying USD in this pair causes USD to depreciate and SEK to appreciate. All other currencies have positive β coefficients, which indicates that the average price of impact is positive. This means that buying USD in these currency pairs induces USD to appreciate and foreign currency to

[24] We also run the regression (23) with order flows standardized recursive scheme and in-sample scheme as a robustness check. We present the results of estimated βs in Table 10-4 and Table 10-5.

depreciate. This finding is in line with Evans and Lyons (2002b) and Cerrato *et al.* (2011). Thus, the individual liquidity measure, constructed by negative βs, captures illiquidity in EUR, GBP, JPY, CHF, CAD, AUD, NOK and NZD. Among these currencies, CHF is the most liquid currency, which can be explained by flight-to-quality and the safe haven property of Swiss franc found by Ranaldo and Söderlind (2010). GBP is estimated as relatively illiquid; Chaboud *et al.* (2007) argue that the GBP/USD pair is mostly traded in Reuters rather than on the UBS platform. AUD, NZD are the most illiquid currencies and are traditionally considered as commodity currencies.

The empirical results in Table 7-3 reveal the cross-sectional differences in exchange rate liquidities which have been documented in recent FX studies. Exchange rates strongly relate to currency liquidity. Currencies with lower interest rate tend to have higher liquidity, whereas currencies with high interest rate tend to be illiquid.

7.4.2 Market-wide liquidity measure

In this section, we use the method proposed by Chordia *et al.* (2000) and Pastor and Stambaugh (2001) to construct a common liquidity component based on individual liquidity proxies. We construct the common liquidity component across individual liquidity via formula (25)(26).

We present the statistics of the common liquidity component constructed by aggregate order flow and disaggregate order flows in Table 7-4. The AC(1) coefficients of the AR(1) process and the CH test show that the common liquidity component for hedge fund customer DL_{HF} and private customer DL_{PR} are auto correlated at 1% significance level. The LM statistics of ARCH effect for the private customer DL_{PR} is significant at 5% level. Thus we run regression (27) and take the residual of AR(1) process of the common liquidity DL_{HF} and DL_{PR} as the proxy to measure the market liquidity for hedge funds and private clients. The autocorrelation and heteroscedasticity are removed in the unexpected components. We do not find the serial correlation in aggregate common liquidity DL, asset manager DL_{AM} nor corporate clients DL_{CO}. Shown by LM statistics and ZA test, none of these liquidity series is heteroscedastic nor non-stationary. Therefore, to keep the most information in the series, we take common liquidity measures DL, DL_{AM}, DL_{CO} directly from regression (26) as the market-wide liquidity proxies for general FX market, asset manager and corporate clients.

We plot the evolution of aggregate liquidity risk factor in panel A of Figure 7-1 and that of disaggregate liquidity risk factor in panel B of Figure 7-1. Firstly, we note that all liquidity series is volatile in the beginning of sample period. This can be attributed by the excess liquidity in euro area, which is associated with past portfolio shifts since the single monetary policy on December 1998. The volatility of liquidity FX market also reflects a spillover effect from the equity market Bakaert *et al.* (2007). Secondly, all liquidity series, except for HF clients, declines sharply from the beginning of mid 2007, which corresponds to the liquidity quickly dries out in the FX market in the financial crisis in 2008. A potential reason to explain the liquidity being rebounded in the HF client is that, at the beginning of the crisis, some investors believe the crisis might soon be over and pick up investment through a hedge fund, which is considered as an inside-trader in the FX market.

7.4.3 Sensitivity of individual liquidity to market-wide liquidity

Next, we run regression (28) to test the ability of the common liquidity component to capture the individual liquidity on a quarterly basis. Table 7-5 reports the commonality test results of common liquidity component extracted from aggregate and disaggregate order flows. We find that all δ_1 coefficients are positive and statistically significant at 5% level. Thus, the liquidity of individual currencies positively relates to the market liquidity. The most liquid currencies, such as AUD and NZD, have large sensitivity coefficients and R^2 larger than 15% in aggregate data. The least liquid currencies, such as CHF and CAD, have low sensitivity coefficients and R^2 is smaller than 0.06. For example, one bp drop in market liquidity with aggregate order flow induces a 1.28 bp drop in AUD but only a 0.46 drop in CHF. AUD is frequently used as investment currency and experienced large depreciation during the 2008 crisis. The finding with segment liquidity of different clients extracted from disaggregate order flow shares the same feature as the aggregate market liquidity. We also report the t-statistics of CH test for autocorrelation under assumption of heteroscedasticity. The residuals of regression (28) for most currencies are not serially correlated, with very few exceptions.

This result suggests that common liquidity component can effectively explain the movement of individual currency liquidity. Importantly, individual currencies have heterogeneous sensitivity to the change of market liquidity. The high interest rate currencies tend to have high sensitivity whereas the low interest rate currencies tend to have low sensitivity. The empirical results imply that more attention is needed to manage the liquidity of illiquid currencies, since they are sensitive to change in the market liquidity. The illiquid currencies may offer a hedge when the liquidity risk is high, since they are not sensitive to the change in market liquidity.

Our results of quarterly commonality test of market liquidity are consistent with previous studies, such as Banti *et al.* (2012) and Mancini *et al.* (2013), which find strong commonality in liquidity proxies across currencies in daily order flow. We interpret the commonality across individual liquidities by the roles of liquidity providers that market maker play in the FX market. Facing order flows from clients of a mix of informed and non-informed traders, dealers do require different levels of excess return to accommodate various size of orders when trading different currencies with different kinds of customers. However, inventory concerns are one of the common components for dealers providing liquidity when they deal with all kinds of customers in all currency trading in the market. Market liquidity extracted from order flows reflects this common component.

7.4.4 Portfolios sorted on interest rate differentials

In this section, we form the carry trade portfolios that are used as the test assets in the cross-sectional asset pricing. We use Lustig and Verdelhan (2007)'s technique and sort currencies on the interest rate differentials IRD_q^j at the end of every 15 weeks (approx. quarterly), which aligns with the size of window to generate the βs when constructing the liquidity factor. We compute the excess return Z_q^i for portfolio i at quarter q by taking the average excess return of individual currencies that are sorted into portfolio i. The individual currency excess return Z_q^j, which is defined in (7), contributes equally to the portfolio excess return Z_q^i.The allocation of carry trade portfolio is: portfolio C_1 contains 3 currencies with the lowest interest rate differential, and portfolio C_3 contains 3 currencies with the highest interest rate differentials. The stylized facts are presents in Table 7-6.

We see that there is a monotonic increase trend in the excess return from 0.0331 in portfolio C_1 to 0.1005 in portfolio C_3. The sharp ratio also increases from 0.05 to 0.23. The HML portfolio, which is the difference of longing portfolio C_3 and shorting portfolio C_1, has the largest excess return and the highest sharp ratio. At the same time, we find a monotonic decline trend in the skewness of excess return from positive in portfolio C_1 to negative in portfolio C_3.This indicates that higher interest rate currencies also suffer larger chance of loss, which is consistent with the results of sorting currencies on monthly basis shown in Table 4-1.

Additionally, none of the AC(1) coefficient and LM statistics is significant at 10% significance level. This means that none of these portfolio excess returns is autocorrelated nor heteroskedastic. To test the stationarity, we run the ZA test; the test statistics are all significant at 1% significance level, meaning all of these portfolio excess returns are I(0).

7.4.5 Cross-sectional asset pricing results

Given the evidence of strong decline of market liquidity, we are interested to know whether investors demand a risk premium for bearing the liquidity risk in the FX market. In this section, we follow Banti *et al.* (2012) and use a GMM procedure to conduct a cross-sectional asset pricing analysis on the dollar risk factor DOL and the liquidity risk factor extracted from order flows. Test assets are portfolios formed by sorting currencies on the interest rate differentials on the quarterly basis. The pricing kernel is:

$$m_{t+1} = 1 - b_{DOL}(DOL_{t+1} - \mu_{DOL}) - b_{DL}(DL_{t+1} - \mu_{DL}) \tag{29}$$

Panel A in Table 7-7 reports the results of liquidity risk factor constructed by aggregate order flow. Panel B in Table 7-7 reports the results of liquidity risk factor constructed by disaggregate order flow of different client types.

1. Aggregate order flows results

Panel A in Table 7-7 shows that the market price of risk factor DOL, which is the average portfolio excess return, has annualized risk premium 0.0119 and is significant at 1% level. The annualized market price for liquidity risk factor DL^C is estimated as 0.0004. These risk factors capture 84% cross-sectional variations in excess returns, with insignificant HJ statistics.

The positive liquidity premium of aggregate liquidity factor reveals liquidity features of various currencies: when the liquidity risk is high, low interest currencies have lower excess returns and high interest rate currencies have higher excess returns. When the liquidity condition is bad in the market, meaning more negative value in our liquidity measure, low interest currencies have high excess returns and high interest rate currencies have low excess returns. This means that low interest currencies provide a hedge against liquidity risk while high interest rate currencies are exposed to liquidity risk. When liquidity improves in the FX market, meaning larger value in our liquidity measure, low interest currencies have low excess returns and high interest rate currencies have high excess returns. These low returns in low interest rate currencies are insurance premiums for holding currencies that tend to deliver higher excess returns in the bad times of liquidity crisis.

Jointly with previous findings in individual currency liquidity, we find an interesting pattern across currencies: low interest currencies tend to have high liquidity and low sensitivity with changes in market liquidity. This translates into the situation of low interest currencies having low excess return in times of good liquidity which play the role of hedge in times of bad liquidity. For example, the CHF, which is a highly liquid currency and is least sensitive to the market liquidity, is usually not involved in large depreciations in carry trade. On the contrary, high interest currencies tend to have low liquidity and high sensitivity to changes in market liquidity, which translates into a situation of high interest rate currencies having high excess return in times of good liquidity to compensate investors bearing the possibility of suffering large loss in bad times.

Overall, our cross-sectional results show that the liquidity risk premium is present, which is consistent with Menkhoff *et al.* (2012a) and Banti *et al.* (2012) who conduct a cross-sectional study of liquidity on a monthly basis. We note that the liquidity risk factor is not significant in explaining the cross-sectional variation of portfolios' excess returns. However, it remains to study whether this is due to low frequency of data. Mancini *et al.* (2013) argue that a high-frequency data set allows for accurate estimation of liquidity in the FX market with empirical evidence of different liquidity proxies. Thus, ours results call for further study with high-frequency data with longer period coverage.

2. Disaggregate order flows results

We next turn to asset pricing analysis in different customer groups. In this section, we also apply GMM procedure to conduct a cross-sectional asset pricing on dollar risk factor DOL and client-specific liquidity risk factor DL_m^c, including asset manager (AM), corporate clients (CO), hedge funds (HF) and private clients (PR).

In Table 7-5, we find different signs of average of market liquidity factor of different customer types. We expect that the difference in excess returns of different customer groups can be explained by the customer-specific risk factor DL_m^c of customer type m extracted from disaggregate order flows. In other words, we expect to see different market price premium λs of liquidity risk factor DL_m^c of different end-user segments.

Panel B in Table 7-7 shows the cross-sectional results of different clients. We find that the estimated risk premium of DOL is positive across all clients and the risk premium of DL_m^c have various features. The estimated risk premium of liquidity risk in asset manager, hedge funds and private clients are positive. The estimated risk premium of liquidity risk in corporate clients is negative. The segment liquidity risk factor in the cross-sectional estimations explains more than 57% of variations in excess returns, with insignificant HJ statistics. The opposite sign of liquidity risk premium in corporate clients shows that they play a counter party role in the FX market: when the market is liquid, high interest rate currencies have high excess return for asset manager, hedge funds and private clients, whereas high interest rate currencies have low excess return for corporate clients. This implies that corporate clients are the liquidity provider in the FX market.

Since our liquidity factor is constructed as the price impact of order flows, the empirical results point to substantial heterogeneity in the impact of customers' order flows and provide a quantitative summary of the economic value of private information. We interpret these results as: asset manager and hedge funds are more capable of gathering high quality private information than corporate clients. Corporate clients do not specialize in FX trading as their core activities and therefore lack the good quality of private information of financial customers. Our cross-sectional asset pricing results fit with the literature which proposes the superior information content of financial clients, such as K. A. Froot and Ramadorai (2005), Evans and Lyons (2007) and Menkhoff and Schmeling (2010) which find that financial customers' order flow helps to forecast future FX returns. Our finding compliments the literature by showing that this information content difference on currency returns can also be found in contemporaneous relationship in quarterly frequency data.

This also suggests that although aggregate order flows are dominated by the financial customers due to the larger trading amount, they cover the differences between the financial customers and non-financial customers. This may lead to an inaccurate inference about the theoretical link between the currency excess returns and liquidity risk factor, which is built based on order flows.

7.6 Conclusion

In this chapter, we propose a measure of market liquidity in the FX market by constructing a common liquidity component associated with order flows. We study liquidity of 9 exchange rates over 7 years. We estimate market liquidity measures by applying the Pastor-Stambaugh type method. We use negative coefficient of price impact of various customers to measure liquidity of different client types. We document the presence of a common component from individual liquidity across currencies which reflects the fact that dealers' inventory concerns and preferences form an important channel influencing price formation. The commonality in liquidity reveals its presence in FX regardless of the segmented structure of the FX market or the heterogeneity of trade players acting in this market.

Through a cross sectional analysis, we find that this order flow implied liquidity risk is a priced risk factor in the cross-sectional currency returns, although it is not significant due to lower frequency and short observation period. We show that the shocks in exchange rate and the excess return in carry trade can be explained by this positive liquidity risk premium. Moreover, benefiting from a unique disaggregate order flow data set, we study the information content of different market players by examining the economic impact of liquidity factor extracted from the order flow of different clients. We contribute to the literature by showing that not all order flows are equal in terms of influence in exchange rate and carry trade excess returns. Due to the high quality of private information gathered and operated on in the core business, it is more likely that asset managers and hedge funds play the roles of informed trader. Corporate clients play the role of liquidity provider in the FX market.

Table 7-1: Standardized weekly aggregate order flows

	EUR	GBP	JPY	CHF	CAD	AUD	NOK	SEK	NZD
Panel A: Rolling window									
Mean	0.2469	0.0578	-0.3511	-0.1479	-0.0842	0.0043	0.0395	-0.1798	0.1675
Std dev	1.08	1.09	1.04	1.06	1.04	1.04	1.04	1.07	1.04
AC(1)	0.10	0.12**	-0.01	0.04	0.02	0.08	-0.08	0.09	0.03
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
ZA test	-16.69***	-16.53***	-18.46***	-17.33***	-17.62***	-16.45***	-19.47***	-16.29***	-17.30***
Panel B: Recursive window									
Mean	0.2566	0.0193	-0.3774	-0.2078	-0.0706	0.0219	0.1170	-0.1572	0.2722
Std dev	1.41	1.60	1.29	1.38	1.26	1.53	1.77	1.42	1.73
AC(1)	0.05	0.21***	-0.03	0.01	0.00	0.06	-0.07	0.16	0.04
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
ZA test	-17.65***	-15.04***	-18.87***	-11.09***	-17.98***	-16.90***	-19.43***	-15.46***	-17.21***
Panel C: In-sample									
Mean	0.1893	-0.0062	-0.2901	-0.1717	-0.0627	-0.0024	0.0881	-0.0493	0.1203
Std dev	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
AC(1)	0.04	0.33***	0.00	0.04	-0.03	0.03	-0.03	0.21	0.05
	(0.06)	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
ZA test	-18.29***	-13.24***	-18.82***	-10.89***	-18.46***	-17.44***	-19.36***	-14.73***	-17.07***

Note: This table contains statistics of standardized order flows of 9 currencies pairs: EUR, GBP, JPY, CHF, CAD, AUD, NOK, SEK and NZD. Order flows are standardized by their standard deviation with (i) using a rolling window over the period of 12 weeks. (Panel A), (ii) using a recursive scheme with 12 weeks initialization horizon (Panel B) and (iii) using the in-sample standard deviation. We report mean and standard deviations. To test serial correlation, we report first order autocorrelation coefficients AC(1), which are the residuals from the AR(1) regression. To test stationarity, we report the statistics of Zivot and Andrews (1992) (ZA) test which accounts for one structural break in the series. The H_0 of ZA test is: the series contains unit root under assumption of one structural break. Optimal lags used in ZA test are selected by the standard of minimal BIC, proposed in Ng and Perron (2001). We mark the statistics that are statistically significant at 1%, 5%, 10% by asterisk ***, ** and *. Data here is weekly data of 9 currencies from November 2001 to November 2007.

Table 7-2: Standardized weekly disaggregate order flows

	Agg	**AM**	**CO**	**HF**	**PR**
Mean	-0.2470	-0.4673	-0.4856	0.4812	-0.1302
Std dev	2.98	3.34	3.02	3.28	3.99
AC(1)	0.04	0.10	0.22	-0.03	0.12
	(0.06)	(0.06)	(0.16)	(0.06)	(0.08)
LM test	1.32***	1.40***	2.97***	1.52***	0.09***
ZA test	-17.19***	-16.15***	-14.97***	-18.16***	-16.22***

Note: This table contains statistics of standardized disaggregate order flows across currencies of different customer groups: AM denotes asset manager, CO denotes corporate clients, HF denotes hedge funds PR denotes private clients. Order flows are standardized by their standard deviation by using a rolling window over 12 weeks. We report mean and standard deviations. To test serial correlation, we report first order autocorrelation coefficients AC(1), which are the residuals from the AR(1) regression. To test stationarity, we report the statistics of Zivot and Andrews (1992) (ZA) test which accounts for one structural break in the series. The H_0 of ZA test is: the series contains unit root under assumption of one structural break. Optimal lags used in ZA test are selected by the standard of minimal BIC, proposed in Ng and Perron (2001). We mark the statistics that are statistically significant at 1%, 5%, 10% by asterisk ***, ** and *. Data here is weekly data of 9 currencies from November 2001 to November 2007.

Table 7-3: Regression of exchange rate changes on standardized aggregate order flow (using rolling window scheme)

	$\boldsymbol{\beta_j}$	$\boldsymbol{R^2}$	**CH test**	**LM test**
EUR	0.0020**	0.05	0.35	0.41
	(0.0006)			
GBP	0.0026***	0.06	0.30	11.42***
	(0.0006)			
JPY	0.0034***	0.07	1.58	0.9
	(0.0007)			
CHF	0.0006	0.01	0.06	0.54
	(0.0006)			
CAD	0.0010**	0.01	1.08	3.7
	(0.0005)			
AUD	0.0033***	0.06	0.74	3.12*
	(0.0007)			
NOK	0.0020*	0.02	0.01	5.0**
	(0.0009)			
SEK	-0.0001	0.01	0.08	0.1
	(0.0007)			
NZD	0.0050***	0.10	0.26	1.38
	(0.001)			

Model: $\Delta S_{j,t} = \alpha_j + \beta_j \times \tilde{x}_{j,t} + \varepsilon_{j,t}$

Notes: Time series results of regressing changes in exchange rate $\Delta S_{j,t}$ on contemporaneous order flow $\tilde{x}_{j,t}$ for currency j. The order flows are standardized by the standard deviation using a rolling window over the period of 12 weeks. Standard errors are calculated according to Newey and West (1987) standard and reported in brackets under coefficients. Adjusted R-square is reported in the second column. The t-stats of Cumby and Huizinga (1992) (CH) test for autocorrelation in the regression residuals are reported in the third column. The H_0 of CH test: the series has no serial correlation under assumption of heteroscedasticity. Highest lag order used in CH test are selected by the Schwert (1989) standard. We test the ARCH effect of series and report the LM statistics in the last column. We mark the statistics that are statistically significant at 1%, 5%, 10% by asterisk ***, ** and *. Data involved here is weekly data of 9 currencies from January 2002 to November 2007.

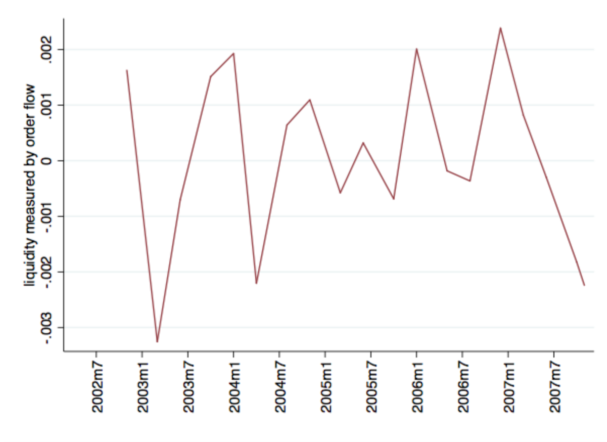
Table 7-4: Descriptive stats of common liquidity components generated from different order flows

	DL^C	DL^C_{AM}	DL^C_{CO}	DL^C_{HF}	DL^C_{PR}
Mean ($\times$ 1000)	-0.22	-0.25	-0.04	0.04	-0.16
Std ($\times$ 1000)	1.60	1.64	1.88	1.52	2.24
Skew	-0.49	0.06	0.34	0.12	-0.41
Kurt	2.67	2.74	2.20	2.49	3.13
AC(1)	-0.23	-0.06	-0.33	-0.72	-0.89
	(0.25)	(0.25)	(0.23)	(0.22)	(0.20)
CH test	0.96	0.07	2.05	7.75***	10.33***
LM test	0.48	0.43	0.29	0.91	7.67**
ZA test	-6.14***	-5.23**	-5.98***	-10.18***	-10.18***

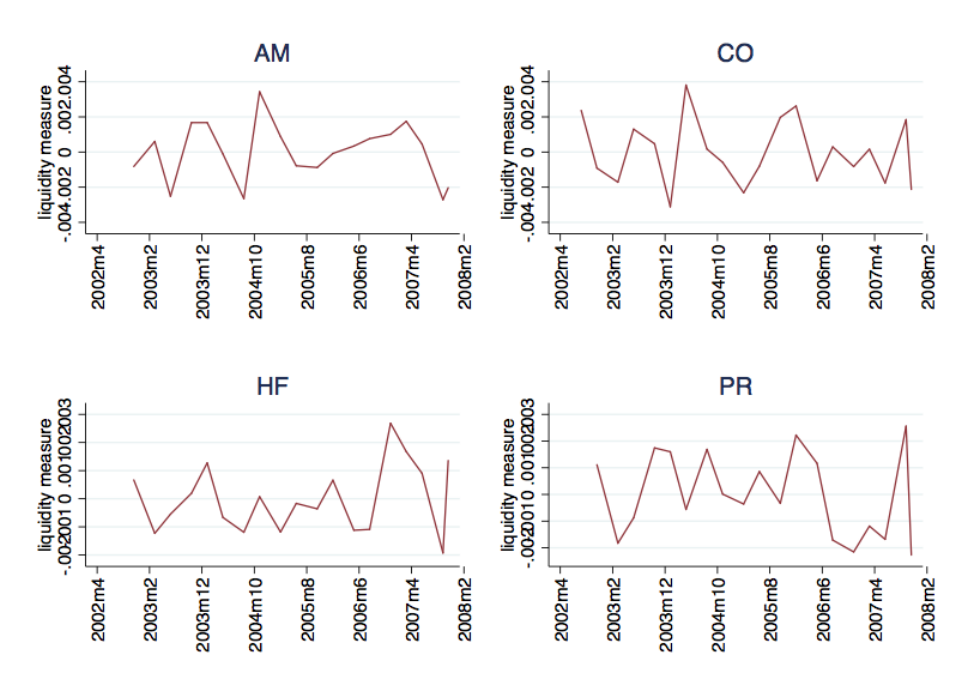
Note: This table reports the statistics of common liquidity component generated by aggregate and disaggregate order flows of different customer groups: AM denotes asset manager, CO denotes corporate clients, HF denotes hedge funds, PR denotes private clients. Common liquidity component is calculated as the trimmed average of individual liquidity measures, excluding the highest and the lowest value of individual liquidity. Individual liquidity measure is obtained by regressing the changes in exchange rates on contemporaneous order flows with a non-overlapping window of size 15 (following in Banti *et al.* (2012)). Order flows are standardized by their standard deviation using a rolling window over the period of 12 weeks, proposed by Menkhoff *et al.* (2012b). We report mean, standard deviations, skewness, kurtosis. To test serial correlation, we report first order autocorrelation coefficients AC(1) and statistics of Cumby and Huizinga (1992) (CH) test. AC(1) coefficients are the residuals from the AR(1) regression. To test auto correlation, we report the statistics of (CH) test. The H_0 of CH test: the series has no serial correlation under assumption of heteroscedasticity. The highest lags order tested for CH test are selected by G.W Schwert (1989) standard. To test heteroscedasticity, we report the LM statistics of the ARCH effect. To test stationarity, we report the statistics of Zivot and Andrews (1992) (ZA) test. ZA test has the null of non-stationarity tested under the assumption of one structural break in the series. Optimal lags used in all stationarity tests are selected by the standard of minimal BIC, proposed in Ng and Perron (2001). We mark the statistics that are statistically significant at 1%, 5%, 10% by asterisk ***, ** and *. Data involved here is quarterly data ranging from August 2002 to November 2007.

Figure 7-1: FX market liquidity risk

Panel A: Constructed by aggregate order flow



Panel B: Constructed by disaggregate order flow



Note: FX market liquidity measured by the price impact coefficient of aggregate order flow and disaggregate order flow of different customer groups: AM denotes asset manager, CO denotes corporate clients, HF denotes hedge funds PR denotes private clients. We use weekly data to generate quarterly liquidity measure ranging from August 2002 to November 2007.

Table 7-5: Regression of currencies' liquidity on common liquidity

	EUR	GBP	JPY	CHF	CAD	AUD	NOK	SEK	NZD
					Panel A: DL^C				
δ_1	0.41**	1.02***	0.96***	0.46**	0.53***	1.28***	1.35***	1.35***	1.60***
	(0.15)	(0.16)	(0.22)	(0.17)	(0.15)	(0.28)	(0.23)	(0.21)	(0.29)
R^2	0.03	0.15	0.11	0.03	0.06	0.18	0.16	0.19	0.19
CH	8.87***	0.62	0.05	2.85	0.10	9.61***	0.88	2.12	0.01
					Panel B: DL^C_{AM}				
δ_1	0.60***	0.61***	1.14***	1.16***	0.67***	1.01***	1.20***	1.51***	1.07***
	(0.14)	(0.18)	(0.23)	(0.21)	(0.15)	(0.23)	(0.20)	(0.23)	(0.22)
R^2	0.06	0.07	0.16	0.19	0.10	0.14	0.13	0.25	0.13
CH	0.06	1.51	1.34	4.74**	2.07	2.69	0.86	0.22	0.44
					Panel C: DL^C_{CO}				
δ_1	0.63**	0.76***	0.87***	0.43*	0.72***	1.40***	0.93***	1.05**	2.16***
	(0.20)	(0.16)	(0.21)	(0.21)	(0.15)	(0.27)	(0.23)	(0.35)	(0.31)
R^2	0.04	0.09	0.09	0.02	0.09	0.15	0.10	0.08	0.30
CH	0.82	0.07	0.11	0.43	3.33*	3.82*	1.67	0.15	0.49
					Panel D: DL^C_{HF}				
δ_1	0.55**	0.71***	0.85***	0.74***	0.68***	1.18***	1.85**	1.03***	1.37***
	(0.18)	(0.13)	(0.17)	(0.14)	(0.17)	(0.21)	(0.60)	(0.24)	(0.35)
R^2	0.05	0.13	0.12	0.12	0.08	0.17	0.21	0.13	0.19
CH	2.21	10.2***	0.22	1.23	1.48	0.17	1.05	0.64	0.49
					Panel E: DL^C_{PR}				
δ_1	0.69***	0.60**	0.81***	1.17***	0.70***	1.37***	1.00***	0.97***	1.68***
	(0.14)	(0.21)	(0.16)	(0.17)	(0.12)	(0.23)	(0.22)	(0.21)	(0.22)
R^2	0.10	0.09	0.12	0.20	0.13	0.25	0.11	0.11	0.24
CH	1.16	0.98	2.12	4.32**	0.92	2.40	0.01	2.48	0.12

Model: $DL_{j,q} = \delta_{0,j} + \delta_{1,j} \times DL^c_q + \varepsilon_{j,q}$

Notes: Quarterly data ranging from August 2002 to November 2007. The table reports time series coefficients estimated in model above by regressing individual liquidity $DL_{j,q}$ for currency j at quarter q on common liquidity component extracted from contemporaneous aggregate (DL^c_q in Panel A) and disaggregate order flows of different customer groups across currencies: asset manager (DL^C_{AM} in panel B), corporate clients (DL^C_{CO} in panel C), hedge funds (DL^C_{HF} in panel D) private clients (DL^C_{PR} in panel E). Standard errors are calculated according to Newey and West (1987) standard and reported in brackets under coefficients. The t-stats of Cumby and Huizinga (1992) (CH) test for autocorrelation under assumption of heteroscedasticity and Adjusted R-square are also reported. ***, **, * respectively indicate significance level of 1%, 5%, 10%.

Table 7-6: Currency portfolios sorted on IRD_q^j

Portfolio	C_1	C_2	C_3	DOL	HML
Mean	0.0331	0.0392	0.1005	0.0576	0.1674
st dev	0.08	0.10	0.10	0.07	0.11
Skew	0.21	-1.14	-1.26	-0.48	-1.57
kurt	2.74	6.43	7.32	3.78	8.16
Sharp Ratio	0.05	0.06	0.23	0.15	0.18
CH test	0.51	1.52	0.93	1.48	1.48
LM test	1.17	0.02	0.37	1.20	0.49
ZA test	-8.50***	-5.90***	-6.20***	-6.00***	-7.02***

Note: This table contains statistics of annualized excess return for carry trade portfolios, DOL and HML portfolio, which are constructed based on the interest rate differentials IRD_q^j relative to USD. Portfolio C_1 contains 3 currencies with smallest interest rate differentials, C_2 contains 3 currencies with second smallest interest rate differentials, C_3 contains 2 currencies with largest interest rate differentials. DOL is the average of portfolio C_1 to C_3. HML is the difference between C_1 and C_3. Portfolios are re-balanced at the end of every quarter. Annualized excess return is calculated as multiplying quarterly means by 4 and multiplying quarterly standard deviations by $\sqrt{4}$. Sharp ratio is computed as ratios of annualized excess returns means to annualized standard deviations, considering US interest rate as the risk-free asset. We also report statistics of Cumby and Huizinga (1992) (CH) test for auto correlation; the LM statistics of the ARCH effect for the heteroscedasticity and the statistic of Zivot and Andrews (1992) (ZA) test for stationarity. Data involved is quarterly data ranging from August 2002 to November 2007.

Table 7-7: Cross-sectional asset pricing results

GMM	Panel A: Factor prices – aggregate order flows			
	β_{DOL}	β_{DL}^{C}	R^2	HJ
b	-20.61**	159.20	0.84	0.25
s.e	(14.55)	(131.56)		[0.61]
λ	0.0119***	0.0004		
s.e	(0.0012)	(0.0003)		

Panel B: Factor prices – disaggregate order flows									
AM	β_{DOL}	DL_{AM}^{C}	R^2	HJ	**CO**	β_{DOL}	DL_{CO}^{C}	R^2	HJ
b	-23.95	-103.95	0.59	0.23	b	-14.03*	-296.82	0.57	0.34
s.e	(15.86)	(98.77)		[0.82]	s.e	(9.55)	(140.57)		[0.56]
λ	0.0122***	0.0001			λ	0.0122***	-0.0012		
s.e	(0.0018)	(0.0001)			s.e	(0.0014)	(0.0008)		
HF	β_{DOL}	DL_{HF}^{C}	R^2	HJ	**PR**	β_{DOL}	DL_{PR}^{C}	R^2	HJ
b	-20.31**	284.71	0.90	0.55	b	-21.49**	94.44	0.85	0.17
s.e	(11.33)	(126.98)		[0.28]	s.e	(10.36)	(50.45)		[0.88]
λ	0.0119***	0.0006			λ	0.0120***	0.0004		
s.e	(0.0015)	(0.0004)			s.e	(0.0020)	(0.0004)		

Notes: This table reports the asset pricing results of the linear factor model on dollar risk factor DOL and liquidity risk DL^C extracted from aggregate order flow (Panel A), and other liquidity risk factor extracted from disaggregate order flow (Panel B) of different customers: asset manager DL_{AM}^{C}, corporate clients DL_{CO}^{C}, hedge funds DL_{HF}^{C} private clients DL_{PR}^{C}. We report the cross-sectional results from SDF parameter estimates b and risk premium λ obtained by GMM procedure. The test assets are portfolio excess returns C_1 C_2 C_3 sorted on interest rate differentials between foreign country and US. Portfolio C_1 contains 3 currencies with smallest interest rate differentials while Portfolio C_3 contains currencies with 2 largest interest rate differentials. Portfolios are rebalanced at the end of every quarter. We report standard errors (s.e.) of coefficients estimates in the parentheses, and Hansen-Jagannathan (HJ) statistics with P-value in the square bracket and the adjusted R^2. Data involved is quarterly data ranging from August 2002 to November 2007.

8. Funding liquidity risk and carry trade

8.1 Introduction

We studied the candidate factors that might explain the excess return of carry trade in previous chapters. In chapter 5 we find that the excess return of carry trade can be explained by currency crash risk and that high interest rate currencies in carry trade are more exposed to crash risk. Chapter 7 explains the carry trade excess return by the liquidity risk which is extracted from the price impact of order flows but the explanatory power of liquidity risk factor is low. In this chapter, we look for a systematic risk factor that effectively explains the negative skewness of excess returns of carry trade portfolios. Previous studies point out that funding liquidity is one of those fundamental problems that affects all currencies in carry trade on both investment position and funding position. In this chapter, we investigate the link between funding liquidity and other aspects of carry trade.

The intention for looking at the funding liquidity problem in carry trade is the following: our empirical results show that currency crash is present and has a spill over effect across countries. Brunnermeier *et al.* (2008) document that currencies with similar level of interest rates co-move with each other, when controlling other effects. The global skewness factor proposed in Chapter 5, which gauges the currency crash risk, relies on the information of the exchange rate movement. As a type of fundamental risk in the market, funding liquidity constraint or the uncertainty about the future economy affects the exchange rate movement of all currencies and consequently should explain the currency crash in carry trade in the global FX market.

The funding liquidity constraint or the uncertainty about the future economy affect the excess return distribution of currencies via the channel of investors’ decisions on carry trade positions and the funding to purchase the crash risk insurance to protect the positions against downside risk. The empirical results in chapter 6 show that excess returns of carry trade are endogenously supported by carry trade positions of both currencies with low interest rate and high interest rate involved in the carry trade portfolio. Increasing or unwinding funding positions changes the asymmetries of distribution of return and consequentially affects the currency crash risk, which is defined as the asymmetries of distribution of return. On the other hand, recent gain of carry trade fund investors to purchase more insurance to protect carry trade positions. Funding liquidity also affects the available capital for investors to purchase crash risk insurance. These findings suggest that the impact of funding liquidity that the investors' face on both trading positions and the purchase of crash risk insurance will finally transmit into excess returns. Therefore, we infer that funding liquidity plays an important role in explaining excess return in carry trade.

Following Brunnermeier *et al.* (2008), Menkhoff *et al.* (2012a) and Mancini *et al.* (2013), we use VIX index and TED spread to measure the funding constraint of investors and apply them in the study of carry trade excess return in the FX market. VIX is an implied volatility index published by Chicago Board Option Exchange (CBOE) which measures the investor's fear and uncertainty level on the financial market. TED spread is the 3-month USD LIBOR minus the 3-month T-Bill yield which measures the level of credit risk and funding liquidity in the interbank market.

We have several contributions to the literature in this chapter: Firstly, we extend the analysis on the individual level in Brunnermeier *et al.* (2008) to a cross-sectional analysis. Also, we include TED spread in the asset pricing model of funding liquidity to form a robust and comparative study on VIX. Secondly, we find that tightening funding liquidity in the FX market causes carry trade to unwind and leads to the loss of carry trade. Thirdly, our cross-sectional results show that funding liquidity has a negative risk premium in carry trade and explains 70% of excess return of carry trade. Currencies with low interest rate act as a hedge against the loss caused by tight funding condition, while currencies with high interest rate demand a compensation in equilibrium. The exposure to funding liquidity risk helps to discourage the violation of UIP and pushes the exchange rate back to its fundamental value.

We organize this chapter in the following way: we introduce related background literature and motivation in section 8.2, followed by section 8.3 in which we describe how variables enter the empirical models. We specify the empirical model of market liquidity in section 8.4. The empirical results are presented in section 8.5 and the robustness check is in section 8.6. We conclude in section 8.7.

8.2 Background and motivation

Standard inventory models, proposed by Stoll (1978), predict that an increase in volatility leads to a widening of bid-ask spread and lower liquidity in general as soon as market makers hold undesired inventories. The inventory model suggests that there exists a common factor which drives the various asset liquidities across the market and should be eventually reflected in the excess return. Nevertheless, the inventory models do not consider the decline in market funding liquidity. Therefore, investors' fear or funding liquidity provides a complementary explanation to the change of market liquidity which is expected to further explain part of excess return variations.

Previous research proposes using VIX and TED as proxy of global funding liquidity. VIX is an implied volatility index published by CBOE. Collin-Dufresne *et al.* (2001) are the first to use VIX in the equity market and corporate credit market. Although VIX index is the implied volatility measure developed based on S&P 500 stock options, VIX is not constrained to be used in the equity market. VIX is widely used in literature to measure the investor's fear and funding liquidity in other asset markets. Pan and Singleton (2008) argue that VIX is valid for use in sovereign credit default swaps. Ang *et al.* (2006) use daily VIX from 1986 January to 2000 December to price the cross-sectional excess returns in stock market.

Brunnermeier *et al.* (2008) propose using VIX and TED to measure the funding constraint for investors to unwind carry trade positions. They find that VIX and TED are effective measures of the impact of funding liquidity for investors in carry trade. Menkhoff *et al.* (2012a) argue that it is reasonable to use VIX and TED to measure the volatility of other markets, because periods of turmoil or distress are often shared across different asset classes rather than specific to one certain group of assets. Therefore, we follow the literature by using VIX and TED as the proxy of investors' fear and funding liquidity in the FX market.

Brunnermeier and Pedersen (2007a) propose a liquidity spiral model in which the decrease of liquidity condition in the market typically starts from an increase of uncertainty of the economy and eventually leads to a decrease in funding liquidity. Brunnermeier and Pedersen (2007a) argue that when it is difficult for investors to secure funding for business activities, the market liquidity level turns to low and investors are forced to liquidate their positions when they hit their funding constraints. This situation not only induces prices to move away from fundamentals, leading to a loss on existing positions, but also causes a further reduction of funding liquidity which creates a downward spiral.

Mancini *et al.* (2013) document that VIX and TED are strongly negatively correlated with FX liquidity as -0.87 for daily latent liquidity, which indicates that investors' fear measured by stock-implied liquidity has spill over effects to the FX market. Even when excluding observations between 2008 September and 2009 December, the negative correlations remains at -0.66. This constant negative correlation means that an increase in investor's uncertain and reduction of funding liquidity is followed by lower FX market liquidity. This finding supports the theory of liquidity spiral proposed by Brunnermeier and Pedersen (2007a).

8.3 Data cleaning

In this thesis, we use VIX index and TED spread to measure the funding liquidity level in the FX market. VIX is the implied volatility index of S&P 500 options and is published by CBOE. It measures the speculators' willingness and ability to put capital at risk. TED spread represents the level of credit risk and funding liquidity in the interbank market. The LIBOR rate is the uncollateralized lending rate in the interbank market which is subject to the default risk. T-Bill is a widely accepted risk free interest rate since it is guaranteed by the US government.

We present the features of original VIX and TED series in Table 3-8 in section 3.2.7. The stylized facts show that original VIX and TED series have autocorrelation, heterogeneity and stationarity problems. We firstly deal with the non-stationarity problem by taking the first difference form of ΔVIX and ΔTED. The reason to use the first difference form is that it is the simplest way to get rid of the non-stationarity problem in the series. We present the statistics of ΔVIX and ΔTED in Table 8-1. We see that both the AC(1) coefficient and CH test statistics for ΔVIX and ΔTED are not significant at 10% level, which means that neither ΔVIX or ΔTED is autocorrelated when accounting for heteroscedasticity. The results of ZA test show that statistics that are statistically significant at 1%, meaning there is no unit root in ΔVIX or ΔTED series. We applied LM test for ARCH effect in ΔVIX or ΔTED, and find that both have significant ARCH effect at 1% significance level. We deal with this heterogeneity problem by using the Newey-West estimator in the model to generate efficient estimates. Menkhoff *et al.* (2012a) uses ΔVIX in the cross-sectional pricing models, we follow their approach and extend it to ΔTED based on the data feature we find here.

We plot the series of ΔVIX or ΔTED with the financial crisis period in Figure 8-1. We see that both ΔVIX or ΔTED strongly peaked up during the financial crisis period in 2008. This means that investors suffer large funding liquidity crisis and large uncertainty in the financial market. This feature in ΔVIX or ΔTED series corresponds to the low liquidity condition shown in Figure 7-1.

8.4 Methodology

8.4.1 Funding liquidity measure of individual currency

Brunnermeier *et al.* (2008) point out that the VIX index and TED spread can be used as a global risk factor. However, when it comes to measuring the funding liquidity of an individual currency, the VIX and TED need to be signed by individual currency's interest rate differentials before being applied in the panel empirical models. Following Brunnermeier *et al.* (2008), we construct the funding liquidity measure of individual currency as the following:[25]

$$sign\Delta VIX_t^j = sign(i_{j,t-1}^* - i_{t-1}) \times \Delta VIX_t \tag{30}$$

$$sign\Delta TED_t^j = sign(i_{j,t-1}^* - i_{t-1}) \times \Delta TED_t \tag{31}$$

where

$$sign(i_{j,t-1}^* - i_{t-1}) = \begin{Bmatrix} +1 & if\ i_{j,t-1}^* > i_{t-1} \\ -1 & if\ i_{j,t-1}^* < i_{t-1} \end{Bmatrix}$$

ΔVIX_t and ΔTED_t are the first difference of VIX index and TED spread at month t. $i_{j,t-1}^*$ is the interest rate of foreign currency j at month $t-1$. i_{t-1} is the interest rate of US dollar at month $t-1$.

The reason to sign the VIX index and TED spread with the interest rate differential is the following: the interest rate differential, future positions and risk reversals of foreign currencies indicate the trading direction of carry trade for a currency by switching the signs of quote. However, the original quote of VIX index and TED spread does not indicate the trading direction for each individual currency. Ranaldo and Söderlind (2010) document a "fly-to-safety" effect in the FX market, which means that speculators sell high interest rate currencies and buy low interest rate currencies when the market turns volatile. This indicates that the original VIX or TED quote means different things to high interest rate currencies

[25] Brunnermeier et al. (2008) apply this definition on weekly data; we apply it on monthly data.

and low interest rate currencies. Positive VIX or TED, meaning tight funding liquidity condition of the market, implies that investors are selling high interest currencies but buying in low interest rate currencies. Negative VIX or TED implies investors are buying high interest currencies but selling in low interest rate currencies. Thus, the trading direction for high interest rate currencies and low interest rate currencies needs to be differentiated by signing the VIX index and TED spread.

$(sign\Delta VIX_t^j > 0)$ or $(sign\Delta TED_t^j > 0)$ means an increase of risk adversity level for foreign currency j at month t, which equals a decline of funding liquidity level. Correspondingly, $sign\Delta VIX_t^j < 0)$ or $(sign\Delta TED_t^j < 0)$ means a decline of risk adversity level or an increase of funding liquidity for foreign currency j at month t.

8.4.2 Empirical models of funding liquidity

In this section, we investigate whether the funding liquidity can explain other aspects of carry trade, including the carry trade activity and the excess return of carry trade. We firstly test the impact of funding liquidity on carry trade positions. Then, we look at how the funding liquidity eventually affects the excess return of carry trade. We study the time-series feature of funding liquidity in currency markets via two sets of empirical models in both contemporary and predictive contexts as the following:

Model set I:

$$FP_t^j = \alpha + \beta_{1,FLIQ} \times FLIQ_t^j + \varepsilon_t^j \qquad \text{Model (1)}$$

$$FP_{t+1}^j = \alpha' + \beta'_{1,FLIQ} \times FLIQ_t^j + \varepsilon'^j_t \qquad \text{Model (2)}$$

Model set II:

$$Z_t^j = \alpha + \beta_{2,FLIQ} \times FLIQ_t^j + \varepsilon_t^j \qquad \text{Model (3)}$$

$$Z_{t+1}^j = \alpha' + \beta'_{2,FLIQ} \times FLIQ_t^j + \varepsilon'^j_t \qquad \text{Model (4)}$$

$FLIQ_t^j$ is the funding liquidity, which is measured by $sign\Delta VIX_t^j$ and $sign\Delta TED_t^j$, for currency j at month t. FP_t^j and Z_t^j are future positions and carry trade excess returns for currency j at month t. FP_{t+1}^j and Z_{t+1}^j are correspondent variables of next month $t+1$.

We note the serial correlation problem in dependent variables FP_t^j, as discussed in section 6.3. In order to remove the serial correlation in these variables and generate effective coefficients, we follow Ang *et al.* (2006) by using the first difference form ΔFP_t^j in the empirical models.[26] We adjust the standard errors for estimation uncertainty by using the Newey-West estimator to get rid of the errors-in-variables problem. In order to control the country-specific effect, we run panel regressions with country fixed effect to estimate all of the above models.[27]

In model set I, we regress ΔFP_t on $FLIQ_t$ of the same period in the contemporary context, (Model (1)). We regress future ΔFP_{t+1} on $FLIQ_t$ explore the predictive relationship (Model (2)). A positive contemporaneous coefficient ($\beta_{1,FLIQ} > 0$) means that higher funding liquidity risk or a tighter funding condition relates to large carry trade positions. A negative contemporaneous coefficient ($\beta_{1,FLIQ} < 0$) means that higher funding liquidity risk or a tighter funding condition relates to small carry trade position, indicating the unwinding of carry trade. In the forecasting context, a positive predictive coefficient ($\beta'_{1,FLIQ} > 0$) means that higher funding liquidity risk or a tighter funding condition forecasts more carry trade activity in the next period. A negative coefficient ($\beta'_{1,FLIQ} < 0$) means that higher funding liquidity risk or a tighter funding condition forecasts less carry trade positions in the future.

Similarly, we regress Z_t on $FLIQ_t$ of the same period in the contemporary context (Model (3)) and we regress future Z_{t+1} on $FLIQ_t$ in the predictive context (Model (4)). A positive contemporaneous coefficient ($\beta_{2,FLIQ} > 0$) means that higher funding liquidity risk or a tighter funding condition is related to the gain of carry trade. In the predictive context, a positive predictive coefficient ($\beta'_{2,FLIQ} > 0$) means that higher funding liquidity risk or a tighter funding condition forecasts carry trade gaining profit in the next period.

8.4.3 Cross-sectional asset pricing

We now proceed to investigate whether funding liquidity risk is priced in the excess returns of the carry trade portfolios via GMM and FMB procedure. In the cross-sectional analysis,

[26] We use ΔFP in the main text. We also report the results of using the lag term of FP to remove the potential serial correlation in the regression residuals in the robustness section. We do not find this biases the estimation results.

[27] We also report the time series regression of individual currency in the robustness check section.

we use VIX index and TED spread as global risk factors instead of individual funding liquidity measure proposed in section 8.4.1.

We follow Burnside (2011) and Lustig *et al.* (2011) in providing a risk-based explanation of the carry trade excess returns which relies on a standard stochastic discount factor (SDF) approach Cochrane (2005). We consider that the funding liquidity factor is included in the framework of linear factor model. The risk-adjusted excess returns should satisfy the non-arbitrage condition in Equation (13). The expected excess return for portfolio i is determined by the beta pricing of risk factor prices λ and risk factor loading β^i in Equation (14).

Following Cochrane (2005), we estimate parameters of Eq (13) via the GMM. We estimate the risk factor prices λ, the covariance matric of risk factors Σ_f along with other SDF parameters simultaneously with moment condition in equation (16) and k moment conditions $E(f_{t+1}) = \mu$. Here, Z^i_{t+1} is the monthly excess return for carry trade portfolio i, m_t is the SDF that prices excess returns. f_t is a $t \times k$ vector of risk factors DOL_{t+1}, which is is defined in equation (11), and $FLIQ_{t+1}$, which is measured by measured by ΔVIX and ΔTED. $\mu = E(f_{t+1})$ and b is the vector parameters.

We report estimates of factor price λ and b from the first stage GMM. We also report the cross-sectional R^2, the J-statistics and P value of Hansen-Jagannathan (HJ) distance measure, which tests the over-identifying restrictions. The standard errors are adjusted by Newey and West (1987) with optimal lag selection. Following Burnside (2011), we pre-specify the weighting matrix as 1.

In terms of the FMB, we first obtain portfolio betas β^i_{DOL} and β^i_{FLIQ} from the two factors model:

$$Z^i_{t+1} = \alpha_i + \beta^i_{DOL} f^{\mathrm{DOL}}_{t+1} + \beta^i_{FLIQ} f^{\mathrm{FLIQ}}_{t+1} + \varepsilon_{i,t+1} \tag{32}$$

Where f^{DOL}_{t+1} is the DOL_{t+1} at dollar risk factor at month t. f^{FLIQ}_{t+1} is the funding liquidity risk factor at month $t+1$, measured by measured by ΔVIX and ΔTED. The test assets are portfolios excess returns Z^i_{t+1} formed based on the interest rate differentials and rebalanced on monthly basis. β^i_{DOL} and β^i_{FLIQ} in regression (32) represent the sensitivities of the portfolios excess returns Z^i_{t+1} to the risk factor DOL and $FLIQ$. Regression (32) test if the global skewness risk factor remains priced when accounting for other sources of systematic risk.

In the second step of FMB procedure, we use estimated β^i_{DOL} and $\beta^i_{FLIQ}$for risk factors DOL and $FLIQ$ in the first step and regress cross-sectional excess returns Z^i_{t+1} of portfolios on β^i_{DOL} and β^i_{FLIQ} as:

$$Z^i_{t+1} = \beta^i_{DOL}\lambda^{\text{DOL}}_{t+1} + \beta^i_{FLIQ}\lambda^{\text{FLIQ}}_{t+1} + \varepsilon_{i,t+1} \tag{33}$$

$\lambda^{\text{DOL}}_{t+1}$ and $\lambda^{\text{FLIQ}}_{t+1}$ are the risk premium of the dollar risk factor DOL and $FLIQ$ at month $t+1$ respectively. Following Lustig *et al.* (2011), we do not include a constant in the second stage of FMB in regression (33), because factor DOL_{t+1} already account for cross-sectional invariant values. We report the standard error with Newey and West (1987) standard with optimal lag selection. We use annualized excess return for all carry trade portfolios Z^i_{t+1} in GMM and FMB procedure and report the annualized estimated risk premium. More details about the GMM estimator and FMB estimator of risk price λ are provided in the Appendix.

In the previous studies, Brunnermeier *et al.* (2008) conduct a panel analysis and find that the diversified carry trade portfolios have negative factor loadings on ΔVIX and ΔTED. In our cross-sectional analysis, we expect to see a significant and negative funding liquidity risk premium λ^{FLIQ} ($\widehat{\lambda^{FLIQ}} < 0$) along with dollar risk factors DOL in the asset pricing model. A negative risk premium λ means that portfolios who co-moves positively with the funding liquidity factor have a low risk premium whereas portfolios who co-moves negative with the funding liquidity factor have a high-risk premium.

8.5 Empirical results

8.5.1 Funding liquidity risk in carry trade

In this section, we present the panel regression results to investigate the contemporary and predictive impact of funding liquidity on carry trade positions and carry trade excess returns.

Although the estimate is insignificant, model 1 in Table 8-2 shows that there is a negative contemporary relationship between the ΔVIX_t^j and the ΔFP_t^j. This means that an increase in investors' uncertainty or a low funding liquidity relates to a decline of carry trade positions; in other words, tighter funding liquidity relates to the unwinding of carry trade positions. Moreover, albeit insignificant, model 2 shows that this negative relationship between ΔVIX_t^j and ΔFP_{t+1}^j continues where tighter funding liquidity forecasts the further unwinding of carry trade positions in the future. We also run time series of regressing ΔVIX_t^j on ΔFP_t^j and ΔFP_{t+1}^j for individual currencies and present results in Table 10-8 in the Appendix. Consistent with the panel results, we see that most currencies have negative significant coefficients in both contemporary and predictive regressions.

The first column of Table 8-3 shows a positive contemporaneous relationship between ΔTED_t on ΔFP_t^j and a negative predictive relationship between ΔTED_t^j on ΔFP_{t+1}^j. We note that contemporaneous relationship in model 1 is not significant. However, the predictive relationship in model 2 is significant on 1% significance level. Table 10-10 shows the time series results of regressing ΔTED_t on ΔFP_t and ΔFP_{t+1}^j for individual currencies. This table shows that half of the currencies have negative contemporary coefficients. The other half of the currencies have positive contemporary coefficient, however none of them are significant. In the predictive context, most coefficients are negative. Both panel results and time series results show that TED does not capture the contemporary unwinding effect of funding liquidity on carry trade positions, but successfully forecasts the significant unwinding of carry trade positions in the next month. This suggests that the unwinding of carry trade position reacts more slowly in the interbank funding liquidity measure than in the stock option implied funding liquidity measure.

Next, the second column in Table 8-2 and Table 8-3 shows that ΔVIX and ΔTED are negatively related to both contemporary excess return $Z_t$and future excess return Z_{t+1}. We note that the contemporary estimates in model 3 are significant at 1% level, while neither of the predictive estimates is significant in model 4 in Table 8-2 and Table 8-3. Table 10-9 and Table 10-11 present the time series results of running current excess return and future excess return on the measure of funding liquidity ΔVIX and ΔTED for each currency. Particularly, currencies typically with low interest rate differential, such as JPY can CHF, have positive coefficients; while currencies with high interest rate differentials have negative coefficients. We also find most currencies show negative coefficient in both contemporary and predictive relationship, using either the measure of ΔVIX or ΔTED. This suggests that low funding liquidity status causes immediate profit loss in carry trade, especially in high interest rate currencies. This loss continues in the next month, although the negative coefficient turns to be insignificant. This is consistent with our previous finding in chapter 5 and chapter 6 that excess return of carry trade is endogenous and is supported by active trading activities. When investors hit their funding constraints, the funding liquidity condition deteriorates and then the excess return decreases as investors unwind positions of carry trade.

The empirical results from Table 8-2 and Table 8-3 suggest to us how the funding liquidity affects carry trade excess returns: when carry traders have their risk tolerance decrease or hit their funding constraints, investors unwind their carry trade positions. This reduction in future positions of investment currencies is accompanied with profit loss of carry trade. Our results are consistent with Brunnermeier *et al.* (2008). The changes of excess returns in both investment and funding currencies are driven by the shift of risk tolerance of traders and that crashes could happen endogenously as part of the trading process where the positions are leveraged and imperfectly capitalized. Another way to view this finding is that the VIX and TED are common risk factors which affect the movement in exchanges rates. The shocks in funding liquidity affect currencies of all legs in a self-financed carry trade portfolio or affect more the high interest rate currencies, which cancels out all profits in the times of low funding liquidity. In other words, it is possible that the heterogeneous exposure to the funding liquidity risk causes the skewness of excess return in high interest rate currencies and low interest rate currencies. This helps to explain why a diversified carry trade portfolio is still subject to crash risk indicated by the skewness shown in Table 4-1 and Figure 4-1. We test whether the funding liquidity, measured by VIX and TED, is a common risk factor in section 8.5.3 with a cross-sectional asset pricing model.

8.5.2 Country exposures to funding liquidity risk

We find that funding liquidity affects carry trade excess return through their positions. We are now interested to know whether there are differences in the exposures to the funding liquidity risk across different countries, since currencies of low interest rates and high interest rate have different positions involved in carry trade. We specifically how currencies respond to the time when market liquidity is low during the crisis period from September 2008 to January 2009, which is referred from Mancini *et al.* (2013). In this way, we investigate the link between the currency crash risk and funding liquidity risk.

We visualize the relationships between the cross-country exposures to funding liquidity risk and: the interest rate differentials; the changes in exchange rates; and the currency skewness. Following Mancini *et al*. (2013) and Farhi *et al.* (2009), we obtain the country-specific funding liquidity risk exposure β by regressing the changes in exchange rates on the global funding liquidity risk innovation, measured by ΔVIX and ΔTED. We then regress the interest rate differentials, changes in exchange rates and currency skewness on these βs. We plot the results using ΔVIX to measure funding liquidity in Figure 8-2 and the results using ΔTED to measure funding liquidity in Figure 8-3.

There is a clear positive relationship between the interest rate differentials and the funding liquidity beta, a positive relationship between the changes in exchange rates and the funding liquidity beta, and a positive relationship between the currency skewness and the funding liquidity beta, regardless the fact that the funding risk is measured by ΔVIX or ΔTED.

This has several important implications: firstly, there is a strong link between interest rates and the exposure to funding liquidity risk. This suggests that countries with higher interest rates, such as AUD and NZD, are more exposed to the funding liquidity risk. In chapter 5 we find that higher interest rate currencies relate to higher excess return of carry trade. This translates into that the excess return of carry trade can be explained by the exposure to funding liquidity risk.

Secondly, the cross-sectional differences in currency skewness, which is measured by the skewness of changes in exchange rates, can be explained by the heterogeneous country exposure to funding risk. Currencies, such as AUD and NZD, with higher excess return and higher chance to have currency crash risk also more exposed to funding liquidity risk.

Thirdly, empirical evidences in chapter 5 show that when currency crash risk is high, high interest rate currencies depreciates. This is exactly what happens when funding liquidity risk is high in FX market. Currencies with larger exposures to the funding risk depreciate, while currencies with small exposures to the funding risk appreciate.

Overall, we find that the currency crash risk and funding liquidity risk aligns. Our graphic cross-sectional results show that when a currency's funding liquidity risk increases, three things contemporaneously happen: 1) the interest rate increases 2) the currency depreciates 3) the chance to have currency crash risk increases. These three patterns documented by our data are in line with Mancini *et al.* (2013) and Farhi *et al.* (2009). Mancini *et al.* (2013) use another liquidity measure constructed by an 'illiquid minus liquid' (IML) currency portfolio. Similar results are obtained by using IML factor in the cross-country analysis. Farhi *et al.* (2009) extract the liquidity information from options and build a disaster risk model. Their disaster model provides theoretical support of the impact of heterogeneous liquidity risk loading. Our liquidity measurements provide direct information on the market liquidity condition and reveal the consistent systematic responses among the exchange rates, interest rates and currency crash risk.

8.5.3 Asset pricing results

In this section, we use GMM and FMB procedure to conduct a cross-sectional asset pricing for annualized portfolio excess returns on dollar risk factor DOL and the funding liquidity factor $FLIQ$. The pricing kernel is:

$$m_{t+1} = 1 - b_{DOL}(DOL_{t+1} - \mu_{DOL}) - b_{FLIQ}(FLIQ_{t+1} - \mu_{FLIQ}) \qquad (34)$$

Table 8-4 and Table 8-5 present the asset pricing results using ΔVIX_t and ΔTED_t to measure $FLIQ_t$ respectively.

Panel A in Table 8-4 and Table 8-5 shows that there is a negative funding liquidity risk premium λ_{FLIQ} in carry trade excess return regardless whether the funding liquidity risk is measured by ΔVIX or ΔTED. In the sample of 8 developed countries, the estimated factor price for ΔVIX is -1.8851 by either GMM or FMB, where the estimation of FMB is significant at 5% level. The factor price for ΔTED is 3.7359 by either GMM or FMB, where the estimation of FMB is significant at 5% level as well. The funding liquidity factor captures more than 90% of the cross-sectional variation in excess returns in the carry trade portfolios by GMM procedure or more than 84% of cross-sectional variation by FMB procedure. The RMSE of both measurements is smaller than 0.01 with insignificant HJ statistics.

Panel B in Table 8-4 and Table 8-5 show the time-series beta estimates for the 3 portfolios sorted based on interest rate differential. There is a monotonic decline trend in betas when moving from the portfolio C_1 to portfolio C_3 in both tables. Estimates of β_{FLIQ} are positive for currencies with low interest rate differential, whereas estimates of β_{FLIQ} are negative for currencies with high interest rate differential.

In both Table 8-4 and Table 8-5, we note that the estimates of factor DOL and $FLIQ$ are more significant in FMB than that in GMM. The estimates of FMB for $FLIQ$ are significant at 1% significance level and the estimates of DOL is significant at 10% significance level, whereas neither of these two estimates of factors in GMM is significant at 10% level for This difference in the significance of estimates may be caused by wider accommodation of GMM estimator in variances than the FMB estimator. And therefore, the standard deviations in GMM procedure are inflated and the estimates turn to be less significant.

We recall that there is an increase trend in excess returns of portfolios which are sorted by interest rate differentials, as shown in Table 4-1. We find that the increase trend in excess returns of portfolios can be explained by this monotonic decline trend in funding liquidity betas. Specifically, portfolios with high interest rate differential have high excess return and are accompanied with negative factor loading of funding liquidity risk; while portfolios with low interest rate differential have low excess return and are accompanied with positive factor loading of funding liquidity risk. Thus, we interpret the time-series results as that currencies with low interest rate provide a hedge when funding condition is tight in the market; whereas currencies with high interest rate demand a premium in equilibrium since they perform poorly when funding liquidity is low. All this empirical evidence supports the presence of negative funding liquidity premium in cross sectional test results.

Our finding of negative funding liquidity risk premium is consistent with other studies, such as Menkhoff *et al.* (2012a) and Mancini *et al.* (2013), who find a negative risk premium and spill over effects to other asset classes. Our asset pricing results provide empirical evidence to support the liquidity spiral model proposed in Brunnermeier and Pedersen (2007a): when the market funding liquidity condition is good, high interest rate currencies appreciate due to the negative funding liquidity beta, and low interest rate currencies depreciate due to the positive funding liquidity beta. This pushes the exchange rates to deviate from UIP. However, when the market funding liquidity drops, the liquidity spiral triggers, which reveals itself as unwinding of carry trade positions and loss of carry trade profit. High interest rate currencies depreciate and low interest rate currencies appreciate, which worsen the currency crashes, induces larger losses on carry trade but alleviates the deviation of UIP.

8.5.4 Sorting currencies on funding liquidity betas

In order to show that funding liquidity is priced in excess return of carry trade, we sort currencies based on the exposure to the global funding liquidity factor. If the funding liquidity risk is a priced factor, it is reasonable to expect that these beta-sorted carry trade portfolios should reveal a spread pattern in the cross sectional mean of excess returns. Given the negative impact of funding liquidity on excess return shown in section 8.5.4, we expect to see a decline trend of excess returns from the portfolio with low funding liquidity beta to the portfolio with high funding liquidity beta.

We apply the beta-sorting technique proposed in Lustig *et al.* (2011) and Menkhoff *et al.* (2012a) by sorting 8 currencies into 3 portfolios according to individual currencies' funding liquidity risk betas. Specifically, we regress each currency j's excess return on a constant and funding liquidity risk measured in ΔVIX and ΔTED using a 36-month rolling window that ends on month $t-1$.[28] This gives us the currency j's exposure to global funding liquidity risk and we denote as $\beta_t^{j,\Delta VIX}$ and $\beta_t^{j,\Delta TED}$. Then we sort currencies into portfolios on the rank of betas. Portfolio P_1 contains currencies with the lowest βs, and portfolio P_3 contains currencies with the highest βs. DOL is the average of portfolio P_1 to P_3. HML is the difference between P_3 and P_1. We re-balance portfolios at the end of every month. We present descriptive statistics of portfolios variables sorted by ΔVIX beta in Table 8-6 and by ΔTED beta in Table 8-7.

[28] We also tried other window size and report the results in the robustness check section. We do not find that different window size to generate funding liquidity beta bias the portfolio excess return results.

Panel C in Table 8-6 and Table 8-7 show the annualized excess return Z of portfolio P_1 P_2 P_3. We find that currencies with high funding liquidity beta have a higher excess return than currencies with low funding liquidity beta, regardless of the funding liquidity risk measured by ΔVIX or ΔTED. There is a decline pattern in the excess returns from portfolio P_1 to P_3 and the spread between P_1 to P_3 is around -5.41% per annum when measured by ΔVIX and -2.86% per annum when measured by ΔTED. The empirical results support our hypothesis that funding liquidity risk is priced in carry trade excess return. Importantly, currencies with small funding liquidity risk loading provide a hedge in carry trade, and currencies with large funding liquidity risk loading yield low excess returns. We consider that currencies that hedge against funding liquidity risk should trade at a premium, while currencies that have a low excess return when funding constraint is tight demand a compensation in equilibrium.

We do not find a clear pattern in skewness, shown in the fifth row of Table 8-6 and Table 8-7, which is different from the skewness of carry trade portfolios sorted on the interest rates. Table 4-1 shows that there is a decline trend in skewness of excess returns from high interest rate portfolio to low interest rate portfolio. That is not the case in the funding liquidity beta sorted portfolios, which suggests that sorting on funding liquidity betas produces portfolios related to, but not identical to, the portfolios sorted on interest rates. The feature of our liquidity beta sorted portfolios is consistent with Menkhoff *et al.* (2012a) who sort currencies on ΔVIX betas and do not find a decline pattern of skewness in the excess return of portfolios.

To sum up, we find that currencies have heterogeneous loading of funding liquidity risk which yields a pattern in carry trade excess return and coincides with the heterogeneous loading of crash risk, as shown in Chapter 5. Our empirical results via the beta-sorting supports the presence of funding liquidity risk and related it as an fundamental risk to explain currency crash risk.

8.6 Robustness

We perform several additional robustness tests regarding different solutions to exclude the serial correlation in time-series regression and different window size to generate funding liquidity betas. We document the results here and include the empirical results in the Appendix.

Firstly, as described in the data section, we find autocorrelation in FP_t, which plays a role as the dependent variables in model set I. In the main text, we deal with the problem by using first difference for ΔFP to remove the autocorrelation in the raw data series. Here, we apply another approach to remove the autocorrelation by adding lag term FP_{t-1} in the time series model set I and II. Specifically, we run panel regressions of ΔFP_t on ΔVIX_t and ΔTED_t with lag term FP_{t-1} in model 1 and model 2. We report the panel results in Table 10-12, in which we find they yield consistent results as shown in Table 8-2 and Table 8-3. Therefore we conclude that lag term and the AR(1) residuals have no difference in absorbing the serial correlation in dependent variable FP_t and generate the same empirical results. They both point to the fact that when funding liquidity is tight, investors unwind their carry trade positions. The empirical results points to the funding liquidity having a negative premium in carry trade excess return.

We next turn sort currencies with different window size when generating funding liquidity betas. We set a smaller rolling window size as 24 months when regressing the individual currencies excess returns on funding liquidity innovations. We present the variables of carry trade portfolios, DOL portfolio and HML portfolio using ΔVIX in Table 10-13 and using ΔTED Table 10-14. We find that the betas of ΔVIX and ΔTED, which are produced by a smaller window size, have a decline trend in annualized excess return from portfolio C_1 to portfolio C_3. This pattern is consistent with beta sorting results of window size 36. The skewness of excess returns does not reveal a clear trend from portfolio C_1 to portfolio C_3. The annualized excess return of HML portfolio is around 4.2% when sorted by ΔVIX beta and 1.27% when sorted by ΔTED beta. Therefore, we conclude that the window size of generate funding liquidity beta does not bias the results of currencies sorting.

8.7 Conclusion

In chapter 5 and chapter 6, we see that carry trade position and crash risk insurance play essential roles in explaining currency crash risk for both currencies with low interest rate and high interest rate. In this chapter, we find that funding liquidity risk is a fundamental factor that affects carry trade positions and the excess returns. We show that a fraction of excess return in carry trade can be attributed to a time-varying funding liquidity premium, which can be captured by VIX index and TED spread in financial market.

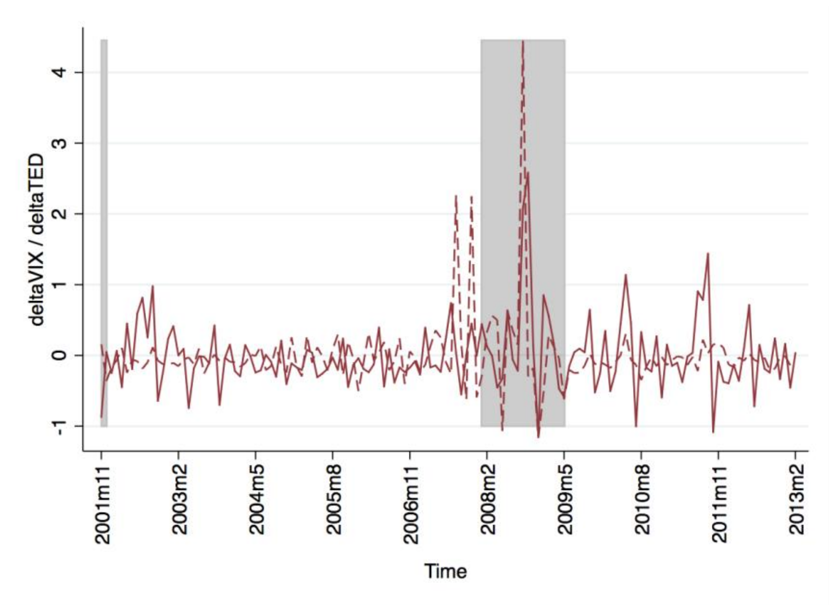
Our empirical results point to the fact that the excess returns of carry trade and currency crash risk are endogenous. Funding constraints applies to all investors and can be considered as an effective systematic risk factor to explain the excess return of carry trade. When capital moves smoothly in a liquid condition and investors have sufficient funding supply, carry trade is prosperous in the FX market. The low interest rate currencies depreciate and high interest rate currencies appreciate. This increases the deviation of exchange rate from the UIP. When investors hit their funding constraints, market-wide liquidity drop, which force the carry trade positions diminishing. This causes the low interest rate currencies appreciate and high interest rate currencies depreciate, exacerbating currency crash risk and inducing large loss to carry traders. However, tight funding liquidity constraints helps the exchange rate shift back to the direction the UIP expects. The cross-sectional analysis provides empirical evidence to support funding constraints helping to explain the forward premium puzzle.

Table 8-1: Stats of funding liquidity measured by ΔVIX and ΔTED

	ΔVIX	ΔTED
Mean	0.0476×10^{-10}	0.0464×10^{-10}
Sd dev	0.51	0.54
Skew	1.61	5.22
Kurt	8.90	40.75
AC(1)	0.12	-0.08
	(0.09)	(0.09)
CH test	1.85	0.78
LM test	21.62***	76.11***
ZA test	-10.79***	-14.05***

Note: This table contains statistics of ΔVIX and ΔTED, ranging from November 2001 to February 2013. We report mean, standard deviations, skewness, kurtosis. To test auto correlation, we report the first order autocorrelation coefficient AC(1) from the AR(1) process and the statistics of Cumby and Huizinga (1992) (CH) test. The standard errors of AC(1) are reported in brackets. The H_0 of CH test: the series has no serial correlation under assumption of heteroscedasticity. The highest lag order tested for CH test is selected by (Schwert, 1989) standard. To test heteroscedasticity, we report the LM statistics of the ARCH effect. To test stationarity, we report the statistic of Zivot and Andrews (1992) (ZA) test which has the null of non-stationarity tested under the assumption of one structural break. The optimal lags used in the ZA test are selected by the standard of minimal BIC, proposed in Ng and Perron (2001). We mark the significant statistics at 1%, 5%, 10% level by asterisk ***, ** and *.

Figure 8-1: ΔVIX and ΔTED with crisis periods



Note: Time series of global ΔVIX (solid line) and ΔTED (dash line) with recession periods published by NBER in shaded area. The sample period is from November 2001 to February 2013.

Table 8-2: Panel results of sensitivity test of monthly future position and carry trade excess returns to ΔVIX

Panel A: Contemporary effect		
	Model 1: FP_t	Model 3: Z_t
$\beta_{sign\Delta VIX}$	-0.0052	-0.0065***
	(0.0073)	(0.0021)
R^2	0.04	0.01
CH test	1.08	4.41*
Panel B: Predictive effect		
	Model 2: FP_{t+1}	Model 4: Z_{t+1}
$\beta'_{sign\Delta VIX}$	-0.0442	-0.0009
	(0.0437)	(0.0017)
R^2	0.03	0.01
CH test	1.08	0.68

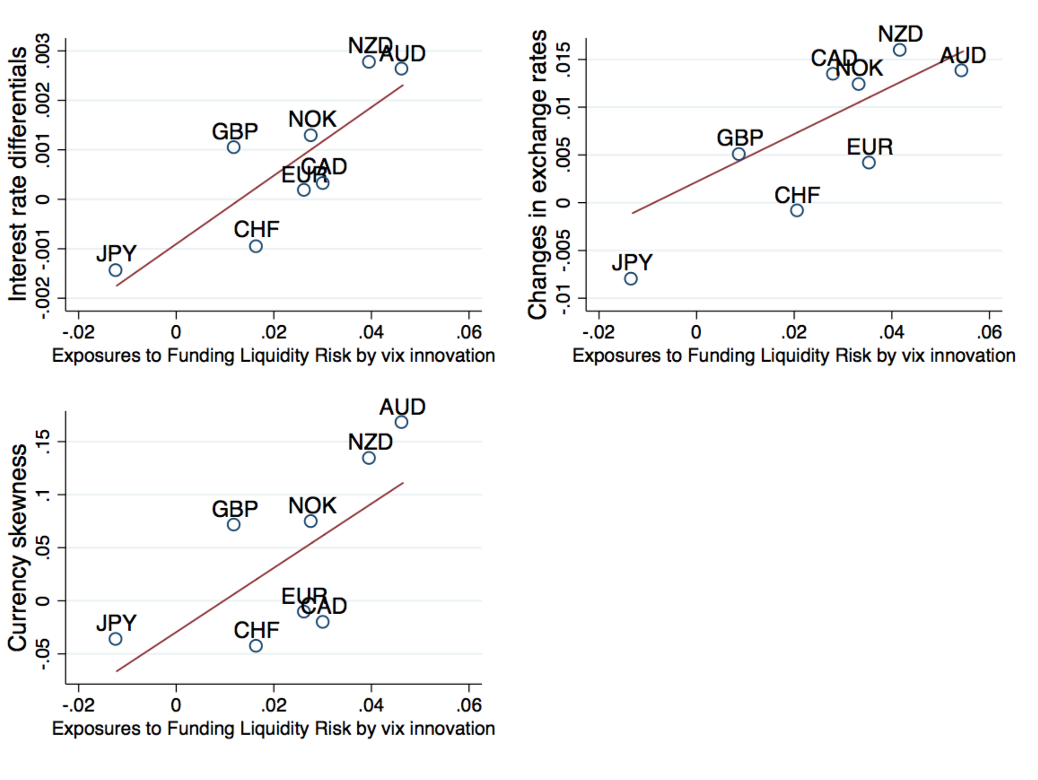
Note: This table reports panel regressions with country-fixed effect results of contemporary effect and predictive effect of VIX on future position and carry trade excess return, using monthly data from November 2001 to February 2013. VIX is the CBOE volatility index. We take $sign\Delta VIX_t^j$ to enter the panel models to remove the non-stationarity and the serial correlation problem found in original VIX series. In panel A, we focus on contemporaneous relationship. In panel B, we focus on predictive relationship. In model 1 and model 2 we use ΔFP as dependent variables to remove the serial correlation detected and shown in FP. Standard errors reported in parentheses are heteroskedasticity and autocorrelation robust, the optimal lags are computed according to the Newey and West (1987) standard and selected by the BIC criteria as follows: 33 lags in Model 1, 20 lags in model 2, 9 lags in model 3, 34 lags in model 4. Adjusted R square is reported for each model. We also report the statistics of Cumby and Huizinga (1992) test of the regression residuals. The H_0 of CH test: the series has no serial correlation under assumption of heteroscedasticity. We mark the statistics that are statistically significant at 1%, 5%, 10% by asterisk ***, ** and *.

Table 8-3: Panel results of sensitivity test of monthly future position and carry trade excess returns to ΔTED

	Panel A: Contemporary effect	
	Model 1: FP_t	Model 3: Z_t
$\beta_{sign\Delta TED}$	0.0091	-0.0085***
	(0.0085)	(0.0024)
R^2	0.01	0.02
CH test	0.90	3.07
	Panel B: Predictive effect	
	Model 2: FP_{t+1}	Model 4: Z_{t+1}
$\beta'_{sign\Delta TED}$	-0.0195***	-0.0026
	(0.0064)	(0.0018)
R^2	0.01	0.00
CH test	0.90	0.56

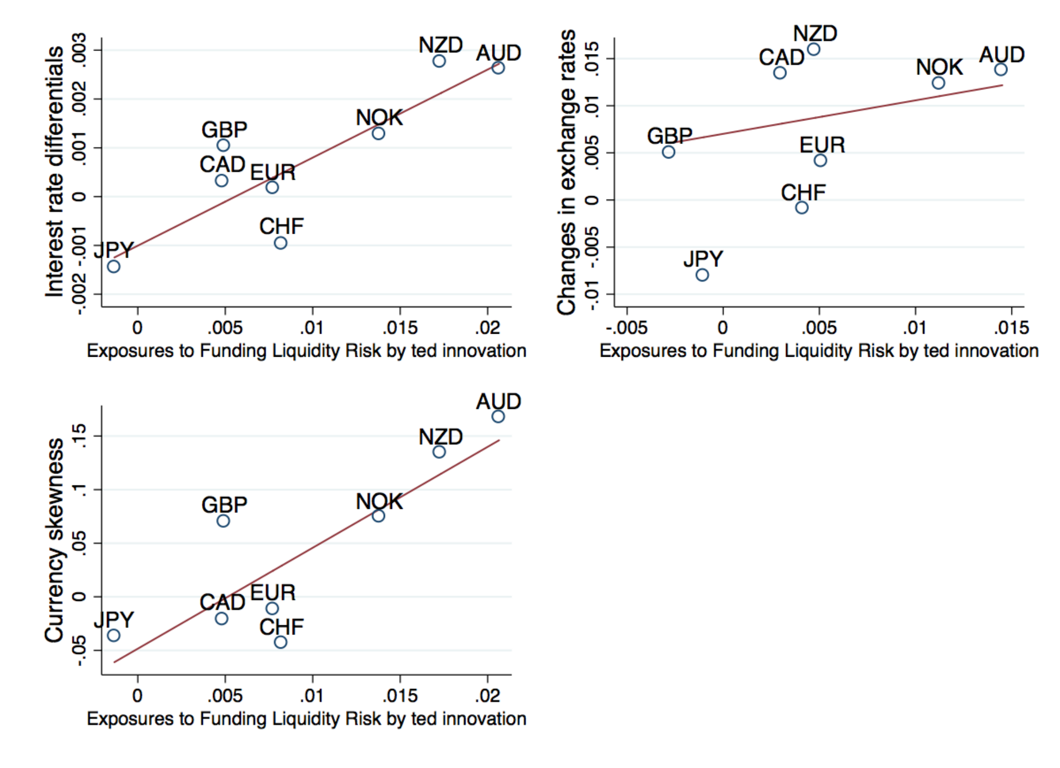
Note: This table reports panel regressions with country-fixed effect results of contemporary effect and predictive effect of TED on future position and carry trade excess return, using monthly data from November 2001 to February 2013. TED is the 3-month USD LIBOR minus the 3-month T-Bill yield. We take $sign\Delta TED_t^j$ to enter the models to remove the non-stationarity and the serial correlation found in original TED series. In panel A, we focus on contemporaneous relationship. In panel B, we focus on predictive relationship. In model 1 and model 2 we use ΔFP as dependent variables to remove the serial correlation detected and shown in FP. Standard errors reported in parentheses are heteroskedasticity and autocorrelation robust, the optimal lags are computed according to the Newey and West (1987) standard and selected by the BIC criteria as follows: 33 lags in Model 1, 33 lags in model 2, 33 lags in model 3, 27 lags in model 4, 34 lags in model 5, 12 lags in model 6. Adjusted R square is reported for each model. We also report the statistics of Cumby and Huizinga (1992) (CH) test of the regression residuals. The H_0 of CH test: the series has no serial correlation under assumption of heteroscedasticity. We mark the statistics that are statistically significant at 1%, 5%, 10% by asterisk ***, ** and *.

Figure 8-2: Country exposures to funding liquidity beta measured by ΔVIX



Note: This figure shows 3 pairs relationship during the crisis period, which ranges from September 2008 to January 2009 and is referred from Mancini *et al.* (2013): the positive relationship between the funding liquidity risk exposure β^j and the interest rate differential IRD^j (top left), positive relationship between the funding liquidity risk exposure β^j and the changes in exchange rates ΔS^j (top right), positive relationship between the funding liquidity risk exposure β^j and the skewness $skew^j$ (bottom left). The country-specific interest rate differential IRD^j, changes in exchange rates ΔS^j and skewness $skew^j$, are the time series average of these variables within each currency j. Following Mancini *et al.* (2013), the funding liquidity risk exposure β^j is obtained by regressing ΔS^j for currency j on global funding liquidity risk innovation ΔVIX. We then regress the IRD^j, ΔS^j and $skew^j$ on β^j respectively. The line is the fitted values of this regression. The significance and the corresponding fit of the line are as follows: slope is significant at 1% level and goodness of fit is 63% for line in top left panel, slope is significant at 10% level and goodness of fit is 30% for line in top right panel, slope is significant at 10% level and goodness of fit is 46% for line in bottom left panel.

Figure 8-3: Country exposures to funding liquidity beta measured by ΔTED



Note: This figure shows 3 pairs relationship during the crisis period, which ranges from September 2008 to January 2009 and is referred from Mancini *et al.* (2013): the positive relationship between the funding liquidity risk exposure β^j and the interest rate differential IRD^j (top left), positive relationship between the funding liquidity risk exposure β^j and the changes in exchange rates ΔS^j (top right), positive relationship between the funding liquidity risk exposure β^j and the skewness $skew^j$ (bottom left). The country-specific interest rate differential IRD^j, changes in exchange rates ΔS^j and skewness $skew^j$, are the time series average of these variables within each currency j. Following Mancini *et al.* (2013), the funding liquidity risk exposure β^j is obtained by regressing ΔS^j for currency j on global funding liquidity risk innovation ΔTED. We then regress the IRD^j, ΔS^j and $skew^j$ on β^j respectively. The line is the fitted values of this regression. The significance and the corresponding fit of the line are as follows: slope is significant at 1% level and goodness of fit is 70% for line in top left panel, slope is not significant at 10% level and goodness of fit is 20% for line in top right panel, slope is significant at 5% level and goodness of fit is 66% for line in bottom left panel.

Table 8-4: Cross-sectional asset pricing for DOL and ΔVIX

Panel A: Factor prices					
GMM	$\boldsymbol{DOL}$	$\boldsymbol{\Delta VIX}$	$\boldsymbol{R^2}$	$\boldsymbol{HJ}$	
b	0.3910	-0.6097	0.90	0.54	
s.e	(5.5038)	(0.7179)		[0.46]	
λ	0.0456	-1.8851			
s.e	(0.0433)	(1.3912)			
FMB	$\boldsymbol{DOL}$	$\boldsymbol{\Delta VIX}$	$\boldsymbol{R^2}$	$\boldsymbol{RMSE}$	
λ	0.0456*	-1.8851**	0.84	0.0097	
(NW)	(0.0264)	(0.9425)	.	.	
Panel B: Factor Betas					
	$\boldsymbol{\alpha}$	$\boldsymbol{DOL}$	$\boldsymbol{\Delta VIX}$	$\boldsymbol{R^2}$	$\boldsymbol{RMSE}$
C_1	-0.0008	0.859***	0.0101***	0.78	0.0108
	(0.0007)	(0.037)	(0.0016)	.	.
C_2	-0.0004	0.967***	-0.0038***	0.90	0.0084
	(0.0009)	(0.026)	(0.0008)	.	.
C_3	0.002**	1.297***	-0.0082***	0.81	0.0168
	(0.0008)	(0.047)	(0.002)	.	.

Notes: This table reports the asset pricing results of the linear factor model on dollar risk factor DOL and funding liquidity factor, where we use ΔVIX to measure. Panel A reports the cross-sectional results from SDF parameter estimates b and risk premium λ obtained by GMM and Fama-Macbeth procedure. The test assets are portfolio excess returns C_1 C_2 C_3 sorted on interest rate differentials of foreign country with respect to US interest rate. Portfolio C_1 contains 3 currencies with smallest interest rate differentials while Portfolio C_3 contains currencies with 3 largest interest rate differentials. For GMM, we report standard errors (s.e.) of coefficients estimates in the parentheses, and Hansen-Jagannathan (HJ) statistics with P-value in the square brackets. For FMB, we report market risk price λ for each factor with standard errors calculated according Newey and West (1987). We do not include a constant in the second step of FMB procedure. Panel B reports results of time series regressions of factor betas. Standard errors reported in parentheses are adjusted to Newey-West standard and computed with the optimal lags according to BIC criteria. The adjusted R^2 and square-root of mean errors $RMSE$ are also reported. We mark the significant statistics at 1%, 5%, 10% level by asterisk ***, ** and *. Data here is from monthly data of 8 currencies ranging from November 2001 to February 2013.

Table 8-5: Cross-sectional asset pricing for DOL and ΔTED

Panel A: Factor prices					
GMM	$\boldsymbol{DOL}$	$\boldsymbol{\Delta TED}$	$\boldsymbol{R^2}$	$\boldsymbol{HJ}$	
b	1.3782	-1.0736	0.97	0.08	
s.e	(5.4237)	(1.2014)		[0.78]	
λ	0.0462	-3.7359			
s.e	(0.0349)	(2.3178)			
FMB	$\boldsymbol{DOL}$	$\boldsymbol{\Delta TED}$	$\boldsymbol{R^2}$	$\boldsymbol{RMSE}$	
λ	0.0462*	-3.7359**	0.84	0.0097	
(NW)	(0.0264)	(1.8779)	.	.	

Panel B: Factor Betas					
	$\boldsymbol{\alpha}$	$\boldsymbol{DOL}$	$\boldsymbol{\Delta TED}$	$\boldsymbol{R^2}$	$\boldsymbol{RMSE}$
C_1	-0.0005	0.784***	0.0038***	0.74	0.0115
	(0.001)	(0.069)	(0.0013)	.	.
C_2	-0.0014	0.949***	0.0022**	0.81	0.0115
	(0.0012)	(0.013)	(0.001)	.	.
C_3	0.0016***	1.254***	-0.0053***	0.90	0.0110
	(0.0005)	(0.067)	(0.0013)	.	.

Notes: This table reports the asset pricing results of the linear factor model on dollar risk factor DOL and funding liquidity factor, where we use ΔTED to measure. Panel A reports the cross-sectional results from SDF parameter estimates b and risk premium λ obtained by GMM and Fama-Macbeth procedure. The test assets are portfolio excess returns C_1 C_2 C_3 sorted on interest rate differentials of foreign country with respect to US interest rate. Portfolio C_1 contains 3 currencies with smallest interest rate differentials while Portfolio C_3 contains 3 currencies with largest interest rate differentials. For GMM, we report standard errors (s.e.) of coefficients estimates in the parentheses, and Hansen-Jagannathan (HJ) statistics with P-value in the square brackets. For FMB, we report market risk price λ for each factor with standard errors calculated according Newey and West (1987). We do not include a constant in the second step of FMB procedure. Panel B reports results of time series regressions of factor betas. Standard errors reported in parentheses are adjusted to Newey-West standard and computed with the optimal lags according to BIC criteria. The adjusted R^2 and square-root of mean errors $RMSE$ are also reported. We mark the significant statistics at 1%, 5%, 10% level by asterisk ***, ** and *. Data here is from monthly data of 8 currencies ranging from November 2001 to February 2013.

Table 8-6: Currency portfolios sorted on betas to the funding liquidity risk innovation ΔVIX, window=36

Portfolio	$\boldsymbol{P_1}$	$\boldsymbol{P_2}$	$\boldsymbol{P_3}$	$\boldsymbol{DOL}$	$\boldsymbol{HML}$
Mean	0.0604	0.0185	0.0063	0.0284	-0.0541
st dev	0.1378	0.1058	0.0811	0.0977	0.1107
Skew	-0.70	-0.76	0.17	-0.46	0.79
kurt	5.71	4.91	2.74	4.48	6.15
Sharp Ratio	0.08	-0.01	-0.05	0.02	-0.14
CH test	0.26	0.14	0.20	0.12	0.11
LM test	0.00	0.85	1.49	0.22	0.05
ZA test	-11.60***	-10.48***	-10.38***	-10.92***	-11.45***
Pre-β	-0.0324	-0.0157	0.0067	-0.0138	0.0391
Post-β	-0.0155	-0.0049	0.0139	-0.0022	0.0293

Note: This table reports statistics of annualized excess return for carry trade portfolios, DOL and HML portfolio, which are constructed by sorting currencies into 3 portfolios based on global funding liquidity beta $\beta_t^{j,\Delta VIX}$. Following Menkhoff *et al.* (2012a), the global funding liquidity beta is obtained by regressing currency j's excess returns Z_t^j on global funding liquidity risk innovation ΔVIX on a 36-period moving window that ends in month $t-1$. Portfolio P_1 contains the lowest βs, portfolio P_3 contains the highest βs. DOL is the average of portfolio P_1 to P_3. HML is constructed by taking the difference between P_1 and P_3. The portfolios are re-balanced at the end of every month. Annualized excess return is calculated as multiplying monthly means by 12 and multiplying monthly standard deviations by $\sqrt{12}$. Sharp ratio is computed as ratios of annualized excess returns means to annualized standard deviations, considering US interest rate as the risk-free asset. We report the average pre-formation βs for each portfolio. The last panel reports the average post-formation βs, which are obtained by regressing currency j excess return Z_t^j on DOL and ΔVIX on a 36-period moving window that ends in month $t-1$. We use Cumby and Huizinga (1992) (CH) test for auto correlation. The H_0 of CH test: the series has no serial correlation under assumption of heteroscedasticity. To test heteroscedasticity, we report the LM statistics of the ARCH effect. To test stationarity, we report the statistic of Zivot and Andrews (1992) (ZA) test which has the null of non-stationarity tested under the assumption of one structural break. We mark the significant statistics at 1%, 5%, 10% level by asterisk ***, ** and *. Data involved here is monthly data ranging from December 2001 to February 2013.

Table 8-7: Currency portfolios sorted on betas to the funding liquidity risk innovation ΔTED, window=36

Portfolio	P_1	P_2	P_3	DOL	HML
Mean	0.0485	0.0127	0.0199	0.0270	-0.0286
st dev	0.1367	0.1046	0.0820	0.0977	0.1079
Skew	-0.69	-0.79	0.45	-0.47	0.77
kurt	5.81	4.98	3.12	4.45	7.00
Sharp Ratio	0.06	-0.02	-0.01	0.02	-0.06
CH test	0.49	0.44	3.53	0.02	0.02
LM test	0.12	0.38	0.64	0.12	0.20
ZA test	-10.16***	-10.99***	-10.93***	-10.66***	-4.86*
Pre-β	-0.0411	-0.0281	-0.0093	-0.0262	0.0318
Post-β	-0.0133	-0.0012	0.0099	-0.0016	0.0232

Note: This table reports statistics of annualized excess return for carry trade portfolios, DOL and HML portfolio, which are constructed by sorting currencies into 3 portfolios based on global funding liquidity beta $\beta_t^{j,\Delta TED}$. Following Menkhoff *et al.* (2012a), the global funding liquidity beta is obtained by regressing currency j's excess returns Z_t^j on global funding liquidity risk innovation ΔTED on a 36-period moving window that ends in month $t-1$ Portfolio P_1 contains the lowest βs, portfolio P_3 contains the highest βs. DOL is the average of portfolio P_1 to P_3. HML is constructed by taking the difference between P_1 and P_3. The portfolios are re-balanced at the end of every month. Annualized excess return is calculated as multiplying monthly means by 12 and multiplying monthly standard deviations by $\sqrt{12}$. Sharp ratio is computed as ratios of annualized excess returns means to annualized standard deviations, considering US interest rate as the risk-free asset. We report the average pre-formation βs for each portfolio. The last panel reports the average post-formation βs, which are obtained by regressing currency j excess return Z_t^j on DOL and ΔTED on a 36-period moving window that ends in month $t-1$. We use Cumby and Huizinga (1992) (CH) test for auto correlation. The H_0 of CH test: the series has no serial correlation under assumption of heteroscedasticity. To test heteroscedasticity, we report the LM statistics of the ARCH effect. To test stationarity, we report the statistic of Zivot and Andrews (1992) (ZA) test which has the null of non-stationarity tested under the assumption of one structural break. We mark the significant statistics at 1%, 5%, 10% level by asterisk ***, ** and *. Data involved here is monthly data ranging from December 2001 to February 2013.

9. General conclusion

In this thesis, we study the risk factors to explain the excess return of carry trade and explore the operation scheme of FX market in the short-term by using a comprehensive currency data set and segmented order flow data set. The failure of UIP reflects the situation that some underlying assumptions regarding the trading process in the FX market have been challenged, which includes that risk neutral market participant, efficient market with complete information digestion, full capital availability with no government control and sufficient number of market participant which enables full liquidity for arbitrage.

This thesis examines several factors which might co-vary with the excess return of carry trade in each empirical chapter. In chapter 5, we find that currencies in carry trade are exposed to crash risk which is measured by the global skewness factor. The currency crash risk explains 81% of the excess return of carry trade with a significant positive risk premium. High interest rate currencies compensate the chance of having currency crash risk by yielding positive risk premium. Low interest rate currencies are hedges against the crash risk. Chapter 6 shows that the profit of carry trade and the currency crash risk are endogenous and created within the carry trade process.[29] The profit of carry trade is enhanced by the large market-wide positions and is subject to currency crash risk. Equivalently, unwinding currency positions induces the loss of carry trade but also alleviate the chance to suffer the currency crash. Chapter 7 tries to explains the carry trade excess return by the liquidity risk which is extracted from the price impact of order flows. Unfortunately, the explanatory power of liquidity risk factor is low due to the low frequency order flow data, which is used to build the liquidity risk factor. In chapter 8, we find that the funding liquidity risk, which is measured by VIX index or TED spread, explains 70% excess returns of carry trade portfolios. We interpret funding liquidity risk as shocks in funding constraints or shifts in investors' risk tolerance. We argue that the funding liquidity factor is one of those systematic factors that fundamentally affects all currencies on both investment and funding position in carry trade.

[29] Currency crash is endogenous in carry trade or, to say it differently, crash risk is inherent in currency trading.

This thesis supports the theoretical liquidity spiral model proposed in Brunnermeier and Pedersen (2007b). They argue that market liquidity, which measures how easy the assets can be traded, and the funding liquidity, which measures the availability of the funding, mutually reinforce each other and lead to a liquidity spiral. This thesis provides empirical evidence on both individual currency level and portfolio level to show that funding liquidity feature rationalizes the market-wide impact of funding liquidity condition on carry trade returns in FX market. Put our empirical results together, a series of market reaction process that bounds all relative concepts can be envisioned as the following way: large interest rate differential profoundly encourages investors to build up carry trade positions. However, high excess return of carry trade accompanies with large chance of currency crash risk, which is large depreciation in high interest rate currencies relative to low interest rate currencies and cause the distribution of excess return negatively skewed. We find that currencies have heterogeneous funding liquidity betas and market funding liquidity risk has a negative premium in excess return of carry trade. When the carry traders are sufficiently funded or their fear to future uncertainty is low, high interest rate currencies tend to appreciate due to their negative funding liquidity betas, low interest rate currencies tend to depreciate due to their positive funding liquidity betas. When the carry traders hit their funding constraints or the fear to future uncertainty increases, carry trade positions are unwound and the endogenous profit of carry trade diminishes. High interest rate currencies depreciate and low interest rate currencies appreciate which exacerbates the currency crashes and leads to the loss of carry trade.

The finding in this thesis have several implications for the economic policy. Firstly, from the central bank perspective, providing the liquidity for a specific exchange rate or loosen the funding constraint when the market liquidity is low may have positive spill over effect to the whole FX market. For example, when the carry trade positions of high interest rate currencies are unwound, an injection of liquidity from the central bank or the adaption of funding constraints on its own currency could alleviate currency crash by reducing the chance to have sudden depreciation (appreciation) of other investment currencies (funding currencies). However, policy makers should be aware of the adverse consequences for the abundant liquidity in the market. Overwhelming liquidity in one currency spreads to other currencies especially into the investment currencies. This attracts more carry trade activity in the market and pushes the exchange rate away from the fundamental values. Secondly, based on the principle of liquidity spiral model, speculators need a safety buffer to prevent triggering the liquidity spiral when doing the risk management. This calls the attention from market player when considering the capital involved in the trading and the guider when making policy about trading in the financial market. Thirdly, the study in the liquidity property of currencies show that risk management on high interest rate currencies is challenging, because they have low liquidity and high sensitivities to the market liquidity. When the market turns lacks of liquidity, the high interest rate currencies turn to be illiquid as well. This increases the liquidity premium that investors potentially receive, but also increases the chance for the investors to suffer the market liquidity crisis, which might wipe out the profit gained from the trading.

We believe that some future work can be done based on the findings in this thesis. In this thesis, we considered simple portfolio strategies with equal weights of individual currencies, but clearly the time variate correlation structure of individual currencies can be exploit to develop more sophisticated portfolio design. This would help to study the change of risk premium of the risk factors that we measure by the skewness, the order flow and the market liquidity index. Furthermore, we can also study the risk-based explanation of carry trade return by constructing hedged carry trade portfolios. We are interested to know whether risks that lead to risk premiums in excess return can be hedged off and the compensation for bearing these risks can be removed in the hedged portfolios. If not, how much of the risk premium can be removed. And what risk can be managed by using the options as insurance, and what risk acts as the systematic risk that cannot be simply hedged with market tools.

Overall, we argue that our findings call for new theoretical macro-theoretical models in which risk premium is affected by factors in a microstructure context, not only factors on a broad macroeconomics sense, which has been proven ineffective to explain the foreign exchange market dynamics.

10. Appendix

Generalized Method of Moments:

We start from carry trade satisfies the non-arbitrage condition:

$$\mathbb{E}[m_t z_t] = 0 \tag{35}$$

Where Z_t^i is the monthly excess return for carry trade portfolio i, m_t is the SDF that prices excess returns. Equation (35) implies:

$$p_t \equiv \mathbb{E}(z_t) = -\frac{cov(m_t, z_t)}{E(m_t)} \tag{36}$$

p_t is the conditional risk premium and corresponds to the conditional expectation of the excess return z_t. Equation (36) suggests that a risk based explanation of the returns can identify the SDF that co-varies with the excess return of carry trade.

On the other hand, equation (35) implies that:

$$\mathbb{E}(z_t) = -cov(m_t, z_t) \tag{37}$$

The empirical test in the thesis is based on SDF:

$$m_t = 1 - b'(f_t - \mu) \tag{38}$$

We have moment condition: $\mathbb{E}\left[Z_t^i\left(1 - b'(f_t - \mu)\right)\right] = 0$ and k moment conditions $E(f_t) = \mu$. Burnside (2011) argues that by substituting equation (38) into equation (37), we obtain $\mathbb{E}(z_t) = cov(z_t, f_t)b$, which can be written as

$$\mathbb{E}(z_t) = cov(z_t, f_t)\Sigma_f^{-1}\Sigma_f b \tag{39}$$

Where

$$\begin{cases} \hat{b}_{k\times 1} = (d_T' W_T d_T)^{-1} d_T' W_T \bar{z} & (40) \\ \beta_{n\times k} = cov(z_t, f_t)\, \hat{\Sigma}_f^{-1} & (41) \\ \hat{\lambda}_{k\times 1} = \hat{\Sigma}_f \hat{b} & (42) \end{cases}$$

z_t is a $t \times n$ vector of n individual mean returns. f_t is a $t \times k$ vector of k risk factors. $d_T = cov(z_t, f_t)$ and is a $n \times k$ vector. $\bar{z}$ is $n \times 1$ vector of individual mean returns. W_T is the weighting matrix, we set it as 1. $\hat{\Sigma}_f$ is the covariance matrix of risk factor f_t.

Fama-MacBeth two-pass procedure:

In this thesis, we also employ traditional Fama-MacBeth (FMB) two-pass OLS method. We follow the standard two-pass procedure in Cochrane (2005). In the first step of FMB procedure, we estimate the β_1^i and β_2^i of two factors respectively:

$$Z_{i,t} = \alpha_i + \beta_1^i f_t^1 + \beta_2^i f_t^2 + \varepsilon_{i,t} \tag{43}$$

these betas are the sensitivities of the portfolios excess returns to the risk factors. In the second step of FMB procedure, we regress cross-sectional excess returns of portfolios on β_a^i and β_2^i as:

$$Z_{i,t} = \beta_1^i \lambda_t^1 + \beta_2^i \lambda_t^2 + \varepsilon_{i,t} \tag{44}$$

λs are the risk premium of the risk factors at month t respectively. Following Lustig *et al.* (2011), we do not include a constant in the second stage of FMB, because factor DOL_t already account for cross-sectional invariant values. We use annualized excess return for all carry trade portfolios in the FMB procedure and therefore report the annualized estimated risk premium.

The risk premium is the average of the λs estimated at each point in time as follow:

$$\widehat{\lambda^1} = \frac{1}{T}\sum_{t=1}^{T} \lambda_t^1 \tag{45}$$

$$\widehat{\lambda^2} = \frac{1}{T}\sum_{t=1}^{T} \lambda_t^2 \tag{46}$$

$$\widehat{\varepsilon_i} = \frac{1}{T}\sum_{t=1}^{T} \varepsilon_{i,t} \tag{47}$$

The standard errors of the estimates are calculated with Newey and West (1987) correction, which adjusts the covariance matrix to create an unbiased t-statistics.

Table 10-1: Currency portfolios sorted on IRD_t^j of different allocation scenario

Portfolio	C_1	C_2	C_3	DOL	HML
Mean	-0.0169	0.0029	0.0788	0.0222	0.0958
st dev	0.06	0.09	0.12	0.06	0.14
Skew	-0.50	-0.49	-0.67	-0.55	-1.12
kurt	3.56	4.47	5.22	9.26	3.27
Sharp Ratio	-0.17	-0.05	0.15	0.02	0.32
CH test	0.00	1.66	0.30	1.93	4.08
LM test	2.04	0.21	3.97*	1.67	1.96
ZA test	-11.96***	-11.29***	-12.23***	-11.41***	-12.32***

Note: The setup of this table is the same as Table 4-1. We consider different number of individual currencies in each portfolio by having 3,2,3 currencies for Portfolio C_1, C_2, C_3. We report the statistics of annualized excess return for carry trade portfolios, DOL and HML portfolio, which are constructed based on the rank of interest rate differentials IRD_t^j relative to USD. Portfolio C_1 contains currencies with smallest interest rate differentials, C_3 contains currencies with largest interest rate differentials. DOL is the average of portfolio C_1 to C_3. HML is the difference between C_1 and C_3. Portfolios are re-balanced at the end of every month. Annualized excess return is calculated as multiplying monthly means by 12 and multiplying monthly standard deviations by $\sqrt{12}$. Sharp ratio is computed as ratios of annualized excess returns means to annualized standard deviations, considering US interest rate as the risk-free asset. We also report statistics of Cumby and Huizinga (1992) (CH) test for auto correlation; the LM statistics of the ARCH effect for the heteroscedasticity and the statistic of Zivot and Andrews (1992) (ZA) test for stationarity. We mark the significant statistics at 1%, 5%, 10% level by asterisk ***, ** and *. Data involved here is monthly data ranging from December 2001 to February 2013.

Table 10-2: Global skewness beta results in different allocation scenarios

Panel A: Factor prices					
GMM	DOL	$signSKW^e$	R^2	HJ	
b	-0.4092	5.9220	0.83	1.38	
s.e	(1.4680)	(4.5615)		[0.24]	
λ	0.0220	3.7949			
s.e	(0.0427)	(2.9144)			
FMB	DOL	$signSKW^e$	R^2	$RMSE$	
λ	0.0215	3.3961*	0.78	0.0123	
(NW)	(0.0183)	(1.8289)	.	.	
Panel B: Factor Betas					
	α	DOL	$signSKW^e$	R^2	$RMSE$
C_1	-0.002**	0.222**	-0.0094***	0.05	0.0171
	(0.001)	(0.108)	(0.0025)	.	.
C_2	-0.002**	1.212***	0.0018	0.66	0.0154
	(0.001)	(0.075)	(0.0035)	.	.
C_3	0.004***	1.657***	0.0074***	0.77	0.0165
	(0.001)	(0.091)	(0.002)	.	.

Notes: The setup of this table is the same as Panel B in Table 5-2. We consider different number of individual currencies in each portfolio: having 3,2,3 currencies for Portfolio C_1, C_2, C_3. Panel A reports the cross-sectional results from SDF parameter estimates b and risk premium λ obtained by GMM and Fama-Macbeth procedure. The test assets are portfolio excess returns C_1 C_2 C_3 sorted on interest rate differentials between foreign country and US. Portfolio C_1 contains 3 currencies with smallest interest rate differentials while Portfolio C_3 contains 3 currencies with largest interest rate differentials. Portfolios are rebalanced at the end of every month. For GMM, we report standard errors (s.e.) of coefficients estimates in the parentheses, and Hansen-Jagannathan (HJ) statistics with P-value in the square bracket. For FMB, we report market risk price λ for each factor with standard errors calculated according Newey and West (1987). Following Lustig *et al.* (2011), we do not include a constant in the second step of Fama-Macbeth procedure. Panel B reports results of time series regressions of factor betas. Standard errors reported in parentheses are adjusted to Newey-West standard and computed with the optimal lags according to BIC criteria. The adjusted R^2 and square-root of mean errors $RMSE$ are also reported. Data involved here is monthly data ranging from December 2001 to February 2013.

Table 10-3: Currency portfolios sorted on betas to the global skewness, window=24

Portfolio	P_1	P_2	P_3	DOL	HML
Mean	-0.0148	-0.0012	0.0234	0.0025	0.0383
st dev	0.0738	0.0915	0.0935	0.0666	0.0824
Skew	-0.72	-0.52	-0.46	-1.16	0.31
kurt	4.85	4.53	6.19	8.41	4.01
Sharp Ratio	-0.14	-0.07	0.01	-0.08	0.15
CH test	0.12	0.17	0.00	0.88	0.88
LM test	0.20	2.66	0.03	1.62	0.27
ZA test	-11.14***	-10.13***	-10.75***	-10.25***	-10.25***
Pre-β	-0.0247	-0.0153	-0.0017	-0.0139	0.0230
Post-β	-0.0193	-0.0108	0.0015	-0.0095	0.0209

Note: The setup of this table is the same as Table 5-3. Here we use window size=24 in the rolling scheme to generate factor betas for each currency. The global skewness beta is obtained by regressing currency j's log change in exchange rate ΔS_t^j on global skewness factor innovation $signSKW^e$on a 24-period moving window that ends in month $t-1$. Portfolio P_1 contains 3 currencies with the lowest βs, portfolio P_3 contains 2 currencies with the highest βs. DOL is the average of portfolio P_1 to P_3. HML is constructed by taking the difference between P_1 and P_3. The portfolios are re-balanced at the end of every month. Annualized excess return is calculated as multiplying monthly means by 12 and multiplying monthly standard deviations by $\sqrt{12}$. Sharp ratio is computed as ratios of annualized excess returns means to annualized standard deviations, considering US interest rate as the risk-free asset. We report the average pre-formation βs for each portfolio. The last panel reports the average post-formation βs, which is obtained by regressing currency j excess return Z_t^j on DOL and $signSKW^e$ on a 24-period moving window that ends in month $t-1$. We also report statistics of Cumby and Huizinga (1992) (CH) test for auto correlation; the LM statistics of the ARCH effect for the heteroscedasticity and the statistic of Zivot and Andrews (1992) (ZA) test for stationarity. We mark the significant statistics at 1%, 5%, 10% level by asterisk ***, ** and *. Data involved here is monthly data ranging from December 2001 to February 2013.

Table 10-4: Correlations between monthly $\boldsymbol{IRD_{t-1}^{j}}$ and monthly $\boldsymbol{Z_{t-1}^{j}}$

	EUR	GBP	JPY	CHF	CAD	AUD	NOK	NZD
Corr	0.04	-0.03	0.08	0.08	0.00	-0.01	0.04	-0.14

Note: This table reports correlation coefficients for each currency between monthly interest rate differentials with monthly excess return. Data involved here ranges from January 2002 to November 2007.

Table 10-5: Multicollinearity test results

Panel A: models predicting $skew_t$				
	model (1)	model (2)	model (3)	model (4)
$IRD_{j,t-1}$	n/a	1.02	1.02	1.03
$FP_{j,t-1}$		1.01	1.05	1.12
$signZ_{j,t-1}$			1.07	1.15
$RR_{j,t-1}$				1.15
mean VIF			1.42	1.41

Panel B: models predicting RR_t			
	model (5)	model (6)	model (7)
$IRD_{j,t-1}$	n/a	1.01	1.01
$FP_{j,t-1}$		1.01	1.07
$signZ_{j,t-1}$			1.08
mean VIF			1.41

Note: This table reports the centered variance inflation factors (VIFs) for the independent variables specified in linear regression models (1)(2)(3)(4) in panel A and model (5)(6)(7) in panel B. VIF values are used to detect the multicollinearity of the independent variables with the constant.

Table 10-6: Regression of exchange rate changes on standardized aggregate order flow (using recursive window scheme)

	β_j	R^2	CH test	LM test
EUR	0.0014**	0.04	0.41	0.54
	(0.0006)	.		
GBP	0.0015***	0.04	0.2	11.06***
	(0.0005)	.		
JPY	0.0028***	0.07	0.98	1.33
	(0.0006)	.		
CHF	0.0001	0	0.16	0.32
	(0.0005)	.		
CAD	0.0009*	0	0.82	3.85**
	(0.0005)	.		
AUD	0.0023***	0.06	0.54	1.76
	(0.0005)	.		
NOK	0.0013***	0.02	0	4.78**
	(0.0005)	.		
SEK	0	-0.01	0.2	0.09
	(0.0006)	.		
NZD	0.0031***	0.1	0.7	0.94
	(0.0006)	.		

Model: $\Delta S_{j,t} = \alpha_j + \beta_j \tilde{x}_{j,t} + \varepsilon_{j,t}$

Notes: The setup of this table is the same as Table 7-3. Weekly data of 9 currencies from January 2002 to November 2007. Time series results of regressing changes in exchange rate $\Delta S_{j,t}$ on contemporaneous order flow $\tilde{x}_{j,t}$, which is standardized by their standard deviation using a recursive window with 12 weeks initialization horizon. Standard errors are calculated according to Newey and West (1987) standard and reported in brackets under coefficients. Adjusted R-square is reported in the second column. The t-stats of Cumby and Huizinga (1992) (CH) test for autocorrelation in the regression residuals are reported in the third column. The H_0 of CH test: the series has no serial correlation under assumption of heteroscedasticity. Highest lag order used in CH test are selected by the Schwert (1989) standard. We test the ARCH effect of series and report the LM statistics in the last column. We mark the statistics that are statistically significant at 1%, 5%, 10% by asterisk ***, ** and *.

Table 10-7: Regression of exchange rate changes on standardized aggregate order flow (using in-sample variance scheme)

	β_j	R^2	CH test	LM test
EUR	0.0015*	0.03	0.27	0.6
	(0.0008)	.		
GBP	0.002**	0.02	0.02	7.56***
	(0.0008)	.		
JPY	0.0034***	0.06	0.69	1.3
	(0.0007)	.		
CHF	0.0004	0	0.13	0.38
	(0.0006)	.		
CAD	0.0011*	0	0.78	4.12**
	(0.0006)	.		
AUD	0.0037***	0.07	0.76	0.86
	(0.001)	.		
NOK	0.0017**	0.01	0	4.18**
	(0.0008)	.		
SEK	-0.0005	-0.01	0.15	0.05
	(0.0008)	.		
NZD	0.005***	0.09	1.37	0.32
	(0.0012)	.		

Model: $\Delta S_{j,t} = \alpha_j + \beta_j \tilde{x}_{j,t} + \varepsilon_{j,t}$

Notes: The setup of this table is the same as Table 7-3. Weekly data of 9 currencies from November 2001 to November 2007. Time series results of regressing changes in exchange rate $\Delta S_{j,t}$ on contemporaneous order flow $\tilde{x}_{j,t-1}$, which is standardized by their standard deviation using the in-sample standard deviation. Standard errors are calculated according to Newey and West (1987) standard and reported in brackets under coefficients. Adjusted R-square is reported in the second column. The t-stats of Cumby and Huizinga (1992) (CH) test for autocorrelation in the regression residuals are reported in the third column. The H_0 of CH test: the series has no serial correlation under assumption of heteroscedasticity. Highest lag order used in CH test are selected by the Schwert (1989) standard. We test the ARCH effect of series and report the LM statistics in the last column. We mark the statistics that are statistically significant at 1%, 5%, 10% by asterisk ***, ** and *.

Table 10-8: Individual time series sensitivity tests of monthly future position to ΔVIX

Panel A: Contemporary effect							
	EUR	GBP	JPY	CHF	CAD	AUD	NZD
$\beta_{\text{sign}\Delta VIX}$	0.0561*	-0.1605**	-0.0753	-0.0643*	0.0391	-0.1780**	-0.1020
	(0.0739)	(0.0686)	(0.0621)	(0.0377)	(0.1502)	(0.0786)	(0.0629)
R^2	0.02	0.01	0.01	0.03	0.01	0.02	0.01
lags	7	11	22	22	9	16	20
CH test	0.12	1.18	0.26	0.12	0.09	0.07	0.62
LM test	0.41	0.08	0.42	0.59	9.02***	0.78	0.01
Panel B: Predictive effect							
	EUR	GBP	JPY	CHF	CAD	AUD	NZD
$\beta'_{sign\Delta VIX}$	-0.2279	-0.2819***	-0.1803***	0.0072	-0.2018***	-0.0701	-0.0502
	(0.1231)	(0.0818)	(0.0348)	(0.0315)	(0.0807)	(0.0773)	(0.0732)
R^2	0.04	0.04	0.06	0.01	0.02	0.01	0.01
lags	20	22	21	22	22	22	20
CH test	0.13	0.82	0.48	0.12	0.05	0.09	0.39
LM test	0.63	0.67	0.01	0.72	12.67***	0.78	0.04

Note: This table reports time series regressions of contemporary effect (Panel A) and predictive effect (Panel B) of ΔVIX on future position, using monthly data from November 2001 to February 2013. VIX is the CBOE volatility index. We take ΔVIX to enter the models to remove the non-stationarity and the serial correlation found in original VIX series. In both contemporary and predictive regressions, we use ΔFP as dependent variables to remove the serial correlation detected and shown in FP. Standard errors reported in parentheses are heteroskedasticity and autocorrelation robust. The optimal lag in each regression is computed according to the Newey and West (1987) standard and selected by the BIC criteria. We report the optimal lags on the fourth row in each panel. Adjusted R square is reported on the third row. For the diagnostic test of residuals, we report the statistics of Cumby and Huizinga (1992) (CH) test for serial correlation and of series and LM statistics for ARCH effect. The H_0 of CH test: the series has no serial correlation under assumption of heteroscedasticity. We mark the statistics that are statistically significant at 1%, 5%, 10% by asterisk ***, ** and *.

Table 10-9: Individual time series sensitivity tests of carry trade excess returns to ΔVIX

	EUR	GBP	JPY	CHF	CAD	AUD	NOK	NZD
Panel A: Contemporary effect								
	EUR	GBP	JPY	CHF	CAD	AUD	NOK	NZD
$\beta_{\text{sign}\Delta VIX}$	0.0040	-0.0065	0.0087***	0.0010	-0.0102**	-0.0044	-0.0121	-0.0093
	(0.0060)	(0.0108)	(0.0015)	(0.0022)	(0.0050)	(0.0088)	(0.0111)	(0.0092)
R^2	0.01	0.01	0.09	0.01	0.03	0.01	0.01	0.01
lags	22	22	22	22	22	22	22	21
CH test	0.02	1.42	0.01	1.24	0.34	0.00	0.02	1.56
LM test	0.28	0.00	0.22	5.26**	3.88*	4.75**	2.33	0.04
Panel B: Predictive effect								
	EUR	GBP	JPY	CHF	CAD	AUD	NOK	NZD
$\beta'_{sign\Delta VIX}$	-0.0060	-0.0030	0.0036***	0.0012	-0.0057***	-0.0065	-0.0016	-0.0063
	(0.0051)	(0.0068)	(0.0011)	(0.0038)	(0.0023)	(0.0061)	(0.0074)	(0.0064)
R^2	0.01	0.00	0.02	0.01	0.01	0.01	0.0	0.01
lags	22	22	22	22	22	22	22	21
CH test	0.05	1.87	0.26	1.39	0.07	0.11	0.01	0.31
LM test	0.23	0.01	0.14	5.17**	2.22	4.30*	1.79	0.07

Note: This table reports time series regressions of contemporary effect (Panel A) and predictive effect (Panel B) of ΔVIX on carry trade excess returns, using monthly data from November 2001 to February 2013. VIX is the CBOE volatility index. We take ΔVIX to enter the models to remove the non-stationarity and the serial correlation found in original VIX series. Standard errors reported in parentheses are heteroskedasticity and autocorrelation robust. The optimal lag in each regression is computed according to the Newey and West (1987) standard and selected by the BIC criteria. We report the optimal lags on the fourth row in each panel. Adjusted R square is reported on the third row. For the diagnostic test of residuals, we report the statistics of Cumby and Huizinga (1992) (CH) test for serial correlation and of series and LM statistics for ARCH effect. The H_0 of CH test: the series has no serial correlation under assumption of heteroscedasticity. We mark the statistics that are statistically significant at 1%, 5%, 10% by asterisk ***, ** and *.

Table 10-10: Individual time series sensitivity tests of monthly future position to ΔTED

Panel A: Contemporary effect							
	EUR	GBP	JPY	CHF	CAD	AUD	NZD
$\beta_{\text{sign}\Delta TED}$	-0.0393	-0.0137	0.0293	-0.0089	-0.0328	0.0949	0.1600
	(0.0745)	(0.0373)	(0.0312)	(0.0331)	(0.0307)	(0.1340)	(0.1087)
R^2	0.00	0.00	0.01	0.01	0.00	0.01	0.02
lags	2	22	22	22	22	5	20
CH test	0.01	0.53	0.00	0.12	0.19	0.25	0.01
LM test	0.18	0.27	0.27	0.64	8.84***	0.99	0.08
Panel B: Predictive effect							
	EUR	GBP	JPY	CHF	CAD	AUD	NZD
$\beta'_{sign\Delta TED}$	-0.0233	-0.0320	-0.0428**	-0.0052	-0.0173**	0.0018	-0.0182
	(0.0148)	(0.0166)	(0.0180)	(0.0122)	(0.0085)	(0.0097)	(0.0172)
R^2	0.01	0.01	0.03	0.01	0.04	0.00	0.01
lags	16	16	2	22	6	22	15
CH test	0.11	4.11**	3.78*	1.61	4.08**	1.68	3.85*
LM test	0.23	0.14	0.08	0.23	10.35***	2.85	1.66

Note: This table reports time series regressions of contemporary effect (Panel A) and predictive effect (Panel B) of TED on future position, using monthly data from November 2001 to February 2013. TED is the 3-month USD LIBOR minus the 3-month T-Bill yield. We take ΔTED to enter the models to remove the non-stationarity and the serial correlation found in original TED series. In both contemporary and predictive regressions, we use ΔFP as dependent variables to remove the serial correlation in FP. Standard errors reported in parentheses are heteroskedasticity and autocorrelation robust. The optimal lag in each regression is computed according to the Newey and West (1987) standard and selected by the BIC criteria. We report the optimal lags on the fourth row in each panel. Adjusted R square is reported on the third row. For the diagnostic test of residuals, we report the statistics of Cumby and Huizinga (1992) (CH) test for serial correlation and of series and LM statistics for ARCH effect. The H_0 of CH test: the series has no serial correlation under assumption of heteroscedasticity. We mark the statistics that are statistically significant at 1%, 5%, 10% by asterisk ***, ** and *.

Table 10-11: Individual time series sensitivity tests of monthly carry trade excess returns on ΔTED

	EUR	GBP	JPY	CHF	CAD	AUD	NOK	NZD
Panel A: Contemporary effect								
$\beta_{\text{sign}\Delta TED}$	-0.0035	-0.0106**	0.0087***	0.0004	-0.0059	-0.0133	-0.0103	-0.0070
	(0.0059)	(0.0048)	(0.0030)	(0.0014)	(0.0051)	(0.0110)	(0.0082)	(0.0087)
R^2	0.00	0.04	0.05	0.00	0.02	0.03	0.02	0.01
lags	22	22	22	22	18	17	22	21
CH test	0.04	1.43	0.47	1.30	0.07	0.16	0.03	1.11
LM test	0.60	0.00	2.57	5.20**	6.11***	5.44	0.23	0.24
Panel B: Predictive effect								
	EUR	GBP	JPY	CHF	CAD	AUD	NOK	NZD
$\beta'_{sign\Delta TED}$	-0.0046***	-0.0052*	-0.0058***	0.0045**	-0.0034***	-0.0012	-0.0037	-0.0055
	(0.0013)	(0.0030)	(0.0011)	(0.0020)	(0.0010)	(0.0043)	(0.0041)	(0.0060)
R^2	0.01	0.01	0.02	0.01	0.01	0.00	0.00	0.01
lags	22	22	22	22	22	22	22	21
CH test	0.03	0.93	0.05	1.66	1.38	0.06	0.03	0.71
LM test	0.72	0.25	0.02	2.72	1.24	3.93**	1.73	0.01

Note: This table reports time series regressions of contemporary effect (Panel A) and predictive effect (Panel B) of ΔTED on carry trade excess returns, using monthly data from November 2001 to February 2013. TED is the 3-month USD LIBOR minus the 3-month T-Bill yield. We take ΔTED to enter the models to remove the non-stationarity and the serial correlation found in original TED series. Standard errors reported in parentheses are heteroskedasticity and autocorrelation robust. The optimal lag in each regression is computed according to the Newey and West (1987) standard and selected by the BIC criteria. We report the optimal lags on the fourth row in each panel. Adjusted R square is reported on the third row. For the diagnostic test of residuals, we report the statistics of Cumby and Huizinga (1992) (CH) test for serial correlation and of series and LM statistics for ARCH effect. The H_0 of CH test: the series has no serial correlation under assumption of heteroscedasticity. We mark the statistics that are statistically significant at 1%, 5%, 10% by asterisk ***, ** and *.

Table 10-12: Panel results of sensitivity test of monthly future position to ΔVIX and ΔTED

Panel A: Contemporary effect on FP_t			
$\beta_{\text{sign}\Delta VIX}$	-0.0169***	$\beta_{\text{sign}\Delta TED}$	0.0047
	(0.0064)		(0.0065)
FP_{t-1}	0.7428***	FP_{t-1}	0.7474***
	(0.0263)		(0.0264)
R^2	0.22	R^2	0.22
CH test	1.08	CH test	0.90
Panel B: Predictive effect on FP_{t+1}			
$\beta'_{sign\Delta VIX}$	-0.0317***	$\beta'_{sign\Delta TED}$	-0.0217***
	(0.0082)		(0.0071)
FP_{t-1}	0.7373***	FP_{t-1}	0.7447***
	(0.0263)		(0.0264)
R^2	0.21	R^2	0.22
CH test	1.08	CH test	0.90

Note: This table reports panel regressions with country-fixed effect results of contemporary effect and predictive effect of ΔVIX and ΔTED on future position using monthly data from November 2001 to February 2013. VIX is the CBOE volatility index. TED is the 3-month USD LIBOR minus the 3-month T-Bill yield. We take ΔVIX and ΔTED to enter the models to remove the non-stationarity and the serial correlation found in original VIX and TED series. In panel A, we regress current future position on ΔVIX and ΔTED. In panel B, we regress future position of next moment on ΔVIX and ΔTED. In model 1 and model 2, we add lag term FP_{t-1} into model to remove the serial correlation detected in FP. Standard errors reported in parentheses are heteroskedasticity and autocorrelation robust, the optimal lags are computed according to the Newey and West (1987) standard and selected by the BIC criteria as follows: 32 lags in Model 1, 33 lags in model 2. Adjusted R square is reported for each model. We also report the statistics of Cumby and Huizinga (1992) (CH) test of the regression residuals. The H_0 of CH test: the series has no serial correlation under assumption of heteroscedasticity. We mark the statistics that are statistically significant at 1%, 5%, 10% by asterisk ***, ** and *.

Table 10-13: Currency portfolios sorted on betas to the funding liquidity risk innovation ΔVIX, window=24

Portfolio	P_1	P_2	P_3	DOL	HML
Mean	0.0664	0.0148	0.0222	0.0345	-0.0442
st dev	0.1296	0.1039	0.0787	0.0942	0.1056
Skew	-0.72	-0.88	0.09	-0.51	0.81
kurt	6.16	5.32	2.76	4.63	6.58
Sharp Ratio	0.10	-0.02	0.01	0.04	-0.10
CH test	0.28	0.01	0.03	0.08	0.05
LM test	0.00	0.66	0.53	0.35	0.04
ZA test	-12.16***	-10.91***	-10.71***	-11.41***	-11.53***
Pre-β	-0.0321	-0.0146	0.0082	-0.0128	0.0402
Post-β	-0.0165	-0.0046	0.0142	-0.0023	0.0307

Note: The setup of this table is the same as Table 8-6. Here we use window size=24 in the rolling scheme to generate factor betas for each currency. The global funding liquidity beta is obtained regressing currency j's excess returns Z_t^j on global funding liquidity risk innovation ΔVIX on a 24-period moving window that ends in month $t-1$. Portfolio P_1 contains the lowest βs, portfolio P_3 contains the highest βs. DOL is the average of portfolio P_1 to P_3. HML is constructed by taking the difference between P_1 and P_3. The portfolios are re-balanced at the end of every month. Annualized excess return is calculated as multiplying monthly means by 12 and multiplying monthly standard deviations by $\sqrt{12}$. Sharp ratio is computed as ratios of annualized excess returns means to annualized standard deviations, considering US interest rate as the risk-free asset. We report the average pre-formation βs for each portfolio. The last panel reports the average post-formation βs, which is obtained by regressing currency j excess return Z_t^j on DOL and ΔVIX on a 24-period moving window that ends in month $t-1$. We also report statistics of Cumby and Huizinga (1992) (CH) test for auto correlation; the LM statistics of the ARCH effect for the heteroscedasticity and the statistic of Zivot and Andrews (1992) (ZA) test for stationarity. We mark the significant statistics at 1%, 5%, 10% level by asterisk ***, ** and *. Data involved here is monthly data ranging from December 2001 to February 2013.

Table 10-14: Currency portfolios sorted on betas to the funding liquidity risk innovation ΔTED, window=24

Portfolio	P_1	P_2	P_3	DOL	HML
Mean	0.0430	0.0223	0.0303	0.0319	-0.0127
st dev	0.1297	0.1054	0.0765	0.0945	0.1043
Skew	-1.05	-0.69	0.14	-0.56	1.36
kurt	6.00	5.36	3.06	4.59	7.43
Sharp Ratio	0.05	0.01	0.04	0.03	-0.01
CH test	0.01	0.22	0.01	0.03	0.03
LM test	1.41	0.00	0.02	0.51	0.36
ZA test	-11.14***	-11.50***	-10.91***	-11.23***	-11.21***
Pre-β	-0.0498	-0.0280	-0.0031	-0.0270	0.0468
Post-β	-0.0204	-0.0006	0.0154	-0.0019	0.0358

Note: The setup of this table is the same as Table 8-7. Here we use window size=24 in the rolling scheme to generate factor betas for each currency. The global funding liquidity beta is obtained by regressing currency j's excess returns Z_t^j on global funding liquidity risk innovation ΔTED on a 24-period moving window that ends in month $t-1$. Portfolio P_1 contains the lowest βs, portfolio P_3 contains the highest βs. DOL is the average of portfolio P_1 to P_3. HML is constructed by taking the difference between P_1 and P_3. The portfolios are re-balanced at the end of every month. Annualized excess return is calculated as multiplying monthly means by 12 and multiplying monthly standard deviations by $\sqrt{12}$. Sharp ratio is computed as ratios of annualized excess returns means to annualized standard deviations, considering US interest rate as the risk-free asset. We report the average pre-formation βs for each portfolio. The last panel reports the average post-formation βs, which is obtained by regressing currency j excess return Z_t^j on DOL and ΔTED on a 24-period moving window that ends in month $t-1$. We also report statistics of Cumby and Huizinga (1992) (CH) test for auto correlation; the LM statistics of the ARCH effect for the heteroscedasticity and the statistic of Zivot and Andrews (1992) (ZA) test for stationarity. We mark the significant statistics at 1%, 5%, 10% level by asterisk ***, ** and *. Data involved here is monthly data ranging from December 2001 to February 2013.

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