Essays in International Finance

by

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Abstract

In this PhD thesis, I first critically review some key findings for the currency market studies throughout the past two decades. Two strands of literature, namely the microstructure approach and risk-based approach, has been found to fit well with the empirical puzzle of the forward premium of foreign exchange rates. I then follow these two strands of literature to discuss the risk premiums on the currency market. This PhD thesis is centred around the following two important issues.

1. The market microstructure and risk-based approach are based on different visions of the model economy. Are the empirical facts in support of two strands of literature consistent with both?

The second chapter studies how the microstructure approach and risk-based approach are consistent with each other. I follow the risk-based framework of asset pricing models to propose a set of pricing factors that are motivated by microstructure models. I use the forward premium sign-adjusted cross-sectional average of standardized order flow to provide a direct measure of buying and selling pressure to carry trade strategy. This factor explains most of the cross-sectional variations of currency portfolios and appears to be a good proxy for currency carry trade crash risk. The high value of this factor corresponds with high on-going carry trade positions, and it also associates with a high probability of the investors' unwinding of their carry trade positions which causes currency carry trade crashes. Similarly, the past return signed order flow factor is also proposed to price most of the cross-sectional variations of currency momentum portfolios.

Additionally, a set of factor constructed from the disaggregated order flow data by four customer types: Asset Manager (AM), Hedge Fund (HF), Corporate (CO) and Private Client (PC) shows different correlation pattern and explanation power for currency portfolios. In particular, it appears that financial customers (AM and HF) are risk-takers while non-financial customers (CO and PC) serve as liquidity providers.

I bring two strands of literature closer by using market microstructure motivated factors to price the currency carry and momentum anomalies.

2. None of the model proposed in the literature is compatible with both carry and momentum anomaly on the currency market. Is currency momentum anomaly related to the carry trade anomaly?

Chapter three focuses on the risk characteristics of the currency momentum anomaly. It provides a detailed analysis of its dynamic risk exposure to currency factors. I find that currency momentum betas to the 'carry trade high minus low' (HML) factor are conditioned on the previous and contemporaneous carry trade returns. Unconditional currency momentum beta to HML is not significant. However, under a bear carry trade state (previous carry trade return is negative), the momentum beta to HML is negative. If the contemporaneous carry trade returns are positive under bear carry trade state, the beta is further decreased.

This risk pattern explains the asymmetric written call-option-like payoff and rare crashes of the currency momentum strategies. I show that currency momentum strategies crash following a bear carry trade market state when volatilities of HML and DOL are high, in particular, when the carry trade is recovering from previous drawdowns. I also detected a significant dynamic beta pattern of currency momentum to the 'dollar risk factor' (DOL). However, dynamic exposures to DOL is symmetric. Thus, it does not result in the momentum crash.

By using the insight of the dynamic risk exposure pattern of currency momentum, I build a dynamic momentum strategy that could hedge the possible momentum crashes which provide high returns and Sharp ratios with positive sample skewness.

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Dedication

To my family

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.

Signature:

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Chapter 1

Literature Review: Foreign Exchange Market

1.1 Introduction

The currency market is the most liquid and largest capital market in terms of daily trading volume: $5.4 trillion (BIS, 2016). However, for decades, the difficulty in forecasting future exchange rates has puzzled the finance literature. Meese and Rogoff (1983) first documented that structural macro models[1] cannot outperform a naive random walk in out-of-sample forecasting, especially for high frequency data less than one year. This problem is termed the Meese-Rogoff puzzle.[2]

On the other hand, empirical facts challenge the theoretical parity conditions, such as the uncovered interest rate parity (UIP) (e.g. Hansen and Hodrick 1980, 1983; Fama 1984) and the purchasing power parity (e.g. Rogoff, 1996; Goldberg and Knetter, 1996; Taylor and Taylor, 2004). The low explanation power of macroeconomics fundamentals to short term exchange rates fertilize two strands of literature, namely, the market microstructure approach and the portfolio (or risk-based approach), which propose interpretations for the exchange rates fluctuations.

Market microstructure theory on foreign exchange market emphasises how order flow information is aggregated to exchange rates through the decentralized dealership market structure. The net order flow, which is the one of the most important microstructure variables, is defined as the difference between buyer initiated orders and seller initiated orders. This literature originates from the studies on the specialist trading structure of the New York stock exchange (see, for example, e.g. Amihud and Mendelson, 1980 and Kyle, 1985). The price deviation could be understood as the risk premium imposed by the market dealer to cover their inventory risk. Given that risk aversion of market dealers is constant, the size of the risk premium is linked with the size of net transactions which could be measured by order flow.

Lyons (1995) first suggests to apply the microstructural hypothesis on the currency market. Lyons (1997) introduced an equilibrium model based on the multi-dealership and decentralized market structure. They found that trading activities within currency market dealers play an important informational role. A notable cornerstone has been laid by Evans and Lyons (2002). They propose the empirical general equilibrium microstructure exchange rate model which augments interdealer order flow information with traditional macro models. They argue that interdealer order flow plays a critical role in forecasting the exchange rate change as it captures the investor's expec-

[1] The macro structural models in their study are the Frenkel-Bilson model, the Dornbusch-Frankel model and the Hooper-Morton model.

[2] Examples of related literature that reach the same conclusion include Meese (1990); Engel and West (2004); Evans and Lyons (2005); Rogoff and Stavrakeva (2008); Molodtsova and Papell (2009); Barroso and Santa-Clara (2015*a*)

tation and risk preferences which are absent from the publicly tracked macroeconomic variables. A general microstructure model for exchange rates combines both macroeconomic variables and order flow variables. For example, Evans and Lyons (2002) propose the following model:

$$\Delta s_t = \Delta(i_t^* - i_t) + \lambda \Delta x_p \tag{1.1}$$

Where Δs_t is the log change of spot exchange rates quoted as foreign currency unit per domestic currency; i_t^* is the foreign currency interest rate; i_t is the domestic currency interest rate; Δx_p is the interdealer order flow; λ is a positive coefficient that depends on the investor's risk aversion, variance of customer order flow and variance of interdealer order flow.

On the other hand, researchers also find important information content between dealer-customer order flow (see, for example, Sager and Taylor, 2008; Cerrato et al., 2011, 2015; Menkhoff et al., 2016). The risk sharing and the price discovery process happen between the dealer and the customer as well.

Risk-based view of exchange determination tries to make a breakthrough by rationalizing the failure of uncovered interest rate parity (UIP) and the 'forward premium puzzle' (e.g. Hansen and Hodrick, 1980, 1983; Fama, 1984). UIP is a simple proposition based on the assumption of risk neutral investors which links the expected spot rate changes to the interest rate changes as in equation 1.2:

$$E(s_{t+1}) - s_t = i_t^* - i_t \tag{1.2}$$

Where s_t is the logarithm of spot exchange rates at time t, $E(s_{t+1})$ is the expected spot rates in logarithm at time $t+1$. Both exchange rates are quoted as foreign currency unit per domestic currency. This equation suggests that, to offset the interest rate difference, low interest rate currencies tend to appreciate and high interest rate currencies tend to depreciate. However, equation 1.2 has been found not to hold empirically.

The 'forward premium puzzle' is strongly linked to the failure of UIP. Consider the covered interest rate parity which links the forward premium with the interest rate difference as in equation 1.3

$$f_t^{t+1} - s_t = i_t^* - i_t \tag{1.3}$$

Where $f_t^{t+1}$is the logarithm of forward exchange rate for time $t+1$; The UIP is governed by the non-arbitrage conditions and has been found to hold in practice. Combine equation 1.2 and equation 1.3, the forward exchange rates are an unbiased estimator of expected future spot exchange rates:

$$E(s_{t+1}) = f_t^{t+1} \tag{1.4}$$

Due to the failure of UIP, equation 1.4 is documented as a failure by extensive literature. Empirical studies even show that spot exchange rates move conversely, as equation 1.4 suggests, very often. This is termed 'the forward premium puzzle' or 'the forward bias puzzle'. Burnside et al. (2009) emphasize that the adverse selection problem faced by market dealers provides a explanation for forward premium puzzle. Burnside et al. (2010) try to understand this puzzle by introducing the 'peso problem' on the currency market. Other studies (see, for example, Hodrick and Srivastava, 1984; Fama, 1984; Korajczyk, 1985) have criticized the risk-neutral assumption of UIP and suggested that a time-varying risk premium is associated with the forward price f_t^{t+1}.

An issue that is closely related to the unpredictability of exchange rates and the forward premium puzzle is two types of return anomalies, namely, the currency carry trade and the currency momentum. Recent literature tries to understand the exchange rate fluctuation by proposing models for currency return anomalies (or equivalently detect factors that well measure the time-varying risk premium) (e.g. Lustig et al. 2011; Menkhoff et al. 2012*a*). Carry trade is a trading strategy that buys high interest rate currencies and shorts low interest rate currencies. The well-documented profitability and high Sharp ratios of carry trade are based on the 'forward premium puzzle' (e.g. Burnside et al. 2006, 2007; Doskov and Swinkels 2015; Daniel et al. 2017). Momentum anomaly was first detected in the equity market by Jegadeesh and Titman (1993) and generalized in other asset classes.[3] This strategy is simply a bet on the price continuation by holding assets that have high past returns and short assets that have low past returns. Menkhoff et al. (2012*b*) document the strong momentum performance on the currency market after transaction costs.

In this chapter, I review key findings of the market microstructure models on the

[3]See, for example, Carhart (1997); Daniel and Moskowitz (2016) for equity momentum; Jostova et al. (2013) for fixed income momentum; Miffre and Rallis (2007); Gorton et al. (2012) for commodity momentum.

currency market, forward premium puzzle and currency anomalies. The rest of this chapter is organized as follows: Section 1.2 reviews the literature on market microstructure. Section 1.3 reviews the risk-based models. Section 1.5 introduces the correlation between two strands of literature. Section 1.6 concludes.

1.2 Market Microstructure Models

The decentralized dealership market structure, where dealers directly provide quotes on request from customers, characterizes the currency market as largely deregulated with low transparency. Hundreds of active dealers are trading amongst themselves in the meantime through the interdealer market. The microstructure theories are built on the assumption that market participants have heterogeneous information which is reflected in their order flow. An equilibrium price would be achieved through aggregation of dispersed information.

1.2.1 Market dealer structure

Seminal studies on the market microstructure focus on the influence of market dealer's behaviour on price discovery process and suggest two mechanisms for how order flow information is aggregated to the asset price through market dealers. For example, Amihud and Mendelson (1980), Ho and Stoll (1983) and O'Hara and Oldfield (1986) are in favor of the 'quote shading' effect in the inventory control model, which states that risk-averse market dealers control their inventory risk by selling redundant inventories at a price which could efficiently attract customers and compete with other market dealers.

Others (e.g. Kyle, 1985; Glosten and Milgrom, 1985; Admati and Pfleiderer, 1988) who proposed information-based models emphasize that market dealers face an adverse selection problem with an informed investor. Market dealers would quote the price at a level which could reflect private information and, as a trading counterparty of informed traders, they would adjust the price to protect themselves from holding devalued inventories. Lyons (1995) extends the framework of Madhavan and Smidt (1991) to the currency market and find evidence in supporting both the inventory control model and the information based model on the Deutschemark and US dollar market. Bjønnes and Rime (2005) find evidence for inventory control theories from bilateral order flow between market dealers and their customers. However, both models suggest the important role of the order flow data to asset prices in the way that buyer initiated orders push up prices and net seller initiated orders lower down prices. Regarding to the currency market, Lyons (1997) emphasizes that interdealer order flow in the decentralized currency market is crucial information to the exchange rate.

1.2.2 Information in the interdealer order flow

A notable study of Evans and Lyons (2002) employs the interdealer order flow to explain exchange rate dynamics on a daily basis. They developed 'the portfolio shifts model' which introduced how the interdealer order flow is aggregated to price information through sequential trading stages. They suggest that the interdealer order flow contains nonpublic information about market-clearing information. On the other hand, from the asset pricing aspect, exchange rate changes are affected by future cash flow inferred by interest rate difference and associated discount rate. Thus, the order flow should also contain the information about them.

The portfolio shift theory Evans and Lyons (2002) assumes that three rounds of trading happen in a day. Uncertain public demands are fulfilled at the start of the day in the first round when customers trade with market dealers based on the public available macro information. The expected payoff increments are designated as Δr_t which is observed and publicly available before trading. Net order C^1_{it} received by dealer i in the first round (known as portfolio shifts) is private information which is assumed to be independent among different dealers and uncorrelated with Δr_t. In round 2, dealers trade between each other with net order flow Δx_t which could be observed by all dealers. In round 3, dealers trade with customers to adjust their inventory risk in which the dealer-customer order flow C^3_{it} is not available to the public.[4] Assume the total public demand for risky asset $C^3_t = \sum_i C^3_{it}$ in round 3 is less than infinitely elastic, then C^3_t is a linear function of expected price change:

$$C^3_t = \gamma(E[P^3_{t+1}|\Omega] - P^3_t)$$

Where P^3_t is the third round quoted price; γ measures the public's aggregated risk bearing coefficient; Ω is publicly available information by the end of the second round(Δx_t and Δr_t). Dealers could infer the aggregate portfolio shifts on round 1 based on interdealer order flow Δx_t. Meanwhile, $C^3_t + C^1_t = 0$ for the risk-averse public to absorb orders on round three. The price change could be written as:

[4] Note that dealers quote the same price each round to satisfy the nonarbitrage condition.

$$\Delta P_t = \Delta r_t + \lambda \Delta x_t \tag{1.5}$$

Where λ is a constant depends on γ and variance of Δr_t and C_t^1. In the empirical analysis of Evans and Lyons (2002), Δr_t is measured as changes of nominal interest differential. They model two bilateral exchange rate pairs Deutsche mark/USD and Yen/USD by using the daily interdealer order flow in a ordinary least squares (OLS) regression of equation 1.5, and find significant λ with expected sign. They conclude that most of the contemporaneous daily exchange variations are modelled.

Following Evans and Lyons (2002), extensive empirical works that test the relationship between interdealer order flow and exchange rates or other variables that determined the exchange rate have been done(see, for example, Evans and Lyons, 2005; Boyer and Van Norden, 2006; Berger et al., 2008; Evans and Lyons, 2007). Among these studies, Rime et al. (2010) argue that a strong correlation exists between order flow and macroeconomic information. Order flow acts as an intermediary that aggregates macroeconomic information into price through two channels: (i) differential interpretation of currently available information; (ii) heterogeneous expectations about future fundamentals. If the information is gradually aggregated to the price, then order flow also has forecast power for future exchange rates. Rime et al. (2010) find that the forecast power of inter-dealer order flow is reliable on a daily basis.

1.2.3 Information in the customer order flow

Meanwhile, as dealer-customer order flow is available over the past decade, researchers find that customer order flow is also informative. Notable pioneer empirical work has been done by Sager and Taylor (2008) (among others, for example, Bjonnes et al., 2005; Evans and Lyons, 2007), who compare the informational value of commercially available customer order flow and interdealer order flow for Euro, Japnese Yen, Sterling and Swiss Franc in terms of contemporaneous explanation power and forecast accuracy. They find both types of order flow perform well in explaining contemporaneous exchange rate changes but fail to forecast on a daily and weekly basis by using lag order flow. The order flow forecast model does not outperform a random walk in terms of root mean squared forecast error (RMSFE). However, the customer dataset of Sager and Taylor (2008) is subject to issues such as market share.[5]

[5]The Sager and Taylor (2008) dataset is from JPMorgan Chase and Royal Bank of Scotland, who were ranking fourth and twelfth on market share, respectively, according to the 2003 Euromoney FX survey.

Cerrato et al. (2011) employ a proprietary customer order flow dataset from UBS for 9 currencies.[6] This dataset takes over 10% of the daily trading volume on the total currency market. It is the largest in terms of cross-sectional and time-series sample size and most recent up to that time. They redo the one-period-lag forecast model of Sager and Taylor (2008) and find that order flow produces a lower RMSFE than a random walk but that the difference is not significantly indicated by the Diebold-Mariano test (Diebold and Mariano, 2002). This dataset is also disaggregated into 4 customer types: Asset manager, Hedge fund, Corporate and Private client. When the disaggregated order flows are included in forecasting, forecast errors are further reduced for all currencies, but still no statistically significant improvement can be concluded.

Cerrato et al. (2015) criticize the linear relationship between exchange rate and order flow assumed in previous literature. Two empirical facts are in favor of the nonlinear models. The first is that of price reversal effects. They show that exchange rate positively comoves with contemporaneous order flows but negatively comoves with one-period lag order flows. Secondly, informativeness of order flow also changes over time due to issues such as market liquidity. In different market environments, a one unit increase in net order flow would generally have a different effect on the price. They introduce two models that account for the nonlinear relationship, namely the time-varying parameter model and the smooth transition model. The time-varying parameter model dynamically updates regression coefficients of the pure order flow model of Rime et al. (2010). The smooth transition model imposes a nonlinear parameter structure that allows both threshold and smooth transition movements on the regression coefficient. However, regarding the forecast evaluation of two nonlinear models, the nonlinear models do produce lower RMSFE, the significant improvements (against a random walk or linear model) suggested by the Diebold-Mariano test are seen in few currencies.

1.3 Risk-based Approach: Empirical Findings

Apart from the difficulty in forecasting exchange rates, a closely related problem, abnormal returns on the currency market, is widely discussed in the risk-based literature. This risk-based strand considers foreign currencies as an investable asset class that could fit in the asset pricing framework. Unlike the microstructure studies, asset pricing framework assumes a frictionless common-information world where any excess returns are compensations for bearing certain types of risk. Hence, an accurate measure of risks should be proposed to explain exchange rate dynamics.

[6] UBS ranks 1st on market share on the 2003 Euromoney FX survey. 9 Currencies are CAD, CHF, EUR, AUD, NZD, GBP, JPY, NOK, SEK.

1.3.1 Forward premium puzzle

The risk strand for exchange rate determination stems from studies about the failure of uncovered interest rate (UIP) parity. Fama (1984) propose a bilateral regression (equation 1.6 and 1.7) to investigate the failure of UIP.

$$s_{t+1} - s_t = \alpha_1 + \beta_1(f_t - s_t) + \epsilon_{t+1} \tag{1.6}$$

$$f_t - s_{t+1} = \alpha_2 + \beta_2(f_t - s_t) + \epsilon_{2,t+1} \tag{1.7}$$

Where s_{t+1}, s_t is the logarithm of spot exchange rate, f_t is the logarithm of forward exchange rate. Equation 1.6 and 1.7 regress the change of spot rate and the currency excess return to the forward premium, respectively. Under the UIP condition, regression coefficients $\alpha = 0$ and $\beta = 1$. Empirical results show that β is less than 1 and often negative. A vast amount of literature critisizes the risk-neutral assumption and argues that there is a time-varying risk premium associated with forward exchange rate: $f_t - E(s_{t+1}) = p_t$. Where p_t is the time-varying risk premium for holding a foreign exchange asset. Take equation 1.6 as example, the regression coefficient then follows:

$$\beta_1 = \frac{Cov(\Delta s_t, f_t - s_t)}{Var(f_t - s_t)} = \frac{Cov(\Delta s_t, p_t + \Delta s_t)}{Var(p_t + \Delta s_t)} = \frac{Cov(p_t, \Delta s_t) + Var(\Delta s_t)}{Var(p_t + \Delta s_t)}$$

If the forward premium p_t is constant, then β_1 is constant. To make$\beta_1 < 0$, two conditions must be satisfied (Fama, 1984):[7]

1. $Cov(p_t, \Delta s_t) < 0$

2. $Var(p_t) > Var(\Delta s_t)$

Others suggest forecast errors of UIP condition is due to investors' slow reaction to news or infrequent portfolios adjustments. However, Froot and Frankel (1989) use survey data of the expected future spot exchange rate to replace s_{t+1} in equation 1.6

[7]Fama condition requires i). The negative covariance between forward premium and expected change of spot exchange rate; ii). Greater variance of forward premium than the expected change of spot rate.

to control for forecast errors. They conclude that forecast error cannot quantify all of the deviations from UIP. A similar test has been done by Breedon et al. (2016) who find that β is increased after accommodate future rates with survey data but still far from one.

1.3.2 Currency portfolio anomalies

By taking advantage of UIP failure, investors could construct a currency carry trade portfolio by investing in high interest rate currencies and selling low interest rate currencies to earn excess returns. The risk-based strand of literature argues that there is a common source of the risk premium associated in the forward exchange rate which is in favour of the asset pricing approach. The key is to find the stochastic discount factor (SDF) that governs the dynamics of risk premium (or currency excess return). Failure of UIP suggests that currency excess return could be predicted by its interest rates. The profit of carry trade has been strong and persistent (e.g. Daniel et al., 2017). Asset pricing literature focuses on the currency portfolio excess return of a US investor, where the country-specific risk has been diversified. A position that borrows 1 US dollar to invest in foreign currency should earn excess r_{t+1} which equals the forward premium p_{t+1} (with accounting for interest rate difference):

$$r_{t+1} = s_t - E(s_{t+1}) + (i_t^* - i_t) = f_t - E(s_{t+1}) = p_{t+1}$$

There is a unique SDF m_{t+1} that makes all tradable assets follow the unconditional moment condition (Cochrane, 2009):

$$E(m_{t+1}p_{t+1}) = 0 \tag{1.8}$$

Empirical results show that grouping currencies according to their interest rates yields an increasing pattern from low interest rate portfolios to high interest rate portfolios. Proposing a SDF that adequately explains the interest rate sorted currency portfolios are equivalent to answer the forward premium puzzle. Backus et al. (2001) first link the forward premium to a SDF by adapting the affine yield model of Duffie and Kan (1996) to exchange rate dynamics. They also show that parameter restrictions to produce a SDF that satisfy the Fama condition. Lustig and Verdelhan (2007) propose a consumption-based CAPM (Merton and Others, 1973) to explain the carry trade anomaly. However, Burnside, 2011*b* questions the econometric method of Lustig and Verdelhan (2007) to estimate the standard errors. Burnside (2011*b*) show that consumption-based SDF are uncorrelated with currency excess return. Thus there is high uncertainty for betas, which leads to the risk premium being very weakly identified. He also show that Lustig and Verdelhan (2007)'s high cross-sectional R^2 is due to the constant pricing error that has been included in their model.

Empirical asset pricing literature generally assumes a linear combination of risk factors as a proxy for the SDF:

$$m_t = 1 - (f_t - \mu)' b$$

Where f_t is a $1 \times k$ random vector with $E(f_t) = \mu$; b is a $k \times 1$ coefficient vector for risk factors. Burnside et al. (2010), Burnside (2011*a*) and Burnside et al. (2011) show that traditional risk factors derived in the equity market (such as CAPM and Fama French 3 factors) do not price interest rate portfolios well. Burnside et al. (2010) provide another angle on the carry trade anomaly by involving the 'peso problem' which refers to the effects caused by low-probability events that do not occur in the sample. They show that potential large losses exist on carry trade by comparing payoffs of option hedged carry trade and unhedged carry trade position.

Several studies then consider pricing factors that more relevant to currency returns in a segmented market scenario. The pioneering work of proposing pricing factors specific to the currency market by using currency portfolios has been done by Lustig et al. (2011). Inspired by studies on the equity market that construct empirical risk factors by the portfolio difference of stocks sorted on properties that predict returns (e.g., Fama and French (1993, 1996)), a currency factor could be constructed by the return difference sorted on interest rates. Lustig et al. (2011) introduce the 'high minus low carry trade factor' (HML) and the 'dollar risk factor' (DOL). DOL is the cross-sectional average of excess return on all available foreign currencies.

$$DOL_{t+1} = \frac{1}{n}(r^1_{t+1} + r^2_{t+1} ...... + r^n_{t+1})$$

Where n is the number of interest rate currency portfolios available. DOL is a measure of the relative value for US dollar against the rest of foreign currencies in the world. DOL could also be considered as the US macroeconomic indicator. Gourinchas and Rey (2007) find that the US current account forecasts the exchange rate of the US dollar against a basket of currencies. HML is the difference between high interest rate portfolios and low interest rate portfolios: this finding is consistent with the microstructure study of Brunnermeier et al. (2008).

$$HML_{t+1} = r^H_{t+1} - r^L_{t+1}$$

Where r^H_{t+1} is the excess return of high interest rate portfolios and r^L_{t+1} is the excess return of low interest rate portfolios. This shows that interest rate sorted portfolios have identical risk exposure to the dollar risk factor (DOL). For HML factor, low interest rate portfolios load negatively to HML factor and high interest rate portfolios load positively to HML factor. Over 90% of crossectional variations of interest rate sorted portfolios have been explained by DOL and HML. However, simply using the linear combinations of interest rate portfolios to price the interest rate portfolio itself could not uncover the property of carry trade risk and it is also not surprising that this model performs well empirically.

Another study of Menkhoff et al. (2012*a*) follows the empirical asset pricing framework by proposing the volatility innovation factor in a linear SDF. Inspired by the work of Ang et al. (2006) on equity market, finding high returns on equity portfolios mainly due to compensations for aggregated volatility innovation, Menkhoff et al. (2012*a*) utilize the contemporaneous crossectional average of volatilities for individual currency excess return to proxy for aggregated volatility on the currency market. Then they take the AR(1) residual of aggregated volatility as the volatility innovation factor. They show that volatility innovation factors along with the DOL of Lustig et al. (2011) could explain over 80% crossectional variations. High interest rate currencies are negatively exposed to volatility innovation factor and low interest rate currencies are positively related to volatility innovation. Therefore, when there is a positive volatility shock on the currency market, high interest rate portfolios would generate losses and low interest rate portfolios would provide a hedge against the volatility innovations. They also show that volatility innovation factor is negatively correlated with the HML factor of Lustig et al. (2011).

However, neither the HML factor of Lustig et al. (2011) nor the volatility innovation factor of Menkhoff et al. (2012*a*) work well for currency momentum returns (Burnside et al., 2011). Allocating portfolios according to past return would provide abnormal returns which have been noted in many asset classes. On the currency market, time series momentum (or technical trading rules) are the main focus among previous studies. It has been shown that profit on such trading strategy would be affected mainly by trading costs and tend to deteriorate over time (e.g. Neely et al. 1997; Menkhoff and Taylor 2007; Neely et al. 2009). The crossectional momentum anomaly on the currency market has been analyzed in detailed by Menkhoff et al. (2012*b*).[8] They show that cross-sectional currency momentum does not correlate with the technical trading rules' returns. Transaction costs and change of spot exchange rate do play a role but not enough to diminish all profits. Burnside et al. (2011) also show that currency momentum does not demonstrate a strong correlation with carry trade excess returns. Burnside et al. (2011) and Menkhoff et al. (2012*a*) show that business cycle state variables and Fama French factors explain very little of the currency momentum. No clear evidence has been found that capital account restrictions and tradability would contribute to momentum anomaly. Instead, Menkhoff et al. (2012*b*) find that idiosyncratic volatility risk and country-specific risk tend to perform better on currency momentum. Currencies with high idiosyncratic volatility risk and country-specific risk are more likely to be selected in the momentum portfolios. This is consistent with the corresponding equity momentum study of Avramov et al. (2007) who find that high credit risk equity performs better on momentum strategy.

Except for momentum and carry trade anomalies, other managed currency portfolios that provide unexplained excess returns are also proposed. Barroso and Santa-Clara (2015*a*) construct an optimal currency portfolio strategy that adjust optimal weights for each currency by using 6 factors: the sign and the level of standardized forward premium; the currency momentum which is the last 3 months' excess return; currencies' long term value reversal measured by previous 5 years real exchange rate changes; the standardized real exchange rate; and the current account of foreign economy relative to the GDP. The out-of-sample Sharpe ratio, after accounting for the transaction cost, is as high as 0.86 which cannot be explained by risk factors or time-varying risk.[9] Barroso and Santa-Clara (2015*a*) also show that forward premium, momentum and long term value reversal are the main drivers of this strategy.

Lustig et al. (2014) propose the dollar carry trade strategy which employs the average interest rate difference (inferred by forward premium) on foreign currency against the US dollar as the prediction indicator. This strategy holds foreign currencies and shorts USD when the average foreign interest rate is above the US interest rate and shorts foreign currencies and holds US dollar otherwise. The after-trading-cost performance of this strategy is superb, with a high Sharpe ratio of 0.66. Note that this strategy largely outperforms the country level carry trade (with a Sharpe ratio of 0.06) and high minus low carry trade strategies (Sharpe ratio 0.31) on the same sample period. Lustig et al. (2014) find that the dollar carry trade return is uncorrelated with carry trade but is linked with the US business cycle. The excess of dollar carry trade strategy is termed countercyclical currency risk premia. Investors holding foreign currencies would have

[8] Earlier studies that form cross-sectional currency momentum portfolios include Okunev and White (2003); Burnside et al. (2011).

[9] This has been shown in the online appendix of Barroso and Santa-Clara (2015*a*)

high returns during good times and low returns during bad times, but overall a positive risk premium is compensated as they are betting on their own SDF.

Della Corte et al. (2016) find that the currency volatility risk premia have a strong predictability power for future exchange rates. In their study, the currency volatility risk premium (VRP) is defined as the difference between the physical and risk-neutral expectations of the future realized volatility which could be intuitively understood as the cost for volatility insurance of underlying currencies. The physical expectation of future volatility is proxied by the lagged realized volatility and the risk neutral volatility is proxied by the synthetic volatility swap rate which is derived by currency options. Currencies with high VRP have a lower cost to hedge against the volatility risk and *vice versa*. A significant excess return of 4.95 per year is realized by a monthly rebalanced long/short strategy that buys top 20% cheap-to-insurance and sells lower 20% expensive-to-insurance currencies. They also show that these results are robust under different estimation methods for the volatility risk premium. The predictability of VRP is primarily sourced from the exchange rate components instead of the interest rate difference. Thus, the cheap-to-insurance currencies tend to appreciate and *vice versa* for expensive-to-insurance currencies. Meanwhile, they also show that this excess return is not explained by standard risk factors such as the carry and the volatility innovation.

1.4 Asset market view of exchange rate

A theoretical framework, which is refer as the asset market view of exchange rates (Brandt et al., 2001), based on the SDF model is proposed for the foreign exchange studies. This model argues that agent's heterogeneous required compensations for foreign asset uncertainty drives the exchange rate dynamics. However, it is open discussion whether difference in SDF reflects the heterogeneous compensations.

1.4.1 Affine term structure model for forward premium

Researchers adapt models of affine term structure for interest rates to a cross-country setting to integrate forward premium puzzle and carry trade anomaly. Earlier studies trying to apply a stochastic setting for interest rates to price a currency option (Amin and Jarrow, 1991; Bakshi et al., 1997). Backus et al. (2001) consider whether term structure models are consistent with the forward premium puzzle by adapting the class of affine yield models of Duffie and Kan (1996) to satisfy the Fama (1984) condition in a bilateral exchange rate case.[10] Consider the short term risk free rate in logarithm r_t^* for foreign currency and r_t for domestic currency which satisfy the Euler equation 1.8:

$$\begin{aligned} r_t &= -ln(E_t(m_{t+1})) \\ r_t^* &= -ln(E_t(m_{t+1}^*)) \end{aligned}$$

Where m_{t+1} and m_{t+1}^* are SDF that price domestic currency denominated asset and foreign currency denominated asset, respectively. By nonabitrage condition, they must satisfy:

$$\begin{aligned} m_{t+1}^*/m_{t+1} &= S_{t+1}/S_t \\ ln(m_{t+1}^*) - ln(m_{t+1}) &= \Delta s_t \end{aligned} \tag{1.9}$$

Where S_t and S_{t+1} are spot exchange rate denominated in foreign currency unit per domestic currency.[11] Brandt et al (2006) term equation 1.9 as the asset matket view.

The expected change of spot rates in logarithm Δs_t and risk premium p_t are:

$$\Delta s_t = E(s_{t+1}) - s_t = E_t(ln(m_{t+1}^*)) - E_t(ln(m_{t+1}))$$

$$p_t = f_t - s_t + s_t - s_{t+1} = (lnE_t(m_{t+1}^*) - E_t(ln(m_{t+1}^*))) - (ln(E_t(m_{t+1})) - E_t(ln(m_{t+1})))$$

Assume the SDFs have a lognormal distribution with means (μ_{1t}, μ_{1t}^*) and variance (μ_{2t}, μ_{2t}^*), then

$$\begin{aligned} \Delta s_t &= \mu_{1t}^* - \mu_{1t} \\ p_t &= (\mu_{2t}^* - \mu_{2t})/2 \end{aligned}$$

[10]Similar studies about the class of affine models also have been done by Frachot (1996); Brennan and Xia (2006)

[11]Consider gross returns vector $R_{t+1}$and $R_{t+1}^*$of traded assets denominated in foreign currency and domestic currency, respectively. They satisfy Euler equations: $1 = E_t(m_{t+1}R_{t+1}) = E_t(m_{t+1}^*R_{t+1}^*)$. When the market is complete, m_{t+1} and $m_{t+1}^*$are unique and equation 1.9 is dictated.

To satisfy the second Fama (1984) condition, which requires $Var(p_t) > Var(\Delta s_t)$, then

$$Var(\mu^*_{2t} - \mu_{2t}) > 4Var(\mu^*_{1t} - \mu_{1t})$$

Therefore a great deal of volatility in the difference of conditional variance is required.

The general affine currency models of Backus et al. (2001) starts from a $n \times 1$ state vector z that follows:

$$z_{t+1} = (I - \Phi)\theta + \Phi z_t + V(z_t)^{1/2}\varepsilon_{t+1}$$

Where ε_{t+1} is $NID(0, I)$; Φ is stable with positive diagonal, V is a diagonal matrix with each elements :

$$v_i = \alpha_i + \beta_i^T z$$

Where α_i is a scaler; β_i^T is a $n \times 1$ vector. Then the SDFs m_{t+1}, m^*_{t+1},

$$-ln(m_{t+1}) = \delta + \gamma^T z_t + \lambda^T V(z_t)^{1/2}\varepsilon_{t+1}$$
$$-ln(m^*_{t+1}) = \delta^* + \gamma^{*T} z_t + \lambda^{*T} V(z_t)^{1/2}\varepsilon_{t+1}$$

The short term risk free rate r^*_t, r_t:

$$r_t = (\delta - \omega) + (\gamma - \tau)z_t$$
$$r^*_t = (\delta^* - \omega^*) + (\gamma^* - \tau^*)z_t$$

where $\omega = \sum_j \lambda_j^2\alpha_j/2$, $\omega^* = \sum_j \lambda_j^{*2}\alpha_j/2$; $\tau = \sum_j \lambda_j^2\beta_j/2 \geqslant 0$ and $\tau^* = \sum_j \lambda_j^{*2}\beta_j/2 \geqslant 0$.

Change of spot exchange rateΔs_t is:

$$\Delta s_t = (\delta - \delta) + (\gamma - \gamma) + (\lambda - \lambda)^T V(z_t)^{1/2}\varepsilon_{t+1}$$

To satisfy the first Fama (1984) condition,

$$Cov(p_t, \Delta s_t) = [(\gamma - \gamma^*) - (\tau - \tau^*)]^T Var(z)(\gamma - \gamma^*) < 0$$

To account for the forward premium puzzle, various models are proposed for the state variable z_t and the country SDF. Backus et al. (2001) show that a simple two-state Cox-Ingersoll-Ross model (Sun, 1992) for z_t cannot meet the Fama (1984) second condition. Backus et al. (2001) proposed two models that satisfy the Fama (1984) condition, namely, the independent factor model and the interdependent factor model.

The independent factor model divides the state variable into three components with currency specific state variable and common factor. However, the short term interest rate is not nonnegative in this model.

Another extension is the interdependent model. It follows two currency specific state variables but allows for cross-currency influence between currencies. However, to accommodate the Fama (1984) condition, an unrealistic coefficient condition that state variables of the specific currency have more influence on another currency must exist.

1.4.2 Reduced form affine models in a multi-currency scenario

Lustig et al. (2011) and Lustig et al. (2014) simplify these models to a multi-currency case to motivate the economic meaning of factor DOL and HML. They assume that a country specific state variable z^i_{t+1} for country i and a global state variable z^w_{t+1} follow the following law of motion:

$$z^i_{t+1} = (1 - \phi)\theta + \phi z^i_t + \sigma\sqrt{z^i_t}u^i_{t+1}$$
$$z^w_{t+1} = (1 - \phi^w)\theta^w + \phi z^w_t + \sigma^w\sqrt{z^w_t}u^w_{t+1}$$

Where u^i_{t+1} is the currency specific innovations and u^w_{t+1} is the common global innovations. In each country i, the SDF follows:

$$-ln(m^i_{t+1}) = \alpha + \chi z^i_t + \tau z^w_t + \sqrt{\gamma z^i_t}u^i_{t+1} + \sqrt{\delta^i z^w_t + \kappa z^i_t}u^w_{t+1}$$

All currencies have the same non-negative parameters of $\alpha, \chi, \tau, \gamma, \kappa$ but different in δ^i which measures the currency correlation with the common factor. Assume the home country has the average of δ^i loading δ on z_t^w. The short term interest rate for currency i is:

$$r_t^i = \alpha + (\chi - \frac{1}{2}(\gamma + \kappa))z_t^i + (\chi - \frac{1}{2}\delta^i)z_t^w$$

High interest currencies have higher value of δ^i given the same country specific state variable z_t^i. The innovations of HML are due to changes in the global state variable and global innovations. DOL reflects changes in average country specific factor and country specific innovations.

$$HML_{t+1} - E_t(HML_{t+1}) = (\sqrt{\delta_t^L} - \sqrt{\delta_t^H})\sqrt{z_t^w}u_{t+1}^w$$
$$DOL_{t+1} - E_t(DOL_{t+1}) = \sqrt{\gamma}\sqrt{z_t}u_{t+1}$$

Where δ_t^L and δ_t^H are the average of δ^i for high and low interest rate currencies repectively; z_t and is the average of country specific state variable; u_{t+1} is the average of country specific innovations. The β_j^{HML} and β_j^{DOL} for currency j could be specified as follows:

$$\beta_j^{HML} = \frac{\sqrt{\delta} - \sqrt{\delta_t^j}}{\sqrt{\delta_t^L} - \sqrt{\delta_t^H}}$$
$$\beta_j^{DOL} = 1$$

Where δ is the average of δ^i of all currencies. This matches the emprirical betas estimates to HML and DOL of Lustig et al. (2011). However the Lustig et al. (2011) parameter setting does not guarantee that the Fama (1984) condition is always satisfied. This simplified model suggests that the HML factor prices the cross-sectional variations of interest rate sorted currency potfolios but DOL does not, since it only serves as an intercept. Verdelhan (2018) finds empirical evidence that DOL also has a risk-based interpretation and he extends the Lustig et al. (2011) model to augment two global shocks that follow an autoregressive Gamma process. Then the SDF for country i is:

$$-ln(m_{t+1}^i) = \alpha + \chi_i\sigma_{i,t}^2 + \tau_i\sigma_{w,t}^2 + \gamma_i\sigma_{i,t}u_{i,t+1} + \delta_i\sigma_{w,t}u_{w,t+1} + \kappa_i\sigma_{i,t}u_{g,t+1}$$

$u_{i,t+1}$ is country specific shocks, $u_{w,t+1}$and $u_{g,t+1}$ are global shocks. $u_{i,t+1}$, $u_{w,t+1}$ and

$u_{g,t+1}$ are i.i.d. Gaussian with zero mean and unit variance. When $i = US$, the subscript is dropped off. Where $\sigma_{i,t}^2$ and $\sigma_{w,t}^2$ follow autoregressive Gamma processes.

$$\sigma_{i,t+1}^2 = \phi_i \sigma_{i,t}^2 + v_{i,t+1}$$
$$\sigma_{w,t+1}^2 = \phi_w \sigma_{w,t}^2 + v_{w,t+1}$$

The following parameter restrictions have been imposed to ensure that HML and DOL are orthogonal with each other:

$$\chi_i = \tfrac{1}{2}(\gamma_i^2 + \kappa_i^2), \text{in all countries except United States}$$
$$\chi < \tfrac{1}{2}(\gamma^2 + \kappa^2), \text{for United States}$$
$$\bar{\delta_i} = \delta$$

Then the conditional DOL and HML betas in an interest rate sorted portfolio j as the number of currencies approaches infinite are:

$$\beta_{limN\to\infty,t}^{DOL,j} = \frac{\gamma^2\sigma_t^2 + (\kappa_j\sigma_{j,t} - \kappa\sigma_t)(\bar{\kappa_i}\bar{\sigma_{i,t}} - \kappa\sigma_t)}{\gamma^2\sigma_t^2 + (\bar{\kappa_i}\bar{\sigma_{i,t}} - \kappa\sigma_t)^2}$$

$$\beta_{limN\to\infty,t}^{HML,j} = \frac{\delta_j - \delta}{\bar{\delta_i}^H - \bar{\delta_i}^L}$$

Where κ_j,$\sigma_{j,t}$ and δ_j are the average coefficients for currencies within portfolio j. $\bar{\kappa_i}$ and $\bar{\sigma_{i,t}}$ are the average coefficients of all currencies. $\bar{\delta_i}^H$ and $\bar{\delta_i}^L$ are the average coeffiecnts that forms high interest rate portfolios and low interest rate portfolios of HML factor.

1.4.3 Critique on the asset market view of currency assets

Burnside and Graveline (2019) find that, in a complete market, the change of real exchange rate does not reflect the difference in the required compensation for bearing risk between agents in different economy, but simply reflect the different units in which SDFs are expressed. To show this, consider a common numeraire C_t^η which is a portfolio with a weight vector η for k frctionlessly traded assets. Thus,

$$C_t^\eta = \dot{R}_t \times \eta'$$

$\dot{R}_t$ is a $k \times 1$ vector of gross returns. R_t^η is the vector of gross returns measured in common numeraire C_t^η,

$$R_t^\eta = \frac{\dot{R}_t}{C_t^\eta}$$

Let $P_{d,t}$ be the number of C_t^ηper unit of the domestic agent's consumption basketof goods services at time t; $P_{f,t}$ be the number of C_t^ηper unit of the foreign agent's consumption basketof goods services at time t. Let $\delta_{d,t+1} \equiv P_{d,t}/P_{d,t+1}$ and $\delta_{f,t+1} \equiv P_{f,t}/P_{f,t+1}$. The return vector R_t and R_t^* denominated in domestic and foreign currency are:

$$R_t = \delta_{d,t} R_t^\eta$$
$$R_t^* = \delta_{f,t} R_t^\eta$$

By nonabitrage condition,

$$m_{t+1}^*/m_{t+1} = \delta_{d,t+1}/\delta_{f,t+1} = S_{t+1}/S_t$$
$$ln(m_{t+1}\delta_{d,t+1}) - ln(m_{t+1}^*\delta_{f,t+1}) = ln(m_{t+1}) - ln(m_{t+1}^*) - \Delta s_t$$

In a complete market, an SDF for R_t^η is given by:

$$m_t = (R_t^\eta \theta^*)^{-1} \quad \text{where} \theta^* = \underset{\theta \cdot 1 = 1}{arg\,max} \mathrm{E}[ln(R_t^\eta \theta)] \Rightarrow \mathrm{E}[(R_t^\eta \theta^*)^{-1} R_t^\eta] = 1$$

The unique SDFs for domestic and foreign agents are:

$$ln(m_t) = -ln(R_t\theta^*) = -ln(R_t^\eta\theta^*) - ln\delta_{d,t}$$
$$ln(m_t^*) = -ln(R_t^*\theta^*) = -ln(R_t^\eta\theta^*) - ln\delta_{f,t}$$

Here the required compensation are the same for agents from different economy which are measured by $-ln(R_t^\eta\theta^*)$, the log difference in SDF is the differents in the common numeraire. Burnside and Graveline (2019) criticize the asset market view of foreign exchange in which the difference of log intertemporal marginal rates of substitution does not reflect the variations of required compensation.

1.5 Overlapped literature

Few papers break the isolation between microstructure literature and risk-based point of view studies. Several notable exceptions are Burnside et al. (2009), Menkhoff et al. (2016) and Breedon et al. (2016).

Instead of criticizing the risk-neutral assumption of UIP, Burnside et al. (2009) provide a theoretical framework that discusses the adverse selection problem faced by a market dealer in a microstructure approach to interpreting the 'forward premium puzzle'. In this model, the forward price is assumed to be determined by interactions among market dealers, informed traders and uninformed traders. All agents are risk neutral and each trader places one order. Percentage change of spot exchange rates are set to be a stochastic process $\%\Delta s_t = \phi_t + \varepsilon_{t+1} + \omega_{t+1}$. Where $\phi_t$and ε_{t+1}follows two-point distribution with equal probability and realizations $\pm\phi$,$\pm\varepsilon$. ω_{t+1} is a mean 0 and variance σ^2_ωcontinuous random variable.$\phi_t$is the expected change given public information at time t; ε_{t+1} is partially known to informed traders but unknown to uninformed traders; ω_{t+1} is the price shock up to time $t+1$. Among all the traders, a fraction of α is the informed traders who have a probability q to receive information about ε_{t+1}. Risk-neutral market dealers face an adverse selection problem when they receive orders from traders without knowing the identity of the traders. Thus they will set the price depending on their expectations to future changes of spot exchange rates which would deviate the exchange rate from the UIP condition. The more adverse selection problem that market dealers are facing, the higher the volatility of bid-ask spread. Given the above assumptions, the forward price set by market dealers should be:

$$F_t^a(\phi_t) = \begin{cases} S_t[1+\phi+(2q-1)\varepsilon\alpha/(2-\alpha)] & if\phi_t = \phi \\ S_t[1+\phi+(2q-1)\varepsilon] & if\phi_t = -\phi \end{cases}$$

$$F_t^b(\phi_t) = \begin{cases} S_t[1+\phi-(2q-1)\varepsilon] & if\phi_t = \phi \\ S_t[1-\phi-(2q-1)\varepsilon\alpha/(2-\alpha)] & if\phi_t = -\phi \end{cases}$$

Under this setting, the least square estimate for slope coefficient of Fama regression (1.6) is:$\hat{\beta} = \frac{\phi}{\phi-(1-\alpha)(2q-1)\varepsilon/(2-\alpha)}$ which could be less than 1 or even negative given different values of α and q. Burnside et al. (2009) provide a theoretical framework of how the adverse selection problem fails the UIP condition. They have the first try to investigate the forward premium puzzle by going deep into the microstructure of a decentralized dealership market. Even the order flow data is not directly used, α and q are market microstructure information that could be measured by the order flow.

Similarly, Breedon et al. (2016) try to answer the forward premium puzzle by involving microstructure information under a risk-based framework. They argue that the missing variable or risk premium in Fama regression (equation 1.6 and 1.7) could be measured by microstructure order flow. Forward and spot transaction price and survey data of three currency pairs (USD/EUR, USD/JPY, USD/GBP) with correponding interdealer order flow are employed in that study. In this chapter, equation 1.2 is modified as:

$$E(s_{t+1}) - s_t = (i_t^* - i_t) + \breve{o}_t$$

Where $\breve{o}_t = \sigma_t^2 \cdot o_t$ is the Time varying bilateral currency premium which is increasing with conditional future expected volatility σ_t^2 and interdealer order flow variable o_t. Thus $\beta_1$in Fama regression (equation 1.6) could be decomposed as

$$\beta_1 = 1 + \beta_0 + \beta_u$$

Where

$$\beta_0 = \frac{cov(\breve{o}_t, f_t - s_t)}{var(f_t - s_t)}, \ \beta_u = \frac{cov(u_{t+1}, f_t - s_t)}{var(f_t - s_t)}$$

β_0 accounts for the beta deviations due to the risk premium and $\beta_u$accounts for the beta deviations from forecast error. GMM estimations modified order flow risk premium $\breve{o}_t$ works better with carry trade related currency pairs USD/EUR and USD/JPY but not for less carry trade-liked USD/GBP. $\breve{o}_t$ explains about 80% bias for USD/JPY and 50% for USD/EUR where USD/JPY is a well-known carry trade funding currency. Breedon et al. (2016) also show that intensive carry trade activity could contribute to the negative covariance between modified order flow variable$\breve{o}_t$and forward premium thus twists $\beta_1$less than 1 or even negative. Another finding of Breedon et al. (2016) is that modified order flow variable$\breve{o}_t$is negatively correlated with the skewness of currency excess return. This is akin to the findings of Brunnermeier et al. (2008) and Burnside et al. (2010) who believe carry trade is not a 'free lunch' as it associates with crash risk.

Menkhoff et al. (2016) employ a daily dataset of customer order flow for 15 currencies to examine currency portfolio returns based on lagged order flow. Several aspects distinguish their study from previous microstructure literature. Firstly, a cross-sectional portfolio approach based on order flow information for a large currency set is used, instead of a time series forecast power to one exchange pair. Similar to the interest rate sorted portfolios in the risk-based literature (see for, example, Lustig et al. 2011; Menkhoff et al. 2012*a*), Menkhoff et al. (2016) construct five daily portfolios based on the lagged aggregated customer order flow. By detecting a significant positive return difference between P5 and P1 of order flow sorted portfolios,[12] they show that lagged order flow has significant forecast power to future currency excess return and thus exchange rates. From the risk-based point of view, they also propose an asset pricing anomaly which cannot be explained by current pricing factors. Secondly, previous microstructure literature uses interdealer order flow. They are the first who use end-user order flow which includes disaggregated data in four different customer types: 'long term demand side investment managers' (LT); short-term demand-side investment managers; commercial corporations (CO); and individual investors (II). Portfolios sorted on different customers types demonstrate substantial heterogeneity. High minus low portfolios based on LT and ST earn positive excess returns but portfolios on CO and II earn negative returns. These empirical facts state that customers in different segments have distinct properties and trading styles. More specifically, LT tends to be the 'trend follower', and II could be recognized as a 'contrarian' which is akin to the equity market findings of Kaniel et al. (2008). This finding provides evidence that risk sharing happens among end-users. By tracking returns of order flow sorted portfolios after the formation period, one could also determine whether lagged order flow indicates permanent or temporary price changes. These authors show that aggregated order flow and disaggregated LT customer order flow have a persistent influence on the price change. Portfolios sorted on other order flow information would experience short-term reversals several periods after the formation period.

1.6 Conclusion

In this paper, I provide an overview of the two fast-growing strands of empirical literature on the foreign exchange market, namely, the market microstructure and risk-based point of view. Both of these two strands have played a significant role in the contemporaneous explanation and future prediction of currency value with models performing well empirically. The market microstructure strand emphasises the channel through which microstructure information is aggregated in the exchange rate and how order flow reflects macroeconomic information. Empirical studies on microstructure then try to use order flow to forecast future exchange rate changes in different ways. In the risk-based strand, anomalies with explainable high returns exist. Researchers are trying to propose a parsimonious set of orthogonal pricing factors to deal with these anomalies.

[12] P5 contains currencies with highest lagged order flow and P1 contains currencies with lowest lagged order flow.

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Chapter 2

Foreign Exchange Order Flow as a Risk Factor

2.1 Introduction

Two strands of the literature on exchange rates offer explanations for anomalies in foreign exchange markets that are at odds with one another. One of these strands tries to explain the behaviour of exchange rates within a frictionless common-information environment where returns to currency based investment strategies are interpreted as compensation for risk.[1] Another strand of the market microstructure is grounded in microstructure models in which customer order flow is a key determinant for bilateral exchange rate changes, in the same way as for currency excess returns.[2]

These two strands of the literature are based on two different visions of the underlying structure of the model economy. In this chapter, I explore whether the empirical facts brought to bear in support of these different visions are, in fact, consistent with both. In other words, is the empirical evidence in favour of, say, the frictionless risk-based view of the world, also compatible with the order-flow-driven view of the world?

For example, a commonly studied anomaly in foreign exchange markets is the profitability of the carry trade, which can be connected to the failure of the uncovered interest-rate-parity (UIP) condition(Fama, 1984). According to the UIP condition, the gap between the foreign interest rate i_t^* and the domestic interest rate i_t is how much foreign currency is expected to depreciate, i.e.

$$E_t s_{t+1} - s_t = i_t^* - i_t \tag{2.1}$$

Where s_t is the logarithm of the spot exchange rate denoted as currency unit per US dollar (FCU/USD). The UIP condition implies that currency excess return of borrowing one USD and investing in the short-term FCU-denominated risk security is expected to be zero.

$$r_{t+1} = i_t - s_t - i_t^* + s_{t+1}$$

Equation 2.1 also suggests that low interest currencies tend to appreciate and high

[1]Examples of articles using this approach include Lustig and Verdelhan (2006); Lustig and Verdelhan (2007); Colacito and Croce (2011); Lustig, Roussanov and Verdelhan (2011); Lustig, Roussanov and Verdelhan (2014); Menkhoff, Sarno, Schmeling and Schrimpf (2012);

[2]See Evans and Lyons (2002); Cerrato, Sarantis and Saunders (2011); Cerrato, Kim and MacDonald (2015); Breedon, Rime and Vitale (2016); and Menkhoff Sarno, Schmeling and Schrimpf (2016) for a review of the recent literature.

interest rate currencies tend to depreciate. There is a vast empirical literature documenting the apparent failure of the UIP condition. Two common approaches establish this failure.

The classic results are based on regressing $s_{t+1} - s_t$ on $i_t - i_t^*$ for different currency pairs (see, for example Fama, 1984). According to equation 2.1 the result of doing this should be a zero constant and a unit slope, but this is not the typical finding. Instead, the slope coefficient is typically well below 1 and even negative. This negative slope coefficient indicates, in the opposite case, high interest currencies would earn a higher return than low interest rate currencies. The second approach exploits this UIP failure by devising currencies portfolios that use time t information of interest rates. Since equation 2.1 implies that $E_t r_{t+1} = 0$, none of the portfolios should be profitable or deficit on average. Empirical studies show that low interest rate currencies tend to earn a significant negative return and high interest rate currencies tend to have a positive return (see, for example Lustig and Verdelhan, 2007). One trading strategy is to borrow in low interest rate currencies and lend in high interest rate currencies (the so-called carry trade), and this has been shown to be highly profitable in the period since the collapse of Bretton Woods.

As the UIP condition is based on the assumption of risk neutral investors, a natural question is whether risk aversion can explain the returns to carry trade, and the failure of UIP. When risk is accounted for, $E_t r_{t+1} = p_t$, where p_t is the risk premium, and equation 2.1 can be rewritten as

$$E_t s_{t+1} - s_t - (i_t^* - i_t) = p_t$$

The strand of literature that focuses on the risk-based explanations of the failure of UIP explores different models of p_t. It follows the asset pricing framework which assumes a unique stochastic discount factor (SDF) or intertemporal marginal rate of substitution. In a frictionless environment, SDF and all tradable assets follow unconditional moment condition restriction,

$$E(m_{t+1} r_{t+1}) = 0$$

In practice, the SDF is difficult to identify and empirical asset pricing would use a linear combination of risk factors as a proxy for SDF,

$$m_t = 1 - (f_t - \mu)'b$$

Thus the risk premium is

$$p_t = E(r_{t+1}) = -Cov(m_{t+1}, r_{t+1}) = cov_t(f_{t+1,}\Delta s_{t+1})'b \qquad (2.2)$$

Risk-based solutions try to find a set of pricing factors that covary with changes in exchange rates for some parameter vector b.[3] Empirical studies have documented the risk premium $p_t < 0$, when $i_t^* > i_t$ and risk premium $p_t > 0$, when $i_t^* < i_t$.

In the microstructure literature, in contrast, the emphasis is on how dispersed information is aggregated into exchange rate changes and how market dealers set the quoted price based on the private information of customer order flow. Past literature finds customer order flow is informative for the discovery process of exchange rates. As the foreign exchange market is a decentralized dealer's market, customers will trade with a market dealer based on the public information and their private view of future economic fundamentals. Market dealers are not only aware of the public information, they also observe customers' order flow and their identities which are privately available to them. Market microstructure theories argue that asymmetric-information and the decentralized trading mechanism play a key role in exchange rate changes. Risk averse market dealers are reluctant to hold foreign exchange asset and they dynamically adjust the inventory by altering the risk premium (quoted price) based on their private knowledge of customers order flow.

A simple model in microstructure literature is linear and relates exchange rate changes to the customer order flow and the interest rate difference

$$E_t s_{t+1} - s_t = \sum_{i=1}^{n} \beta_i x_{i,t+1} + \gamma(i_t^* - i_t)$$

Where $x_{i,t+1}$ is the order flow for currency i between t and $t+1$;[4] β_i and γ are the regression coefficients.

[3] See, for example, Lustig et al. (2011) and Menkhoff, Sarno and Schmeling (2012) for two recent examples, and Burnside (2012) for a review.

[4] Other currencies' order flow is included to reflect the possible correlations between different currencies (Cerrato et al. 2011).

The seminal work in microstructure literature had been done by Evans and Lyons (2002). Due to the poor explanation power of macroeconomic models for high frequency exchange rate changes, they introduced a hybrid model that employs macroeconomic data (such as interest rate differentials and GDP growth etc.) and order flow data together to explain the exchange rate changes. Past literature argues that there are two main channels of how order flow relates to exchange rates. Firstly, order flow reflects customer views about economic fundamentals. Customers will place their orders not only according to the common public knowledge,[5] but also their private view about the future of economic fundamentals. A study by Evans and Lyons (2009) shows that order flow has significant forecasting power for future GDP growth, money growth and inflation, etc. Incorporating this information into the market will likely alter the exchange rate and the risk premium persistently. Secondly, there is the price pressure effect. A high value of order flow imbalance may be due to a short term liquidity problem. Price changes subject to this effect may experience a reversal afterwards.

My interpretation is that order flow and risk factors contain equivalent information on exchange rate changes or currency excess return. The hypothesis I explore in this chapter is that the empirical facts brought to bear in support of these different vision are, in fact, consistent with each other. A natural idea to combine two strands of literature is to create a common risk factor by using microstructure order flow that fits in a risk-based asset pricing framework. If the order flow does have the equivalent information of risk-based pricing factors, it should also have high explanation power to carry trade anomaly.

In this study, I construct two sets of pricing factors based on aggregated and disaggregated customer order flow. The first set of factors are the size-adjusted cross-sectional average order flow of all available currencies which are referred to as global order flow factors. They measure the capital inflow or outflow from US dollars to other currencies. The second set are the carry sign adjusted cross-sectional average of size-adjusted order flow, referred to as the carry trade order flow factor, which directly reflects the relative degree of carry trade activity. I find both order flow factors have high explanation power for currency excess returns but argue that they stand for two different kinds of risk. I find carry trade order flow factors outperform the global order flow factors in explaining interest rate sorted portfolios in terms of aggregated or disaggregated data. This indicates that market dealers are more sensitive to the relative degree of carry trade activity more than to capital inflow or outflow from the US dollar to other currencies.

Another question studied in this chapter is whether the risk premium has different

[5] Interest rate differential is an example of common public knowledge.

sensitivity to order flows from different customers. To answer this question, I collect disaggregated order flow data which are categorized into four different customer types: asset manager; hedge fund; corporate; and private clients. My second hypothesis is that disaggregated order flow factors have different explanation power for the currency market risk premium, as different customers vary in terms of sophistication. Meanwhile, private information exists and is only available to some informed customers. In a decentralized dealer's market, market dealers set the risk premium. Information about current customer order flow, customers' identity and historical performances are available to market dealers. Customers are categorized as informed and uninformed investors. When informed investors place a buy order, market dealers will increase the ask price to reduce their adverse selection problem(Burnside et al., 2009) and *vice versa* for uninformed investors. Correspondingly, the exchange rate will have different sensitivity to order flow from different customer types.

As well as explaining the traditional carry trade anomaly, order flow pricing factors also explain the currency momentum excess returns. I build quintile currency momentum portfolios in the way of Menkhoff et al. (2012*b*) by using 4 weeks formation period and 1-week holding period as the test assets. The corresponding momentum order flow factor set has a significant risk premium.

Risk-based literature on carry trade proposes different models for the risk premium p_t. Lustig and Verdelhan (2007) first tried to fit the interest rate sorted currency returns into a consumption CAPM framework(Yogo, 2006; Breeden, 1979). Their study was conducted in the perspective of US investors. They conclude that high interest rate currencies are subject to US consumption growth risk. When US consumption growth is low, high interest currencies depreciate but the low interest rate currencies appreciate and thus provide a hedge. However their statistical results are questioned by Burnside (2011*b*). He shows the consumption-based discount factor of Lustig and Verdelhan (2007) has jointly zero correlation with excess portfolio returns and argues that consumption risk explains none of the cross-sectional variations in interest rate sorted portfolios.

Another common method is to find pricing factors f which could work as a proxy. Traditional stock market's pricing factors have been documented as a failure for pricing foreign exchange market premium. Burnside (2011*a*) reports poor performance of traditional factors such as CAPM Lintner (1965), Sharpe and Pnces (1964) and the Fama French three-factor modelFama and French (1993). One plausible reason would be the market segmentation between the stock market and the currency market. Therefore, researchers focus on identifying the risk factors specific to the currency market. In empirical studies for equity risk premium, researchers sort portfolios according to a variable that predicts the returns then construct a pricing factor as the difference of extremal portfolios. Inspired by this research technique, Lustig et al. (2011) propose two risk factors: the dollar risk factor (DOL) and the high minus low carry trade factor (HML), that are themselves a linear combination of interest rated sorted portfolios. They show that HML and DOL together explain most of currencies' cross-sectional variation. Similar results could be found in subsequent empirical studies such as Burnside (2011a), Burnside et al. (2011) and Byrne et al. (2018). However, it is not surprising that the factors proposed by Lustig et al. (2011) have a statistical success since the factors themselves are a linear combination of test portfolios. One criticism of this model is that it does not identify what kind of risk is shared between investors and it uses carry trade return to explain carry trade itself.

Probing further what risk has been borne by investors who hold high interest rate currencies, Menkhoff et al. (2012a) propose a volatility factor and show that carry trade strategies generate poor returns when volatility innovation is high.[6] They find that high interest rate currencies are negatively related to volatility innovation and hence deliver a low return in periods of high volatility innovation while low interest rate currencies can serve as hedging currencies in these periods and provide a positive return. This part of the risk-based literature shows solid empirical results in support of the idea that excess returns on carry trade are mainly driven by compensation for risk. In this chapter, I take a further step to show that the classical factors proposed in the literature are linked to order flow and that it is the latter factor that contains the relevant information which helps to understand carry trade excess returns. From this point of view, this chapter can also provide theoretical ground to the recent risk-based literature on the carry trade.

Burnside et al. (2010) show that carry trade excess return is a compensation for crash risk or the 'peso problem'. My carry trade order flow factors are directly related to the peso risk. The peso problem refers to low probability events that do not recur in the sample. During the peso state or currency crash, the funding currencies will experience a sharp appreciation and investment currencies a sudden depreciation which causes large losses for the carry trade strategy. Burnside et al. (2010) suggest that currency crash is due to the high value of stochastic discount factor m instead of the high negative value of excess return r in equation 2.2. This finding is important since it shows that currency crashes are attributed to a common factor within the investable universe on the currency market. The country specific macroeconomic fundamentals would certainly affect the country's currency strength. However under the portfolios scenario, country risk has been hedged out. The peso problem is another source of risk that is common to all currencies which is unrelated to the country-specific risk.

[6] They are inspired by corresponding equity study of Ang et al. (2006) that finds high return on equity portfolios is mainly due to compensation for volatility innovation risk.

The risk-based study of Burnside et al. (2010) may be linked to the market microstructure study of Brunnermeier et al. (2008). Brunnermeier et al. (2008) try to explain the currency crash or peso problem by involving the trading mechanism of the informed investor. They conclude that sudden exchange rate drops are due to the unwinding of carry trade when speculators near their funding constraints. In practice, investors who exploit the carry return would build their position gradually but liquidate their position suddenly. The losses of carry trade positions force investors to further liquidate their positions causing, in this way, the liquidity to dry out quickly. Empirical evidence that signals this phenomenon is that high interest rate currencies are highly negatively skewed. As investors build up their carry trade position, the risk premium increases since the probability of currency crash also increases. Brunnermeier et al. (2008) performed a country-specific regression by using the previous period's bilateral order flow to successfully forecast the future skewness of exchange returns. In that study, both the common peso risk and country-specific risk are modelled. In this chapter, I focus on modelling the common peso risk and try to diversify the country-specific risk by forming portfolios. Another paper which attempts to model the common peso risk is that of Rafferty (2012) who uses the carry sign adjusted contemporaneous cross-sectional average of monthly skewness as a pricing factor to explain the currency risk. However one criticism is that contemporaneous high negative skewness does not necessarily correspond to high peso risk. This is because speculators may already unwind the position and release the price pressure when the sample skewness is high. Thus my order flow factors are a better measure of crash risk.

This chapter is related to the traditional foreign exchange microstructure literature which focuses on the importance of order flow to explain exchange rate behaviour. Evans and Lyons (2002) show that order flow maps a significant part of the information, which is not publicly available, into price discovery and it can explain a large part of the exchange rate variation. Evans and Lyons (2009) propose a novel theoretical model which links (customer) order flow from a large US bank to currency excess return via the risk premium. The prediction of the model is that order flows convey part of the information for the future macroeconomic conditions and that this information filters into the exchange rate. Therefore, market dealers use the information in the order flow to adjust the risk premium when they quote the spot rate. My study is related to that of Evans and Lyons (2009) in that it shows that customer order flow is important to understand carry trade excess returns and that difference in carry trade trading behaviour (and risk sharing) give rise to different risk premia across different customers.

This chapter is also related to the study of Menkhoff et al. (2016) who use a large data-set of customers order flow from a large FX dealer; they show that order flow carries important information which can be used for predicting currency returns. They also show that financial customer's flow contains information which has a long-term impact on currency returns. Meanwhile, financial and non-financial customers trade in opposite directions, therefore these authors provide evidence of risk sharing taking place in the customer market. Differently from Menkhoff et al. (2016), this chapter focuses mainly on carry trade and how order flow relates to carry trade risk premium across different trade segments rather than exchange rate predictability.

As for the econometric method, I employ the traditional general method of moments (GMM) of Cochrane (2005) and the Fama-Macbeth method. Burnside (2016) argues that the covariance matrix of pricing factor with excess returns sometimes violates the full rank condition, thus the inference from both these methods would be wrong. Therefore, along with traditional GMM, I also report the reduced rank test of Kleibergen and Paap (2006). If the covariance matrix does have a reduced rank, I then report the reduced rank method of moments of Burnside (2016) along with the traditional GMM results. Following Burnside (2016), I develop a reduced rank Fama-Macbeth method to report the reduced rank adjusted portfolio betas and risk price.

Finally, this chapter stresses the role of aggregated customer order flow and informed customers order flow to understand cross-sectional carry trade excess returns and how dealers use private information to change the (carry trade) risk premium. Doing this shows that the two strands of the literature cited above are closer than previously believed. This chapter is structured as follows: Section 2.2 introduces data and currency portfolios; in section 2.3, the pricing factors are introduced. Section 2.4 is the econometric models. The empirical asset pricing results are presented in section 2.5. Section 2.6 tests the currency momentum strategies. Section 2.7 is the conclusion.

2.2 Data and portfolio construction

This section discusses the data of custom order flow, and exchange rates on the spot and forward market. The currency excess return basics, portfolio constructions based on the interest rate and order flow are also introduced.

2.2.1 Data

My weekly dataset covers the period from the first week of November 2001 to the fourth week of March 2012. There are 543 observations in total available for 20 currencies: EUR, JPY, GBP, CHF, AUD, NZD, CAD, SEK, NOK, MXN, BRL, ZAR, KRW, SGD, HKD, TRY, HUF, PLN, CZK, SKK. All exchange rates are quoted against US dollar which means the exchange rate is measured as the number of foreign currency units (FCU) per US dollar (USD).[7]

I collect the spot and forward exchange rates for the sample period. The weekly and daily spot exchange rates as well as 1 week forward exchange rates are collected from WM/Reuters (via Datastream). For currencies AUD and NZD with 1-week forward exchange rates unavailable on WM/Reuters, I obtain the data from Bloomberg terminal.

My order flow dataset is provided by UBS, one of the largest market makers on the currency market. According to the Euromoney foreign exchange survey from 2001 to 2011, UBS took 12.77% share of the global foreign exchange market during the sample period and has been ranked as first third largest market dealer almost every year except for year 2001 in which only a few data are covered in my dataset. Table 2.2 lists the top 10 banks that took the highest market share on the currency market. It seems reasonable to take the UBS customer order flow data as a qualified proxy for overall customer order flows. I collect aggregated order flow data and the trading volume for 20 currencies. The order flow is measured as the US dollar value of buyer-initiated minus seller initiated trades of a currency. A positive net order flow indicates net buying for foreign currency and selling of the US dollar. The trading volume is measured as the US dollar value of all the transactions.

I also have a smaller sample of disaggregated order flow data for 9 developed country currencies (EUR, JPY, GBP, CHF, AUD, NZD, CAD, SEK, NOK) for the same sample period. This disaggregated dataset is categorized by four customer types: Asset Manager; Corporate; Hedge Fund; and Private Client. Asset manager and hedge fund are categorized as financial customers.

2.2.2 Market Microstructure Analysis

In this section, I perform the classic microstructure model of Evans and Lyons (2002) for 20 currencies in a weekly basis.[8] For each currency, spot exchange rate changes are regressed on the interest rate difference (proxied by forward premium assuming CIP holds) and dealer-customer order flow:

[7] I use a smaller dataset compared with previous empirical studies (see, for example Lustig et.al, 2011). Due to the restricted time span of order flow data, I conduct my empirical experiment on a weekly basis to have more observations to validate the statistical inference.

[8] Note that **?** do the same analysis for 9 currencies.

$$\Delta s_t = \beta_0 + \beta_1(\ln(F_t) - \ln(S_{t+1})) + \beta_2 X_t + \varepsilon_t$$

Where Δs_t is the weekly change of the logarithm of the exchange rate; X_t is the aggregated customer order flow; f_t^{t+1} is the logarithm of 1-week forward exchange rate; s_t is the logarithm of spot exchange rate. Table 2.1 reports the regression coefficients, standard errors and adjusted R-squares. The regression results are generally consistent with findings in Cerrato et al. (2011), Sager and Taylor (2008) and Evans and Lyons (2002). Coefficient β_1s are not significantly different from zero. Coefficient β_2s are broadly negative and significant which indicates significant relation between contemporaneous order flow and exchange rate changes.

[Table 2.1 about here]

2.2.3 Currency excess return

I discuss the currency excess return from the perspective of a US investor. US dollar is the home currency and the exchange rate is expressed as units of foreign currency per US dollar (FCU/USD). As a US investor who borrows at US dollar to invest in foreign currency k, the excess return consists of the interest rate differential plus the fluctuation of the exchange rate. The excess return for currency k during the period $[t, t+1]$ is:[9]

$$r^e_{k,t+1} = \ln(S_t) - \ln(S_{t+1}) + i^*_t - i_t \tag{2.3}$$

Where ln() is the natural logarithm operation. S_t and S_{t+1} is the spot exchange rate at time t and t+1. i^*_t is log interest rate for currency k of period $[t, t+1]$. i is the log interest rate for US dollar of the same period.

Recall the covered interest rate parity (CIP)

$$\ln(F_t) - \ln(S_t) = i^* - i$$

[9] I do not take bid-ask spread into account when I calculate excess returns due to the weekly frequency of my dataset. A detailed explanation is found in Appendix 1

Here F_t is the forward exchange rate on time t and delivery date at time $t+1$ for foreign currency. In this study, I assume CIP holds, thus the interest differential is equal to the forward premium. Substituting CIP into equation2.3, I have

$$r^e_{k,t+1} = \ln(F_t) - \ln(S_{t+1})$$

Hence I could synthesize the zero-cost foreign currency long position for the period $[t, t+1]$ by entering into a forward contract to buy foreign currency at time t and then exchanging to US dollar in the spot market at the delivery date $t+1$.

Accordingly, for a US investor borrowing foreign currency and investing in US dollars, the return from a forward-synthetic short position of currency k is

$$r^e_{k,t+1} = -\ln(F_t) + \ln(S_{t+1})$$

The carry trade strategy is to borrow at low interest rate currency and invest in high interest rate currency. It is a managed portfolio given the current information of interest rate differential. By involving forward contracts, the return for carry trade performed on currency k and US dollar is computed as

$$r^{carry}_{k,t+1} = \begin{cases} \ln(F_{k,t}) - \ln(S_{k,t+1}), & \ln(F_{k,t}) - \ln(S_{k,t}) > 0; \\ -\ln(F_{k,t}) + \ln(S_{k,t+1}), & \ln(F_{k,t}) - \ln(S_{k,t}) < 0. \end{cases} \tag{2.4}$$

2.2.4 Interest rate portfolio and currency trading strategy

I allocate 20 currencies into 5 portfolios according to their interest rate in which portfolio 1 contains currencies with the lowest interest rates while portfolio 5 contains currencies with the highest interest rate. I assume the CIP holds, so sorting on interest rate is equivalent to sorting on forward discount. At time t, currencies are sorted by interest rate differentials with the US interest rate at the beginning of the week and ranked from low to high. It is assumed that investors close the position and set up a new position at the end of each week. Thus, I reconstruct portfolios each week and calculate the equally weighted portfolio excess return according to conditional forward discount. The excess return for portfolio i, $r_{i,t+1}$ during $[t, t+1]$ is computed as

$$r_{i,t+1} = \frac{1}{K_{i,t}} \sum_{k \in K_{i,t}} r^e_{k,t+1} = \frac{1}{K_{i,t}} \sum_{k \in K_{i,t}} (\ln(F_{k,t}) - \ln(S_{k,t+1}))$$

Where $K_{i,t}$, is the number of currencies included in portfolio i at time t, $r^e_{k,t+1}$ is the excess return for currency k. I have different numbers of currencies from portfolio 1 to 5 in the early period due to unavailability of forward price. At least 3 currencies are included in one portfolio. During most of the sample period, each portfolio includes 4 currencies.

I introduce several carry trade strategies according to the literature. Burnside (2011*a*) introduces the equal weighted carry trade (EWC). EWC implements the carry trade for all the foreign currencies available based on equal weightings. The total bet of this strategy is normalized at 1 USD. The return for portfolio EWC during period $[t, t+1]$ is

$$EWC_{t+1} = \sum_{k=1}^{N_t} \frac{r^{carry}_{k,t+1}}{N_t} = \sum_{k=1}^{N_t} \frac{sign(\ln(F_{k,t}) - \ln(S_{k,t}))}{N_t} r^e_{k,t+1}$$

Where N_t is the total number of currencies available at time t, r^{carry}_k is the carry trade return in equation 2.4 implemented between currency k and US dollar.

I follow Daniel et al. (2017) in constructing the spread weighted carry trade portfolio (SPD) and Dollar neutral carry trade portfolio (DNC). SPD portfolio modifies equal weightings by the relative size of interest differential according to the total interest differentials. The total interest rate differential is measured as the sum of absolute values of all the interest rate differentials. The return of SPD portfolio is

$$SPD_{t+1} = \sum_{k=1}^{N_t} \frac{\ln(F_{k,t,t+1}) - \ln(S_{k,t})}{\sum_{j=1}^{N_t} |\ln(F_{k,t,t+1}) - \ln(S_{k,t})|} r^e_{k,t+1}$$

Where N_t is the total number of currencies available at time t.

All carry trade strategies introduced above are performed from the perspective of a US investor. Whether selling or buying a currency depends on the relative interest rate differential compared with the US interest rate. The Dollar neutral carry trade portfolio (DNC) switches from the perspective of US investor to the median currency of interest rate differentials. DNC forms each currency as equal weight but the buy or sell decision depends on the median currency. The return for portfolio DNC is

$$DNC_{t+1} = \sum_{k=1}^{N_t} \frac{sign(\ln(F_{k,t,t+1}) - \ln(S_{m,t}))}{N_t} r^e_{k,t+1}$$

Where $S_{m,t}$ denotes the exchange rate for the median currency, N_t is the total number of currencies available at time t.

In asset pricing test of following sections, interest rate sorted portfolios 1 to 5 are test portfolios in asset pricing framework. I also report the factor betas of EWC and SPD. Portfolio DNC is excluded because, by construction, it is the linear combination of interest rate sorted portfolio 1 to 5.

Lustig et al. (2011) introduce foreign exchange portfolios that work as a pricing factor to explain the interest rate portfolio return. They are the high minus low carry trade portfolio (HML^c) and the dollar risk factor (DOL) portfolio. The high minus low carry trade portfolio (HML^c) is constructed by borrowing at low interest rate currencies in portfolio 1 and investing in high interest rate currencies in portfolio 5. It is analogous to the return difference between portfolio 5 and portfolio 1.

$$HML^c_{t+1} = r_{5,t+1} - r_{1,t+1} \tag{2.5}$$

The market dollar risk factor (DOL) is built as the return of equal-weighted long position for each currency.

$$DOL_{t+1} = \frac{1}{N_t} \sum_{k \in K_{i,t}} r^e_{k,t+1}$$

Where N_t is the number of currency available at time t. DOL and HML^c are the most popular pricing factors used in risk-based explanation of carry trade excess return. Since the interest rate sorted portfolios have equal weightings for different currencies, I also calculate the DOL as the average of 5 interest rate sorted portfolios.

$$DOL_{t+1} = \frac{1}{5} \sum_{i=1}^{5} r_{i,t+1} \tag{2.6}$$

In addition, following Lustig et al. (2011), I construct unconditional currency portfolios according to the full sample average interest sorted currencies. Instead of setting up the currency portfolio each week, I group currencies that have similar average interest rate into one portfolio. Thus, 5 currency portfolios are based on 'unconditional' information.[10] Similarly, I construct carry trade portfolios according to average interest rate differentials. As suggested by Lustig et al. (2011), these portfolios help answer the question whether investors are compensated by investing in currencies with on-average high interest rates or in currently high interest rate currencies.

The descriptive statistics for conditional and unconditional interest rate sorted portfolios 1-5, EWC, SPD, DNC, HML^c and DOL are summarized in table 2.3. It reports the weekly mean return, median returns, standard deviation, skewness, kurtosis, Sharpe ratio and the first order autocorrelation coefficient. I also calculate two coskewness measures. Following Harvey and Siddique (2000), a direct measure for coskewness, $\hat{\beta}_{SKD,i}$ is constructed as

$$\hat{\beta}_{SKS,i} = \frac{E[\varepsilon_{i,t+1}\varepsilon^2_{M,t+1}]}{E[\varepsilon_{i,t+1}]^{0.5}E[\varepsilon^2_{M,t+1}]}$$

Where $\varepsilon_{i,t+1}$ is the excess return innovations of portfolio i with respect to the market factor (DOL) and $\varepsilon_{M,t+1}$is the market excess return innovation. I estimate these from the following regression:

$$r_{i,t+1} = a_i + \beta_i DOL_{t,t+1} + \varepsilon_{i,t+1}$$

and $\varepsilon_{i,t+1}$ from the following autoregressive model:

$$DOL_{t,t+1} = \varphi_0 + \varphi_1 DOL_{t-1,t} + \varepsilon_{M,t+1}$$

The second coskewness measure is defined in terms of sensitivity of excess returns to market volatility in a regression of excess returns on the market factor and the market volatility:

$$r_{i,t,t+1} = a_0 + \hat{\beta}_{i,1} DOL_{t,t+1} + \hat{\beta}_{SKD,i} DOL^2_{t,t+1} + u_{i,t,t+1}$$

[10] Lustig et.al (2011) construct the unconditioned portfolio according to the average interest rate differentials in the first half of the sample, then computing the return in the second half of the sample. In this chapter, the full sample average interest rate differentials are conditioned on the full sample data and I also compute the return for the full sample. The relative rankings for the average interest rate of different currencies are stable on the sample period and the returns for the second half of the sample contain the financial crisis.

Where $DOL^2_{t,t+1}$is a proxy for market volatility and as a consequence $\hat{\beta}_{SKD}$ can be interpreted as a measure of skewness. The higher the coskewness, the more effective hedge against global volatility the asset could provide, since the portfolios with high coskewness earn a higher return when global volatility is high.

[table 2.3 interest rate portfolio statistics about here]

In table 2.3, the first panel reports currency portfolios based on conditional interest rate differences. The mean returns monotonically increase from portfolio 1 to 5 with the lowest 0.026% for portfolio 1 and highest 0.237% for portfolio 5. The return from the DOL portfolio is the average of 5 portfolios: 0.117%. This means that US investors require a positive risk premium for investing in foreign currencies, which is intuitive since the US dollar generally has been recognized as the most liquid and riskless currency. I find that high interest rate currencies offer more return but are also subject to more risk as there is an increasing pattern for standard deviation from portfolio 1 to 5.[11] In this case, portfolio 5 has a standard deviation of 1.779% which is about 2 times of standard deviation for portfolio 1 (0.942%). Nevertheless, even though both average return and volatility show increasing pattern, Sharpe ratios increase from portfolio 1 to 5. This means that high interest rate currencies still yield more risk-adjusted returns. The profitability of the carry trade is not influenced by the increasing risk. All portfolios have negative skewness. Portfolio 1 has highest skewness, close to 0, which means the low interest portfolio is less subject to potentially big losses. The measures for coskewness have a roughly decreasing pattern from portfolio 1 to portfolio 5. According to Menkhoff et al. (2012) and Ang et al. (2006), the portfolio with large positive coskewness achieves higher return when market volatility innovation is high thus it serves as a volatility hedge. Portfolio 1 reaches the highest value among the 5 portfolios in both of the coskewness measures. Hence, low interest rate currencies serve as a hedge for volatility innovations.

For carry trade portfolios, the HML^c portfolio is the combination of portfolio 1 and portfolio 5. Hence the return of HML^c portfolio is the difference between portfolio 5 and portfolio 1, 0.21%, which is highest among the carry trade portfolios. Portfolio SPD has the highest Sharpe ratio, 15.726%. It is followed by HML^c, DNC and EWC. This is not surprising as it shows that profitability of carry trade varies with the absolute weights of extremely high or low interest rate currencies. However HML^c also has the highest standard deviation among carry trade strategies. Including intermediate currencies could diversify the risk. Other carry trade portfolios have lower standard

[11]Previous literature uses alonger sample period starting from the 1980s, finding minor standard deviation differences between highest and lowest interest rate portfolios (see, for example Lustig et al. 2011, Burnside et al. 2011). The increasing volatility pattern is mainly because my dataset is shorter and contains the period of the financial crisis.

deviations since they all have nonzero weights on currencies that have a moderate interest rate. All carry trade portfolios have a negative skewness coefficient around -1 which indicates potential big losses. The coskewness does not have a monotone pattern. Low interest rate currencies in portfolio 1, 2 and 3 have a positive coskewness which means, in my case, that portfolios with lowest interest currency serve as a hedge against volatility (portfolio yields high return when volatility is high).

The lower panel of table 2.3 reports the statistics for portfolios constructed from 'unconditional' interest rate differentials. There is also a clear increasing pattern for average returns, standard deviations and sharp ratios from portfolio 1 to 5. For carry trade strategies based on average interest differentials, average returns are close to those based on conditional interest rate sorts. Therefore, the unconditional information could explain a large part of portfolio variations from portfolio 1 to 5.

2.2.5 Order flow portfolios

First, I analyze basic statistical properties of order flow for different currencies. Figure 2.1 presents the average weekly trading volume, and the average of weekly absolute value of aggregated order flow. These plots demonstrate that trading scales vary widely across currencies. In particular, the magnitude of trading scales of 9 developed country currencies dominates that of other emerging market currencies. EUR has the highest average trading volume and SKK the lowest trading volume. Accordingly, the high average trading volume also corresponds to a significant deviation of order flow.

I continue to investigate the time series characteristics of order flow data for each currency. The result is shown in table 2.4. It presents the mean and standard deviation. These two statistics vary across different currencies. AC(1) reports the first-order autocorrelation coefficient from AR(1) and its significance level. ARCHLM reports the LM test statistics for heteroscedasticity of residuals from AR(1).

[table 2.4 aggregated order flow statistics about here]

The average order flow is about zero for most currencies which means there is no explicit selling/ buying pressure imbalance over the sample period. A few exceptions are EUR, JPY and CHF. The standard deviation is higher for developed countries and relatively small in emerging markets. Column AC(1) shows the first order autocorrelation coefficient and significance. Column ARCHLM shows the F-statistic for the heteroscedasticity test. Similarly to the currency excess returns, the order flow data are usually first order auto-correlated and demonstrate heteroscedasticity.

I then perform an analysis by using the portfolio approach based on contemporaneous order flow data. The raw order flow data is not comparable due to the size heterogeneity. Thus I adjust the aggregated order flow with standard deviation,

$$y_{k,t} = \frac{x_{k,t}}{\sigma_k}$$

Where $y_{k,t}$ is the sample standard deviation-adjusted order flow for currency k, $x_{k,t}$ denotes the aggregated net order flow for the currency k during time $[t-1, t]$. σ_k denotes the sample standard deviation of net order flow for currency k. Then I have net order flow data variates in the same range for different currencies. Figure 2.2 shows the time series plot of standardized order flow for EUR and SGD.

However, the size heterogeneity is inconspicuous within developed countries. I do not normalize disaggregated order flow data by standard deviation when sorting currencies based on disaggregated order flow.

I allocate 20 currencies into 5 portfolios according to their contemporaneous aggregated order flow. P1 groups currencies with the highest selling pressure (lowest order flow) while P5 groups currencies with the highest buying pressure. It is assumed that investors close the position and set up a new position at the end of each week. I allocate the developed currencies into 4 portfolios based on disaggregated order flow from 4 different customer types. The average (Avg.) and long/short (BMS) portfolios are also constructed.

[table 2.5 about here]

Table 2.5 reports the annualized average return, standard deviation and Sharpe ratio for each portfolio. There is a clear increasing trend of average return and Sharpe ratios for portfolios sorted on aggregated order flow and portfolio BMS earns positive return.[12] This indicates that my customer order flow data are informative as to the exchange rate changes. Unlike the interest rate sorted portfolios, the standard deviations are of similar magnitude across portfolios. Unsurprisingly, the average aggregated order flow sorted portfolio (Avg.) is close to the *DOL* portfolio. There is a similar pattern for portfolios sorted on asset manager (AM) and hedge fund (HF) order flow. For

[12] I argue that the 'buy minus sell' BMS portfolios cannot serve as pricing factors for the following reasons. Firstly, the order flow information is contemporaneous such that it is not an actionable characteristic. Secondly, contemporaneous order flow is directly related to currency returns which make the variable too informative in that it contains both risk premium and currency characteristic information. Portfolio-sorted factors (Fama and French, 1993) are generally based on the inherent asset properties such as the size of equity and interest rate of currency.

corporate (CO), the portfolio return roughly decreases from P1 to P5. There is a more clear decreasing trend for private client's order flow. Both of the BMS portfolios for CO and PC earn a negative return.

Next, I compare the informational content of order flow with that of interest differentials and volatility innovations. Menkhoff et al. (2012*a*) show that a global volatility proxy contains important information which can be used to price returns of carry trade portfolios. Relatedly, Menkhoff et al. (2012*b*) show that momentum strategies are more profitable among currencies that have greater idiosyncratic volatility. In both cases, the implication is that volatility has an association with the riskiness of, and return to, holding different currencies and currency portfolios. I believe that the apparent importance of volatility is strongly linked to order flow, and that order flow contains the relevant information to price returns of carry trade portfolios.

To provide a first intuitive view of this, I double sort 20 currencies in two different ways with the results shown in tables 2.6 and 2.7. In table 2.6, I first sort currencies into three portfolios based on their short term interest rates. Thereafter, within each portfolio, I sort currencies into two bins based on the magnitude of order flow.[13] The main conclusion of table 2.6 is that even after considering interest rates, a strategy consisting of buying a portfolio with the highest buying pressure (high order flow) and selling a portfolio with the highest selling pressure (low order flow) gives a positive and statistically significant return. In other words, taking interest rates into account does not drive out order flow as an important apparent determinant of currency returns.

In table 2.7, I first sort currencies into three portfolios based on their idiosyncratic volatility innovation, and thereafter on the magnitude of order flow. Again, even after considering idiosyncratic volatility innovations, a portfolio of the currencies with the highest buying pressure has an economically and statistically significantly higher return than the one with the greatest selling pressure.

2.3 Pricing factors for interest rated portfolios

In this chapter, I analyze pricing factors have been tested in past literature to price the currency excess return. Then I propose the global order flow factors and carry trade order flow factors by using the customer order flow data.

[13] I build a total of just six portfolios due to the limited number of currencies in my sample.

2.3.1 A preliminary analysis of Betas for DOL and HML^c

Lustig et al. (2011) propose two pricing factors DOL and HML^c (in equation 2.5 and 2.6) constructed directly from interest rate portfolios (test portfolios). I developed the relationship between portfolio variances and portfolio betas for factor DOL and HML. Assume the $n \times n$ variance-covariance matrix of test portfolios is a diagonal matrix where the covariances are 0.

$$\Pi = \begin{pmatrix} \sigma_1^2 & & \dots & & 0 \\ & \sigma_2^2 & & & \\ \vdots & & \ddots & & \vdots \\ & & & \sigma_{n-1}^2 & \\ 0 & & \dots & & \sigma_n^2 \end{pmatrix}$$

Let

$$d \equiv \sigma_n^2 - \sigma_1^2$$

$$s \equiv \sigma_1^2 + \sigma_2^2 + \dots + \sigma_n^2$$

Since DOL and HML are built from interest rate sorted portfolios, then

$$Var(DOL) = \frac{s}{n^2}$$

$$Var(HML) = \sigma_n^2 + \sigma_1^2$$

$$Cov(DOL, HML) = \frac{d}{n}$$

In the first case, I estimate the betas of DOL and HML^c by using two independent OLS regression then

$$\hat{\beta}_i^{DOL} = \frac{n\sigma_i^2}{s} \text{ for } i = 1, 2, ..., n$$

$$\hat{\beta}_i^{HML} = \begin{cases} \frac{-\sigma_i^2}{\sigma_n^2+\sigma_1^2}, & i = 1; \\ 0 & i = 2, 3, ..., n; \\ \frac{\sigma_i^2}{\sigma_n^2+\sigma_1^2}, & i = n. \end{cases}$$

Meanwhile, I could also estimate betas of DOL and HMLC in a two-variable multivariate regression. I have

$$\hat{\beta}_i^{DOL} = \begin{cases} \frac{2n\sigma_1^2\sigma_n^2}{\sigma_1^2(s+d)+\sigma_n^2(s-d)}, & \text{for } i = 1 \text{ and } n; \\ \frac{\sigma_i^2(\sigma_1^2+\sigma_n^2)}{\sigma_1^2(s+d)+\sigma_n^2(s-d)}, & \text{for } i = 2, 3, ..., n-1. \end{cases}$$

$$\hat{\beta}_i^{HML} = \begin{cases} \frac{-\sigma_1^2(s+d)}{\sigma_1^2(s+d)+\sigma_n^2(s-d)}, & \text{for } i = 1; \\ \frac{-d\sigma_i^2}{\sigma_1^2(s+d)+\sigma_n^2(s-d)} & \text{for } i = 2, 3, ..., n; \\ \frac{\sigma_n^2(s-d)}{\sigma_1^2(s+d)+\sigma_n^2(s-d)}, & \text{for } i = n. \end{cases}$$

If I impose another assumption that variances of 5 interest rate sorted portfolios are all the same from portfolio 1 to 5, then $\hat{\beta}_i^{DOL}$s are 1 in both cases. $\hat{\beta}_i^{HML}$s are -0.5 and 0.5 for portfolio 1 and portfolio 5 respectively. $\hat{\beta}_i^{HML}$ for other portfolios are all 0. The covariance and correlation between DOL and HML are 0, so there are no collinearity issues. The empirical results from Lustig et al (2011) and Burnside (2011) use more than 20 years monthly data (include financial crisis) find that factor betas are consistent with the theoretical value under the assumption of same variances.

I argue since we have a relative short dataset, thus, the effect of the financial crisis could not diminish in such a short period. Hence there is an increasing variance pattern from portfolio 1 to 5. If I set up assumptions based on the characteristic of our data set that portfolio variances are $\sigma_1^2 < \sigma_2^2 < \cdots < \sigma_n^2$. I also assume the variance difference for two adjacent portfolios is small compared with $\sigma_n^2 - \sigma_1^2$, then $\hat{\beta}_i^{DOL}$s in the single variable regression case have increasing pattern from portfolio 1 to portfolio 5. In the two-variable regression with HML, $\hat{\beta}_i^{DOL}$s are still around 1 and $\hat{\beta}_i^{HML}$s increase from negative to positive. Therefore, DOL factor would still serve as intercept in the model (DOL, HML). However, this model might subject to multicollinearity issue since there is a nonzero positive covariance between DOL and HML. If I replace HML with another factor that has 0 correlation with DOL, the DOL would not serve as an intercept, instead, there is an increasing pattern for DOL from portfolio 1 to 5.

I collect the monthly exchange rates from January 1989 to September 2017 for the same currencies. Accordingly we construct 5 currency portfolios then plot the 3-year and 10-year rolling variance for portfolio 1 and portfolio 5 in figure 2.3. The left panel of figure 2.3 shows the short term 3-year variance difference is higher during the financial crisis in 2009 to 2010 and is also diminishing after 2011. The 10-year long term variance difference, which is shown in the right panel, does not demonstrate an apparent convergence instead. If the long term 10-year data is used, I will get a large variance difference from portfolio 1 to 5 and increasing beta pattern for DOL. Therefore, the increasing pattern for portfolio variances due to the financial crisis period included.

The financial crisis has influences on our asset pricing test results on section V. Thus I redo all the model by using a dataset exclude the financial crisis period in Appendix section 2.7.2.

2.3.2 Global volatility innovations

I follow the procedure used in Menkhoff et al. (2012*a*) to construct the global volatility innovation factor. First, I use daily spot exchange rates to construct a weekly realized volatility by using the daily log return for each currency k on trading day τ. I then average overall currencies available on day τ and then average all daily average values within week t. Thus the global realized volatility proxy in week t is given by

$$\sigma_t = \frac{1}{T_t}\sum_{\tau\in T_t}(\frac{1}{K_\tau}\sum_{k\in K_\tau}|\Delta\ln(S_{kt})|)$$

Where K_τ denotes the number of available currencies on day τ and T_t denotes the number of trading days in week t. I use absolute returns rather than squared returns is to minimize the impact of outliers since my data includes periods of the financial crisis (2007-8) and the European sovereign debt crisis (2010).

In this study, I use the volatility innovations as a factor for the empirical analysis. Although the innovations are usually measured by the first difference of the volatility, the first difference shows a strong autocorrelation. Hence, volatility innovations are proxied by residuals from AR(1) estimation of the volatility series. AR(1) residuals are not autocorrelated with their lags. We denote volatility innovations as $DVOL$. I also test the model with equity volatility innovation factor in Appendix section 2.7.4

2.3.3 Order flow pricing factors

Apart from the existing pricing factors ($DOL, HML^c, DVOL$) in the literature, in this section, I investigate whether it is possible to construct a risk factor that fits in the asset pricing framework Cochrane (2009) by using order flow data. To this end, I build a global order flow factor which is a cross-sectional average of the order flow. To make the order flow data for different currencies comparable, I adjust the aggregated order flow by the sample standard deviation. Then, I take the cross-sectional average of standard deviation adjusted order flow, the 'aggregated global order flow factor' series, denoted as OF.[14]

$$OF_t = \frac{1}{N_t} \sum_{k \in K_t} y_{k,t}$$

Here N_t is the number of currencies available at time t which is less or equal to 20. $y_{k,t}$ is the standard deviation adjusted order flow for currency k. A positive value of OF factor measures the relative capital outflow from US dollar to the other currencies. On the contrary, negative OF factor measures the total capital inflow from the world currencies to US dollar. It indicates the US investor's enthusiasm for investing the foreign currencies.

I also construct disaggregated order flow factors from a smaller dataset of developed country currencies according to 4 customer types, namely: asset manager; corporate; hedge fund; and private client. As the size heterogeneity is inconspicuous within developed countries, to maintain the information as much as possible, I take a simple cross-sectional average of the original order flow data for disaggregated order flow factor. Therefore, four disaggregated global order flow factors, according to different customer type, are denoted as AM, CO, HF, PC.

$$AM_t = \frac{1}{N_t^{AM}} \sum_{k \in N_t^{AM}} x_{k,t}^{AM}$$

$$CO_t = \frac{1}{N_t^{CO}} \sum_{k \in N_t^{CO}} x_{k,t}^{CO}$$

[14]Note that I use a similar standardization method as Menkhoff et al. (2016) for the individual order flow data except that I focus on the common information and contemporaneous co-variation in net order flow to explain currency excess return.

$$HF_t = \frac{1}{N_t^{HF}} \sum_{k \in N_t^{HF}} x_{k,t}^{HF}$$

$$PC_t = \frac{1}{N_t^{PC}} \sum_{k \in N_t^{PC}} x_{k,t}^{PC}$$

$x_{k,t}^{AM}, x_{k,t}^{CO}, x_{k,t}^{HF}$ and $x_{k,t}^{PC}$ denote the disaggregated net order flow for the currency k during time $[t-1,\ t]$ of different customer types. $N_t^{AM}, N_t^{CO}, N_t^{HF}$ and N_t^{PC} is the number of currencies available at time t for disaggregated order flow of different customer types. My disaggregated order flow factor measures the absolute value of capital inflow or outflow between US dollar and other 8 developed currencies for different customer types.

The simple cross-sectional average is a measure of the total buying pressure from US investors to the foreign currency market. Burnside (2012) suggests that most of the trading activities are triggered by the carry trade. An empirical analysis of Breedon et al. (2016) has shown the relationship between bilateral order flow data with their corresponding carry trade risk premium. Since carry trades include both short and long positions but my order flow factors are constructed by a cross-sectional average, these factors are not explicitly correlated with carry trade returns. Assuming investors have equal amount of long position for high interest rate currencies and short position of low interest rate currencies, order flow factors would realize a positive value when the US interest rate ranks lower than the median and they would realize a negative value when the US interest rate ranks higher than the median. Thus, global order flow pricing factors constructed from cross-sectional average do not have a direct relationship with the US interest and the US investor desire to conduct carry trade.

However, I could also construct a carry trade order flow factor that directly correlates with on-going carry trade positions. I modify the order flow data for each currency by multiplying the sign of their interest rate differentials. The global carry trade aggregated order flow factor ($CTOF$) is

$$CTOF_t = \frac{1}{N_t} \sum_{k \in K_t} y_{k,t}$$

$$y_{k,t} = \frac{x_{k,t}}{\sigma_k} \times sign(\ln(F_{k,t-1}) - \ln(S_{k,t-1}))$$

Where $x_{k,t}$ is aggregated order flow for period $[t-1,t]$, σ_k is the sample standard deviation of aggregated order flow for currency k. $F_{k,t-1}$ and $S_{k,t-1}$ is the forward price and spot price for currency k at time $t-1$.

Accordingly, the global carry trade disaggregated order flow factors for $CTAM$, $CTCO$, $CTHF$, $CTPC$ is calculated as

$$CTAM_t = \frac{1}{N_t^{CTAM}} \sum_{k \in N_t^{AM}} x_{k,t}^{AM} \times sign(\ln(F_{k,t-1}) - \ln(S_{k,t-1}))$$

$$CTCO_t = \frac{1}{N_t^{CTCO}} \sum_{k \in N_t^{CO}} x_{k,t}^{CO} \times sign(\ln(F_{k,t-1}) - \ln(S_{k,t-1}))$$

$$CTHF_t = \frac{1}{N_t^{CTHF}} \sum_{k \in N_t^{HF}} x_{k,t}^{HF} \times sign(\ln(F_{k,t-1}) - \ln(S_{k,t-1}))$$

$$CTPC_t = \frac{1}{N_t^{CTPC}} \sum_{k \in N_t^{PC}} x_{k,t}^{PC} \times sign(\ln(F_{k,t-1}) - \ln(S_{k,t-1}))$$

Where $x_{k,t}^{AM}$, $x_{k,t}^{CO}$, $x_{k,t}^{HF}$ and $x_{k,t}^{PC}$ are unstandardized raw order flow. N_t^{CTAM}, N_t^{CTHF}, N_t^{CTCO} and N_t^{CTPC} is the number of currencies used at time t to construct the disaggregated order flow factors. The carry trade order flow factors measure the degree of carry trade activities from different customer types.

2.3.4 Pricing factor statistics

Table 2.8 summarizes the descriptive statistics of all pricing factor introduced in this section. I report single factor Kleibergen and Paap (2006) reduced rank test with null hypothesis of zero rank of covariance matrix C. The single factor KP test is equivalent to test whether covariance or correlation between pricing factor and test portfolios are jointly 0. The single factor KP zero rank test suggests that covariance matrix for factor $DVOL$, $SKEW$ and $CTCO$ with 5 test portfolios have zero rank. For other factors, I strongly reject the null hypothesis. Thus pricing factors $DVOL$, $SKEW$ and $CTCO$ could perform poorly to price the excess return of interest sorted portfolios as they contain linear information with DOL factor. Meanwhile, the volatility innovations factor is particularly interesting to note. By construction,

$DVOL$ has zero mean thus $Cov(r_{i,t}, DVOL) = E(r_{i,t} \times DVOL)$. Here $r_{i,t}$ is the excess return for interest rate sorted portfolio 1 to 5. The KP test result also implies $Cov(r_{i,t}, DVOL) = E(r_{i,t} \times DVOL)$. As documented in Burnside (2016), under this circumstance the stochastic discount factor coefficients are not identified by the standard general method of moments (GMM) approach Cochrane (2005) and they do not follow the asymptotic distribution. Thus the statistical inference is improper.

For global order flow factors, unsurprisingly, aggregated order flow factor OF has the highest standard deviation among the four disaggregated order flow factors. Among the disaggregated global order flow factors, AM and HF have a higher standard deviation than CO and PC. Factor OF has negative skewness which means extreme large negative order flow could be realized. The skewness also varies in disaggregated order flow and it is positive for AM, HF and PC, and negative for CO. Among the carry trade order flow factors, a similar pattern for standard deviation could be observed. $CTOF$ has the highest standard deviation, then it is followed by $CTAM$, $CTHF$, $CTPC$ and $CTPC$. Both factors from corporates and private clients are more stable than other customer types. This means corporates and private clients overall less frequently adjust their portfolio according to different market conditions. In contrast, asset managers and hedge funds may be more likely to alter their positions according to varying market conditions for return maximization. This potentially indicates that corporate and private client order flow may contain less information.

[Table 2.8 about here]

I now explore the relationship between the order flow pricing factors and the excess returns of carry trade strategies. To do this, I divide the sample into four sub-samples that are selected according to the order flow size. The first sub-sample contains the 25% of the weeks within the full sample with the lowest values of order flow pricing factors, and the fourth sub-sample contains the 25% of the weeks within the full sample with the largest values of order flow pricing factors. Finally, I compute the mean return across the sub-samples after employing four different carry trade strategies (i.e. HML, SPD, EWC and DNC). Figures 2.5 and 2.6 show the main results with respect to the aggregated order flow factors, OF and $CTOF$. High yield currencies are highly affected by the order flow factor and vice versa. The average excess return of portfolios generally increases as I move from the left to the right.

[Figure 2.5 about here]

[Figure 2.6 about here]

Figures 2.8 and 2.8 show the same results across the different customer segments described above.[15] For the disaggregated global order flow factors, there is no clear monotonic pattern of carry trade excess return from left to right. The only exception is HF factor in that high carry trade returns correspond to low HF factor value. For the disaggregated carry trade order flow factors in figure 2.8, a clear monotonic pattern could be observed. The financial customers (i.e. asset managers and hedge funds) are the most highly affected in periods of high carry trade activity while non-financial customers (i.e. corporate customers and private clients) can even profit during these times. These results suggest that there is a clear relationship between carry trade order flow and the excess returns of carry trade strategies, and that this relationship differs from the customer segment. I explore these results further in what follows.

[Figure 2.7 about here]

[Figure 2.8 about here]

2.4 Econometric models

In this chapter, I first discuss the standard general method of moments (GMM) approach Cochrane (2005). This is followed by the reduced rank general method of moments approach of Kleibergen and Paap (2006) and Burnside (2016). I then report the asset pricing test results for different pricing factors.

2.4.1 Standard GMM

I follow the standard general method of moments (GMM) approach (Cochrane, 2005), which is also used in Lustig et al. (2011), Burnside et al. (2011) and Menkhoff et al. (2012). Note that I follow Lustig et al. (2011) and Menkhoff et al. (2012) and use the effective return instead of a continuous compound return. The test assets are the return of portfolio 1 to portfolio 5 sorted on the interest rate differentials, I do not include EWC and SPD as test portfolios but I report portfolio betas. In this section, I denote excess return vector during period $[t, t+1]$ for portfolio i as rx_t.

[15] To save space, only the HML carry trade strategy is reported with the disaggregated order flow factors.

$$rx_t = \begin{pmatrix} r_{1,t} \\ r_{2,t} \\ r_{3,t} \\ r_{4,t} \\ r_{5,t} \end{pmatrix}$$

Under the usual no-arbitrage conditions and risk aversion, risk adjusted currency excess return satisfies unconditional discounted mean equation (or the Euler equation).

$$E_T[m \times rx] = 0 \tag{2.7}$$

Where rx is a $5 \times t$ matrix and m denotes the stochastic discount factor (SDF) that satisfies

$$m = 1 - (f - \mu)'b \tag{2.8}$$

Where f denotes a vector of pricing factor size $k \times 1$, b is the vector of SDF parameters, μ is the mean vector of risk factors, $\mu = E[f]$. Here, I normalize the mean of SDF to 0 and set a unit intercept.

$$E_T[f - \mu] = 0 \tag{2.9}$$

Let $C \equiv Cov(rx, f)$, then

$$b = (C'WC)^{-1}C'W \times E_T(rx)$$

The above linear SDF specification leads to a beta representation model as follows:

$$E(rx) = Cov(rx, f) \times b = Cov(rx, f)\Sigma_f^{-1} \times \Sigma_f b = \beta \times \lambda$$

Where Σ_f is the covariance matrix of factor vector f. β here are population coefficients which are the sensitivity matrix to risk factors. λ is the factor price matrix.

I estimate the SDF parameters by GMM. Since I am interested in explaining the cross-section of expected currency excess returns by this model, I use the unconditional expected discounted payoffs equation 2.7 plus the risk factor mean equation 2.9 as the moment conditions in GMM. I perform two-stage GMM but mainly focus on factor means μ and factor covariance matrix Σ_f estimated in first stage GMM.

2.4.2 Reduced rank GMM

Meanwhile, I apply a model reduction procedure developed by Burnside (2016). By performing the Kleibergen and Paap (2006) reduced rank test, I find that $Cov(rx, f)$ often violates the full rank condition. Under zero mean and unit intercept SDF normalization in equation 2.8, reduced rank of $Cov(rx, f)$ indicates that parameter estimates of classical GMM (Cochrane, 2005) are not consistent and do not have standard asymptotic distributions. Assuming n test assets and k factors in the model and matrix C has a rank z where $z < k$. Burnside (2016) suggests estimating an intermediate reduced rank factor vector $\tilde{f}$, where $\tilde{f} = Af$, a linear combination of original vector f instead in GMM. $\tilde{f}$ is a vector of size $z \times 1$ where z is the rank of $Cov(rx, f)$. The new factor $\tilde{f}$ is mutually orthogonal and has unit variance, $\Sigma_{\tilde{f}} = I_{z\times z}$ by construction of matrix A which is shown in Appendix 1. Let $\tilde{C} \equiv Cov(rx, \tilde{f})$ then matrix $\tilde{C}$ has full rank thus parameter estimates $\tilde{b}$ are consistent. Meanwhile, since $\tilde{C} = Cov(rx, f)A' = CA'$, there is a linear relation between $\hat{b}$ and $\tilde{b}$.

$$\tilde{b} = (\tilde{C}'W\tilde{C})^{-1}\tilde{C}'W \times E_T(rx)$$

$$\hat{b} = A\tilde{b}$$

The next step is to back out estimates for original SDF, $\hat{b}$. Covariance matrix of estimates for $\hat{b}$ are shown in Appendix 2 by using the Delta method. I name this reduction procedure as GMM with reduced rank adjustment. In this study, if the p-value is higher than 1% significance level in KP test, I would also report reduced rank GMM results.

To choose a matrix of A that converts factor vector f to $\widetilde{f}$, which is mutually orthogonal and has unit variance, consider forming a scaled matrix of Θ for matrix C,

$$\Theta = GCF'$$

Where $G = \Sigma_{rx}^{-1/2}$, the Cholesky decomposition of the inverse of covariance of rx; $F = \Sigma_f^{-1/2}$, the Cholesky decomposition of the inverse of covariance of f. Since matrix G and F are both invertible, matrix Θ is invariant to invertible transformations of the data and $rank(\Theta) = rank(C) = z$. Consider the singular value decomposition (SVD) for matrix Θ

$$\Theta = USV'$$

Where matrix U is a $n \times n$ orthogonal matrix; V is a $k \times k$ orthogonal matrix; S is a $n \times k$ matrix where its upper $k \times k$ is a diagonal matrix with nonincreasing singular value in the diagonal.

A choice of matrix A could be the first z row of $\widetilde{A}$ where $\widetilde{A} = V'F$. The covariance matrix of $\widetilde{A}f$ is $\Sigma_{\widetilde{A}f} = V'Fff'F'V = V'V = I$, thus $\widetilde{f}$ is a vector of mutually orthogonal vector with unit variance.

2.4.3 Reduced rank FMB

Following Burnside (2016), I develop the reduced rank FMB method. Similiarly, I estimate the intermeidate factor $\tilde{\mathbf{f}}$ instead and then back out parameters for f. Let $\tilde{f} \equiv [\mathbf{1}, \tilde{\mathbf{f}}]$ and $f \equiv [\mathbf{1}, \mathbf{f}]$ where $\mathbf{1}$ is a column matrix of ones that has same number of rows as $\tilde{f}$ and f. In the first step, I estimate betas for reduced factors

$$\tilde{\beta}_i = (\tilde{f}'\tilde{f})^{-1}\tilde{f}' rx^i$$

I construct intermediate matrix Γ which has size $(k+1) \times (z+1)$

$$\Gamma = \begin{bmatrix} 1 & 0 \\ 0 & A_z \end{bmatrix}$$

Then the beta estimation of the original factor is

$$\hat{\beta}_i = \Gamma\tilde{\beta}_i$$

In the second step of FMB, I do not include an intercept thus I construct another intermediate matrix $\hat{B}$ which has size $n \times k$

$$\hat{B} \equiv \begin{bmatrix} \hat{\beta}_1' \\ \vdots \\ \hat{\beta}_n' \end{bmatrix}$$

and size $n \times z$ matrix $\tilde{B}$

$$\tilde{B} \equiv \begin{bmatrix} \tilde{\beta}_1' \\ \vdots \\ \tilde{\beta}_n' \end{bmatrix} = \begin{bmatrix} \hat{\beta}_1' \\ \vdots \\ \hat{\beta}_n' \end{bmatrix} A_z^{'} = \hat{B}A_z^{'}$$

For the risk price estimation in the second step of FMB, I cannot use matrix $\hat{B}$ directly because it does not have the full rank. I estimate the risk price of intermediate factor $\tilde{\mathbf{f}}$ first. For each time t, the risk price $\tilde{\lambda}_i$ is

$$\tilde{\lambda}_i = (\tilde{B}'\tilde{B})^{-1}\tilde{B}'rx_i \quad i = 1, 2, ...t$$

To figure out the relationship between $\tilde{\lambda}_i$ and $\hat{\lambda}_i$, note that $A = F'V$ where F and V are from the first and second step KP reduced rank test. The matrix V is orthogonal matrix, thus

$$\hat{\lambda}_i = F^{-1}V_z\tilde{\lambda}_i \quad i = 1, 2, ...t$$

Therefore, the Newey-West standard error for the risk price could be either calculated from the delta method or simply estimated from $\hat{\lambda}_i$.

2.5 Empirical evidence for interest rate portfolios

In the following table, I first report the KP reduced rank test for which the null hypothesis ranges from $rank(C) = 0$ to $rank(C) = z$. If $z = k$, then the standard GMM is used. If $z < k$, the reduced rank GMM is also used. I report estimates of SDF parameter vector b, implied risk factor prices λ, cross-sectional R^2, and the Hansen-Jagannathan distance measure for over-identifying restrictions. This is followed by the factor price estimated in the second step of the Fama-MacBeth method and sum of squared pricing error. The second panel reports portfolio betas and the time series adjusted R^2 for each test portfolio. Standard errors are based on Newey and West (1987) with optimal lag length selection according to Andrews (1991).

2.5.1 High minus low carry trade and volatility innovation factor

Table 2.9 and table 2.10 report asset pricing results of the 'high minus low' HML of Lustig et al. (2011) and the 'volatility innovation factor' $DVOL$ of Menkhoff et al. (2012*a*) along with 'dollar risk factor' DOL, respectively.

For HML factor, KP reduced rank test strongly rejects the reduced rank of matrix C. Therefore, the traditional GMM is used in asset pricing test. The SDF coefficient b for DOL factor is positive and not significant which is not surprising as DOL is an intercept in the cross-sectional portfolio. The SDF coefficient associated with HML factor is significant and so is the risk premium. Similar results are found in the Fama-MacBeth estimation. The risk price estimation is close to the factor mean reported in table 2.8. In the existence of HML factor, DOL factor is not priced since it serves as an intercept in 5 test portfolios. Due to the variance difference between portfolio 1 and 5 reported in table 1, there is a positive correlation between DOL and HML. Thus, the model is subject to the collinearity issue to some extent. The cross-sectional R^2 of first stage GMM estimation is high at 97.63% which means that most cross-sectional return variations have been explained by this model. I cannot reject the null hypothesis that the pricing error is zero according to HJ-distance and χ^2 test.

The bottom panel of table 2.9 shows that the beta coefficients of DOL factor are roughly around 1. The betas for DOL are about the same for portfolio 1 and portfolio 5. All of the empirical results match the theoretical analysis in section 2.3.1. In this case, DOL factor could serve as the intercept in second stage FMB. There is an increasing trend of betas for HML from -0.4 to 0.6, since the HML carry factor contains the information of interest rate differentials. The time-series R^2 shows a U-shape pattern which has the highest value for portfolio 1 and portfolio 5. This indicates HML has high explanation power on portfolio1 and portfolio 5 which is also intuitive since HML itself is a linear combination of portfolio 1 and portfolio 5.

[table 2.9 about here]

In table 2.10, the first panel of KP reduced rank result shows that matrix C has reduced rank 1. This is not surprising because in table 4 the single factor KP test of $DVOL$ also indicates a reduced rank. However, $DVOL$ was a significant factor in Menkhoff et al. (2012*a*). I attribute this result to the inclusion of financial crisis data since the robust tests in Appendix II use the pre-financial crisis data and have similar significant statistical results to Menkhoff et al. (2012*a*). In this case, I report both standard GMM and reduced rank GMM. Under the standard GMM procedure reported in the lower-left panel, results show that SDF coefficients and risk premium are not significant in first stage GMM. The cross sectional R^2 is still high 90.23%. I cannot reject the null hypothesis of HJ distance test. In FMB, the risk premium is significant at 5% level. The risk loadings for DVOL show a similar pattern as reported in Menkhoff et al. (2012*a*).

The reduced rank GMM result is reported in the lower-right panel. The SDF coefficients and risk premium are negative and significant which is in accord with Menkhoff et al. (2012*a*). The SDF coefficient and risk premium for DOL factor are significant. However, the cross sectional R^2 is low 57.18% compared with traditional GMM results. $DVOL$ factor has small SDF coefficient b compared with DOL which means DOL consists mostly of the intermediate reduced rank factor $\tilde{f}$. Overall, I can reject the null of zero pricing error by the Hansen-Jagannathan test at 5% and χ^2 test at 10% significance level. All test portfolios have negative reduced-rank-adjusted risk loadings for $DVOL$ factor which means positive volatility innovations decreases the return for all test portfolios. This may be because, during the extreme financial crisis, even the lowest interest rate portfolio does not provide a volatility innovation hedge. This result advocates for another argument brought by Menkhoff et al. (2012*a*) that carry trades earn more return when volatility is low. When the market volatility is decreasing, the $DVOL$ realizes negative volatility innovation, the low interest rate portfolio is less influenced by $DVOL$ as portfolio betas decrease from portfolio 1 to portfolio 5, and thus higher carry trade return is achieved.

[table 2.10 about here]

2.5.2 Aggregated order flow factors

In this section, two aggregated factors, aggregated global order flow factor (OF) and carry trade aggregated order ($CTOF$) are tested in table 2.11 and table 2.12, respectively.

In table 2.11, the first panel of KP reduced rank result indicates that the matrix C only has rank 1, which suggest that DOL and OF actually contain similar information. Therefore, I also perform the reduced rank GMM as shown in the lower right panel of table 7. In the lower left panel, the traditional GMM result is reported. In the first stage of GMM, SDF coefficients are not significant. Only the risk price for DOL is significant. The cross-sectional R^2 is low at only 70.15%. I accept that there is zero pricing error from HJ distance test. In the FMB method, the risk premium for OF factor is significant. The portfolio betas for OF factor are increasing from portfolio 1 to 5 but the betas are not significant for low interest rate portfolio 1 to 5. However the insignificance of OF factor may not be due to the inclusion of financial crisis data as in Appendix II I still cannot reject that OF and DOL are collinear. In FMB, risk price for DOL and OF are significant at 5% and 10%, respectively.

In the reduced rank GMM result, both the SDF parameters and risk premium are significant which is not surprising as no collinearity issue exists in reduced rank GMM. OF factor has positive risk premium. The significant positive risk premium can be interpreted as low risk premium for portfolios with returns that co-move positively with the dollar risk factor, whilst portfolios with a positive covariance with OF factor demand a higher risk premium. Compared with reduced rank GMM for $DVOL$, replacing $DVOL$ with OF factor does not boost the cross-sectional R^2 very much. I reject that there is zero pricing error from HJ distance test at 5% and χ^2 test at 10%. Betas for OF factor are relatively small, all positive and increasing from portfolio 1 to 5. Since I cannot reject the reduced rank from KP test, DOL could be treated as the factor-mimicking portfolio for OF. Thus DOL must have a dominant effect in the intermediate portfolio.

[table 2.11 about here]

Table 2.12 shows the test results of $CTOF$. The KP reduced rank indicates I can strictly reject the null. Thus only traditional GMM is used. Both the risk price and SDF coefficient b of factor $CTOF$ are significant in GMM 1 and FMB. For DOL factor in this model, the risk premium is significant but the SDF coefficient b is not. The cross-sectional R-square is high 82.85% in first stage GMM. I cannot reject the null of nonzero pricing error of this model from HJ distance and χ^2 test.

There is an increasing portfolio beta pattern for $CTOF$ factor from negative to positive for portfolio 1 to 5. The CTOF factor could work as a measure for the total carry trade activities on the market. Thus $CTOF$ could be explained as a proxy of currency crash risk or peso riskBurnside et al. (2010). Therefore, it is intuitive that low interest rate portfolios negatively correlate with $CTOF$ and high interest rate portfolios positively correlate with CTOF.

[table 2.12 about here]

2.5.3 Global order flow factors: financials

In this section I analyze the disaggregated global order flow factor of financial customers' order flow $CTAM$, $CTHF$ along with DOL factor.

In table 2.13, I report the global order flow factor from financial customers AM,HF. The first panel of table 2.13 reports the KP reduced rank test for AM and HF. I reject that matrix C has reduced rank at 5%. Hence financial customers order flow factors contain different information from DOL. Only the traditional GMM is reported.

For factor AM in lower left panel, the SDF coefficient and risk price for DOL is significant in the first stage GMM. The SDF coefficient and risk price for AM is also significant in first stage GMM but only at 10% significance level. One of reasons is that this model is subject to collinearity issue, even if I reject the null of KP test, but the p-value of KP reduced rank test is high at 2%. The risk premium is negative thus portfolios that are negatively correlated with AM factor earn excess return. The cross-sectional R^2 is 88.86% which means that most of the cross-sectional variation is explained by this model. I accept that there are zero pricing errors in this model from the HJ distance test. Portfolio betas for DOL factor are increasing. There is a decreasing beta pattern from positive to negative for factor AM. Only the betas for portfolio 1 and portfolio 5 are significant. High interest rate portfolios are negatively correlated with AM factor thus earn positive expected returns since the risk price is also negative for AM factor.

The test results for HF are similar to those for AM; the difference is that I could strongly reject that HF is collinear with DOL. The risk price and SDF coefficient for HF is significant. The cross-sectional R^2 is high at 94.07%. I argue that AM and HF contain similar information about market volatility innovation. When financial customers are investing in the world currency market with US dollar, the market volatility innovation is high. The low interest rate portfolios provide a hedge under this circumstance.

[Table 2.13 about here]

2.5.4 Global order flow factors: nonfinancials

Nonfinancial customers are corporate (CO) and private client (PC). The test results are in table 2.14 and table 2.15.

Table 10 has the test results of CO. According to the KP reduced rank test result, I cannot reject the null of reduced rank for factor CO at 1% significant level. This means the CO factor has the serious collinearity issue of the $DVOL$ factor. As shown in the lower left panel, the first stage traditional GMM suggests that only the risk price for DOL is significant. However, the cross-sectional explanation power is high at 96.73% and I still cannot reject the HJ test null that pricing error is zero. Even if CO and DOL are subject to collinearity issue as reported in KP test, I still have the significant risk premium in FMB for both factors. The risk price for CO is positive and risk loadings are increasing from negative to positive. In the I do not have the multicollinearity issue in reduced rank GMM estimates. Thus both the SDF parameters and risk prices are significant. Similarly, the DOL has the dominant position in the construction of intermediate reduced rank factor $\tilde{f}$. Due to the low cross-sectional adjusted R^2, beta estimates for DOL are very similar to those in model 1. I could observe that the sign of risk price and portfolio betas has reversed compared with traditional GMM estimates.

[Table 2.14 about here]

In the first panel of table 11, I still cannot reject the null of KP test at 1% significant level. Only the traditional GMM is used. In this model both SDF coefficients and risk prices for DOL and PC are significant. Cross-sectional R^2 is high at 87.52%. The portfolio betas are increasing from negative to positive.

[Table 2.15 about here]

2.5.5 Carry trade order flow factors: financials

In table 2.16, I report test results of carry trade order flow factors from financial customers $CTAM$ and $CTHF$. The first panel of table 2.16 reports the KP reduced rank test for $CTAM$ and $CTHF$. I reject that matrix C has reduced rank at 5%. Hence financial customer carry trade order flow factors contain different information from DOL. Only the traditional GMM is reported.

The SDF coefficient and risk price are significant in the first stage GMM for $CTAM$ and $CTHF$. The risk premium are positive thus portfolios that positively correlate with $CTAM$ and $CTHF$ factor earn excess return. The cross-sectional R^2 is 73.16% for $CTAM$ and 82.59% for $CTHF$ which means most of the cross-sectional variation is explained by this model. I accept that there are zero pricing errors in this model from the HJ distance test. Portfolio betas of DOL factor are roughly around 1. There is a increasing beta pattern from negative to positive for factors $CTAM$ and $CTHF$.

Since $CTAM$ and $CTHF$ are the proxies for peso risk sourcing from financial customer unwinding of carry trade strategy, high interest rate portfolios are positively correlated with $CTAM$ and $CTHF$ factor and earn positive returns. This result means the market dealer views the financial customers as informed investors and they adjust exchange rate price according to their order flow. Meanwhile, it could be found that test results of financials customer are consistent with the aggregated carry trade order flow factor $CTOF$. This means the financial customer's order flows are most effective to price the currency excess return.

[table 2.16 about here]

2.5.6 Carry trade order flow factors: nonfinancials

In table 2.17 and 2.18, I report the carry trade order flow factor from nonfinancial customers $CTCO$ and $CTPC$.

Table 2.17 reports the asset pricing results of $CTCO$; I cannot reject the null of KP reduced rank test. Therefore $CTCO$ may contain the same information as DOL. I also report the reduced rank GMM in the lower right panel of table 2.17. However as a comparison, in Appendix II, I reject the null of KP test. The lower left panel has the traditional GMM result. The risk price of $CTCO$ is not significant in first stage GMM and FMB. The cross-sectional R-square is 74.45%. The risk price is negative for $CTCO$ and corresponding risk loadings are decreasing from positive to negative. This means that when the corporates are conducting carry trade activities, the carry trade return decreases. One possible explanation is that corporate customers work as a counterparty with financial customers. Financial customers' order flow have effective information that positively correlate with exchange rates. In the reduced rank GMM result, the risk price is significant in both first stage GMM and FMB since there are no collinearity issues. However the cross-sectional R-square is low (57.852%). Therefore the DOL dominates $CTCO$ in the construction of reduced rank intermediate factors.

Table 2.18 reports the asset pricing results of $CTPC$. The KP reduced rank indicates I can strictly reject the null. $CTPC$ contains different information from DOL and the traditional GMM is used. Asset pricing results show that the risk price in first stage GMM is not significant but it is significant in FMB. The cross-sectional R^2 is 80.65%. The risk price is negative and portfolio betas decreasing from positive to negative. $CTPC$ shows a similar pattern to the $CTCO$ factor. I argue that private client customers also serve as counterparty for financial customers. Nevertheless, corporates tend to trade foreign currencies with no preference for high interest rate portfolios since

I cannot reject that they contain linear information as does the DOL. Private clients trade oppositely to financial customers thus provide direct liquidity.

[table 2.17 about here]

[table 2.18 about here]

2.5.7 Exchange Rate and Interest Rate Differences

In this section, I discover if the pricing power of CTOF for currency excess return is from the exchange rate changes or the forward premium. An regression analysis of the portfolio betas to CTOF of each components is performed. I estimate the portfolio betas to CTOF for exchange rates components $\ln(S_t) - \ln(S_{t+1})$ and forward premium components $\ln(F_t) - \ln(S_{t+1})$, repectively.

[Table 2.19 about here]

Table 2.19 reports the estimation results. Exchange rate changes betas are broadly consistent with the estimations for the currency excess portfolio in previous table. Beta estimates for forward premiums are not significant for portfolio 1 to 4 but significant and positive for portfolio 5. Thus, the pricing effect of CTOF is mainly sourced from exchange rate changes this is not suprising as market microstructure studies links the exchange rate directly with order flow. The empirical results also show that order flow could explain the forward premium of high interest rate portfolios.

2.5.8 Factor mimicking portfolios

To better understand the risk factors, I build factor-mimicking portfolios for factors not directly constructed from test assets. The factor-mimicking portfolio weights and average returns are reported in table 2.20. Following Breeden et al. (1989) and Menkhoff et al. (2012), I estimate portfolio weights by regressing each factor on excess returns of 5 test portfolios.

$$y = c + b \times rx + u$$

Where y is the pricing factor, b is a 1×5 row vector of factor mimicking portfolio weights, rx is a $5 \times T$ matrix of test portfolio returns, T is the sample size, c is the regression intercept and u is the regression residuals. The return for the factor mimicking portfolio y_t^{FM} is

$$y_t^{FM} = b \times rx$$

In table 2.20, the sign of average factor-mimicking-portfolio returns are overall consistent with the risk price estimation in asset pricing results except for factor $CTCO$. The FMP return for $CTCO$ is positive but small (0.03%) and risk price estimates in GMM are negative but not significant.

The factor mimicking portfolio for $DVOL$ loads positively on low interest rate portfolios and negatively on high interest rate portfolios. These results are in line with Menkhoff et al. (2012). Therefore, low interest rate portfolios could provide a hedge for volatility innovation. The factor mimicking portfolios have similar absolute proportion on each test portfolio. A preliminary analysis of covariance of $DVOL^{FM}$ indicates that there is significant negative covariance exists. It is not surprising that I cannot reject the null of reduced rank for KP test of model 3. The average return from $DVOL^{FM}$ is negative.

For aggregated pricing factors, weightings of OF do not show a clear pattern. It has negative loadings for portfolio 2 and positive loadings for the rest of the 4 portfolios. Thus I could see why there is positive correlation between OF and DOL. Note that OF did not pass the KP reduced rank test on KP reduced rank test. Thus OF contains similar information to the DOL factor. Meanwhile factor OF weightings are only significant in 3 high interest rate portfolios. Correspondingly, OF^{FM} has positive average return. The weightings for carry trade order flow factor $CTOF$ are negative in low interest rate portfolio 1 and portfolio 2 and it has a long position for intermediate portfolios and high interest rate portfolio 5. All weightings are significant and portfolio $CTOF^{FM}$ earns positive returns.

For disaggregated global order flow factors, portfolio weightings for AM and HF both show a roughly decreasing pattern from positive to negative for test portfolios 1 to 5. They have significant positive loadings in the lowest third portfolios and around zero loadings on highest second portfolios. The absolute weightings are also skewed to low interest rate portfolios since the absolute value of weightings on other portfolios are relatively small. From a factor mimicking portfolio point of view, factor AM and HF contain different information to the DOL factor as there is a clear pattern. Factor-mimicking portfolios of CO show negative weightings on the first 4 low interest rate portfolios and positive weightings on portfolio 5. Thus there is negative correlation between CO and DOL. However none of these weightings are statistical significant. Correspondingly, the average return of CO^{FM} is negative. The weightings in PC^{FM} also do not show a clear pattern, with negative weights for extreme portfolios 1, 2, 5 and positive weights for intermediate portfolio 3, 4. I cannot reject the reduced rank condition in KP test. PC^{FM} earns negative returns and only the weighting in portoflio 1 is significant.

Disaggregated carry trade order flow factor of financials $CTAM$ and $CTHF$ have loadings which are similar to the aggregated $CTOF$ factor. This indicates that financial customers have the dominant effect in aggregated factors. Weightings are significant and have a clear pattern. Factor mimicking returns are positive. Factor $CTCO$ loads positively except for portfolio 3, however none of the loadings are significant at 5% and the average return is also around 0. Factor $CTPC$ has the reversed sign of loadings compared with $CTAM$ and $CTHF$. It loads positively on low interest rate portfolio and negatively on high interest rate portfolio.

In general, considering the KP reduced rank test in section 2.5, I argue that factors that pass this test normally have clear weighting patterns in factor mimicking portfolios. For pricing factors that perform well in asset pricing tests, such as $CTOF$, $CTHF$ and $CTAM$, their factor mimicking portfolios could be considered as carry trade strategies. They all have negative loadings on low interest rate currencies and have positive loadings on high interest rate currencies.

2.5.9 Pricing factors relations

I further investigate the relationships between different pricing factors. As discussed in the previous section, factor mimicking portfolios are carry trade strategies that have different weightings on extreme currencies; I suggest different factors are not mutually othorgonal, instead, they are correlated with each other. The reason why carry trade order flow factors perform well in asset pricing practice is because they are proxies for currency crash risk. High positive value of carry trade order flow corresponds to high probability of currency crash and high risk premium. However, currency crash generally happens with sudden cashing out of carry trade positions, thus the carry trade order flow factor would realize a large negative value during this period. On the other hand, currency crashes are also accompanied by sudden increase in volatility innovation. Thus I expect to see the carry trade order flow negatively correlated with volatility innovation factor. Similarly, currency crash would also negatively affect the sample skewness of currency excess return. I expect to see carry trade order flow factors positively correlated with skewness factor.

To support the above arguement, I perform simple regression analysis for carry trade order flow factors with volatility innovation factor and sample skewness factors, to see whether regression coefficients have the expected sign and are statistically significant. Table 2.21 reports the results.

[Table 2.21 about here]

2.6 Currency Momentum Anomaly

2.6.1 Momentum portfolios

Menkhoff et al. (2012*b*) document the significant positive currency momentum excess returns on a monthly basis. In this chapter, I employ the same method as Menkhoff et al. (2012*b*) to construct weekly currency momentum portfolios (M1 to M5) based on previous 4-week cumulative returns on the same sample period from the first week of November 2001 to the fourth week of March 2012. For each week t, 20 currencies are categorized in 5 portfolios based on the previous 4-week returns. M5 contains currencies with highest past returns. The descriptive statistics are reported in table 2.22. Due to the results of Menkhoff et al. (2012*b*) being based on the prefinancial crisis period, I also report the prefinancial crisis results in panel B.

[Table 2.22 about here]

Table 2.22 reports the annulized average return, Newey-West test statistics in parentheses, annulized standard deviation, Sharpe ratio and sample skewness. It shows there is a clear increasing pattern from M1 to M5. The momentum HML portfolio earns significant positive excess return in all cases even though inclusion of financial crisis indeed decreases $HML(MOM)$. The sample skewness of $HML(MOM)$is negative which indicates possible momentum crashes. In the following studies, portfolios M1 to M5 based on full sample data are used as the test asset.

2.6.2 Momentum order flow factors

Burnside et al. (2011) show that DOL and HML fail to explain momentum anomaly. In this chapter, I propose momentum order flow factor which is inspired by the carry trade order flow factor. The momentum order flow factor ($MOOF$) is

$$MOOF_t = \frac{1}{N_t} \sum_{k \in K_t} z_{k,t}$$

$$z_{k,t} = \frac{x_{k,t}}{\sigma_k} \times sign(r^e_{k,t-1} + r^e_{k,t-2} + r^e_{k,t-3} + r^e_{k,t-4})$$

Where $z_{k,t}$ is the prevous-4-week-return-signed standardized order flow factor. The aggregated momentum order flow factor ($MOOF$) is the cross-sectional average. This factor captures the relative degree of momentum activities on the market. Similarly, the disaggregated momentum order flow factors $MOAM, MOHF, MOCO, MOPC$, for asset manager, hedge fund, coporate, and private client, respectively, are defined as follow:

$$MOAM_t = \frac{1}{N_t^{MOAM}} \sum_{k \in N_t^{AM}} x^{AM}_{k,t} \times sign(r^e_{k,t-1} + r^e_{k,t-2} + r^e_{k,t-3} + r^e_{k,t-4})$$

$$MOCO_t = \frac{1}{N_t^{MOCO}} \sum_{k \in N_t^{CO}} x^{CO}_{k,t} \times sign(r^e_{k,t-1} + r^e_{k,t-2} + r^e_{k,t-3} + r^e_{k,t-4})$$

$$MOHF_t = \frac{1}{N_t^{MOHF}} \sum_{k \in N_t^{HF}} x^{HF}_{k,t} \times sign(r^e_{k,t-1} + r^e_{k,t-2} + r^e_{k,t-3} + r^e_{k,t-4})$$

$$MOPC_t = \frac{1}{N_t^{MOPC}} \sum_{k \in N_t^{PC}} x^{PC}_{k,t} \times sign(r^e_{k,t-1} + r^e_{k,t-2} + r^e_{k,t-3} + r^e_{k,t-4})$$

Where notations are akin to definitions of carry trade disaggregated order flow factors.

2.6.3 Empirical evidence for momentum portfolios

2.6.3.1 Aggregated momentum order flow factor

Table 2.23 reports the asset pricing results of the linear SDF with DOL and $MOOF$. I strictly reject the null of reduced rank. In the GMM test, the risk premium for both

DOL and *MOOF* are significant with high 90.22% cross-sectional R-square. Factor MOOF has a positive risk premium. The FMB suggests the same results. In the portfolio time series regression, exposures to *DOL* are all around 1. There is an increasing pattern to betas for *MOOF* from M1 to M5. Past loser portfolio(M1) has a negatively beta to *MOOF* and vice versa for past winner portfolios. I find supportive evidence that aggregated momentum order flow factor price the currency momentum returns.

[Table 2.23 about here]

2.6.3.2 Momentum order flow factors: financials

Table 2.24 and 2.25 report the asset pricing results for two financial customers' momentum order flow factors, asset manager and hedge fund, respectively, with *DOL*. For *MOAM*, I cannot reject the null of reduced rank from KP test at 5% significance level, thus the reduced rank method is also reported. Factor *MOHF* passes the KP test. In the traditional GMM for both factors, results are akin to *MOOF* with significant positive risk premiums and increasing beta patterns. However, the cross-sectional R-square is lower in first stage GMM with 65.40% for *MOAM* and 62.92% for *MOHF*. In the reduced rank GMM for *MOAM*, the model does not pass the HJ test in GMM nor the χ^2 test in FMB.

[Table 2.24 about here]

[Table 2.25 about here]

2.6.3.3 Momentum order flow factors: nonfinancials

Table 2.26 and 2.27 report the asset pricing results for nonfinancial customers' momentum order flow factors, coporate and private client, respectively, with *DOL*. Both *MOCO* and *MOPC* pass the KP reduced rank test. Both factors show negative risk premium where *MOCO* is only significant in FMB. Both models pass the HJ test in GMM and χ^2 test in FMB. The first stage cross-sectional R-square is 33.83% for *MOCO* which is much lower than *MOPC* (79.09%). In the lower panel, momentum portfolios have a decreasing risk pattern from M1 to M5.

[Table 2.26 about here]

[Table 2.27 about here]

2.7 Conclusion

In this paper two strands of literature have been combined together. I construct a pricing factor by using the microstructure order flow data that directly relates to the peso risk or currency crash risk to price the interest rate sorted portfolios. For aggregated carry trade order flow factor, I find the risk price is positive and significant. High value of aggregated carry trade order flow corresponds to the high probability of currency crashes thus high risk premium. Low interest rate portfolios are negatively correlated with aggregated carry trade order flow factor and they provide a hedge when there is currency crash.

Another conclusion is that carry trade activities from differerent customers also deliver different effects on exchange rate changes. I find that carry trade order flow factors from asset manager and hedge fund play a key role since they have same estimation as the aggregated carry trade order flow factor. For the corporate carry trade order flow factor, I show that it contains the same information as the dollar risk factor which means it does not have clear preference for low or high interest rate portfolios. Meanwhile there is no significant risk premium for corporate. For private client, the risk premium and portfolio betas are reversed compared with the financial customer carry trade factor. Thus, the exchange rate tends to negatively react to the private client carry trade order flow. Thus private clients are viewed as the trading counterparty of asset managers and hedge funds.

This chapter uses microstructure data to fit into a risk-based explanation of currency excess return and I find clear evidence that investor microstructure trading behaviour could actually affect the risk premium of the asset. Form the traditional risk based point of view, I find clear evidence that investors would be rewarded by holding a negative skewed asset while they are also facing currency crash risk. The skewness of high interest portfolios is sourced from the market microstructure fact that investors build up their carry trade strategy gradually and unwind suddenly. Therefore, I conclude that currency premium has been reflected on the currency price is also contained in the investor order flow. Therefore, two strands of literature, risk based and market microstructure, are in fact consistent with each other.

Appendices

2.7.1 Influence of bid-ask spread for weekly dataset

In most past literature which is conducted on a monthly basis, the bid-ask spread is accounted to reflect transaction cost. However this chapter is based on weekly data. The variance of weekly return is smaller than for monthly return but the average bid-ask spread is indifferent to the data frequency. The left panel of figure 4 shows the average weekly and monthly bid-ask spread which does not vary with data frequency for EUR, GBP, CHF, AUD, NZD, CAD. The right panel of figure 4 shows the standard deviation of the exchange rate change for each currency. The standard deviation of monthly data is higher and about 2 times that of the weekly data. The bid-ask spread certainly could have more influence on the weekly return compared with the monthly return. Therefore, this chapter uses the mid-price and does not account for market friction by bid-ask spread.

2.7.2 Robust test: Empirical results with Pre-Financial crisis data

As discussed in section 2.3.1, due to the inclusion of the financial crisis period, DOL factor cannot serve as an intercept. It could take over the pricing effect from the second pricing factor. In this chapter I use a subset that excludes the financial crisis period. The subset spans the period from the first week of November 2001 to the third week of May 2007; 290 observations in total. I report the same asset pricing results as in chapter 2.5.

To see whether the DOL factor serves as an intercept, I perform a single factor asset pricing test with only DOL. The results are shown in table 2.28. Unsurprisingly, the DOL factor passes the single factor KP test. Both SDF coefficient and risk price are significant for DOL. The cross-sectional R-square is low (20.203%) indicates weak cross-sectional explanation power for this factor. This is because test portfolios have same risk loading for DOL factor. The model is also strictly rejected for the null of zero pricing error in GMM and FMB method. Portfolio betas in the last panel are all around 1 for 5 test portfolios which explains the low cross-sectional R^2. The time series adjusted R^2 are low for extreme portfolios 1 and 5 and carry trade portfolios.

[Table 2.28 about here]

I then test the model with DOL and $DVOL$ factor. Table 2.29 reports the results. $DVOL$ and DOL pass the KP reduced rank test. In the GMM and FMB asset pricing test, I find similar results to Menkhoff et al. (2012*a*). The first stage GMM suggests that both the SDF coefficients and risk price for DOL are not significant since the cross-sectional variation is very small compared with the one for $DVOL$ factor. The SDF coefficient and risk price for DVOL factor are both negative and significant either in GMM or FMB. The cross-sectional R^2 is high (96.67%) compared with the full sample results in table 2.10. The betas for DOL factor are all around 1. A decreasing pattern for DVOL can be observed. Thus, low interest rate portfolios provide a hedge when the market volatility is high. The time series adjusted R-square is increased from the results shown in table 17. However, the model still has lower explanation power for extreme portfolios and carry trade portfolios. Also, portfolio 2, 3 and 4 have highest adjusted R^2.

[Table 2.29 DVOL about here]

I continue to test the model with aggregated order flow factors OF and $CTOF$. The results are shown in table 2.30 and table 2.31. In table 2.30 OF and DOL do not pass the KP reduced rank test. Even though financial crisis data is excluded, I still cannot reject the null that OF and DOL contain similar information. In the first stage of traditional GMM estimation, shown in the lower left panel of table 18, both of the SDF coefficients are significant but the risk prices are not significant due to the collinearity issue. Even though I cannot reject the null of HJ distance test, the explanation power of this model is low (51.897% cross-sectional R^2). Since DOL factor serves as an intercept for portfolios, I expect that aggregated order flow is indifference to interest sorted portfolios. The portfolio betas for OF factor are only significant for portfolio 4. This also could be due to the multicollinearity issue. Table 2.31 has the test results of DOL with $CTOF$, the test results are akin to the ones in table 2.12. I find the SDF coefficient and risk price significant but the cross-sectional R^2 is much lower.

[Table 2.30 OF about here]

[Table 2.31 CTOF about here]

I redo the disaggregated global order flow model, which includes the DOL factor and four disaggregated order flows, AM, HF, CO, PC respectively, in table 2.32 to table 2.35.

[Table 2.32 AM about here]

[Table 2.33 HF about here]

[Table 2.34 CO about here]

[Table 2.35 PC about here]

Factors AM and CO do not pass the KP reduced rank test at 1%. However, I cannot simply conclude that AM and CO contain similar information to the DOL factor. Firstly, in the traditional GMM results in table 2.32 and table 2.34, the cross-sectional R-squares are high, at 96.517% and 88.079%, respectively. There is a clear monotonic beta pattern for AM and CO from portfolio 1 to 5 but the betas for DOL just serve as intercept in both models. For the reduced rank GMM results reported in table 2.32 and 2.34, the overall fitting results are similar to the results in table 2.11. This means the DOL still takes a dominant proportion in the intermediate factor.

<stop here>

Table 2.33 reports the test result of factor DOL and HF. The KP test suggests the full rank of matrix C. In the first stage GMM estimates, SDF coefficients and risk price are significant for both DOL and HF. The risk price for HF is negative. Thus portfolios negatively correlated with HF would earn excess return. The cross-sectional R-square is 95.347% which means most of the cross-sectional variation has been explained by this model. I cannot reject the null of zero pricing error from HJ test. In FMB, I have similar significant risk price estimates. Portfolio betas of DOL are all around 1 thus it serves as an intercept. The betas for HF are decreasing from positive to negative. Meanwhile the betas for portfolio 3 and 4 are not significant. The HF factor has similar property with volatility innovation $DVOL$ and HML. Table 2.35 reports the test result of model 9 which include factor DOL and PC. I also reject the null that matrix C has reduced rank. In the first stage GMM estimates, SDF coefficients and risk price are significant for both factors at 5% level. PC has a positive risk price, thus the portfolios positively correlated with PC earn positive excess return. The cross-sectional R^2 is 85.30%. I cannot reject the null of zero pricing error from HJ test. In FMB, I have similar significant risk price estimates but I reject the at 5% significance level. In the last panel of table 23, the betas of DOL are all around 1. The betas for PC are increasing from portfolio 1 to portfolio 5.

In this section, I test the disaggregated carry trade factor $CTAM$, $CTHF$, $CTCO$ and $CTPC$ respectively. The results are shown in table 2.36 to table 2.39. For factor $CTAM$ in table 2.36, I cannot reject the null of KP reduced rank test at. However there is clear increasing beta pattern from portfolio 1 to 5 in the lower left panel of table 2.36

and the cross-sectional R^2 is 77.16%. Meanwhile, the risk price is significant in GMM1 and FMB. In the right panel is the reduced rank GMM, the cros-ssetional R^2 is low 20.00%. This means DOL take the dominant effect. In table 2.37, I have the similar test results for factor $CTHF$ compared with the one in table 2.16. One thing surprises is that in FMB, I actually reject that the pricing error is 0 at 5% confidence level. For test results of factor $CTCO$ in table 2.38, I could reject the null of KP reduced rank test. The risk price and SDF coefficients are significant. The cross-sectional R^2 is 87.948%. It has similar betas patterns compared with the results in table 2.17. For factor $CTPC$, I cannot reject the null of KP reduced rank test so I report traditional asset pricing and reduced rank asset pricing results. In the lower left panel of table 2.39, I have similar but strong results as shown in table 2.18.

[Table 2.36 CTAM about here]

[Table 2.37 CTHF about here]

[Table 2.38 CTCO about here]

[Table 2.39 CTPC about here]

2.7.3 Trading volume as a risk factor

In this section I proceed to investigate whether a cross sectional average of trading volume is a priced factor. The trading volume is measured as the US dollar value of all the transactions. I collect the trading volume for 20 currencies during the same sample period. Our global trading volume factor are built from the cross sectional average of sample standard deviation adjusted trading volume. The test results are shown in table 2.40.

Firstly, the first panel of KP reduced rank result indicates that the matrix C only has rank 1. Therefore, the reduced rank GMM is also used. For the traditional GMM, the risk price is not significant. In first stage GMM, both of the SDF parameters and risk premium are significant. $VLUM$ factor has negative risk premium.

[Table 2.40 VLUM]

2.7.4 Equity market volatility innovation as a risk factor

In this section, I use the equity volatility innovation as a pricing factor. To construct the equity volatility innovation factor, I following Ang et al. (2006) to use the changes of VIX index based on S&P 500 as a proxy. I collect the weekly changes data for VIX index from first week of November 2001 to the fourth week of March 2012 as the pricing factor and it is denoted as $DVIX$ (full sample including financial crisis). I suggest that the equity volatility innovation factor DVIX should have similar pricing effect with currency volatility innovation factor $DVOL$.

The asset pricing results are shown in table 2.41. In the first panel, the KP test result shows I strictly reject the null of reduced rank. In the first stage GMM, I have negative risk premium estimation for $DVIX$ but both of SDF coefficients and risk premium is not significant. The cross-sectional R^2 is high 85.12%.and HJ distance test suggests I accept the null of zero pricing error. In FMB, the risk premium for DOL and $DVIX$ are both significant.

Last panel of table 2.41 reports the portfolio betas. I find betas for DOL are roughly around 1. Betas for $DVIX$ decreasing from positive to negative. Thus low interest rate portfolios could provide a volatility innovation hedge. It shows the similar pattern as the betas for $DVOL$ in table 15 when the pre-financial crisis data is used in testing $DVOL$.

[Table 2.41 DVIX]

2.7.5 Sample skewness as a risk factor

In this section, the sample skewness factorRafferty (2012) is tested. I build a weekly skewness factor from a cross sectional average of each currency. For each week, I calculate the sample skewness from daily currency excess return for past 30 days. The results are shown in following table. I cannot reject that covariance matrix C has a reduced rank at 1% significance level. In first stage GMM results, both of DOL and SKW's risk price is not significant, but the cross sectional R^2 is high. This is due to the collinearity issue suggested in KP test. In the lower panel of portfolio betas and time series R^2, the betas for SKW has a roughly decreasing pattern as theory suggested but they are not significant for all portfolios. Compare the results in table 2.12 and table 2.16, factor $CTOF$, $CTAM$ and $CTHF$ are better measures for peso risk.

[Table 26 SKW]

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Table 2.41 – Factor DOL and DVIX

DOL, DVIX				
KP reduced rank test				
	t-stat	Dof	p-val	
Rank(0)	416	10	{0.00}	
Rank(1)	51	4	{0.00}	
Crossectional asset pricing				
GMM1	DOL	DVIX		HJ dist
b	0.83	-0.06	0.85	1.44
s.e.	(5.84)	(0.04)		{0.70}
$\lambda(\times 100)$	0.13	-67.13		
s.e.	(0.09)	(39.79)		
GMM2				
b	33.11	-25.40	0.88	3.31
s.e.	(10.86)	(9.17)		{0.35}
$\lambda(\times 100)$	0.18	-4.86		
s.e.	(0.09)	(1.79)		
FMB	DOL	DVIX	$\chi^2(NW)$	
$\lambda(\times 100)$	0.13	-67.13	5.20	
NW s.e.	(0.06)	(0.25)	{0.27}	
Portfolios' beta and time series R^2				
	$\alpha(\times 100)$	β-DOL	β-$DVIX(\times 100)$	adj. R^2
1	-0.05	0.65	0.08	0.57
	(0.03)	(0.03)	(0.01)	
2	-0.03	1.03	0.08	0.82
	(0.02)	(0.03)	(0.02)	
3	-0.01	0.99	0.01	0.86
	(0.02)	(0.03)	(0.01)	
4	-0.01	1.20	-0.05	0.89
	(0.02)	(0.03)	(0.01)	
5	0.11	1.12	-0.12	0.79
	(0.04)	(0.03)	(0.02)	
EWC	0.01	0.58	-0.05	0.73
	(0.02)	(0.04)	(0.02)	
SPD	0.01	0.05	-0.01	0.76
	(0.00)	(0.00)	(0.00)	

This table reports the asset pricing test results for factor DOL and DVIX by using a subset of pre-financial crisis data. This table has the similar structure from previous asset pricing table.

Table 2.1 – Market Microstructure Regression

	$\beta_0 \times 100$	β_1	$\beta_2 \times 100$	adj. R^2		$\beta_0 \times 100$	β_1	$\beta_2 \times 100$	adj. R^2
EUR	-0.17	-1.44	-0.27	0.06	BRL	-0.34	0.83	-1.66	0.02
	(0.06)	(2.25)	(0.06)			(0.21)	(0.95)	(0.59)	
JPY	-0.07	-1.78	-0.51	0.08	ZAR	0.38	-2.87	-3.79	0.07
	(0.08)	(1.77)	(0.09)			(0.23)	(1.89)	(0.56)	
GBP	-0.08	2.69	-0.26	0.02	KRW	-0.04	-1.25	-1.47	0.02
	(0.07)	(1.87)	(0.09)			(0.10)	(2.32)	(0.51)	
CHF	-0.15	-2.76	-0.37	0.02	SGD	-0.05	1.29	-1.04	0.04
	(0.12)	(2.86)	(0.11)			(0.05)	(1.75)	(0.26)	
AUD	-0.14	-0.17	-1.15	0.05	HKD	-0.01	-1.14	-0.04	0.03
	(0.25)	(3.79)	(0.30)			(0.00)	(0.36)	(0.02)	
NZD	-0.76	8.88	-4.21	0.11	TRY	0.69	-3.14	-4.91	0.10
	(0.27)	(4.22)	(0.58)			(0.31)	(1.57)	(1.08)	
CAD	-0.06	-0.32	-0.58	0.02	HUF	0.12	-1.49	-5.74	0.03
	(0.06)	(2.48)	(0.20)			(0.19)	(1.43)	(1.50)	
SEK	-0.10	1.55	0.48	0.00	PLN	-0.18	1.34	-4.11	0.04
	(0.08)	(1.39)	(0.45)			(0.12)	(1.07)	(1.11)	
NOK	-0.09	0.75	-2.46	0.0386	CZK	-0.13	0.10	-0.05	0.02
	(0.08)	(1.55)	(0.49)			(0.08)	(2.09)	(0.02)	
MXN	-0.02	0.77	-1.12	0.0027	SKK	-0.09	-2.35	1.00	0.00
	0.13	1.48	0.84			0.08	1.31	2.25	

Note: This table reports results of the estimated coefficients, standard errors in the brackets and adjust R^2 for 20 currencies of the standard regression of Evans and Lyons (2002). The regressions are $\Delta s_t = \beta_0 + \beta_1(\ln(F_t) - \ln(S_{t+1})) + \beta_2 X_t + \varepsilon_t$; Where Δs_t is the weekly change of the logarithm of the exchange rate; X_t is the aggregated customer order flow; f_t^{t+1} is the logarithm of 1-week forward exchange rate; s_t is the logarithm of spot exchange rate. β_0 and β_2 are scaled by 100.

Table 2.2 – Market Share of Exchange Rate Dealers

TOP 10 Market Share in Customer Orders in 2003	
UBS	11.53%
Citigroup	9.87%
Deutsche Bank	9.79%
JPMorgan Chase	6.79%
Goldman Sachs	5.56%
Credit Suisses First Boston	4.23%
HSBC	3.89%
Morgan Stanley	3.87%
Barclays Captial	3.84%
ABN Amro	3.63%

Note: This table reports the top 10 banks' market share data accordding to Euromoney FX Survey 2003.

Table 2.3 – Interest rate portfolio and carry trade strategies

Portfolio	P1	P2	P3	P4	P5	DOL	EWC	SPD	HML	DNC
	Conditional - sorts on previous period's interest rate differentials									
Average Return (%)	1.56	4.68	5.72	6.24	12.48	6.24	4.68	0.52	10.92	2.60
Std. dev. (%)	6.78	9.30	9.30	11.97	12.84	8.87	6.63	0.50	11.75	3.53
Skewness	-0.07	-0.89	-0.62	-1.09	-0.96	-0.85	-1.13	-0.93	-0.96	-1.14
Sharpe ratio	0.23	0.50	0.61	0.52	0.97	0.70	0.71	1.03	0.93	0.74
AC(1)	0.07	-0.01	0.06	-0.01	-0.10***	0.01	-0.11**	-0.08*	-0.17***	-0.17***
Coskew1	0.50	0.04	0.00	-0.25	-0.20	0.86	-0.27	-0.28	-0.38	-0.41
Coskew2	5.11	0.37	0.03	-2.11	-2.67	0.00	-2.07	-0.17	-8.01	-2.54
	Unconditional - sorts on full sample interest rate differentials									
Average Return (%)	2.08	5.20	4.68	6.76	12.48	6.24	5.20	0.52	10.40	2.60
Std. dev. (%)	5.41	10.10	9.23	11.97	13.48	8.87	7.72	0.50	12.62	3.39
Skewness	-0.21	-0.57	-0.56	-1.73	-0.73	-0.85	-1.23	-1.12	-0.81	-1.51
Sharpe ratio	0.38	0.52	0.51	0.56	0.93	0.70	0.67	1.03	0.82	0.77

Note: This table reports the descriptive statistics for currencies portfolios. It reports the weakly mean/median return, standard deviation, skewness and Sharpe ratios for each currency portfolios, I also reports the AR(1) coefficient and its significane (***1% , **5%, *10%) . Two measure of coskewness are following Harvey and Siddique(2000). The first coskewness measures is defined as: $\tilde{\beta}_{SKD,i} = E[\varepsilon_{i,t+1}\varepsilon^2_{M,t+1}]/(E[\varepsilon_{i,t+1}]^{0.5}E[\varepsilon^2_{M,t+1}])$.Where $\varepsilon_{i,t+1}$ and $\varepsilon^2_{M,t+1}$ are residual series from following regressions $r_{i,t,t+1} = \alpha_i + \beta \times DOL_{t,t+1} + \varepsilon_{i,t+1}$ and $DOL_{t,t+1} = \varphi_0 + \varphi_1 \times DOL_{t-1,t} + \varepsilon_{M,t+1}$.The second coskewness is defined as the regression coefficient as following equation: $r_{i,t,t+1} = \alpha + \tilde{\beta}_{i,1} \times DOL_{t,t+1} + \tilde{\beta}_{SKD,i} \times DOL^2_{t,t+1} + u_{i,t,t+1}$

Table 2.4 – Aggregated order flow descriptive statistics

Currency	Average	Std.dev	AC(1)	ARCHLM
EUR	-0.38	1.38	0.08**	3.40*
JPY	0.15	0.81	0.07*	22.47***
GBP	0.00	0.76	0.24***	22.60***
CHF	0.08	0.61	0.11***	19.03***
AUD	-0.01	0.42	0.12***	13.40***
NZD	-0.01	0.15	0.01	9.32***
CAD	0.03	0.34	0.05	0.31
SEK	0.01	0.17	0.07	4.01**
NOK	0.00	0.15	-0.09**	3.87**
MXN	-0.01	0.11	-0.09**	5.63**
BRL	-0.03	0.19	0.13***	3.13*
ZAR	0.01	0.18	0.10***	25.91***
KRW	-0.02	0.16	0.15***	2.13
SGD	0.00	0.14	0.19***	20.73***
HKD	0.02	0.18	0.14***	12.60***
TRY	0.00	0.14	0.12**	1.19
HUF	0.00	0.07	0.00	41.34***
PLN	-0.01	0.10	0.01	137.51***
CZK	0.00	0.05	0.10**	20.88***
SKK	0.00	0.04	-0.18***	0.27

Note: This table reports the average and standard deviation of aggregated order flow data for full sample 20 currencies. Column AC(1) is the first order autocorrelation coefficient. Column is the F-statistic for the Lagrange multiplier heteroscedasticity test. The null is no heteroscedasticity on residuals. The significant code: ***0.01, **0.05 and *0.1 significant.

Table 2.5 – Order flow portfolios

	P1	P2	P3	P4	P5	Avg.	BMS
	Aggregated order flow/Full sample						
Average Return (%)	-0.13	0.07	0.15	0.21	0.36	0.13	0.48
	[-2.12]	[1.35]	[2.93]	[3.96]	[7.06]	[2.74]	[11.03]
Std.dev. (%)	1.25	1.19	1.19	1.15	1.20	1.23	0.88
Sharpe ratio	-0.10	0.06	0.13	0.18	0.30	0.11	0.55
	Disaggregated order flow/Developed sample						
	Asset manager						
Average Return (%)	-0.11	0.09	0.12	0.27		0.09	0.38
	[-2.17]	[1.48]	[2.03]	[5.22]		[1.90]	[9.82]
Std.dev. (%)	1.19	1.39	1.37	1.17		1.14	0.85
Sharpe ratio	-0.21	-0.28	-0.41	-0.35		-0.39	0.06
	Hedge fund						
Average Return (%)	-0.15	0.08	0.13	0.30		0.09	0.44
	[-2.56]	[1.41]	[2.43]	[5.67]		[1.84]	[9.97]
Std.dev. (%)	1.24	1.40	1.31	1.18		1.14	0.94
Sharpe ratio	-0.12	-0.31	-0.26	-0.54		-0.36	0.09
	Corporate						
Average Return (%)	0.14	0.15	0.17	0.04		0.12	-0.10
	[2.45]	[2.74]	[3.11]	[0.70]		[2.51]	[-2.85]
Std.dev. (%)	1.20	1.34	1.37	1.21		1.13	0.88
Sharpe ratio	-0.30	-0.59	-0.31	-0.23		-0.41	-0.08
	Private client						
Average Return (%)	0.45	0.17	0.04	-0.10		0.14	-0.56
	[9.13]	[2.61]	[0.73]	[-1.94]		[2.84	[-13.49]
Std.dev. (%)	1.20	1.36	1.34	1.22		1.13	0.96
Sharpe ratio	-0.63	-0.54	-0.29	-0.11		-0.42	-0.37

Note: This table reports weekly average portfolio excess return,Newey-West HAC t-statistic in brackets, sample standard deviation and sharpe ratio for currencies sorted on contemporaneous order flow. Column 'Avg.' shows the average across all portfolios. Column 'BMS' (buy minus sell) reports the long-short portfolio return of highest versus lowest order flow. In first panel, it reports the statistics of portfolios sorted on aggregated order flow for full sample of 20 currencies. I normalized the aggregated order flow by sample standard deviation due to the size heterogeneity. In the lower panel, it reports portfolios sorts on disaggregated order flow of smaller sample of 9 developed country currencies. The four customer types are asset manager, hedge fund, corporate and private client. Note that disaggregated order flow is not normalized by standard deviation.

Table 2.6 – Double Sorts on Interest Rate and Order Flow: Mean Returns (%)

	Interest rate			
Order flow	**Low**	**Medium**	**High**	**HML**
Sell	-2.61	3.50	4.09	6.70
	(2.22)	(2.91)	(3.47)	(2.67)
Buy	6.67	10.78	16.41	9.73
	(2.23)	(2.63)	(3.45)	(2.99)
BMS	9.28	7.28	12.32	
	(1.56)	(1.43)	(2.63)	

Note: This table reports the annualized mean returns (with heteroskedasticity consistent standard errors in parentheses) for six double-sorted portfolios based on interest rate and the value of aggregated order flow.

Table 2.7 – Double Sorts on Volatility Innovation and Order Flow: Mean Returns (%)

	Volatility Innovation			
Order flow	**Low**	**Medium**	**High**	**HML (Vol)**
Sell	6.44	0.73	-3.70	-10.14
	(2.46)	(2.48)	(3.51)	(2.35)
Buy	14.19	12.76	10.98	-3.21
	(2.10)	(2.50)	(3.51)	(2.69)
BMS	7.75	12.03	14.68	
	(1.56)	(1.33)	(2.21)	

Note: This table reports the annualized mean returns (with heteroskedasticity consistent standard errors in parentheses) for six double sorted portfolios based on volatility innovations and the value of aggregated order flow.

Table 2.8 – Pricing factor descriptive statistics

	DOL	HML	DVOL	SKEW	
Mean (×100)	0.12	0.22	0	-7.51	
Median (×100)	0.24	0.35	-6.16	-7.38	
Std.dev. (×100)	1.22	1.62	50	15.06	
Skewness	-0.77	-0.78	1.38	-0.33	
Kurtosis	5.98	8.74	13.22	3.35	
KP rank test	0.00	0.00	0.24	0.52	
	OF	AM	CO	HF	PC
Mean (×100)	-0.90	0.23	-2.07	-0.56	1.06
Median (×100)	-0.08	0.01	-1.50	-0.98	1.39
Std. dev. (×100)	26.54	16.11	5.77	13.70	8.58
Skewness	-0.08	0.19	-0.42	0.41	0.16
Kurtosis	5.18	6.43	5.17	5.05	6.01
KP rank test	0.00	0.00	0.00	0.00	0.00
	CTOF	CTAM	CTCO	CTHF	CTPC
Mean	-3.27	-1.14	-0.79	-1.66	0.16
Median	-2.37	-1.42	-0.98	-1.79	0.13
Std. dev.	24.32	16.18	6.25	14.06	7.80
Skewness	-0.04	0.93	-0.02	0.07	0.00
Kurtosis	4.73	10.95	6.53	4.47	7.89
KP rank test	0.00	0.00	0.12	0.00	0.00

Note: This table reports the mean standard deviation, skewness and kurtosis for each pricing factor. It also shows *p-value*s of a single factor Kleibergen and Paap (2006)'s test for the reduced rank of covariance vector C for pricing factor with 5 portfolio return. Here C is a 5×1 matrix. The null hypothesis of single factor KP reduced rank test is that matrix C does not have full rank.

Table 2.9 – Asset pricing results of DOL and HML

DOL, HML				
KP reduced rank test				
	t-stat	Dof	p-val	
Rank(0)	521	10	{0.00}	
Rank(1)	73	4	{0.00}	
Cross-sectional asset pricing				
GMM1	DOL	HML	R^2	HJ dist
b	4.16	10.02	0.98	1.06
s.e.	(4.58)	(3.58)		{0.79}
$\lambda(\times 100)$	0.17	0.31		
s.e.	(0.06)	(0.08)		
GMM2				
b	4.58	9.85	0.97	1.06
s.e.	(4.55)	(3.55)		{0.79}
$\lambda(\times 100)$	0.17	0.31		
s.e.	(0.06)	(0.08)		
FMB	DOL	HML	$\chi^2(NW)$	
$\lambda(\times 100)$	0.17	0.31	1.47	
NW s.e.	(0.06)	(0.08)	{0.83}	
Portfolios' beta and time series R^2				
	$\alpha(\times 100)$	β-DOL	β-HML	adj R^2
1	0.02	0.76	-0.37	0.84
	(0.02)	(0.02)	(0.01)	
2	0.03	0.98	-0.19	0.81
	(0.03)	(0.04)	(0.03)	
3	0.03	0.90	-0.10	0.82
	(0.02)	(0.03)	(0.03)	
4	0.03	1.04	-0.02	0.84
	(0.03)	(0.04)	(0.03)	
5	0.08	0.72	0.44	0.87
	(0.03)	(0.04)	(0.06)	
EWC	0.01	0.38	0.17	0.74
	(0.02)	(0.04)	(0.03)	
SPD	0.00	0.03	0.02	0.80
	(0.00)	(0.00)	(0.00)	

Note: This table shows the asset pricing results for the linear stochastic discount factor based on 'dollar risk factor' (DOL) and 'carry trade High minus Low factor'(HML), the test asset are excess returns of five portfolios sorted on forward discount but I alos report the time series results for portfolio EWC and SPD. The first panel shows KP reduced rank test. The second panel shows the cross-sectional asset pricing results from first stage GMM, Second stage GMM and Fama-MacBeth method. In GMM, it reports the SDF coefficient b for each factor and factor price estimate (λ) along with their corresponding standard error. It is followed by cross-sectional R^2. I also report the HJ statistic and its p-value. Note that I did not include an intercept in second pass of FMB approach and standard errors are obtained by the Newey and West (1987) with optimal lag selection according to Andrews (1991). In FMB, I report the factor price with standard error, Chi-square statistic and its p-value. The second panel reports the αs, factor betas and their corresponding standard error for these five portfolios. It is followed by the times-series R^2 for each portfolio.

Table 2.10 – Asset Pricing result for DOL and $DVOL$

DOL, DVOL								
KP reduced rank test								
	t-stat	Dof	p-val					
Rank(0)	212	10	{0.00}					
Rank(1)	9	4	{0.07}					
Cross-sectional asset pricing results								
	Traditional				Reduced rank			
GMM1	DOL	DVOL	R^2	HJ dist	DOL	DVOL	R^2	HJ dist
b	-0.04	-1.62	0.90	2.42	11.20	0.00	0.52	9.72
s.e.	(7.63)	(0.79)		{0.49}	(3.96)	(0.00)		{0.05}
$\lambda(\times100)$	0.17	-40.49			0.17	-1.28		
s.e.	(0.11)	(19.45)			(0.06)	(0.45)		
GMM2								
b	1.99	-1.54	0.84	2.50	1.99	0.00	0.45	2.21
s.e.	(7.02)	(0.77)		{0.48}	(7.02)	(0.00)		{0.54}
$\lambda(\times100)$	0.20	-38.76			0.20	-5.13		
s.e.	(0.10)	(18.88)			(0.10)	(18.88)		
FMB	DOL	DVOL	$\chi^2(NW)$		DOL	DVOL	$\chi^2(NW)$	
$\lambda(\times100)$	0.17	-40.49	4.94		0.17	-1.28	8.75	
NW s.e.	(0.06)	(14.20)	{0.29}		(0.06)	(0.42)	{0.07}	
Portfolios' beta and time series R^2								
	$\alpha(\times100)$	β-DOL	β-$DVOL(\times100)$	adj R^2	$\alpha(\times100)$	β-DOL	β-$DVOL(\times100)$	adj R^2
1	-0.03	0.51	0.17	0.50	-0.03	0.50	-0.01	0.49
	(0.03)	(0.05)	(0.08)		(0.03)	(0.05)	(0.00)	
2	0.00	0.85	0.15	0.77	0.00	0.84	-0.02	0.76
	(0.03)	(0.06)	(0.11)		(0.03)	(0.06)	(0.00)	
3	0.01	0.84	0.03	0.81	0.01	0.83	-0.02	0.81
	(0.02)	(0.05)	(0.08)		(0.02)	(0.05)	(0.00)	
4	0.02	1.02	-0.02	0.84	0.02	1.02	-0.03	0.84
	(0.03)	(0.05)	(0.11)		(0.03)	(0.05)	(0.00)	
5	0.14	1.02	-0.15	0.71	0.14	1.03	-0.03	0.71
	(0.04)	(0.05)	(0.11)		(0.04)	(0.05)	(0.00)	
EWC	0.03	0.50	-0.04	0.65	0.02	1.02	-0.03	0.84
	(0.02)	(0.03)	(0.05)		(0.03)	(0.05)	(0.00)	
SPD	0.01	0.04	-0.01	0.67	0.14	1.03	-0.03	0.71
	(0.00)	(0.00)	(0.00)		(0.04)	(0.05)	(0.00)	

Note: This table shows the asset pricing results for the linear stochastic discount factor based on 'dollar risk factor'(DOL) and 'volatility innovation factor'($DVOL$). The left panel shows the traditional GMM results. The right panel is the reduced rank GMM results. This table has the same structure as in previous table. the test asset are excess returns of five interest rate portfolios but I alos report the time series results for portfolio EWC and SPD.

Table 2.11 – Aggregated global order flow

DOL, OF									
KP reduced rank test									
			t-stat	Dof	p-val				
		Rank(0)	230	10	0.00				
		Rank(1)	6	4	0.23				
Cross-sectional asset pricing results									
Traditional					Reduced rank				
GMM1	DOL	OF	R^2	HJ dist	DOL	OF	R^2	HJ dist	
b	-18.49	3.17	0.70	5.56	11.01	0.03	0.53	9.32	
s.e.	(17.65)	(1.89)		{0.14}	(3.87)	(0.01)		{0.05}	
$\lambda(\times 100)$	0.14	17.99			0.17	1.65			
s.e.	(0.08)	(9.97)			(0.06)	(0.58)			
GMM2									
b	-0.45	1.19	0.63	7.75	-0.45	1.19	0.63	7.75	
s.e.	(12.97)	(1.35)		{0.05}	(12.97)	(1.35)		{0.05}	
$\lambda(\times 100)$	0.15	7.62			0.15	7.62			
s.e.	(0.06)	(7.07)			(0.06)	(7.07)			
FMB	DOL	OF	$\chi^2(NW)$		DOL	OF	$\chi^2(NW)$		
$\lambda(\times 100)$	0.14	17.99	7.53		0.17	1.65	8.31		
NW s.e.	(0.06)	(7.14)	{0.11}		(0.06)	(0.54)	{0.08}		
Portfolios' beta and time series R^2									
	$\alpha(\times 100)$	β-*DOL*	β-*OF*	adj. R^2	$\alpha(\times 100)$	β-*DOL*	β-*OF*	adj. R^2	
1	-0.03	0.51	-0.12	0.49	-0.03	0.48	0.13	0.49	
	(0.03)	(0.05)	(0.12)		(0.03)	(0.05)	(0.01)		
2	0.0	0.86	-0.16	0.77	0.00	0.82	0.23	0.76	
	(0.03)	(0.07)	(0.15)		(0.03)	(0.06)	(0.02)		
3	0.02	0.82	0.14	0.81	0.02	0.81	0.22	0.81	
	(0.02)	(0.05)	(0.12)		(0.02)	(0.04)	(0.01)		
4	0.03	0.99	0.35	0.84	0.03	1.00	0.28	0.84	
	(0.03)	(0.06)	(0.13)		(0.03)	(0.05)	(0.01)		
5	0.15	1.00	0.30	0.71	0.15	1.00	0.28	0.71	
	(0.04)	(0.05)	(0.16)		(0.04)	(0.05)	(0.01)		
EWC	0.03	0.49	0.10	0.65	0.03	1.00	0.28	0.84	
	(0.02)	(0.04)	(0.09)		(0.03)	(0.05)	(0.01)		
SPD	0.01	0.04	0.01	0.67	0.15	1.00	0.28	0.71	
	(0.00)	(0.00)	(0.01)		(0.04)	(0.05)	(0.01)		

Note: This table shows the asset pricing results for the model of DOL and 'aggregated global order flow factor' OF. On the left panel is traditional GMM results. The reduced rank GMM is on the right. This table has the same structure as in previous table. The test asset are excess returns of five interest rate portfolios. I also report the time series results for portfolio EWC and SPD.

Table 2.12 – Aggregated carry trade order flow factor

DOL, CTOF				
KP reduced rank test				
	t-stat	Dof	p-val	
Rank(0)	275	10	{0.00}	
Rank(1)	34	4	{0.00}	
Crossectional asset pricing				
GMM1	DOL	CTOF		HJ dist
b	-0.22	1.75	0.83	5.43
s.e.	(6.19)	(0.74)		{0.14}
$\lambda(\times 100)$	0.16	10.31		
s.e.	(0.06)	(3.95)		
GMM2				
b	4.20	1.07	0.78	5.86
s.e.	(5.5512)	(0.6311)		{0.12}
$\lambda(\times 100)$	0.16	6.68		
s.e.	(0.06)	(3.40)		
FMB	DOL	CTOF	$\chi^2(NW)$	
$\lambda(\times 100)$	0.16	10.31	6.25	
NW s.e.	(0.06)	(3.55)	{0.18}	
Portfolios' beta and time series R^2				
	$\alpha(\times 100)$	β-DOL	β-$CTOF(\times 100)$	adj. R^2
1	-0.06	0.54	-0.69	0.53
	(0.03)	(0.05)	(0.12)	
2	-0.01	0.86	-0.31	0.77
	(0.03)	(0.07)	(0.10)	
3	0.03	0.82	0.22	0.81
	(0.02)	(0.05)	(0.09)	
4	0.04	1.01	0.31	0.84
	(0.03)	(0.05)	(0.10)	
5	0.16	0.99	0.61	0.71
	(0.04)	(0.05)	(0.15)	
EWC	0.05	0.47	0.54	0.68
	(0.02)	(0.03)	(0.10)	
SPD	0.01	0.04	0.04	0.69
	(0.00)	(0.00)	(0.01)	

Note: This table has similar structure as previous table. The two factor model is based on DOL and 'aggregated carry trade order flow' factor $CTOF$.

Table 2.13 – Disaggregated global order flow factor: Financial customers

DOL, AM					DOL, HF				
KP reduced rank test									
	t-stat	Dof	p-val			t-stat	Dof	p-val	
Rank(0)	214	10	{0.00}		Rank(0)	226	10	{0.00}	
Rank(1)	12	4	{0.02}		Rank(1)	31	4	{0.00}	
Cross-sectional asset pricing results									
GMM1	DOL	AM		HJ dist	GMM1	DOL	HF		HJ dist
b	36.45	-4.30	0.89	3.48	b	24.64	-3.47	0.94	2.17
s.e.	(13.05)	(2.07)		{0.32}	s.e.	(7.15)	(1.31)		{0.54}
$\lambda(\times 100)$	0.16	-8.96			$\lambda(\times 100)$	0.17	-0.06		
s.e.	(0.07)	(4.79)			s.e.	(0.07)	(0.02)		
GMM2					GMM2				
b	28.32	-2.88	0.8487	4.21	b	23.99	-3.26	0.94	2.21
s.e.	(11.07)	(1.70)		{0.24}	s.e.	(7.01)	(1.29)		{0.53}
$\lambda(\times 100)$	0.17	-5.66			$\lambda(\times 100)$	0.17	-5.14		
s.e.	(0.06)	(3.94)			s.e.	(0.07)	(0.02.28)		
FMB	DOL	AM	$\chi^2(NW)$		FMB	DOL	HF	$\chi^2(NW)$	
$\lambda(\times 100)$	0.16	-0.09	5.08		$\lambda(\times 100)$	0.17	-5.53	3.18	
NW s.e.	(0.06)	(0.04)	{0.28}		NW s.e.	(0.06)	(2.24)	{0.53}	
Portfolios' beta and time series R^2									
	$\alpha(\times 100)$	β-DOL	β-$AM(\times 100)$	adj. R^2		$\alpha(\times 100)$	β-DOL	β-$HF(\times 100)$	adj. R^2
1	-0.03	0.45	0.75	0.51	1	-0.02	0.46	1.04	0.525
	(0.03)	(0.05)	(0.18)			(0.03)	(0.05)	(0.20)	
2	0.00	0.83	0.16	0.77	2	0.01	0.81	0.91	0.78
	(0.03)	(0.07)	(0.15)			(0.03)	(0.07)	(0.22)	
3	0.02	0.82	0.21	0.81	3	0.02	0.83	0.18	0.81
	(0.02)	(0.05)	(0.15)			(0.02)	(0.05)	(0.16)	
4	0.02	1.04	-0.19	0.84	4	0.02	1.03	-0.06	0.84
	(0.03)	(0.05)	(0.16)			(0.03)	(0.06)	(0.24)	
5	0.14	1.06	-0.65	0.71	5	0.12	1.07	-1.12	0.71
	(0.04)	(0.05)	(0.22)			(0.04)	(0.06)	(0.29)	
EWC	0.03	0.54	-0.62	0.66	EWC	0.02	0.53	-0.70	0.66
	(0.02)	(0.03)	(0.16)			(0.02)	(0.03)	(0.21)	
SPD	0.01	0.04	-0.04	0.68	SPD	0.01	0.04	-0.06	0.68
	(0.00)	(0.00)	(0.01)			(0.00)	(0.00)	(0.01)	

Note: This table shows the asset pricing result of two linear stochastic discount factor models of financial customers: asset manager(AM) and hedge fund(HF). The left panel is the pricing results of two factor model DOL and AM. On the left, it is the result of model DOL and HF. Both of two model pass the KP reduced rank test at 0.05. Only traditional GMM is used. This table also has similar structure as previous tables. The test asset are excess returns of five interest rate portfolios but I also report the time series results for portfolio EWC and SPD.

Table 2.14 – Disaggregated global order flow: Corporate

DOL, CO

KP reduced rank test

	t-stat	Dof	p-val
Rank(0)	199	10	{0.00}
Rank(1)	8	4	{0.09}

Cross-sectional asset pricing results

	Traditional				Reduced rank			
GMM1	DOL	CO	R^2	HJ dist	DOL	CO	R^2	HJ dist
b	34.14	17.52	0.97	0.81	11.32	2.34	0.53	9.35
s.e.	(12.64)	(8.67)		{0.85}	(3.98)	(0.82)		{0.05}
$\lambda(\times 100)$	0.17	5.46			0.17	-0.21		
s.e.	(0.08)	(2.81)			(0.06)	(0.07)		
GMM2								
b	34.09	17.19	0.96	0.82	34.09	17.19	0.96	0.82
s.e.	(12.48)	(8.39)		{0.84}	(12.48)	(8.39)		{0.84}
$\lambda(\times 100)$	0.17	5.34			0.17	5.34		
s.e.	(0.08)	(2.71)			(0.08)	(2.71)		
FMB	DOL	CO	$\chi^2(NW)$		DOL	CO	$\chi^2(NW)$	
$\lambda(\times 100)$	0.17	5.46	2.03		0.17	-0.21	8.34	
NW s.e.	(0.06)	(2.03)	{0.73}		(0.06)	(0.07)	{0.08}	

Portfolios beta and time series R^2

	$\alpha(\times 100)$	β-*DOL*	β-*CO*$(\times 100)$	adj. R^2	$\alpha(\times 100)$	β-*DOL*	β-*CO*$(\times 100)$	adj. R^2
1	-0.05	0.48	-1.26	0.50	-0.03	0.50	0.10	0.49
	(0.03)	(0.05)	(0.47)		(0.03)	(0.05)	(0.01)	
2	-0.01	0.83	-0.65	0.77	0.00	0.84	0.17	0.76
	(0.03)	(0.06)	(0.38)		(0.03)	(0.06)	(0.01)	
3	0.01	0.83	-0.16	0.81	0.02	0.84	0.17	0.81
	(0.02)	(0.05)	(0.36)		(0.02)	(0.05)	(0.01)	
4	0.02	1.02	-0.05	0.84	0.03	1.03	0.21	0.84
	(0.03)	(0.05)	(0.37)		(0.03)	(0.05)	(0.01)	
5	0.16	1.04	1.42	0.71	0.14	1.0293	0.21	0.71
	(0.04)	(0.05)	(0.53)		(0.04)	(0.05)	(0.01)	
EWC	0.04	0.51	0.63	0.65	0.03	1.0266	0.21	0.84
	(0.02)	(0.03)	(0.33)		(0.03)	(0.05)	(0.01)	
SPD	0.01	0.0433	0.07	0.67	0.14	1.0293	0.21	0.71
	(0.00)	(0.0021)	(0.02)		(0.04)	(0.05)	(0.01)	

Note: This table shows the asset pricing results for the two factor model of *DOL* and 'Corporate global order flow factor' *CO*. On the left panel is traditional GMM results. The reduced rank GMM is on the right. This table has the same structure as in previous table. The test asset are excess returns of five interest rate portfolios. I also report the time series results for portfolio EWC and SPD.

Table 2.15 – Disaggregated global order flow: Private client

	DOL, PC			
	KP reduced rank test			
	t-stat	Dof	p-val	
Rank(0)	231	10	{0.00}	
Rank(1)	28	4	{0.00}	
	Cross-sectional asset pricing			
GMM1	DOL	PC	R^2	HJ dist
b	26.45	4.60	0.88	4.15
s.e.	(7.77)	(1.87)		{0.25}
$\lambda(\times 100)$	0.17	2.08		
s.e.	(0.06)	(1.07)		
GMM2				
b	22.33	3.34	0.85	4.43
s.e.	(7.17)	(1.67)		{0.22}
$\lambda(\times 100)$	0.17	1.36		
s.e.	(0.06)	(0.96)		
FMB	DOL	PC	$\chi^2(NW)$	
$\lambda(\times 100)$	0.17	2.08	5.25	
NW s.e.	(0.06)	(1.01)	{0.26}	
	Portfolios' beta and time series R^2			
	$\alpha(\times 100)$	β-DOL	β-$PC(\times 100)$	adj. R^2
1	0.01	0.41	-2.77	0.55
	(0.03)	(0.04)	(0.40)	
2	0.02	0.79	-1.63	0.78
	(0.03)	(0.06)	(0.31)	
3	0.02	0.83	-0.02	0.81
	(0.02)	(0.05)	(0.26)	
4	0.02	1.04	0.55	0.84
	(0.03)	(0.05)	(0.26)	
5	0.11	1.09	2.03	0.71
	(0.04)	(0.05)	(0.46)	
EWC	-0.01	0.58	2.45	0.71
	(0.02)	(0.03)	(0.38)	
SPD	0.00	0.05	0.15	0.70
	(0.00)	(0.00)	(0.02)	

Note: This table has similar structure as previous table. The two factor model is based on *DOL* and 'private client's global order flow factor' *PC*.

Table 2.16 – Disaggregated carry trade order flow: Financials

DOL, CTAM					DOL, CTHF				
KP reduced rank test									
	t-stat	Dof	p-val			t-stat	Dof	p-val	
Rank(0)	250	10	{0.00}		Rank(0)	235	10	{0.00}	
Rank(1)	19	4	{0.00}		Rank(1)	49	4	{0.00}	
Cross-sectional asset pricing results									
GMM1	DOL	CTAM	R^2	HJ dist	GMM1	DOL	CTHF	R^2	HJ dist
b	5.93	2.41	0.73	6.88	b	9.87	2.97	0.83	4.93
s.e.	(4.82)	(1.20)		{0.08}	s.e.	(4.19)	(1.25)		{0.18}
$\lambda(\times 100)$	0.17	6.49				0.16	5.91		
s.e.	(0.06)	(3.06)			s.e.	(0.06)	(2.46)		
GMM2					GMM2				
b	8.55	1.07	0.67	7.72	b	10.62	1.76	0.78	5.56
s.e.	(4.40)	(0.99)		{0.05}	s.e.	(3.98)	(1.03)		{0.14}
$\lambda(\times 100)$	0.17	3.11				0.17	3.52		
s.e.	(0.06)	(2.52)			s.e.	(0.06)	(2.03)		
FMB	DOL	CTAM	$\chi^2(NW)$		FMB	DOL	CTHF	$\chi^2(NW)$	
$\lambda(\times 100)$	0.17	6.49	7.39			0.16	5.91	6.3797	
NW s.e.	(0.06)	(2.56)	{0.12}		NW s.e.	(0.06)	(2.25)	{0.17}	
Portfolios' beta and time series R^2									
	$\alpha(\times 100)$	β-DOL	β-$CTAM(\times 100)$	adj. R^2		$\alpha(\times 100)$	β-DOL	β-$CTHF(\times 100)$	adj. R^2
1	-0.05	0.5219	-1.04	0.53	1	-0.05	0.50	-1.31	0.54
	(0.03)	(0.05)	(0.21)			(0.03)	(0.05)	(0.20)	
2	-0.01	0.86	-0.61	0.77	2	0.00	0.84	-0.19	0.77
	(0.03)	(0.06)	(0.18)			(0.03)	(0.06)	(0.22)	
3	0.02	0.83	0.06	0.81	3	0.02	0.83	0.21	0.81
	(0.02)	(0.05)	(0.15)			(0.02)	(0.05)	(0.16)	
4	0.03	1.02	0.33	0.84	4	0.03	1.02	0.28	0.84
	(0.03)	(0.05)	(0.17)			(0.03)	(0.05)	(0.19)	
5	0.14	1.02	0.30	0.70	5	0.15	1.02	0.89	0.71
	(0.04)	(0.05)	(0.27)			(0.04)	(0.05)	(0.27)	
EWC	0.04	0.48	0.77	0.67	EWC	0.05	0.50	1.08	0.69
	(0.02)	(0.03)	(0.19)			(0.02)	(0.03)	(0.17)	
SPD	0.01	0.04	0.04	0.68	SPD	0.01	0.04	0.06	0.69
	(0.00)	(0.00)	(0.01)			(0.00)	(0.00)	(0.01)	

Note: This table reports the asset pricing results of two models for financial customer's carry trade order flow factors which has similar structure as previous table. The first model in the left panel is based on DOL and ' asset manager's carry trade order flow' factor $CTAM$. The second model on the right panel is based on DOL and ' hedge fund's carry trade order flow' factor $CTHF$.

Table 2.17 – Disaggregated carry trade order flow: Corporate

DOL, CTCO

KP reduced rank test

	t-stat	Dof	p-val
Rank(0)	199	10	0.00
Rank(1)	8	4	0.09

Cross-sectional asset pricing results

	Traditional				Reduced Rank			
GMM1	DOL	CTCO	R^2	HJ dist	DOL	CTCO	R^2	HJ dist
b	19.19	-18.35	0.74	3.48	11.29	0.01	0.53	9.37
s.e.	(7.709)	(12.07)		{0.32}	(3.96)	(0.00)		{0.05}
$\lambda(\times 100)$	0.19	-7.05			0.17	0.07		
s.e.	(0.08)	(4.68)			(0.06)	(0.02)		
GMM2								
b	13.34	-7.65	0.63	6.13	13.34	-7.65	0.6287	6.13
s.e.	(5.11)	(7.11)		{0.11}	(5.11)	(7.11)		{0.11}
$\lambda(\times 100)$	0.16	-2.91			0.16	-2.91		
s.e.	(0.06)	(2.76)			(0.06)	(2.76)		
FMB	DOL	CTCO	$\chi^2(NW)$		DOL	CTCO	$\chi^2(NW)$	
	0.19	-7.05	7.31		0.17	0.07	8.36	
NW s.e.	(0.06)	(2.83)	{0.12}		(0.06)	(0.02)	{0.08}	

Portfolios' beta and time series R^2

	$\alpha(\times 100)$	β-DOL	β-$CTCO(\times 100)$	adj. R^2	α	β-$DOL(\times 100)$	β-$CTCO(\times 100)$	adj. R^2
1	-0.03	0.49	0.80	0.50	-0.03	0.50	0.04	0.49
	(0.03)	(0.05)	(0.45)		(0.03)	(0.05)	(0.00)	
2	0.01	0.84	0.89	0.77	0.00	0.84	0.07	0.77
	(0.03)	(0.06)	(0.41)		(0.03)	(0.06)	(0.01)	
3	0.01	0.83	-0.18	0.81	0.02	0.83	0.07	0.81
	(0.02)	(0.05)	(0.35)		(0.02)	(0.05)	(0.00)	
4	0.02	1.02	0.11	0.84	0.02	1.02	0.09	0.84
	(0.03)	(0.05)	(0.40)		(0.03)	(0.05)	(0.00)	
5	0.14	1.03	-0.16	0.70	0.14	1.03	0.09	0.70
	(0.04)	(0.05)	(0.51)		(0.04)	(0.05)	(0.00)	
EWC	0.02	0.51	-0.90	0.65	0.02	1.02	0.09	0.84
	(0.02)	(0.03)	(0.40)		(0.03)	(0.05)	(0.00)	
SPD	0.01	0.04	-0.04	0.67	0.14	1.03	0.09	0.70
	(0.00)	(0.00)	(0.02)		(0.04)	(0.05)	(0.00)	

Note: This table has similar structure as previous table. The model is based on DOL and 'corporate's carry order flow' factor $CTCO$.

Table 2.18 – Disaggregated carry trade order flow factor: Private client

DOL, CTPC				
KP reduced rank				
	t-stat	Dof	p-val	
Rank(0)	215	10	{0.00}	
Rank(1)	21	4	{0.00}	
Cross-sectional asset pricing results				
GMM1	DOL	CTPC	R^2	HJ dist
b	10.88	-4.41	0.81	5.73
s.e.	(4.52)	(2.09)		{0.13}
$\lambda(\times 100)$	0.17	-2.70		
s.e.	(0.07)	(1.27)		
GMM2				
b	10.58	-2.73	0.76	6.21
s.e.	(4.23)	(1.81)		{0.10}
$\lambda(\times 100)$	0.16	-1.68		
s.e.	(0.06)	(1.10)		
FMB	DOL	CTPC	$\chi^2(NW)$	
$\lambda(\times 100)$	0.17	-2.70	6.60	
NW s.e.	(0.06)	(1.05)	{0.16}	
Portfolios' beta and time series R^2				
	$\alpha(\times 100)$	β-DOL	β-$CTPC$	adj. R^2
1	-0.04	0.50	2.95	0.56
	(0.03)	(0.04)	(0.38)	
2	0.00	0.84	1.02	0.77
	(0.03)	(0.06)	(0.38)	
3	0.02	0.83	0.09	0.81
	(0.02)	(0.05)	(0.27)	
4	0.02	1.02	-0.50	0.84
	(0.03)	(0.05)	(0.27)	
5	0.14	1.02	-1.29	0.71
	(0.04)	(0.05)	(0.50)	
EWC	0.03	0.50	-2.94	0.74
	(0.02)	(0.03)	(0.35)	
SPD	0.01	0.04	-0.14	0.70
	(0.00)	(0.00)	(0.03)	

Note: This table has similar structure as previous table. The model is based on *DOL* and 'private client's carry trade order flow' factor CTPC.

Table 2.19 – Portfolio beta Decomposition

	$\ln(S_t) - \ln(S_{t+1})$					$\ln(F_t) - \ln(S_{t+1})$			
	$\alpha(\times 100)$	β-DOL	β-$CTOF$ $(\times 100)$	adj. R^2		$\alpha(\times 100)$	β-DOL $(\times 100)$	β-$CTOF$ $(\times 100)$	adj. R^2
1	0.03	0.62	-0.64	0.64	1	-2.80	0.05	-0.43	-0.21
	(0.02)	(0.04)	(0.10)			(0.24)	(0.09)	(0.43)	
2	0.01	0.94	-0.06	0.82	2	0.15	0.07	-0.17	-0.22
	(0.02)	(0.03)	(0.09)			(0.23)	(0.07)	(0.29)	
3	-0.01	0.92	0.58	0.84	3	2.45	0.05	-0.07	-0.31
	(0.02)	(0.03)	(0.11)			(0.26)	(0.08)	(0.35)	
4	0.03	1.13	0.76	0.78	4	6.52	0.01	0.24	-0.31
	(0.04)	(0.06)	(0.15)			(0.27)	(0.09)	(0.39)	
5	0.01	0.99	1.21	0.56	5	1.93	0.16	2.18	0.19
	(0.06)	(0.09)	(0.21)			(0.83)	(0.26)	(1.23)	

Note: This table reports intercepts, regression coefficients (Newey-west standard errors are in brackets) and adjusted R-squares of regression analysis for exchange rate change $\ln(S_t) - \ln(S_{t+1})$ and forward premium $\ln(F_t) - \ln(S_{t+1})$ with CTOF factor of five interest rate portfolios. Where both of the regression intercept α, β-$CTOF$, and β-DOL for forward premium is scaled by 100.

Table 2.20 – Factor mimicking portfolios

	Factor-mimicking portfolio weights					Factor mimicking portfolio return
	P1	P2	P3	P4	P5	
DVOL	5.08	5.00	-3.64	-4.69	-5.16**	-1.84%
OF	0.03	-1.33	3.42**	3.86***	1.44**	1.16%
AM	4.16***	0.88	2.15**	0.54	0.02	0.53%
HF	2.80**	3.37***	0.40	0.13	-1.15	0.18%
CO	-0.94	-0.44	-0.22	-0.30	0.16	-0.09%
PC	-3.45***	-2.27	0.49	0.34	-0.12	-0.25%
CTOF	-7.98***	-2.47***	6.71***	3.83***	2.55***	1.57%
CTAM	-5.62***	-1.97	3.30***	3.53***	0.11	0.58%
CTHF	-7.01***	0.80	2.40**	0.49	0.63	0.40%
CTCO	0.61	0.80*	-0.77	0.03	0.05	0.03%
CTPC	4.34	0.03	-1.10**	-1.06**	-0.20	-0.21%

Note: This table reports the asset pricing results of two models for financial customer's carry trade order flow factors which has similar structure as previous table. The first model in the left panel is based on DOL and ' asset manager's carry trade order flow' factor $CTAM$. The second model on the right panel is based on DOL and ' hedge fund's carry trade order flow' factor $CTHF$.

Table 2.21 – Factor regression analysis

	DVOL					SKEWNESS		
	Intercept(×100)	β(×100)	adj. R-square			Intercept(×100)	β(×100)	adj. R-square
CTOF	-3.28	-8.63	2.96%		CTOF	-3.04	4.93	0.58%
	[1.04]	[2.14]				[1.02]	[2.20]	
CTAM	-1.14	-4.62	1.85%		CTAM	-1.17	-0.43	-0.17%
	[0.71]	[1.48]				[0.72]	[1.61]	
CTHF	-1.67	0.0127	0.02%		CTHF	-1.52	3.08	0.71%
	[0.66]	[1.79]				[0.67]	[1.39]	
CTCO	-0.79	-111	0.60%		CTCO	-0.79	0.08	-0.18%
	[0.39]	[0.49]				[0.38]	[0.73]	
CTPC	0.16	0.41	-0.12%		CTPC	0.17	0.41	-0.14%
	[0.33]	[0.70]				[0.33]	[0.80]	

Note: This table reports intercepts, regression coefficients (Newey-west standard errors are in brackets) and adjusted R-squares of regression analysis for five carry trade factors with volatility innovation factor and sample skewness of DOL returns where the carry trade order flow factors are dependent variables and DVOL and volatility innovations are independent variables repectively. The significane table is ***0.01, **0.05 and *0.1.

Table 2.22 – Momentum Portfolios: Summary Statistics

	M1	M2	M3	M4	M5	HML (Mom)
A) Full Sample						
Mean (%)	3.86	5.40	6.61	8.57	10.61	6.75
	(2.83)	(2.98)	(2.72)	(2.75)	(3.03)	(2.51)
SD	8.90	8.96	8.61	8.70	9.19	8.77
SR	0.44	0.60	0.77	0.99	1.16	0.77
Skew	-0.44	-0.40	-0.36	-0.41	-0.60	-0.13
B) Pre-financial crisis						
Mean (%)	4.14	9.09	9.55	9.04	17.24	13.10
	(2.90)	(3.19)	(3.24)	(3.30)	(3.35)	(2.85)
SD	7.15	7.36	7.61	7.83	8.40	7.63
SR	0.58	1.23	1.25	1.15	2.05	1.72
Skew	-0.24	-0.18	-0.17	-0.52	-0.71	-0.29

Note: The table reports the descriptive statistics for currency portfolios M1–M5, which are sorted on the basis of lagged currency returns over four weeks. It reports the annualized mean return (%) (with heteroskedasticity consistent standard errors reported in parentheses), standard deviation (SD), Sharpe ratio (SR), and skewness (Skew) for each portfolio. The holding period of the portfolios is one week in both cases. I report results for both our full sample (panel A) and the pre-financial crisis sample (panel B).

Table 2.23 – Aggregated momentum order flow factor: MOOF

DOL, MOOF				
KP reduced rank test				
	t-stat	Dof	p-val	
Rank(0)	132	10	{0.00}	
Rank(1)	20	4	{0.00}	
Cross-sectional asset pricing				
GMM1	DOL	MOOF	R^2	HJ dist
b	10.53	1.93	0.90	1.66
s.e.	(4.38)	(0.79)		{0.65}
$\lambda(\times 100)$	0.12	12.03		
s.e.	(0.06)	(5.00)		
GMM2				
b	10.44	1.94	0.90	1.66
s.e.	(4.38)	(0.79)		{0.65}
$\lambda(\times 100)$	0.12	12.09		
s.e.	(0.06)	(4.97)		
FMB	DOL	MOOF	$\chi^2(NW)$	
$\lambda(\times 100)$	0.12	12.03	1.55	
NW s.e.	(0.06)	(3.76)	{0.82}	
Portfolios' beta and time series R^2				
	$\alpha(\times 100)$	β-DOL	β-MOOF$(\times 100)$	adj. R^2
M1	-0.07	1.07	-0.65	0.77
	(0.03)	(0.05)	(0.14)	
M2	-0.01	1.06	-0.14	0.86
	(0.02)	(0.04)	(0.11)	
M3	-0.03	1.01	0.03	0.85
	(0.02)	(0.02)	(0.09)	
M4	0.02	0.94	0.32	0.78
	(0.03)	(0.03)	(0.10)	
M5	0.09	0.88	0.74	0.61
	(0.04)	(0.08)	(0.16)	

Note: This table shows the asset pricing results for the linear stochastic discount factor based on 'dollar risk factor' (*DOL*) and 'momentum carry trade order flow'(*MOOF*), the test asset are weekly currency excess returns of five portfolios sorted on previous 4-week return. The first panel shows KP reduced rank test. The second panel shows the cross-sectional asset pricing results from first stage GMM, Second stage GMM and Fama-MacBeth method. In GMM, it reports the SDF coefficient b for each factor and factor price estimate (λ) along with their corresponding standard error in parenethese. It is followed by cross-sectional R^2. I also report the HJ statistic and its p-value in square brakets below. In FMB, I did not include an intercept in second pass and standard errors are obtained by the Newey and West (1987) with optimal lag selection according to Andrews (1991). In FMB, I report the factor price with standard error, Chi-square statistic and its p-value. The second panel reports the αs, factor betas and their corresponding standard error for these five portfolios. It is followed by the times-series R^2 for each portfolio.

Table 2.24 – Aggregated global order flow

DOL, MOAM

KP reduced rank test

	t-stat	Dof	p-val
Rank(0)	193	10	{0.00}
Rank(1)	9	4	{0.06}

Cross-sectional asset pricing results

	Traditional				Reduced rank			
GMM1	DOL	MOAM	R^2	HJ dist	DOL	MOAM	R^2	HJ dist
b	13.47	3.79	0.65	5.51	8.00	-2.47	-0.39	8.84
s.e.	(4.88)	(1.61)		{0.14}	(3.87)	(1.19)		{0.07}
$\lambda(\times 100)$	0.12	9.86			0.12	-0.24		
s.e.	(0.06)	(4.23)			(0.06)	(0.12)		
GMM2								
b	8.66	1.98	-0.02	5.50	8.33	-0.03	-0.40	8.78
s.e.	(4.80)	(1.37)		{0.14}	(3.88)	(0.01)		{0.07}
$\lambda(\times 100)$	0.09	5.13			0.13	-0.25		
s.e.	(0.06)	(3.60)			(0.06)	(0.12)		
FMB	DOL	MOAM	$\chi^2(NW)$		DOL	MOAM	$\chi^2(NW)$	
$\lambda(\times 100)$	0.12	9.86	5.44		0.12	-0.24	11.83	
NW s.e.	(0.06)	(3.30)	[0.24]		(0.06)	(0.11)	[0.02]	

Portfolios' beta and time series R^2

	$\alpha(\times 100)$	β-DOL	β-MOAM($\times$100)	adj. R^2	$\alpha(\times 100)$	β-DOL	β-MOAM($\times$100)	adj. R^2
M1	-0.07	1.07	-0.80	0.76	-0.08	1.08	-0.33	0.76
	(0.03)	(0.05)	(0.27)		(0.03)	(0.05)	(0.02)	
M2	-0.01	1.06	-0.13	0.85	-0.01	1.06	-0.33	0.85
	(0.02)	(0.04)	(0.16)		(0.02)	(0.04)	(0.01)	
M3	-0.04	1.01	0.32	0.85	-0.03	1.00	-0.31	0.85
	(0.02)	(0.02)	(0.14)		(0.02)	(0.03)	(0.01)	
M4	0.02	0.94	0.19	0.78	(0.03	0.93	-0.29	0.78
	(0.03)	(0.04)	(0.17)		(0.03)	(0.04)	(0.01)	
M5	0.08	0.88	0.72	0.60	0.10	0.86	-0.27	0.59
	(0.04)	(0.08)	(0.26)		(0.04)	(0.08)	(0.03)	

Note: This table shows the asset pricing results for the model of DOL and 'asset manager's momentum order flow factor' $MOAM$. On the left panel is traditional GMM results. The reduced rank GMM is on the right. This table has the same structure as in previous table. The test asset are excess returns of five interest rate portfolios. I also report the time series results for portfolio EWC and SPD.

Table 2.25 – Aggregated momentum order flow factor: MOHF

DOL, MOHF				
KP reduced rank test				
	t-stat	Dof	p-val	
Rank(0)	126	10	{0.00}	
Rank(1)	22	4	{0.00}	
Cross-sectional asset pricing				
GMM1	DOL	MOHF	R^2	HJ dist
b	8.30	2.58	0.63	3.89
s.e.	(4.19)	(1.20)		{0.27}
$\lambda(\times 100)$	0.12	5.42		
s.e.	(0.06)	(2.53)		
GMM2				
b	7.61	2.07	0.55	4.16
s.e.	(4.00)	(1.20)		{0.24}
$\lambda(\times 100)$	0.11	4.34		
s.e.	(0.06)	(2.30)		
FMB	DOL	MOHF	$\chi^2(NW)$	
$\lambda(\times 100)$	0.12	5.42	{4.46}	
NW s.e.	(0.06)	(1.83)	{0.35}	
Portfolios' beta and time series R^2				
	$\alpha(\times 100)$	β-DOL	β-MOHF$(\times 100)$	adj. R^2
M1	-0.10	1.08	-1.42	0.78
	(0.03)	(0.05)	(0.25)	
M2	-0.02	1.07	-0.36	0.86
	(0.02)	(0.04)	(0.17)	
M3	-0.03	1.01	0.35	0.85
	(0.02)	(0.03)	(0.15)	
M4	0.03	0.94	0.97	0.79
	(0.03)	(0.03)	(0.20)	
M5	0.11	0.87	1.06	0.60
	(0.04)	(0.081)	(0.28)	

Note: This table shows the asset pricing results for the linear stochastic discount factor based on 'dollar risk factor' (DOL) and 'hedge fund's momentum order flow from'($MOHF$), the test asset are weekly currency excess returns of five portfolios sorted on previous 4-week return.

Table 2.26 – Aggregated momentum order flow factor: MOCO

DOL, MOCO				
KP reduced rank test				
	t-stat	Dof	p-val	
Rank(0)	122	10	{0.00}	
Rank(1)	17	4	{0.00}	
Cross-sectional asset pricing				
GMM1	DOL	MOCO	R^2	HJ dist
b	7.12	-9.17	0.34	5.66
s.e.	(4.56)	(4.75)		{0.13}
$\lambda(\times 100)$	0.12	-3.93		
s.e.	(0.07)	(2.03)		
GMM2				
b	7.59	-5.68	0.2331	6.51
s.e.	(4.16)	(4.13)		{0.09}
$\lambda(\times 100)$	0.12	-2.44		
s.e.	(0.06)	(1.76)		
FMB	DOL	MOCO	$\chi^2(NW)$	
$\lambda(\times 100)$	0.12	-3.93	7.19	
NW s.e.	(0.06)	(1.50)	{0.13}	
Portfolios' beta and time series R^2				
	$\alpha(\times 100)$	β-DOL	β-MOCO($\times 100$)	adj. R^2
M1	-0.08	1.08	1.73	0.76
	(0.03)	(0.06)	(0.52)	
M2	-0.01	1.07	0.40	0.85
	(0.02)	(0.04)	(0.37)	
M3	-0.04	1.01	-0.78	0.85
	(0.02)	(0.02)	(0.35)	
M4	0.02	0.94	-1.20	0.78
	(0.03)	(0.04)	(0.37)	
M5	0.09	0.87	-0.85	0.59
	(0.04)	(0.08)	(0.56)	

Note: This table shows the asset pricing results for the linear stochastic discount factor based on 'dollar risk factor' (*DOL*) and 'Coporate's momentum order flow'(*MOCO*), the test asset are weekly currency excess returns of five portfolios sorted on previous 4-week return.

Table 2.27 – Aggregated momentum order flow factor: MOPC

DOL, MOPC				
KP reduced rank test				
	t-stat	Dof	p-val	
Rank(0)	161	10	{0.00}	
Rank(1)	37	4	{0.00}	
Cross-sectional asset pricing				
GMM1	DOL	MOPC	R^2	HJ dist
b	8.85	-4.12	0.79	2.65
s.e.	(4.15)	(1.75)		{0.45}
$\lambda(\times 100)$	0.12	-2.81		
s.e.	(0.06)	(1.21)		
GMM2				
b	8.48	-4.00	0.78	2.67
s.e.	(4.11)	(1.69)		{0.44}
$\lambda(\times 100)$	0.11	-2.73		
s.e.	(0.06)	(1.16)		
FMB	DOL	MOPC	$\chi^2(NW)$	
$\lambda(\times 100)$	0.12	-2.81	2.48	
NW s.e.	(0.06)	(0.90)	{0.65}	
Portfolios' beta and time series R^2				
	$\alpha(\times 100)$	β-DOL	β-MOPC($\times 100$)	adj. R^2
M1	-0.10	1.07	2.88	0.78
	(0.03)	(0.05)	(0.43)	
M2	-0.02	1.07	0.50	0.86
	(0.02)	(0.04)	(0.26)	
M3	-0.03	1.01	-0.25	0.85
	(0.02)	(0.02)	(0.26)	
M4	0.03	0.94	-1.84	0.79
	(0.03)	(0.03)	(0.37)	
M5	0.11	0.88	-2.52	0.61
	(0.04)	(0.08)	(0.58)	

Note: This table shows the asset pricing results for the linear stochastic discount factor based on 'dollar risk factor' (DOL) and 'Private Client's momentum order flow'($MOPC$), the test asset are weekly currency excess returns of five portfolios sorted on previous 4-week return.

Table 2.28 – Factor DOL

		DOL		
		t-statistic	Dof	p-value
Rank(0)		141	51	{0.00}
	b^{DOL}	$\lambda^{DOL}(\times 100)$	R^2	HJ dist
GMM1				
b	21.38	0.18	0.20	23.63
s.e.	(7.23)	(0.06)		{0.00}
GMM2				
b	18.22	0.16	0.14	23.86
s.e.	(7.02)	(0.06)		{0.00}
FMB		DOL		Chi-square(NW)
λ		0.18		26.70
NW s.e.		(0.05)		{0.00}
		Portdolio beta and time series R^2		
	$\alpha(\times 100)$	β-DOL	adj R^2	
1	-0.14	0.81	0.70	
	(0.03)	(0.05)		
2	-0.03	1.10	0.83	
	(0.03)	(0.04)		
3	0.02	0.87	0.76	
	(0.02)	(0.03)		
4	-0.03	1.15	0.84	
	(0.02)	(0.03)		
5	0.17	1.07	0.61	
	(0.05)	(0.05)		
EWC	0.08	0.39	0.38	
	(0.03)	(0.07)		
SPD	0.01	0.04	0.10	
	(0.00)	(0.00)		

Note: This table reports the asset pricing test results for a single factor DOL by using a subset of pre-financial crisis data. The subset spans from the first week of November 2001 to the third week of May 2007, 290 observations in total..

Table 2.29 – Factor DOL and DVOL

		DOL, DVOL		
		KP reduced rank		
	t-stat	Dof	p-val	
Rank(0)	215	10	{0.00}	
Rank(1)	21	4	{0.00}	
		Cross-sectional asset pricing results		
GMM1	DOL	DVOL	R^2	HJ dist
b	5.22	-3.82	0.97	1.10
s.e.	(16.02)	(1.48)		{0.78}
λ	0.18	-10.21		
s.e.	(0.13)	(6.04)		
GMM2				
b	10.58	-2.73	0.76	6.21
s.e.	(4.23)	(1.81)		{0.10}
λ	0.16	-1.68		
s.e.	(0.06)	(1.10)		
FMB	DOL	DVOL	$\chi^2(NW)$	
λ	0.18	-10.21	4.91	
NW s.e.	(0.05)	(3.10)	{0.30}	
		Portfolios' beta and time series R^2		
	$\alpha(\times 100)$	β-DOL	β-$DVOL(\times 100)$	adj. R^2
1	-0.11	0.75	1.01	0.72
	(0.03)	(0.04)	(0.30)	
2	-0.02	1.06	0.58	0.84
	(0.04)	(0.05)	(0.22)	
3	0.02	0.87	-0.03	0.79
	(0.02)	(0.03)	(0.19)	
4	-0.03	1.15	-0.00	0.84
	(0.03)	(0.04)	(0.24)	
5	0.13	1.16	-1.49	0.63
	(0.05)	(0.06)	(0.44)	
EWC	0.06	0.44	-0.87	0.41
	(0.03)	(0.06)	(0.32)	
SPD	0.01	0.04	-0.07	0.43
	(0.00)	(0.00)	(0.02)	

Note: This table reports the asset pricing test results for factor DOL and DVOL by using a subset of pre-financial crisis data. The subset spans from the first week of November 2001 to the third week of May 2007, 290 observations in total.

Table 2.30 – Factor DOL and OF

DOL, OF

KP reduced rank test

	t-stat	Dof	p-val
Rank(0)	164	10	{0.00
Rank(1)	11	4	{0.03

Cross-sectional asset pricing results

	Traditional				Reduced rank			
GMM1	DOL	OF	R^2	HJ dist	DOL	OF	R^2	HJ dist
b	63.65	-9.01	0.52	5.57	21.47	-0.02	0.20	23.60
s.e.	(23.7715)	(4.5617)		{0.13}	(7.26)	(0.01)		{0.00}
$\lambda(\times100)$	0.19	-17.51			0.18	0.81		
s.e.	(0.10)	(9.34)			(0.06)	(0.28)		
GMM2								
b	49.46	-6.82	0.40	7.82	18.33	-0.02	0.14	23.82
s.e.	(16.90)	(3.09)		{0.05}	(7.05)	(0.01)		{0.00}
$\lambda(\times100)$	0.151	-13.22			0.15	0.69		
s.e.	(0.08)	(6.33)			(0.00)	(0.27)		
FMB	DOL	OF	$\chi^2(NW)$		DOL	OF	$\chi^2(NW)$	
$\lambda(\times100)$	0.19	-17.51	18.63		0.18	0.81	26.65	
NW s.e.	(0.05)	(5.35)	{0.00}		(0.05)	(0.23)	{0.00}	

Portfolios' beta and time series R^2

	$\alpha(\times100)$	β-DOL	β-$OF(\times100)$	adj. R^2	$\alpha(\times100)$	β-DOL	β-$OF(\times100)$	adj. R^2
1	-0.14	0.81	0.12	0.70	-0.14	0.82	-0.07	0.70
	(0.03)	(0.05)	(0.23)		(0.03)	(0.05)	(0.00)	
2	-0.03	1.10	-0.14	0.83	-0.03	1.10	-0.10	0.83
	(0.03)	(0.04)	(0.20)		(0.03)	(0.04)	(0.00)	
3	0.02	0.87	-0.04	0.79	0.02	0.87	-0.08	0.79
	(0.02)	(0.03)	(0.15)		(0.02)	(0.03)	(0.00)	
4	-0.02	1.12	0.57	0.85	-0.03	1.15	-0.10	0.84
	(0.03)	(0.04)	(0.20)		(0.03)	(0.03)	(0.00)	
5	0.16	1.09	-0.46	0.61	0.16	1.07	-0.09	0.61
	(0.05)	(0.05)	(0.41)		(0.05)	(0.05)	(0.00)	
EWC	0.08	0.40	-0.36	0.39	0.08	0.39	-0.03	0.38
	(0.03)	(0.07)	(0.18)		(0.03)	(0.07)	(0.01)	
SPD	0.01	0.04	-0.04	0.41	0.012	0.04	-0.00	0.40
	(0.00)	(0.00)	(0.02)		(0.00)	(0.00)	(0.00)	

Note: This table reports the asset pricing test results for factor DOL and OF by using a subset of pre-financial crisis data. The subset spans from the first week of November 2001 to the third week of May 2007, 290 observations in total.

Table 2.31 – Factor DOL and CTOF

DOL, CTOF				
KP reduced rank test				
	t-stat	Dof	p-val	
Rank(0)	150	10	{0.00}	
Rank(1)	13	4	{0.01}	
Crossectional asset pricing				
GMM1	DOL	CTOF		HJ dist
b	23.05	8.52	0.50	6.69
s.e.	(10.21)	(3.82)		{0.08}
λ	0.18	15.07		
s.e.	(0.09)	(6.78)		
GMM2				
b	26.17	5.84	0.39	9.19
s.e.	(8.90)	(2.72)		{0.03}
λ	0.21	10.31		
s.e.	(0.08)	(4.83)		
FMB	DOL	CTOF	$\chi^2(NW)$	
λ	0.18	15.07	15.00	
NW s.e.	(0.05)	(3.70)	{0.00}	
Portfolios' beta and time series R^2				
	$\alpha(\times 100)$	β-DOL	β-$CTOF(\times 100)$	adj. R^2
1	-0.16	0.81	-0.76	0.71
	(0.03)	(0.05)	(0.23)	
2	-0.03	1.10	-0.03	0.83
	(0.03)	(0.04)	(0.19)	
3	0.03	0.87	0.26	0.79
	(0.02)	(0.03)	(0.16)	
4	-0.02	1.15	0.36	0.84
	(0.03)	(0.03)	(0.17)	
5	0.17	1.07	0.10	0.61
	(0.05)	(0.05)	(0.39)	
EWC	0.10	0.39	0.80	0.41
	(0.02)	(0.07)	(0.22)	
SPD	0.01	0.04	0.04	0.41
	(0.00)	(0.00)	(0.02)	

Note: This table reports the asset pricing test results for factor DOL and CTOF by using a subset of pre-financial crisis data. The subset spans from the first week of November 2001 to the third week of May 2007, 290 observations in total.

Table 2.32 – Factor DOL and AM

DOL, OF								
KP reduced rank test								
	t-stat	Dof	p-val					
Rank(0)	159	10	{0.00}					
Rank(1)	7	4	{0.14}					
Cross-sectional asset pricing results								
	Traditional				Reduced rank			
GMM1	DOL	AM	R^2	HJ dist	DOL	AM	R^2	HJ dist
b	80.46	-11.61	0.97	1.41	21.50	-0.02	0.20	23.54
s.e.	(30.25)	(5.56)		{0.70}	(7.27)	(0.01)		{0.00}
$\lambda(\times 100)$	0.177	-12.43			0.18	0.92		
s.e.	(0.10)	(6.43)			(0.06)	(0.31)		
GMM2								
b	84.90	-12.35	0.96	1.31	18.42	-0.02	0.15	23.76
s.e.	(30.50)	(5.55)		{0.73}	(7.06)	(0.01)		{0.00}
$\lambda(\times 100)$	0.18	-13.24			0.16	0.79		
s.e.	(0.10)	(6.42)			(0.06)	(0.30)		
FMB	DOL	AM	$\chi^2(NW)$		DOL	AM	$\chi^2(NW)$	
$\lambda(\times 100)$	0.18	-12.43	4.65		0.18	0.92	26.62	
NW s.e.	(0.05)	(3.53)	{0.32}		(0.05)	(0.26)	{0.00}	
Portfolios' beta and time series R^2								
	$\alpha(\times 100)$	β-DOL	β-$AM(\times 100)$	adj. R^2	$\alpha(\times 100)$	β-DOL	β-$AM(\times 100)$	adj. R^2
1	-0.15	0.76	0.99	0.71	-0.14	0.82	-0.08	0.70
	(0.03)	(0.05)	(0.31)		(0.03)	(0.05)	(0.01)	
2	-0.03	1.08	0.23	0.83	-0.03	1.10	-0.01	0.83
	(0.03)	(0.04)	(0.27)		(0.03)	(0.04)	(0.00)	
3	0.02	0.87	0.08	0.79	0.03	0.87	-0.09	0.79
	(0.02)	(0.03)	(0.16)		(0.02)	(0.03)	(0.00)	
4	-0.03	1.15	-0.03	0.84	-0.03	1.15	-0.12	0.84
	(0.03)	(0.04)	(0.26)		(0.03)	(0.03)	(0.00)	
5	0.18	1.13	-1.25	0.62	0.17	1.07	-0.11	0.61
	(0.05)	(0.05)	(0.44)		(0.05)	(0.05)	(0.01)	
EWC	0.09	0.45	-1.14	0.42	0.08	0.39	-0.04	0.38
	(0.03)	(0.06)	(0.30)		(0.03)	(0.07)	(0.01)	
SPD	0.01	0.04	-0.08	0.4.	0.01	0.04	-0.00	0.40
	(0.00)	(0.00)	(0.02)		(0.00)	(0.00)	(0.00)	

Note: This table reports the asset pricing test results for factor DOL and AM by using a subset of pre-financial crisis data. The subset spans from the first week of November 2001 to the third week of May 2007, 290 observations in total.

Table 2.33 – Factor DOL and HF

DOL, HF				
KP reduced rank test				
	t-stat	Dof	p-val	
Rank(0)	160	10	{0.00}	
Rank(1)	20	4	{0.00}	
Cross-sectional asset pricing				
GMM1	DOL	HF	R^2	HJ dist
b	64.36	-7.10	0.95	1.90
s.e.	(18.32)	(2.42)		{0.59}
$\lambda(\times 100)$	0.18	-10.25		
s.e.	(0.09)	(3.86)		
GMM2				
b	67.28	-7.75	0.94	1.77
s.e.	(17.98)	(2.35)		{0.62}
$\lambda(\times 100)$	0.17	-11.30		
s.e.	(0.09)	(3.76)		
FMB	DOL	HF	$\chi^2(NW)$	
$\lambda(\times 100)$	0.18	-10.21	4.91	
NW s.e.	(0.05)	(3.10)	{0.30}	
Portfolios' beta and time series R^2				
	$\alpha(\times 100)$	β-DOL	β-HF	adj R^2
1	-0.11	0.75	1.01	0.72
	(0.03)	(0.04)	(0.30)	
2	-0.02	1.06	0.58	0.84
	(0.04)	(0.05)	(0.22)	
3	0.02	0.87	-0.03	0.79
	(0.02)	(0.03)	(0.19)	
4	-0.03	1.15	-0.00	0.84
	(0.03)	(0.04)	(0.24)	
5	0.13	1.16	-1.49	0.63
	(0.05)	(0.06)	(0.44)	
EWC	0.06	0.44	-0.87	0.41
	(0.03)	(0.06)	(0.32)	
SPD	0.01	0.04	-0.07	0.43
	(0.00)	(0.00)	(0.02)	

Note: This table reports the asset pricing test results for factor DOL and HF by using a subset of pre-financial crisis data. The subset spans from the first week of November 2001 to the third week of May 2007, 290 observations in total.

Table 2.34 – Factor DOL and CO

DOL, CO

KP reduced rank test

	t-stat	Dof	p-val
Rank(0)	157	10	{0.00}
Rank(1)	8	4	{0.08}

Cross-sectional asset pricing results

	Traditional				Reduced rank			
GMM1	DOL	CO	R^2	HJ dist	DOL	CO	R^2	HJ dist
b	65.75	27.06	0.88	3.96	21.49	0.06	0.15	23.78
s.e.	(25.27)	(13.21)		{0.27}	(7.27)	(0.02)		{0.00}
$\lambda(\times 100)$	0.18	5.84			0.18	-0.29		
s.e.	(0.10)	(2.99)			(0.06)	(0.10)		
GMM2								
b	72.12	28.88	0.81	3.64	18.40	0.05	0.96	0.82
s.e.	(25.85)	(13.56)		{0.30}	(7.06)	(0.02)		{0.84}
$\lambda(\times 100)$	0.206	6.21			0.16	-0.25		
s.e.	(0.10)	(3.07)			(0.06)	(0.10)		
FMB	DOL	CO	$\chi^2(NW)$		DOL	CO	$\chi^2(NW)$	
$\lambda(\times 100)$	0.18	5.84	14.95		0.18	-0.29	26.64	
NW s.e.	(0.05)	(1.78)	{0.00}		(0.05)	(0.08)	{0.00}	

Portfolios beta and time series R^2

	$\alpha(\times 100)$	β-DOL	β-CO	adj. R^2	$\alpha(\times 100)$	β-DOL	β-$CO(\times 100)$	adj. R^2
1	-0.14	0.79	-1.52	0.70	-0.14	0.82	0.24	0.70
	(0.03)	(0.05)	(0.53)		(0.03)	(0.05)	(0.01)	
2	-0.03	1.08	-0.90	0.83	-0.03	1.10	0.32	0.83
	(0.03)	(0.04)	(0.51)		(0.03)	(0.04)	(0.01)	
3	0.02	0.86	-0.53	0.79	0.03	0.87	0.25	0.79
	(0.02)	(0.03)	(0.44)		(0.02)	(0.03)	(0.01)	
4	-0.03	1.15	0.22	0.84	-0.03	1.15	0.34	0.84
	(0.03)	(0.03)	(0.52)		(0.03)	(0.03)	(0.01)	
5	0.17	1.11	2.75	0.62	0.17	1.07	0.32	0.61
	(0.05)	(0.05)	(0.91)		(0.05)	(0.05)	(0.01)	
EWC	0.08	0.41	1.19	0.39	0.08	0.39	0.12	0.38
	(0.03)	(0.07)	(0.51)		(0.03)	(0.07)	(0.02)	
SPD	0.01	0.04	0.10	0.41	0.01	0.037	0.01	0.40
	(0.00)	(0.00)	(0.04)		(0.00)	(0.00)	(0.00)	

Note: This table reports the asset pricing test results for factor DOL and CO by using a subset of pre-financial crisis data. The subset spans from the first week of November 2001 to the third week of May 2007, 290 observations in total.

Table 2.35 – Factor DOL and PC

DOL, PC				
KP reduced rank test				
	t-stat	Dof	p-val	
Rank(0)	181	10	{0.00}	
Rank(1)	38	4	{0.00}	
Cross-sectional asset pricing				
GMM1	DOL	PC	R^2	HJ dist
b	68.76	8.61	0.86	5.63
s.e.	(18.24)	(2.95)		{0.13}
$\lambda(\times 100)$	0.18	3.21		
s.e.	(0.07)	(1.51)		
GMM2				
b	60.31	7.04	0.83	6.14
s.e.	(14.81)	(2.23)		{0.11}
$\lambda(\times 100)$	0.18	2.43		
s.e.	(0.70)	(1.15)		
FMB	DOL	PC	$\chi^2(NW)$	
$\lambda(\times 100)$	0.18	3.21	11.70	
NW s.e.	(0.05)	(1.15)	{1.97}	
Portfolios' beta and time series R^2				
	$\alpha(\times 100)$	β-DOL	β-$PC(\times 100)$	adj. R^2
1	-0.08	0.63	-3.34	0.76
	(0.03)	(0.04)	(0.38)	
2	-0.01	1.03	-1.17	0.84
	(0.04)	(0.05)	(0.36)	
3	0.02	0.88	0.26	0.79
	(0.03)	(0.04)	(0.36)	
4	-0.05	1.22	1.28	0.85
	(0.03)	(0.04)	(0.33)	
5	0.12	1.23	2.89	0.63
	(0.06)	(0.07)	(0.72)	
EWC	0.02	0.59	3.60	0.57
	(0.03)	(0.05)	(0.41)	
SPD	0.01	0.05	0.22	0.48
	(0.00)	(0.00)	(0.03)	

This table reports the asset pricing test results for factor DOL and PC by using a subset of pre-financial crisis data. The subset spans from the first week of November 2001 to the third week of May 2007, 290 observations in total.

Table 2.36 – Factor DOL and CTAM

DOL, CTAM								
KP reduced rank test								
	t-stat	Dof	p-val					
Rank(0)	147	10	{0.00}					
Rank(1)	7	4	{0.15}					
Cross-sectional asset pricing results								
	Traditional				Reduced rank			
GMM1	DOL	CTAM	R^2	HJ dist	DOL	CTAM	R^2	HJ dist
b	36.72	10.56	0.77	4.88	21.34	-0.02	0.20	23.71
s.e.	(11.47)	(4.49)		{0.18}	(7.22)	(0.01)		{0.00}
$\lambda(\times 100)$	0.18	10.45			0.18	-0.30		
s.e.	(0.09)	(4.59)			(0.06)	(0.10)		
GMM2								
b	33.72	7.10	0.68	6.51	18.09	-0.02	0.13	23.94
s.e.	(9.80)	(3.01)		{0.09}	(7.00)	(0.01)		{0.00}
$\lambda(\times 100)$	0.20	6.91			0.16	-0.25		
s.e.	(0.08)	(3.06)			(0.06)	(0.10)		
FMB	DOL	CTAM	$\chi^2(NW)$		DOL	CTAM	$\chi^2(NW)$	
$\lambda(\times 100)$	0.18	10.45	10.62		0.18	-0.30	26.79	
NW s.e.	(0.05)	(2.54)	{0.03}		(0.05)	(0.09)	{0.00}	
Portfolios beta and time series R^2								
	$\alpha(\times 100)$	β-DOL	β-$CTAM(\times 100)$	adj. R^2	$\alpha(\times 100)$	β-DOL	β-$CTAM(\times 100)$	adj. R^2
1	-0.15	0.79	-1.46	0.72	-0.0014	0.82	-0.07	0.70
	(0.03)	(0.04)	(0.31)		(0.0003)	(0.05)	(0.00)	
2	-0.03	1.09	-0.10	0.83	-0.0003	1.094	-0.10	0.83
	(0.03)	(0.04)	(0.24)		(0.0003)	(0.04)	(0.00)	
3	0.03	0.87	0.26	0.79	0.0002	0.87	-0.08	0.79
	(0.02)	(0.03)	(0.20)		(0.0002)	(0.03)	(0.00)	
4	-0.02	1.15	0.49	0.84	-0.0003	1.14	-0.10	0.84
	(0.03)	(0.03)	(0.24)		(0.0003)	(0.03)	(0.00)	
5	0.17	1.08	0.77	0.61	0.0017	1.06	-0.10	0.61
	(0.05)	(0.05)	(0.49)		(0.0005)	(0.05)	(0.00)	
EWC	0.10	0.41	1.70	0.47	0.0008	0.38	-0.04	0.38
	(0.02)	(0.06)	(0.29)		(0.0003)	(0.07)	(0.01)	
SPD	0.01	0.04	0.10	0.44	0.0001	0.037	-0.00	0.40
	(0.00)	(0.00)	(0.03)		(0.0000)	(0.00)	(0.00)	

This table reports the asset pricing test results for factor DOL and CTAM by using a subset of pre-financial crisis data. The subset spans from the first week of November 2001 to the third week of May 2007, 290 observations in total.

Table 2.37 – Factor DOL and CTHF

DOL, CTHF				
KP reduced rank test				
	t-stat	Dof	p-val	
Rank(0)	162	10	{0.00}	
Rank(1)	23	4	{0.00}	
Crossectional asset pricing				
GMM1	DOL	CTHF		HJ dist
b	36.85	7.66	0.81	5.21
s.e.	(11.22)	(2.76)		{0.16}
$\lambda(\times 100)$	0.18	10.38		
s.e.	(0.08)	(3.88)		
GMM2				
b	34.92	6.27	0.78	6.01
s.e.	(10.24)	(2.09)		{0.11}
$\lambda(\times 100)$	0.19	8.40		
s.e.	(0.08)	(2.93)		
FMB	DOL	CTHF	$\chi^2(NW)$	
$\lambda(\times 100)$	0.18	10.38	11.29	
NW s.e.	(0.05)	(2.65)	{0.02}	
Portfolios' beta and time series R^2				
	$\alpha(\times 100)$	β-DOL	β-$CTOF(\times 100)$	adj. R^2
1	-0.15	0.79	-1.41	0.73
	(0.03)	(0.05)	(0.26)	
2	-0.03	1.09	-0.28	0.83
	(0.03)	(0.04)	(0.25)	
3	0.03	0.87	0.19	0.79
	(0.02)	(0.03)	(0.21)	
4	-0.02	1.16	0.52	0.84
	(0.03)	(0.03)	(0.24)	
5	0.17	1.08	0.90	0.62
	(0.05)	(0.05)	(0.45)	
EWC	0.09	0.42	1.39	0.46
	(0.02)	(0.06)	(0.30)	
SPD	0.01	0.04	0.08	0.43
	(0.00)	(0.00)	(0.02)	

This table reports the asset pricing test results for factor DOL and CTHF by using a subset of pre-financial crisis data. The subset spans from the first week of November 2001 to the third week of May 2007, 290 observations in total.

Table 2.38 – Factor DOL and CTCO

DOL, CTCO				
KP reduced rank test				
	t-stat	Dof	p-val	
Rank(0)	162	10	{0.00}	
Rank(1)	23	4	{0.00}	
Crossectional asset pricing				
GMM1	DOL	CTCO		HJ dist
b	34.18	-27.23	0.88	3.09
s.e.	(11.76)	(10.73)		{0.38}
$\lambda(\times 100)$	0.18	-5.22		
s.e.	(0.09)	(2.09)		
GMM2				
b	33.11	-25.40	0.88	3.31
s.e.	(10.86)	(9.17)		{0.35}
$\lambda(\times 100)$	0.18	-4.86		
s.e.	(0.09)	(1.79)		
FMB	DOL	CTCO	$\chi^2(NW)$	
$\lambda(\times 100)$	0.18	-5.22	10.24	
NW s.e.	(0.05)	(1.40)	{0.04}	
Portfolios' beta and time series R^2				
	$\alpha(\times 100)$	β-DOL	β-$CTCO(\times 100)$	adj. R^2
1	-0.14	0.80	2.34	0.71
	(0.03)	(0.05)	(0.68)	
2	-0.03	1.09	1.39	0.84
	(0.03)	(0.04)	(0.58)	
3	0.03	0.87	-0.48	0.79
	(0.02)	(0.03)	(0.45)	
4	-0.03	1.15	-0.76	0.84
	(0.03)	(0.03)	(0.68)	
5	0.17	1.08	-2.54	0.62
	(0.05)	(0.05)	(0.95)	
EWC	0.09	0.40	-2.61	0.42
	(0.03)	(0.06)	(0.72)	
SPD	0.01	0.04	-0.19	0.42
	(0.00)	(0.00)	(0.05)	

This table reports the asset pricing test results for factor DOL and CTCO by using a subset of pre-financial crisis data. The subset spans from the first week of November 2001 to the third week of May 2007, 290 observations in total.

Table 2.39 – Factor DOL and CTPC

DOL, CTPC

KP reduced rank test

	t-stat	Dof	p-val
Rank(0)	161	10	{0.00}
Rank(1)	13	4	{0.01}

Cross-sectional asset pricing results

	Traditional				Reduced rank			
GMM1	DOL	CTPC	R^2	HJ dist	DOL	CTPC	R^2	HJ dist
b	46.55	-9.31	0.91	3.56	21.34	0.01	0.20	23.67
s.e.	(11.69)	(3.08)		{0.31}	(7.22)	(0.00)		{0.00}
$\lambda(\times 100)$	0.18	-4.20			0.18	0.51		
s.e.	(0.08)	(1.59)			(0.06)	(0.17)		
GMM2								
b	42.94	-7.86	0.89	3.81	18.14	0.01	0.14	23.90
s.e.	(10.51)	(2.31)		{0.28}	(7.01)	(0.00)		{0.00}
$\lambda(\times 100)$	0.18	-3.46			0.16	0.44		
s.e.	(0.07)	(1.18)			(0.06)	(0.17)		
FMB	DOL	CTPC	$\chi^2(NW)$		DOL	CTPC	$\chi^2(NW)$	
$\lambda(\times 100)$	0.18	-4.20	6.18		0.18	0.52	26.76	
NW s.e.	(0.05)	(1.17)	{0.19}		(0.05)	(0.15)	{0.00}	

Portfolios' beta and time series R^2

	$\alpha(\times 100)$	β-DOL	β-$CTPC(\times 100)$	adj. R^2	$\alpha(\times 100)$	β-DOL	β-$CTPC(\times 100)$	adj. R^2
1	-0.12	0.72	3.37	0.77	-0.14	0.81	0.04	0.70
	(0.03)	(0.04)	(0.34)		(0.03)	(0.05)	(0.00)	
2	-0.03	1.08	0.55	0.83	-0.03	1.10	0.05	0.83
	(0.03)	(0.04)	(0.36)		(0.03)	(0.04)	(0.00)	
3	0.02	0.88	-0.45	0.79	0.02	0.87	0.04	0.79
	(0.02)	(0.03)	(0.33)		(0.02)	(0.03)	(0.00)	
4	-0.03	1.17	-0.69	0.84	-0.03	1.14	0.05	0.84
	(0.03)	(0.04)	(0.34)		(0.03)	(0.03)	(0.00)	
5	0.15	1.14	-2.69	0.63	0.17	1.06	0.05	0.61
	(0.06)	(0.06)	(0.64)		(0.05)	(0.05)	(0.00)	
EWC	0.06	0.50	-4.07	0.63	0.08	0.39	0.02	0.38
	(0.02)	(0.05)	(0.33)		(0.03)	(0.07)	(0.00)	
SPD	0.01	0.04	-0.23	0.49	0.01	0.04	0.00	0.40
	(0.00)	(0.00)	(0.03)		(0.00)	(0.00)	(0.00)	

This table reports the asset pricing test results for factor DOL and CTPC by using a subset of pre-financial crisis data. The subset spans from the first week of November 2001 to the third week of May 2007, 290 observations in total.

Table 2.40 – Factor DOL and VLUM

DOL, VLUM								
KP reduced rank test								
				t-stat	Dof	p-val		
			Rank(0)	215	10	{0.00		
			Rank(1)	5	4	{0.30		
Cross-sectional asset pricing results								
	Traditional				Reduced rank			
GMM1	DOL	VLUM	R^2	HJ dist	DOL	VLUM	R^2	HJ dist
b	4.23	-8.19	0.80	1.02	8.93	0.01	0.58	6.91
s.e.	(7.58)	(6.42)		{0.80}	(3.95)	(0.01)		{0.14}
$\lambda(\times 100)$	0.13	-12.61			0.13	-0.05		
s.e.	(0.11)	(9.84)			(0.06)	(0.02)		
GMM2								
b	4.10	-5.08	0.61	1.10	8.10	0.013	0.5466	6.94
s.e.	(5.92)	(4.55)		{0.78}	(3.84)	(0.01)		{0.14}
$\lambda(\times 100)$	0.10	-7.83			0.12	-0.05		
s.e.	(0.08)	(6.96)			(0.06)	(0.02)		
FMB	DOL	VLUM	$\chi^2(NW)$		DOL	VLUM	$\chi^2(NW)$	
$\lambda(\times 100)$	0.13	-12.61	4.91		0.13	-0.05	6.73	
NW s.e.	(0.06)	(5.47)	{0.30}		(0.06)	(0.02)	{0.15}	
Portfolios' beta and time series R^2								
	$\alpha(\times 100)$	β-DOL	β-$VLUM(\times 100)$	adj. R^2	$\alpha(\times 100)$	β-DOL	β-$VLUM(\times 100)$	adj. R^2
1	-0.12	0.55	0.33	0.51	-0.06	0.55	0.09	0.51
	(0.06)	(0.05)	(0.22)		(0.03)	(0.05)	(0.01)	
2	-0.02	0.93	-0.03	0.79	-0.06	0.93	0.15	0.79
	(0.05)	(0.04)	(0.20)		(0.03)	(0.04)	(0.01)	
3	0.05	0.98	-0.22	0.86	-0.05	0.98	0.15	0.86
	(0.05)	(0.03)	(0.18)		(0.02)	(0.03)	(0.00)	
4	-0.10	1.27	0.34	0.89	-0.07	1.27	0.20	0.89
	(0.05)	(0.04)	(0.19)		(0.02)	(0.04)	(0.01)	
5	0.18	1.26	-0.32	0.76	0.05	1.26	0.20	0.76
	(0.01)	(0.06)	(0.35)		(0.04)	(0.06)	(0.01)	
EWC	0.04	0.64	-0.14	0.71	-0.02	0.64	0.10	0.71
	(0.05)	(0.04)	(0.17)		(0.02)	(0.04)	(0.01)	
SPD	0.01	0.05	-0.03	0.73	0.00	0.05	0.01	0.72
	(0.01)	(0.00)	(0.02)		(0.00)	(0.00)	(0.00)	

This table reports the asset pricing test results for factor DOL and VLUM by using the full sample data. This table has the similar structure from previous asset pricing table.

Figure 2.1 – This figure shows the average trading volume and average aggregated order flow for 20 currencies

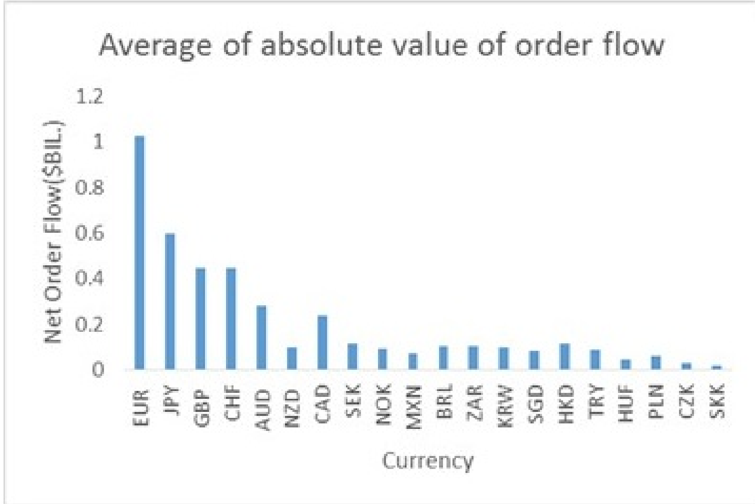


Figure 2.2 – This figure plots the time series of standardized order flow for Currency EUR and SGD

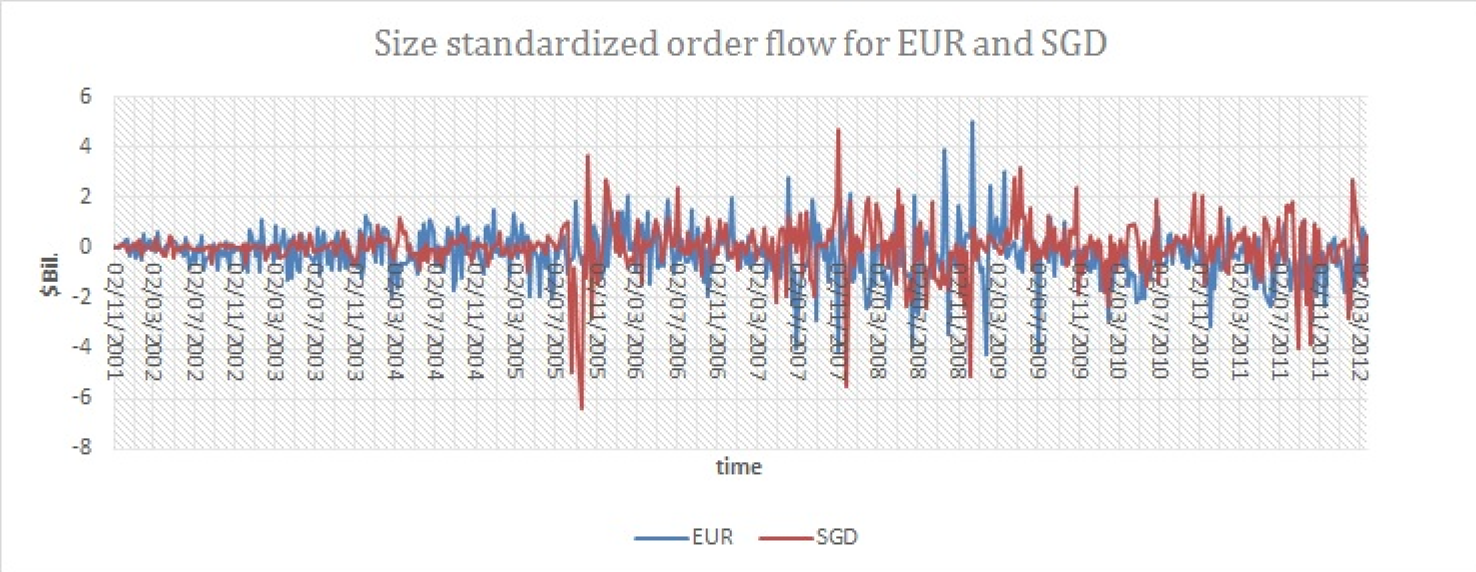


Figure 2.3 – This figure plots the 3-year and 10-year rolling variance for portfolios that contains high interest rate currencies and low interest rate currencies.

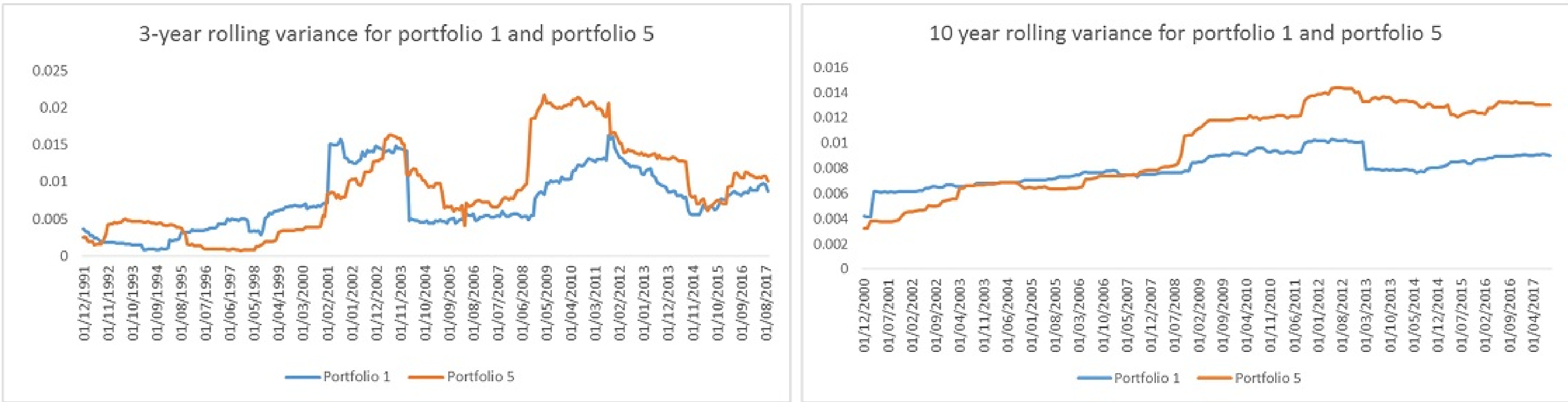
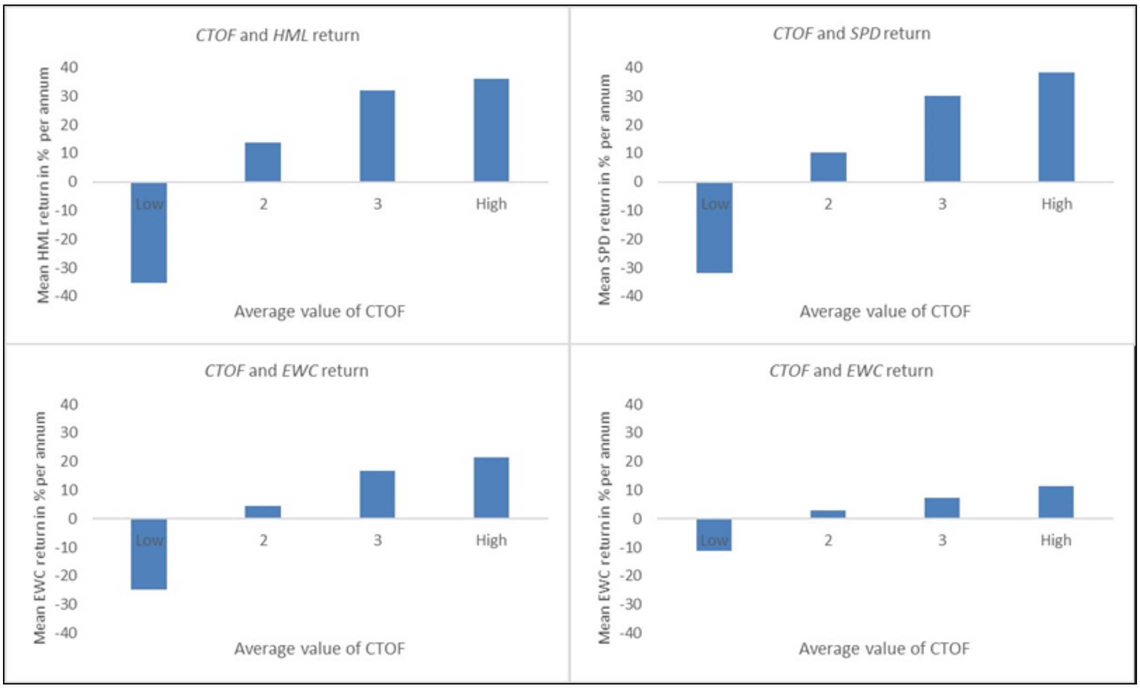


Figure 2.4 – This figure shows the histogram of monthly and weekly bid ask spread and standard deviation for currency changes.

Figure 2.5 – Global Order flow and Carry trade returns

Figure 2.6 – Aggregate Carry-Trade Order-Flow and Carry-Trade Returns



Note: This figure shows mean excess returns for the carry-trade portfolios HML, SPD, EWC and DNC depending on the quartile of the distribution of the carry-trade order-flow factor (CTOF).

Figure 2.7 – Disaggregated Global Order Flow and HML Returns

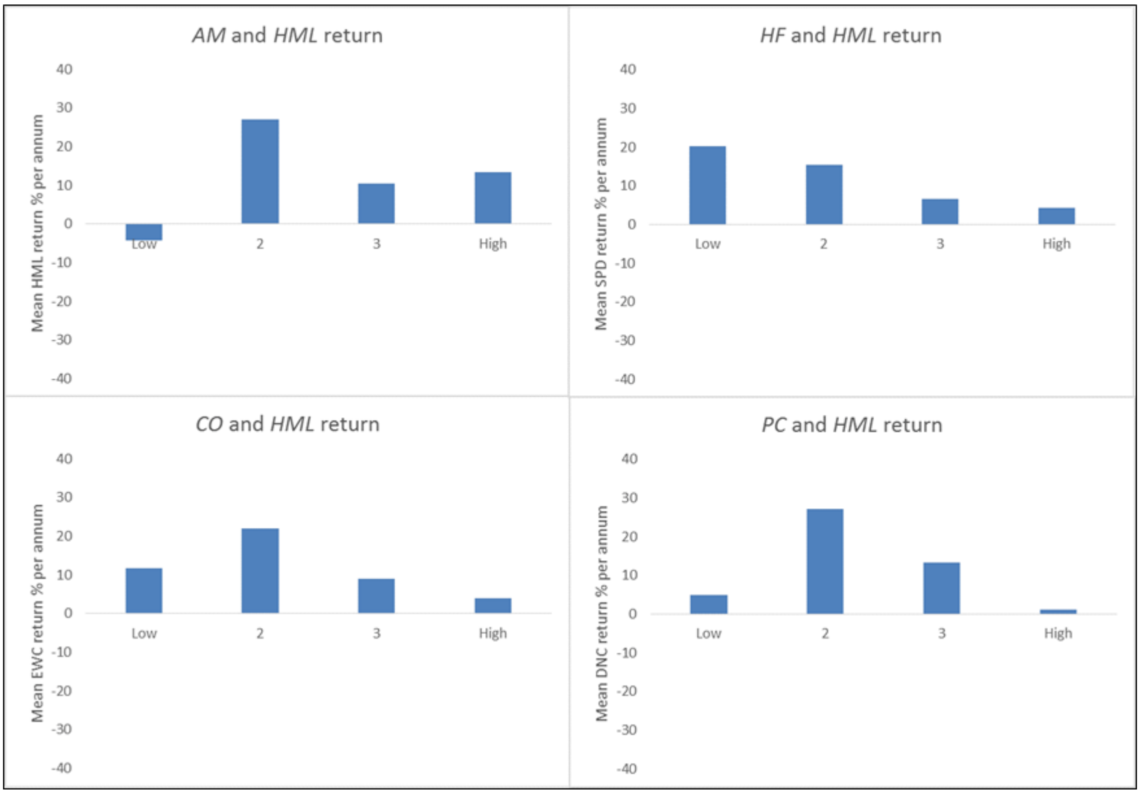
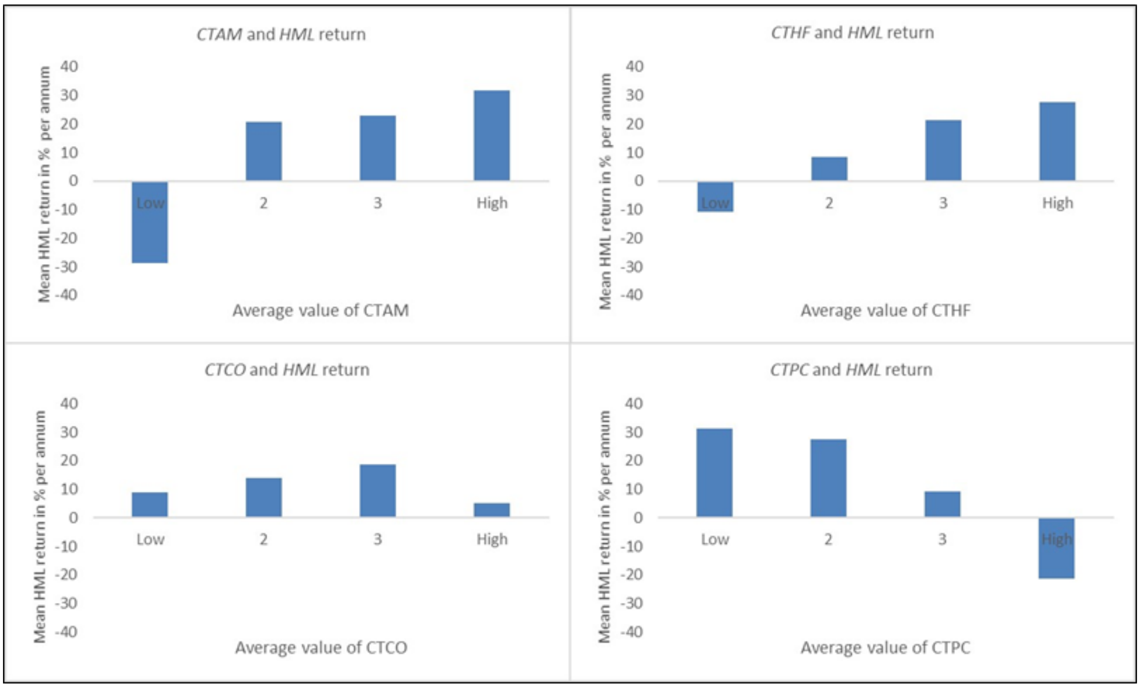


Figure 2.8 – Disaggregated Carry-Trade Order-Flow and HML Returns



Note: This figure shows mean excess returns for the HML portfolio depending on the quartile of the distribution of the disaggregated carry-trade order-flow factors CTAM, CTHF, CTCO and CTPC.

Chapter 3

Currency Momentum's Dynamic Risk Exposure

3.1 Introduction

A momentum strategy consists of shorting assets that have recently yielded low returns and buying the ones that have yielded high returns. Properties of this simple strategy have been extensively studied in the finance literature. Jegadeesh and Titman (1993) were amongst the first to show the profitability of a momentum strategy in the US equity market. Similar results have been reported for the equity markets in different regions and across different asset classes.[1] The momentum returns are difficult to explain by their unconditional risk exposure to standard risk factors (Jegadeesh and Titman, 1993; Grundy and Martin, 2001; Fama and French, 1996). To rationalise such a high excess return in economic terms , different explanations have been suggested but no consensus have been reached yet. For example, Carhart (1997) suggests adding momentum as a fourth factor to the Fama French model. Lesmond et al. (2004) emphasis the role of trading costs and argue that profits have been balanced out as assets with high momentum return are generally associated with high trading costs. This result has been challenged in the subsequent literature. Korajczyk and Sadka (2004) show that the excess return from an equal-weighted momentum stragegy drops dramatically after considering trading costs but investors could easily amend equal weightings to lower the trading cost and still earns a significant excess return.

One explanation in the equity literature suggests ro consider time-varying risk exposures of momentum strategy. This is intuitive as the momentum strategy is to buy past winners that have positive loadings when the past factor realization is positive and vice versa for past losers (Kothari and Shanken, 1992). Thus momentum risk exposures are conditioned on the realized value of pricing factors (see for example, Cooper et al. 2004; Stivers and Sun 2010). Notably, a recent study of Daniel and Moskowitz (2016) finds that this time-varying risk pattern introduced an asymmetric written-call option-like momentum payoff during a bear market. That is, under a bear market condition, if the market continues to fall, momentum gains little; when the market is recovering from previous draw down, momentum crashes.

In the currency literature, very little has been done on this important issue. As the currency market is the largest and most liquid financial market, with low transaction costs and without any short-selling constraints, currency momentum anomaly is a more difficult challenge for asset pricing models to accomodate, compared with the equity market. This chapter tries to fill this gap. Previous literature has mainly focused

[1]For momentum on international equity market, see for example, Rouwenhorst (1998) and Chan et al. (2000). For studies on different asset class, see for example, Shen et al. (2007) and Miffre and Rallis (2007) for commodity market; Jostova et al. (2013) for fixed income instrutments; Okunev and White (2003) and Menkhoff et al. (2012*b*) for the foreign exchanges. A comprehensive study of momentum anomaly for different asset class could be seen in Asness et al. (2013).

on the time-series momentum and technical trading rules on the currency market.[2] Two exceptions are Okunev and White (2003) and Menkhoff et al. (2012*b*) who investigate cross-sectional momentum. They show significant positive cross-sectional momentum profits from the currency market as with equity momentum strategies. I follow Menkhoff et al. (2012*b*) and Okunev and White (2003) to design cross-sectional currency momentum strategies and extend the sample until the post-financial crisis period. In line with Menkhoff et al. (2012*b*), currency momentum strategies are still profitable, even including the 2008 financial crisis deteriorates the profitibility. A 1$ long/short momentum strategy Mom(9,1) with 1-month holding period and 9-month formation period, yields a significant annulized return of 5.96% with Sharpe ratio 0.87.

In this chapter, I find that, apart from high returns, currency momentum strategies are mostly negative skewed which indicates potential momentum crashes on currency market. I show that dynamic risk models of Daniel and Moskowitz (2016) are appropriate to provide an explanation. Menkhoff et al. (2012*b*) suggest that momentum profits are based on the the risk characteristics of underlying assets. To capture specific properties of the currency market, I consider momentum exposure to the carry trade high minus low factor (HML) proposed by Lustig et al. (2011). I build the HML factor from buying top 10% currencies with highest interest rates and selling bottom 10% currencies with lowest interest rates. Burnside et al. (2011) and Menkhoff et al. (2012*b*) document that there are basically no correlation between long/short momentum strategies with HML which is also verified in our uncondition regression model.

I find that the existence of significant time-variation for momentum risk exposure to HML depends on different market conditions. That is, when the carry trade has fallen over the momentum formation period, currency momentum returns are negatively correlated with carry trade returns; when the carry trade has a previous positive return, a significant positive exposure is observed. Similarly, when there is an abrupt rise in contemporaneous carry trade returns under previous carry trade falls, currency momentum exposures are further decreased to a significant negative value which results in currency momentum crashes. This is an asymmetric beta change pattern since it is only identified given bear carry trade conditions but with no clear changes under a bull carry trade market. From the time series point of view, currency momentum crashes when the carry trade is recovering from previous drawdowns. Thus, under bear carry trade market condition, the currency momentum effectively demonstrates a written call-option-like payoff with an underlying asset of carry trade returns. That is, currency momentum gains little when the underlying asset falls and loses a lot when the underlying asset earns positive returns.

[2] A corresponding literature review has been done by Menkhoff and Taylor (2007)

Our paper links the currency momentum crash with the carry trade crash. We argue that the asymmetric risk exposure of momentum is closely related to the carry-trade-dominanted trading patterns on the currency market.[3] The holdings of momentum strategies are indicated by previous formation period returns. Thus, high (low) interest rate currencies are very likely to be included in the buy (sell) side of momentum which results in similar holdings and positive correlation between currency momentum strategies and carry trade strategies.

This chapter links the currency momentum crash with the carry trade crash. I argue the asymmetric risk exposure of momentum is closely related to the carry-trade-dominanted trading patterns on the currency market.[4] The holdings of momentum strategies are indicated by previous formation period returns. Thus, high (low) interest rate currencies are very likely to be included in the buy (sell) side of momentum which results in positive correlations between currency momentum strategies and carry trade strategies. I show that momentum crash are sourced from the carry trade crash. Brunnermeier et al. (2008) states that the high interest rate 'investment currencies' for carry trades go up gradually but collapse due to the sudden unwind by speculators when they reach their liquidity constraints, while the reverse holds for the low interest rate 'funding currencies'. Once the carry trade crashes, due to sudden change of formation period returns, momentum switch the long-short holdings rapidly by selling high interest rate currencies and buying low interest rate currencies. Thus, momentum will not crash with carry trade simultaneously and they are negatively exposed to the carry trade risk. However, when the carry trade gradually recovers from a crash, momentum will not adjust previous positions in time, as frequent small gains (losses) of high (low) interest currencies will not mitigate the previous huge decrease (increase). During this time, consecutive losses happen to momentum strategies which lead to momentum crashes.

Since the DOL factor does not exhibit a sudden crash pattern, I argue that HML is the decisive source for the asymmetric risk exposure and written call-option-like payoff in the currency momentum strategies. This is also consistent with empirical findings of Daniel and Moskowitz (2016) who investigate currency momentum's time varying betas to DOL and find insignificant conditional betas. I show that, since currency momentum return is effectively a written-call-option in bear HML market, it is correlated with the volatility of factors under bear HML market but no significant correlation in bull HML market.

I run a battery of robustness check. At first, I show the risk pattern to HML are robust when DOL is also considered in the estimation of betas. Secondly, I test the

[3] Burnside (2011*a*) suggests that a significant part of trading activity is triggered by carry trade

[4] Burnside (2011*a*) suggest that a significant part of trading activity is triggered by carry trade

profitibility of time-varying beta-adjusted portfolio as in Grundy and Martin (2001) and Daniel and Moskowitz (2016), to show that the dynamic beta pattern is the main driver of excess momentum return. In a detailed analysis, I investigate whether long or short position contribute more to the asymmetric dynamic risk, the results are mixed and no decisive conclusion can be made.

Since the main results suggest that currency momentum crash is predictible, I design two optimized currency momentum strategies by using the insight of the dynamic risk model. The first strategy simply close the momentum position when previous cumulative HML return are negative. This strategy could avoid the possible crash but also wastes investment opportunities. The second strategy is a dynamic weighting strategy of Daniel and Moskowitz (2016) which adjusts the weigtings by using the predictbility of HML's volatility. I find that both strategies outperform the main momentum strategy in terms of Sharpe ratios. Most impotantly, the negative skewness is largely mitigated as well.

The reminder of this chapter is orgnized as follow: Section 3.2 is a breif literature review on the momentum anomaly in different markets and possible expalanations. Section 3.3 describes our data and the currency momentum anomaly. Section 3.4 documents the time varying beta structure of currency momentum strategies. Section 3.5 introduces the economic implication of the model by constructing optimal currency momentum portfolios. Section 3.6 concludes.

3.2 Literature review

Jegadeesh and Titman (1993) first documented there is about 1% monthly excess momentum return from the US equity market. Similarly, significant momentum returns have been observed in equity markets of different regions and asset class[5]. Different explanations are discussed on the literature, yet no consensus have been widely accepted. Carhart (1997) suggests to add the momentum as fourth fator to Fama French model. However Avramov and Chordia (2006) show the momentum factor of Carhart (1997) can not model the return of all the momentum strategies. Lesmond et al. (2004) emphasis the role of trading costs and argue profits have been balanced out as assets with high momentum return are generally associated with high trading costs. However it

[5]For momentum on international equity market, see for example, Rouwenhorst (1998) and Chan et al. (2000). For studies on different asset class, see for example, Shen et al. (2007) and Miffre and Rallis (2007)'s work for commodity market; Jostova et al. (2013) on fixed income instrutments; Okunev and White (2003) and Menkhoff et al. (2012*b*) on currency market. A comprehensive study of momentum anomaly for different asset class could be seen in Asness et al. (2013).

has been challenged by subsequent literature. Korajczyk and Sadka (2004) document that profits from equal-weighted momentum stragegies are dramatically deteriorated by trading cost. Nevertheless, they also show that one could amend equal weightings to lower the trading costs and still earns significant excess return. Menkhoff et al. (2012*b*) find the significant momentum profit on currency market after the trading cost. Meanwhile, with the development of trading technologies, transaction costs are declining for the past decade. But the momentum strategies are still extremely profitable as usual.

Furthermore, interpretations based on risk features of certain asset class are proposed in the literature. For equity momentum, linking firm specific risk to momentum anomaly in equity market has drawn attentions. Small firms with less analyst coverage(Hong et al., 2000) and firms with high credit risk(Avramov et al., 2007; Eisdorfer, 2008) tend to be included in the momentum portfolio. On the fixed income market, Jostova et al. (2013) domenstrate fix income momentum is mainly sourced from non-investment grade corporate bonds of private companies. Meanwhile, momentum spillover effect from equity market does not play a key role to bond market. For commodity futures momentum, the momentum return are shown to be related to commodities with low level of inventories(Gorton et al., 2012). Also, it is found to be related to the propensity of the market to be in backwadation or contango(Miffre and Rallis, 2007). For currency markets, Menkhoff et al. (2012*b*) show that currencies has high idiosyncratic volatiltity and high country risk tend to domenstrate high momentum returns.

Others try to interpret momentum profits under behavioral bias of investors. For example, Chan et al. (1996) propose that investors tend to underreact as information is gradually incorporated into prices. Hong and Stein (1999) document that momentum is due to investors' initial underraction and subquent overreaction. Chui et al. (2010) attribute momentum return to investors' overconfidence and self-attribution. Most of empirical results based on behaviroal models are compatible with the conditional risk loadings.

The strand of dynamic risk loadings of momentum strategies is widely discussed on equity market and first brought by Kothari and Shanken (1992). Grundy and Martin (2001). They argue equity momentums cannot be explained by the dynamic exposure to market and size factor. They show that after hedging dynamic exposures to size and market factor, the momentum return are increased. However, their results are based on *ex post* betas for hedged position which has been shown have strong bias. Daniel and Moskowitz (2016) examine the similar hedged momentun return by using *ex ante* betas and find different results. In addition, Daniel and Moskowitz (2016) document the momentum strategies' written call-option-like behavioral and show that momentum crash happens when market rebounds from previous drawdown. Daniel and Moskowitz (2016) extend their study to currency market as a robust check but find no significant beta changes to DOL. Cooper et al. (2004) provide empirical results that is consistent with dynamic betas. They show significant momentum return difference conditioned on previous three-year market returns. It performs better following a positive market return. Stivers and Sun (2010) also find that momentum premiums are higher during strong economic times.

Previous literature on currency market mainly concentrates on time series momentum or technical trading strategies[6]. Suprisingly, very few studies focus on cross-sectional currency momentum return. Two exceptions are Okunev and White (2003) and Menkhoff et al. (2012*b*). They show currency momentum has similar properties as equity momentum. Several possible explanations, such as transaction costs and limits of arbitrage, could only partially justify the excess currency momentum anomaly. This study extents early studies in several ways. At First, I use a large cross-sectional data set of developed and developing currencies that spans to post financial crisis periods. The inclusion of post financial crisis period are important as there might be a structural changes. Secondly, I test the dynamic betas pattern to currency specified risk factors, DOL and HML. Thirdly, a closer look at effects of factor volatility innovations and predictibility for possible crash has been done. Overall, I add to current literature by introducing the dynamic beta pattern, which has been documented on equity market, to currency market and find most of currency momentum are drived by this pattern. It is could be applied to construct an efficient currency momentum portfolio to avoid possible currency crashes.

3.3 Data and currency momentum portfolios

This section describes the data, currency excess returns, currency portfolios and currency momentum strategies based on the different formation period and holding period.

3.3.1 Data sample

The sample of exchange rates are obtained from WM/Reuters (via Datastream) which consists of end of month spot exchange rates, daily spot exchange rates and 1-month forward rates for 31 currenies. It includes G10 currencies: AUD, CAD, CHF, DKK, EUR, GBP, JPY, NOK, NZD, SEK; emerging market currencies: CZK, HUF, ILS, ISK, PLN, RUB, TRY, ZAR; Asia country currencies: HKD, KRW, MYR, PHP, SGD, THB;

[6]A corresponding literature review has been done by Menkhoff and Taylor (2007)

Latin America country currencies: BRL, CLP, COP, MXN, PEN; middle east country currencies: JOD, KWD. The sample spans from January 1997 to February 2017. All exchange rate are denoted as units of foreign currency per US dollar(FCU/USD). Compared to previous literature (Lustig et al., 2011; Menkhoff et al., 2012*a*), the maximum currencies available in this sample is smaller because I do not include the euro-zone country's currencies before they adopt to euro. Meanwhile, our sample starts in late 1990s but includes recent periods when more influential economic events happens, such as the US subprime mortgage crisis in 2008 and European sovereign debt crisis in 2013. Number of currencies available varies over time at the beginning but reach the maximum and keep stable for most of our sample as illustrated in figure 3.1. The data set is supplemented by the monthly market return which is the value weighted return of all listed firms in Center for Research in Security Prices (CRSP) from Ken French's website for period from January 1997 to February 2017.

3.3.2 Currency excess return and portfolios

In this study, I follow the covention in the literature to calculate the currency excess return as the US dollar return of the position that borrows US dollar in US risk free interest rate i_t and invests in foreign currency and earn foreign currency interest rate i_t^k. Combine the covered interest parity, the currency excess return rx_{t+1}^k for currency k of period $[t, t+1]$ is,

$$rx_{t+1}^k = i_t^k - i_t - (s_{t+1}^k - s_t^k) \approx f_t^k - s_{t+1}^k$$

Where i_t^k, is the one-week interest rate for currency k, i_t is the US dollar interest rate. s_t^k and f_t^k denotes the logarithm spot and 1-week forward exchange rate for currency k in foreign currency unit per US dollar(FCU/USD). The average return of all the assets is the dollar risk factor (DOL) introduced by Lustig et al. (2011). It is calculated as

$$DOL_{t+1} = \frac{1}{N_t} \sum_{k \in N_t} rx_{t+1}^k$$

Where N_t is the number of currencies available on time t.

I also construct currency portfolios sorted on the past interest rates and track the return of buying top decile high interest rate currencies and selling bottom decile low interest rate currencies, which denoted as 'high minus low' HML carry trade portfolios

(Lustig et al., 2011).

To separate the contribution of spot exchange rates and interest rate differentials to currency momentum returns Menkhoff et al. (2012*b*), I also calculate the monthly logarithm changes of spot rates.

$$\Delta s_{t+1}^k = s_{t+1}^k - s_t^k \tag{3.1}$$

Note that s_{t+1}^k is denoted as foreign currency unit per US dollar, a positive number of Δs_{t+1}^k suggests that appreiciation of US dollar and depreciation of foreign currencies during $[t, t+1]$.

3.3.3 Currency momentum returns

For each month t, I rank currencies according to their cumulative lagged excess returns from period $[t-f,\ t-1]$, according to different formation period of $f = 1, 3, 6, 9, 12$ months. All currencies are then grouped in ten decile portfolios and these portfolios are held for $h = 1, 3, 6, 9, 12$ months. Assume investors liquidate their positions every month, I track the return difference between top decile winner portfolio and bottom decile loser portfolio as the 'winner minus loser' momentum strategy and denoted it as $Mom(f, h)$ for different formation period f and holding period h [7].

[Table 3.1 about here]

The left panel of table 3.1 shows the annulized excess return of decile 'winner minus loser' momentum strategies for varing combinations of formation period f and holding period h from 1 to 12 months. It is followed by the t-statistic based on Newey-West standard errors in brackets, sample standard deviation, skewness and Sharpe ratio. Momentum strategies provide a significant positive return as high as 5.96% for Mom(9,3) and the highest sharpe ratios of 0.93 for Mom(6,6)[8].

Daniel and Moskowitz (2016) show that equity momentum strategies experiences a

[7] It is worth noting that I do not follow the equity momentum portfolio convention where the most recent month is not considered in the formation period to avoid short term reversal(see for example, Jegadeesh and Titman (1993); Fama and French (1996); Daniel and Moskowitz (2016)). Indeed the foreign exchange markets suffer less from liquidity issues(Asness et al., 2013).

[8] Some studies, see for example Menkhoff et al. (2012*b*), find higher return and sharpe ratios(9.46% per annum with shape ratio 0.95). This may be due to our sample which covers higher proportion to market rebound periods(Barroso and Santa-Clara, 2015*b*).

huge loss during the recover period from a fiancial crisis. This pattern has already been reported in other studies (see for example Menkhoff et al., 2012*b*). As the holding period h increases, currency momentum returns gradually declines. The excess return first increases and then declines with the formation period f. This result is different from what reported in Menkhoff et al. (2012*b*) who find a decreasing currency momentum return with longer formation period f. Another finding is that the sample standard deviation also decreases when the holding period h increases, as longer holding period could mitigate the short term reversal during crisis periods. This also may explain why the highest Sharpe ratio is achieved at mid-term 6-month holding and formation periods instead of Mom(1,1) as reported in Menkhoff et al. (2012*b*). I find that currency momentum returns are mostly negative skewed, especially for the most profitable strategies, which is similar to the equity momentum literature (Daniel and Moskowitz, 2016), but in contrast with Menkhoff et al. (2012*b*).

In the right panel of table 3.1, there is the corresponding momentum spot rate changes. I follow Menkhoff et al. (2012*b*), for the ease of exposotion, that report the negative of the equation 3.1 to reflect the positive spot changes correponding to appreciation of foreign currencies. The spot rate changes show a continuity pattern as most of annualized mean returns are postive, thus the spot rate changes positively contribute to the momentum strategies. However, compared with currency excess returns, the spot rate changes are smaller and less significant in most cases.

Even though the Sharpe ratios are highest for 6-month holding period strategies, the 1-month holding period strategies are more stable across different formation periods. Therefore in the following analysis, I follow the convention in previous literature and focus on the 1-month holding period momentum strategies that has highest annualized returns which are Mom(6,1) and Mom(9,1). To give a simple graphical analysis, I plot the cumulative excess return of Mom(6,1) and Mom(9,1) in figure 3.2 along with the dollar risk factor (DOL) and US equity market excess return ($Mkt - rf$) as a comparison. The shaded aeras are financial crisis period corresponding to the burst of dot-com bubble (2001), the subprime debt crisis (2008) and European sovereign debt crisis (2010). From figure 3.2, currency momentum strategies underperform the US equity market portfolio but earn higher return than DOL. Large drawdowns of currency momentum strategies could be viewed in subprime debt crisis and European sovereign debt crisis.

3.3.4 Transaction cost

To investigate the influence of transaction costs to currency momentum anomaly, I report the currency momentum returns after transaction costs. Two ways available to construct momentum portfolios after taking account for the transaction costs. At first, one could rank currencies according to the after-transaction-cost cumulative past return. The second method apply transaction costs to the holding period but ranking currencies based on past return without transaction costs. Generally the second method is used since transaction cost is a external influence of the portfolio returns which does not influence the risk property of the strategy.

Left panel of table 3.2 shows currency momentum excess returns after accounting for the full quoted bid-ask spread. While impose the full quoted bid-ask spread clearly overestimates the effective bid-ask spread and transaction costs (Lyons and Others, 2001). Meanwhile, in practice, the actual turnover ratios of momentum strategies are lower which also refers to lower transaction costs. I use 50% of full quoted bid-ask spread as the proper estimate for transaction costs and report the portfolio results in right panel of table 3.2.

[Table 3.2 about here]

Table 3.2 shows currency momentum returns are diminished by imposing transaction cost. But it is unclear transaction costs would fully explain the currency momentum anormaly since several strategies still earn significant positive returns. Due to transaction costs are external and do not influence the risk structure of the momentum portfolio, I mainly study the momentum return without transaction costs in following sections except specified otherwise.

3.4 Momentum crash on currency market

It has been well documented in equity literature that momentum portfolio are subject to large losses. Daniel and Moskowitz (2016) introduced the idea of time-varying beta to the maket portfolio. Momentum strategies have long positions on past winners and short on past losers. They have positive loading on factors which, in the past, had a positive realisation and negative loading on factors which have had a negative realisation. This may induce a dynamic pattern in the momentum strategy betas and cause an asymmetry in the bear market condition. This beta pattern in bear markets behave like the payoff of a written call option, that is when the market falls, it gains a little, but when the market increases, it loses a lot. Since the currency market is one of the largest markets and yet largerly unregulated, it is interesting to better understand if this feature is also a characterictic of this market and the main economic drivers of it. The next sections will look into this important aspect.

3.4.1 Time-varying betas of currency momentum strategies

I start with a simple graphic analysis for betas of currency momentum strategies to the US equity portfolio and currency specific pricing factors DOL and HML. Figure 3.3 shows the dynamic betas estimated using rolling 48-month regressions[9]. In panel A, currency momentum exposures to US equity market portfolio is estimated by regression $R_t^{Mom} = \alpha_0 + \beta_0^m \times R_t^m + \varepsilon_t$. Dynamic exposures to currency pricing factors DOL and HML in panel B and Panel C of figure 3.3 is jointly estimated in a two variable regression.

It is evident from figure 3.3 that currency momentum strategies have variations in risk exposures to all three pricing factors. This exposure is more evident for currency specific pricing factors DOL and HML as the beta to US equity portfolio is stable during the European sovereign debt crisis in panel A. However, during the financial crisis period in figure 3.3, the momentum betas change is not consistent in different periods. In panel C, momentums' beta to HML factor increases in dot-com crisis and European sovereign debt crisis but decreases in subprime debt crisis period. Meanwhile outside the financial crisis period, betas also change significantly. For example, exposures to US equity market portfolio and DOL drop sharply between 2014 to 2015. From figure 3.3, it is clear that currency momentum strategies changes over time and it is related to all three pricing factors. In next sections I will investigate this behaviour and its economic drivers more in detail.

3.4.2 Exposure to the equity market portfolio

In this section I test for the time-varing risk exposure and option-like payoff of currency momentum strategy to the equity factor. I perform three monthly time series regressions as in Daniel and Moskowitz (2016), where the dependent variable is the

[9] I used the following regression in Panel A: $R_t^{Mom} = \alpha_0 + \beta_0^m \times R_t^m + \varepsilon_t$. Where R_t^{Mom} is the currency momentum return and R_t^m is the US equity return; α_0 and β_0^m are the regression coefficients; and ε_t is the error term. Dynamic betas to DOL and HML are estimated in the following equation: $R_t^{Mom} = \alpha_0 + \beta_0 \times R_t^{DOL} + \gamma_0 \times R_t^{HML} + \varepsilon_t$. Where R_t^{Mom}, β_0, γ_0, α_0 and ε_t are the same as mentioned above. R_t^{DOL} and R_t^{HML} are factor returns of for DOL and HML. I used the first 48 months of data a cutoff point.

return of currency momentum strategy Mom(6,1) and Mom(9,1), denoted as R^{Mom}. I use the value weighted return of all listed firms in CRSP from Ken French's website as a proxy for US equity market portfolio R^m.

Three time series models used are specified as following: In the first regression, I estimate the full sample beta to the market portfolio by performing a simple univariate regression.

$$R_t^{Mom} = \alpha_0 + \beta_0^m \times R_t^m + \varepsilon_t. \tag{3.2}$$

Where R_t^{Mom} is the currency momentum return; R_t^m is the US equity return; α_0 and β_0^m are the regression coefficients; and ε_t is the error term.

The second regression fits a conditional regression with a bear market indicator variable I_B^m that equals 1 if the cumulative CRSP VW index return in past 6 month is negative and 0 otherwise. This models aims to find supporttive evidence of the significant beta changes(β_B^m) and momentum return change(α_B^m) in bear market condition.

$$R_t^{Mom} = \alpha_0 + \alpha_B^m \times I_{B,t-1}^m + (\beta_0^m + \beta_B^m \times I_{B,t-1}^m) R_t^m + \varepsilon_t. \tag{3.3}$$

The third regression adds an up-market return indicator $I_{U,t}^m$ which equals 1 if R_t^m is positive or 0 otherwise. This regression is designed to test whether there is a significant beta changes when the market rebounds following a bear market. This model is also used by Henriksson and Merton (1981) to assess fund managers' market timing ability.

$$R_t^{Mom} = \alpha_0 + \alpha_B^m \times I_{B,t-1}^m + (\beta_0^m + I_{B,t-1}^m(\beta_B^m + I_{U,t}^m \times \beta_{B,U}^m)) R_t^m + \varepsilon_t. \tag{3.4}$$

[Table 3.3 about here]

Table 3.3 reports the estimated coefficients, t-statistics and the time series adjusted R^2. Regression 1 in table 3.3 performs the full sample market model on currency momentum return of Mom(6,1) and Mom(9,1). Currency momentum portfolios have negative market betas, which is in line with the equity momentum literature, but only the beta of strategy $Mom(6,1)$ is statistical significant. Equation 3.3(regression 2 in table 3.3) tests the time varing betas in different market enviornment by adding the *ex ante* bear market indicator(Grundy and Martin, 2001). It shows that, following a 6-month bear market, the expected return and the market betas fall (see the estimated α_B and β_B^m that are negative) and the change is statistically significant. Equation 3.4(regression 3 in table 3.3) tests the written call-option-like payoff on momentum strategies following a down market. The contemporaneous up-market return indicator

$I^m_{U,t}$ that interacts with market return and *ex ante* bear market indicator is added to equation 3.4. The empirical results show that during a market rebound, the exposure of currency momentum strategies further decrease (-0.4238($\beta_0^m + \beta_B^m + \beta_{B,U}^m$) for Mom(6,1) and -0.3590 for Mom(9,1)). Therefore, the currency momentum strategy generates big losses. However, when the market continue to go down, currency momentum strategy will be profitable but the size is rather small. Indeed, the sign of coefficients($\beta_0^m, \beta_B^m, \beta_{B,U}^m$) indicates evidence of written call-option-like payoff. Finally, currency momentum strategies have a similar option-like payoff profile in bear markets in line with what documented in the equity literature by Daniel and Moskowitz (2016).

3.4.3 Exposure to currency specific pricing factors

In the next sections, I shall now focus on currency specific risk factors. The recent literature has focused on specified pricing factors such as the 'dollar risk' factor(DOL) and the 'carry trade high minus low' factor(HML) of Lustig et al. (2011), and found these sucessful to price currency carry trade portfolios. DOL is the equal-weighted cross-sectional average in all currencies excess return which is a measure of the relative strength of the US dollar to foreign currencies. HML is the return difference between highest interest rate portfolio and lowest interest rate portfolio which is a mesure of return level of currency carry trade strategy. However it have been documented by Burnside et al. (2011) that these two factors fail to explain the currency momentum returns. One possible explanation would be the time varying exposure to currency specific pricing factors. In this section, the time variation of currency momentum exposure to DOL and HML will be tested.

3.4.3.1 Dollar risk factor(DOL)

I first invesgate if the excess return of currency momentum strategies is driven by time varying risk exposure to factor DOL. To test this hypothesis, I use the same time series regressions as in Daniel and Moskowitz (2016) and in section 3.4.2 except I replace the market factor with DOL[10]. The first regression employed estimates the full sample betas exposure to DOL. The second and third regressions test the return and beta changes when the US Dollar appreciates with respect to the rest of the currencies (i.e. the previous cumulative DOL return is negative). The third regression tests the beta change when the US Dollar suddnly depreciates with respect to the rest of the currencies

[10] Note that Daniel and Moskowitz (2016) tested the same models for a smaller dataset of currencies. However they used the previous 12-month comulative DOL factor return as a bear market indicator and find insignificant exposure changes in different market conditions.

(i.e. the contemporaneous DOL return is positive following negative cumulative return of DOL portfolio). This corresponds to the written call-option-like payoff of currency momentum return.

Table 3.4 reports the estimated coefficients, the t-statistics based on Newey-West standard errors and time series adjusted R^2. The empirical results from the first regression show that two momentum strategies have negative and significant exposure to DOL. The second regression introduces a down-DOL indicator to capture the expected return difference in the scenario of a fall of DOL portfolio return (i.e. in a bear-DOL market).The estimated return difference is not significant (i.e. α_B^{DOL} is not significant). Regression 3 adds a dummy variable $I_{B,t-1}^{DOL}$ to the slope to test the DOL exposure in the scenario of previous drop and currently recover of the DOL return. A positive and significant β_0 combined with a negative and significant β_B, suggest that currency momentum has a significant positive exposure to the DOL factor in normal time and negative following a bear market.

In last model of Table 3 I test the option-like payoff of the momentum strategy. The estimated coefficient $\beta_{B,U}$ is negative and significant which suggests that currency momentum strategies behave effectively like a short call option on DOL factor. Thus, currency momentum strategies have similar option-like payoff properties as the equity momentum strategies reported in Daniel and Moskowitz (2016).

[Table 3.4 about here]

3.4.3.2 Carry trade high minus low factor(HML)

In this section, I test the risk exposure to the HML factor. I replace the DOL factor with the HML factor in the main regressions above. Here I_B^{HML} is the down carry trade indicator which equals 1 if the the previous 6 month cumulative carry trade return is negative and 0 otherwise. I_U^{HML} is the contemporaneous HML-up market indicator which is 1 if the contemporaneous carry trade return is positive and 0 otherwise.

Table 3.5 reports the empirical results. In the first two models, the currency momentum exposure to HML γ_0 is not significant, which is consistent with Burnside et al. (2011) and Menkhoff et al. (2012*b*) who find insignificant correlation between currency carry trade and currency momentum returns. However after adding the interaction terms in third regression, I find a significant and positive beta estimates of γ_0 durning normal market condition.

In the final specification equation I test for a beta change during periods when the profit of carry trade strategy is recovering from a period of decline. I find that there is a change in the sign of the beta exposure to the carry trade factor. This means that large losses occur for momentum portfolio under this scenario[11]. Results from table 3.5 suggest that momentum strategy has a time varying exposure to HML. The time varying exposure also causes the momentum strategies to have a written call option-like payoff when the carry trade portfolio return falls[12].

[Table 3.5 about here]

3.4.3.3 Collective effect of currency pricing factors

The analysis so far shows that both the DOL and HML factors are important to better understand the possible crash(or option like payoff) for a currency momentum strategy. In this section I do a horse racing between these two factors to empirically asses the single contribution of each of them as well as the joint contribution. I are interested in the collective effcts of two factors[13].

The estimation results in Table 3.6, are reported using Newey-West t-statistics and time series R^2. Regression 1 collectively test whether there is a return change and risk exposure change following a bear DOL or HML market.

$$
\begin{aligned}
R_t^{Mom} = {} & \alpha_0 + \alpha_B^{DOL} \times I_{B,t-1}^{DOL} + \alpha_B^{HML} \times I_{B,t-1}^{HML} + \\
& \gamma_0 \times R_t^{HML} + (\beta_0 + \beta_B \times I_{B,t-1}^{DOL}) R_t^{DOL} + (\gamma_0 + \gamma_B \times I_{B,t-1}^{HML}) R_t^{HML} + \varepsilon_t;
\end{aligned}
$$

The estimated coefficient β_0 and γ_0 are positive and significant which suggests momentum strategies have positive risk exposures to these factors when $I_{B,t-1}^{DOL} = 0$, $I_{B,t-1}^{HML} = 0$. When $I_{B,t-1}^{DOL} = 1$, $I_{B,t-1}^{HML} = 1$, the estimated betas for both DOL and HML decline significantly. The overall risk exposure to the HML factor decreases which suggests that during a period when the carry trade strategy generates losses, momentum strategy

[11] Note that in this model, the estimated γ_B is not statistical significance anymore.

[12] Another interesting result from table 3.5 in comparison with table 3.4 is that the intercept α_0 in four regression models are significant (as opposed to table 3.4). This suggests that, unlike momentum strategies' time varying exposure to DOL, time varying exposures to HML factor cannot fully explain the currency momentum returns. The adj R^2s is also smaller in table 3.5 relative to table 3.4.

[13] Note that I also test the mdels with interaction terms between factor return and dummy variables derived from another factor. The empirical results could be found in Appendix 3.6.1 which suggests that coefficients associated with the cross interaction terms are mostly not siginificant.

has zero risk exposure to the HML factor.

The second and third regressions test the written call option like payoff for DOL and HML factor respectively:

$$\begin{aligned} R_t^{Mom} &= \alpha_0 + \alpha_B^{DOL} \times I_{B,t-1}^{DOL} + \alpha_B^{HML} \times I_{B,t-1}^{HML} \\ &+ (\beta_0 + \beta_B \times I_{B,t-1}^{DOL}) R_t^{DOL} \\ &+ (\gamma_0 + IB_{t-1}^{HML}(\gamma_B + \gamma_{B,U} \times I_{U,t}^{HML})) R_t^{HML} + \varepsilon_t \\ R_t^{Mom} &= \alpha_0 + \alpha_B^{DOL} \times I_{B,t-1}^{DOL} + \alpha_B^{HML} \times I_{B,t-1}^{HML} \\ &+ (\beta_0 + I_{B,t-1}^{DOL}(\beta_B + \beta_{B,U} \times I_{U,t}^{DOL})) R_t^{DOL} \\ &+ (\gamma_0 + \gamma_B \times I_{B,t-1}^{HML}) R_t^{HML} + \varepsilon_t \end{aligned}$$

In the second colum of table 3.6, the HML factor coefficient, γ_B is not significant while $\gamma_{B,U}$ is negative and significant. This may indicate that when the carry trade strategy generates losses, the risk exposure change to HML factor is not significant. On the other hand the risk exposure to the HML factor becomes very significant when the carry trade portfolio genrates profits after a period of losses (i.e. $IB_{t-1}^{HML}{=}I_{U,t}^{HML}{=}1$). In the third column of table 3.6 the coefficient $\beta_{B,U}$ is now istatistically insignificant as opposed to the results in Table 3.6. This result may indicate that written call payoff like in a momentum strategy is hihly related to the carry trade portfolio.

In the final regression of table 4, all interaction terms are included. Thus the regression model becomes:

$$\begin{aligned} R_t^{Mom} &= \alpha_0 + \alpha_B^{DOL} \times I_{B,t-1}^{DOL} + \alpha_B^{HML} \times I_{B,t-1}^{HML} \\ &+ (\beta_0 + I_{B,t-1}^{DOL}(\beta_B + \beta_{B,U} \times I_{U,t}^{DOL})) R_t^{DOL} \\ &+ (\gamma_0 + IB_{t-1}^{HML}(\gamma_B + \gamma_{B,U} \times I_{U,t}^{HML})) R_t^{HML} + \varepsilon_t \end{aligned}$$

Some interesting conclusions could be made from the empirical results in the fourth column of Table 3.6. Since $\beta_{B,U}$ is not significant and therefore the option like payoff of currency momentum strategy is not related to the DOL factor. However, when the carry trade portfolio gains negative excess return, there is possibility of momentum crash as evidenced by a beta change related to the HML factor. Finally, momentum crash is likely to happen when both DOL and HML recover from previous negative return (i.e. $I_{B,t-1}^{DOL} = I_{U,t}^{DOL} = I_{B,t-1}^{HML} = I_{U,t}^{HML} = 1$).

[Table 3.6 about here]

3.4.4 Hypothesis for momentum crash

So far, I find currency momentum are conditionally correlated with carry trade. Momentum crash could be predicted by previous drawdown of carry trades. Investors builts up their carry trade position gradually but unwind in a sudden(Brunnermeier et al., 2008). Momentum strategies are indicated by previous cumulative return. When they are building up positions, momentum are positively correlated with carry trade. Because high(low) interest rate currencies tend to appreciate which would be included in winner(losser) portfolio. During the carry trade crash, suden large decreases(increases) of high(low) interest rate currencies could wipe out the previous several periods significant return which could lead to a quick position reverse for momentum. On carry trade crash, high(low) interest rate currencies are included in losser(winner) portfolio. Hence, momentum would not crash with carry trade strategy simultaneously. However, when carry trade gradually recover from a crash, momentum would not quickly adjust previous positions as frequently small gains(losses) of high(low) interest currencies would not mitigate the previous huge drawdown. During this time, consecutive loss happens to momentum strategies which results in momentum crashes. This empirical facts validate that most of transactions on currency market are due to carry trade activity.

3.4.5 Hedging the unconditional risk exposure

Grundy and Martin (2001) argue the dynamic risk hedged momentum portfolios outperform the unhedged momentum portfolio on US equity market. Thus, dynamic risk structure is not the dominant driver for momentum anomalies. To show that currency excess momentum return is mainly driven by the dynamic risk exposure pattern. I test profits of risk adjusted currency momentum returns by using *ex post*(Grundy and Martin, 2001) or *ex ante*(Daniel and Moskowitz, 2016) information. Under the two factor model, following regressions are used to examine the dynamic risk exposure at time t:

$$R_\tau^{Mom} = \alpha_0 + \beta_{0,t} \times R_\tau^{DOL} + \gamma_{0,t} \times R_\tau^{HML} + \varepsilon_\tau$$

If $\tau = t, t-1, t-2, t-3, ...$ then *ex ante* information is used. If $\tau = t, t+1, t+2, t+3, ...$, the *ex post* information is used. I ran the regression each time to dynamically estimate risk exposure $\hat{\beta_{0,t}}$ and $\hat{\gamma_{0,t}}$. The risk adjusted momentum $R_t^{risk.adj.}$ is calculated as

$$R_t^{risk.adj.} = R_t^{Mom} - \hat{\beta_{0,t}} \times R_t^{DOL} - \hat{\gamma_{0,t}} \times R_t^{HML}$$

I use the 36/5 months *ex ante* or *ex post* information to form the risk adjusted portfolios based on strategy Mom(6,1) and Mom(9,1). The annulized return, t-statistics, annulized standard deviation, sample skewness and sharpe ratios are listed in table 3.7

[Table 3.7 about here]

None of the risk adjusted portfolios outperform the plain strategies in table 3.1. Most of strategies in table 3.7 do not have significant positive return. One exception is *ex ante* betas adjusted Mom(6,1) based on 36 month rolling data, but the Sharpe ratio of this strategy is decreased due to increased standard deviation. Therefore, the dynamic beta pattern is the main drive of the excess momentum return.

3.4.6 Winner versus Losser

To further investigate whether the dynamic risk pattern comes for loser or winner portfolios, especially for coefficients $\beta_{B,U}$ and $\gamma_{B,U}$ which is used to test the option-like payoff of momentum strategy, I test the risk structure of loser group and winner group respectively by following three specifications:

$$\begin{aligned}
R_t^{Mom} &= \alpha_0 + \alpha_B^{DOL} \times I_{B,t-1}^{DOL} \\
&\quad + (\beta_0 + I_{B,t-1}^{DOL}(\beta_B + \beta_{B,U} \times I_{U,t}^{DOL}))R_t^{DOL} + \varepsilon_t \\
R_t^{Mom} &= \alpha_0 + \alpha_B^{HML} \times I_{B,t-1}^{HML} \\
&\quad + (\gamma_0 + I_{B,t-1}^{HML}(\gamma_B + \gamma_{B,U} \times I_{U,t}^{HML}))R_t^{HML} + \varepsilon_t \\
R_t^{Mom} &= \alpha_0 + \alpha_B^{DOL} \times I_{B,t-1}^{DOL} + \alpha_B^{HML} \times I_{B,t-1}^{HML} \\
&\quad + (\beta_0 + I_{B,t-1}^{DOL}(\beta_B + \beta_{B,U} \times I_{U,t}^{DOL}))R_t^{DOL} \\
&\quad + (\gamma_0 + I_{B,t-1}^{HML}(\gamma_B + \gamma_{B,U} \times I_{U,t}^{HML}))R_t^{HML} + \varepsilon_t
\end{aligned}$$

Table 3.8, 3.9 show results for past loser portfolios and past winner portfolios respectively. In first two columns, key coefficients are $\beta_{B,U}$ and $\gamma_{B,U}$ which is associated with the optionality to DOL or HML. The difference in absolute value of $\beta_{B,U}$ for loser and winner portfolios is negligible. In regression 2, I find that opionality comes mainly from the past loser portfolio as $\gamma_{B,U}$ is larger in absolute value for the past winner portfolios. However, the asymetry on $\gamma_{B,U}$ weakens when the *DOL* factor is introduced in regression 3. The asymmetry on $\gamma_{B,U}$ is negligible between past losser and past winner portfolios. There is no clear cut evidence supporting the beta asymmety for past winner and past losser portfolio in currency momentum portfolio. Our results contradict with findings of Daniel and Moskowitz (2016) on US equity market who find winner portfolio contribute more to dynamic risk structure. One of the possible reasons for that might be there are less restrictions on short selling on currency market. However, this hypothesis needs other empirical evidence to support.

[Table 3.8 about here]

[Table 3.9 about here]

3.4.7 Currency momentum and pricing factor volatility

The analysis so far shows that currency momentum strategies behave like a written call-option to both DOL and HML factors in down-HML market. Therefore, one could expect currency momentum return to be negatively correlated to the voaltility of DOL and HML following a down HML market. In fact, the higher the market volatility, the higher the call option value, the lower expect return of currency momentum portfolios. In this section I introduce a set of regressions to cross-validate previous results and investigate the relationship between momentum return and factor volatility. I first model the conditional variance of DOL and HML by using ARMA(1,1)-GARCH(1,1) with Normal error term. The estimation results are listed in Table 3.10.

[Table 3.10 about here]

The associated ARCH and GARCH coefficients are all significant for both factors which indicates ARMA(1,1)-GARCH(1,1) could properly model the dynamic of factor volatility. From this model, the implied in-sample conditional variance $h^2_{t,DOL}$ and $h^2_{t,HML}$ are obtained. Along with down-HML indicator $I^{HML}_{B,t-1}$. I specifiy three regression models to investigated the momentum return and currency market factor's volatility. The empirical results are listed in table 3.11.

[Table 3.11 about here]

I begin with testing the relationship between momentum return and conditional variance of DOL and HML independently. In first model, I regress returns of Mom(6,1) and Mom(9,1) to conditional variance of DOL, $h^2_{t,DOL}$ and the interaction with $I^{HML}_{B,t-1}$, $R^{Mom}_t = \alpha_0 + (\kappa_o + \kappa_B \times I^{HML}_{B,t-1}) \times h^2_{t,DOL} + \varepsilon_t$. In the second model the conditioal variance is replaced by $h^2_{t,HML}$: $R^{Mom}_t = \alpha_0 + (\lambda_o + \lambda_B \times I^{HML}_{B,t-1}) \times h^2_{t,HML} + \varepsilon_t$. The first two colums of table 3.11 show that estimated coefficients κ_B and λ_B are significantly negative but κ_0 and λ_0 are not significantly different from 0. This suggests that only when the previous 6-month HML factor return is negative, momentum portfolios behave like written call option and they are negatively correlated with the conditional variance of DOL and HML. When previous 6-month HML return is positive, there is no significant correlation between currency momentum return and factors' volatility. In the last model of table 3.11, two conditional volatility are added together $R_t^{Mom} = \alpha_0 + (\kappa_o + \kappa_B \times I_{B,t-1}^{HML}) \times h_{t,DOL}^2 + (\lambda_o + \lambda_B \times I_{B,t-1}^{HML}) \times h_{t,HML}^2 + \varepsilon_t$. In this case, only the coefficient λ_B is significant. One possible explanation would be the colinearity issue, which indicates that significant correlation exists between factors' voaltility. Meanwhile, variance of DOL takes the dominant effect over volatility of HML.

3.5 Economic implication

Based on the analysis of the time-varying betas to currency specific factors DOL and HML for currency momentum portfolio, I evaluate two modified currency momentum strategies that could hedge momentum crashes. Both strategies are implementable in pratice and use results of momentum's risk analysis to adjust portfolios weights. I show that hedged currency momentum strategies outperfom the plain Mom(6,1) and Mom(9,1) strategies in Sharpe ratio and sample skewness.

3.5.1 Avoid the currency momentum crash

The most simple way to hedge the momentum crash based on our analysis of dynamic risk exposure, is to close the position when previous 6 months cumulative HML return is negative. Since the asymetric payoff or momentum crash is conditioned on $I_{B,t-1}^{HML} = 1$, I propose the avoid crash strategy(ACS) which modifies the currency momentum strategy Mom(6,1) and Mom(9,1) by putting zero weight on time $t-1$ when $I_{B,t-1}^{HML} = 1$. Note that this strategy is implemetable in pratice as information needed to make the investment decision is *ex ante.* The profit of this strategy sources from return continuation durning normal time.

3.5.2 Dynamic weighting strategy

ACS wastes the investment opportunity as momentum crash happens only when $I^{HML}_{B,t-1} = I^{HML}_{U,t} = I^{DOL}_{U,t} = 1$. ACS does not impose negative weights as well. Thus, a dynamic weighting strategy of Daniel and Moskowitz (2016) is employed. To maxmize the in-sample uncontidional sharpe ratio, the optimal weight for risky asset at time $t-1$ is[14]

$$w_{t-1} = (\frac{1}{2\lambda})\frac{\mu_{t-1}}{\sigma^2_{t-1}}$$

Where $\mu_{t-1} \equiv E_{t-1}[R^{Mom}_t]$ is the conditional expected return given time $t-1$ information. $\sigma^2_{t-1} \equiv E_{t-1}[(R^{Mom}_t - \mu_{t-1})^2]$ is the conditional expected variance of comming month given time $t-1$ information. λ is a time-invariant scalar that controls the unconditional risk. When expected return are constant propotion to expected variance overtime, this strategy is equivalent to Barroso and Santa-Clara (2015*b*)'s constant volatility strategies.

To work out the dynamic weigths, the conditional variance σ^2_{t-1} is proxied by previous 72-month sample variance of Mom(6,1) and Mom(9,1). The expected return μ_{t-1} is then estimated in two stages by using insigts that currency momentuns are effectively a written call option. Firstly, I employed a dynamic 36-month rolling window $ARMA(1,1) - GARCH(1,1)$ to make one-step-ahead forecast for the factors' conditional variance $\hat{h}^2_{t-1,DOL}$ and $\hat{h}^2_{t-1,HML}$ given $t-1$ information. In the second stage, I use the insights of first and second regression in table 3.11 to estimate conditioanl expected return μ_{t-1} in which it relates currency momentums to factors conditional variance and down-HML market indicator. One thing different is that, I replace the contemporaneous variance of $h^2_{t,DOL}$ and $h^2_{t,HML}$ by the one-step-ahead forecast from first stage. Due to the colinearity issue between conditional variance of DOL and HML, expected return μ_{t-1} are estimated seperately by using variance of DOL and HML respectively. Meanwhile, the conditional expectation cannot be estimated through coefficents from the full sample regression as in table 3.11. A dynamic regression is performed in a 36-month rolling window. That is each time t, I use previous 36 months up to time $t-1$ to get estimations of parameter set $[\alpha_0, \lambda_o, \lambda_B, \kappa_0, \kappa_B]$. Thus this strategy is fully implementable in practice and subject to information at time $t-1$. λ is choosen that the annulized standard deviation is 19%. Hence, two strategies, namely dynamic weighting strategy infered by DOL(DWSD) and dynamic weighting strategy infered by HML(DWSH), are proposed.

This stragety exploit the momentum crash as its profit source. When $I^{HML}_{B,t-1} = 0$,

[14] The proof of this equation is shown in Appendix 3.6.2.

factors' conditional variances do not correlated with momentum return which results in around 0 estimate for μ_{t-1} and thus 0 for w_{t-1}. When $I^{HML}_{B,t-1} = 1$, momentum returns are negatively correlated with factor's conditional variance. High volatility of HML or DOL suggest large negative value of w_{t-1}. When currency crashes, large positive return would be achieved.

3.5.3 Momentum strategies performance

To make zero cost currency momentum strategies comparable with each other, I normalized the in-sample annulized volatility to 19% by multiplying a time invariant constant. I compare profitbility of avoid crash strategies(ACS) and dynamic weighting strategies(DWS) with the plain momentun strategies for the a smaller sample from Nov. 2003 to Feb. 2018(because the beginning 72 months have been used to rolling estimate the conditional return for dynamic weighting strategy). Table 3.12 reports the annulized average return, t-statistic based on Newey-West standard error, annulized standard deviation, sample skewness and annulized sharpe ratio. In first panel of table 3.12, no transaction cost are imposed. In the second panel and third panel, it reports the statistics with full quoted spreads and 50% of full quoted spreads as transaction cost estimates.

[Table 3.12 about here]

It shows that average returns and Sharpe ratios are significantly improved from optimized currency momentum portfolios. The sample skewness is around 0 for ACS and positive for DWS which indicates that the currency momentum crash has been hedged. Unlike the plain momentun strategies which has been seriesly affected by transaction costs, the optimized strategies also domenstrate significant positive returns after transaction costs.

Figure 3.4 plots the the cumulative return of the plain currency momentum strategy MOM(6,1) MOM(9,1); the avoid crash strategy ACS(6, 1), ACS(9, 1);and dynamic weighting strategy DWSD and DWSH.

3.6 Conclusion

This chapter shows that, on the currency market, momentum strategies are subject to the dynamic exposure to currency market specific pricing factors DOL and HML.

When the previous HML and DOL return are positive, currency momentums positively exposured factors. Following the drawdown of HML return, the expected momentum return are decreased. In particular, momentum crash happens when HML rebounds. During the meantime, if DOL is also rebounding from previous negative return, the loss on moentum strategy would be larger. Due to the asymetric payoff pattern, under the down-HML market, currency momentum strategis work effectively like a wrriten call option. I also prove this dynamic risk structure is the main driver for the momentum anomaly by showing dynamice hedged portfolios do not earn excess return. By answering the risk structure of currency momentum strategies, this study contribute to the study about relationship between currency momentum and currency carry trade. I show currencu momentum are positively correlated with carry trade in normal time but negarively correlated when carry trade reverse from previous drawdown.

The written call like payoff makes the currency momentum return negatively correlated with factor volatility under down-HML market and not correlated under up-HML market. This empiracal findings of negative correlation between factor conditional volatility and momentum return are in favor of the momentum's option-like property. By using this insights, one could modify the momentum trading strategy to avoid possible momentum crash. I proposed two strategies that adjust the time series weights on plain momentum strategies based on the insight of this risk structure. The optimized portfolios outperform in terms of higher Sharpe ratio and positive skewness.

Appendices

3.6.1 Additional test of time varying exposures

First I test the time varying exposure to DOL when the carry trade HML factor is introduced. Unlike equity market pricing factors of value, size and market which are considered as nearly orthogonal to each other in most studies, the correlation between currency market pricing factors DOL and HML has not been definitive among literature which could possibly impact the estimated risk exposures. Thus, I add HML and its interaction terms with $I_{B,t-1}^{DOL}$ and $I_{U,t}^{DOL}$ in the regression as a robustness check of results in table 3.4. Note that this is also a test to see whether exposures to 'high minus low carry trade' HML factor changes given different market conditions as proxied by the DOL factor. Four time series regressions are specified below and the test results are reported in table 4.

$$
\begin{aligned}
R_t^{Mom} &= \alpha_0 + \beta_0 \times R_t^{DOL} + \phi_0 \times R_t^{HML} + \varepsilon_t \\
R_t^{Mom} &= \alpha_0 + \alpha_B^{DOL} \times I_{B,t-1}^{DOL} \\
&\quad + (\beta_0 + I_{B,t-1}^{DOL}(\beta_B + I_{U,t}^{DOL} \times \beta_{B,U}))R_t^{DOL} \\
&\quad + \gamma_0 \times R_t^{HML} + \varepsilon_t \\
R_t^{Mom} &= \alpha_0 + \alpha_B^{DOL} \times I_{B,t-1}^{DOL} \\
&\quad + (\beta_0 + I_{B,t-1}^{DOL}(\beta_B + I_{U,t}^{DOL} \times \beta_{B,U}))R_t^{DOL} \\
&\quad + (\gamma_0 + \phi_B \times I_{B,t-1}^{DOL}) \times R_t^{HML} + \varepsilon_t \\
R_t^{Mom} &= \alpha_0 + \alpha_B^{DOL} \times I_{B,t-1}^{DOL} \\
&\quad + (\beta_0 + I_{B,t-1}^{DOL}(\beta_B + I_{U,t}^{DOL} \times \beta_{B,U}))R_t^{DOL} \\
&\quad + (\gamma_0 + IB_{t-1}^{DOL}(\phi_B + \phi_{B,U} \times I_{U,t}^{DOL}))R_t^{HML} + \varepsilon_t
\end{aligned}
$$

I add the carry trade factor and intereaction terms to the regression models of table 3. The first regression estimates the betas to DOL and HML. The second regression tests whether the return and beta difference is robust in the existence of carry trade factor term. In the third regression, I test if the betas to carry trade factor changes given the different market condition as proxied by the previous return of DOL. The fourth regression test beta changes to both factors when the contemporaneous DOL is positive .

The first column of table 3.13 shows the two variable time series regression of factor DOL and HML. Although the estimated coefficnets β_0 have same sign and significant as in the univariate regression of table 3.13, the estimated value changes after the inclusion of HML which indicates two factors are not entirely orthogonal to each other. Coefficients γ_0 of HML are not significant in 5% for both strategies which is consistent with Daniel and Moskowitz (2016) and Menkhoff et al. (2012*b*). The second specification in table 3.13 tests time varying exposure to DOL when the factor HML is included. The coefficients β_B and $\beta_{B,U}$ have the same sign and significance as in Table 3.13. In latter two models, two dummy variables based on the interaction between DOL and HML factors are introduced in the regression. the estimated β_B and $\beta_{B,U}$ do not vary much relative to second regression of table 3.13 and and the fourth regression of table 3.13. Therefore the time varying exposure to DOL of momentum strategies seems to be a robust empirical result. Meanwhile all the estimated coefficients associated wiith HML are not significant at 5% level.

[Table 3.13 about here]

Similar as the test of DOL factor, I proceed to investigate whether the time varying property of HML exposure is robust when the DOL factor is included in the regression. I also add the ineraction terms of DOL with bear carry trade market indicator I_B^{HML} and I_U^{HML} into the current model. There are 4 regression models specified below.

$$
\begin{aligned}
R_t^{Mom} &= \alpha_0 + \alpha_B^{HML} \times I_{B,t-1}^{HML} \\
&\quad + (\gamma_0 + I_{B,t-1}^{HML}(\gamma_B + \gamma_{B,U} \times I_{U,t}^{HML}))R_t^{HML} \\
&\quad + \beta_0 \times R_t^{DOL} + \varepsilon_t \\
R_t^{Mom} &= \alpha_0 + \alpha_B^{HML} \times I_{B,t-1}^{HML} \\
&\quad + (\gamma_0 + I_{B,t-1}^{HML}(\gamma_B + \gamma_{B,U} \times I_{U,t}^{HML}))R_t^{HML} \\
&\quad + (\beta_0 + \varphi_B \times I_{B,t-1}^{HML}) \times R_t^{DOL} + \varepsilon_t \\
R_t^{Mom} &= \alpha_0 + \alpha_B^{HML} \times I_{B,t-1}^{HML} \\
&\quad + (\gamma_0 + I_{B,t-1}^{HML}(\gamma_B + \gamma_{B,U} \times I_{U,t}^{HML}))R_t^{HML} \\
&\quad + (\beta_0 + I_{B,t-1}^{HML}(\varphi_B + \varphi_{B,U} \times I_{U,t}^{HML}))R_t^{DOL} + \varepsilon_t
\end{aligned}
$$

The first regression equation test HML beta change in the presence of DOL factor. The second regression is designed to test whether DOL betas have significant change in the different market condion once the HML factor is included. The third regression tests whether there are significant beta changes for both fators when the contempraneous HML return is positive following a previous drawdown of negative return as showed by the HML factor.

Table 3.14 reports the estimated results for above 3 regression models. In first colum, the DOL return is added in the regression. The estimated coefficients associated with the HML factor are consistent with the last model of table 3.14. Meanwhile, the estimated exposure to DOL factor is negative and significant. The interaction term $I^{HML}_{B,t-1} \times R^{DOL}_t$ and $I^{HML}_{B,t-1} \times I^{HML}_{U,t} \times R^{DOL}_t$ is introduced. The estimated model is still robust for coefficients of HML, however the estimated coefficients of DOL is not signifcant any more which indicates that exposure to DOL do not vary according to the HML conditions. Meanwhile the intercept for all three regressions are significant which means part of the momentum return is not explained.

[Table 3.14 about here]

3.6.2 Maximum Sharpe ratio strategy

Daniel and Moskowitz (2016) proposed a weighting sscheme for risky asset to maximum their in sample sharpe ratio which is inspired by an intertemporal version of Markowitz (1952) portfolio optimization. The setting is discrete time with T periods from $1, ..., T$. I can trade in two assets, a risky asset and a risk free asset. Our objective is to maximize the sharpe ratio of a portfolio in which, each period, I can trade in or out of the risky asset with no cost.

Over period $t+1$ which is the span from t to $t+1$, the excess return on a risky asset $\tilde{r}_{t+1}$ is distributed normally, with time-t conditional mean μ_t and conditional variance σ^2. That is,

$$\mu_t = E_t[\tilde{r}_{t+1}]$$

and

$$\sigma_t^2 = E_t[(\tilde{r}_{t+1} - \mu_t)^2],$$

where I assume that at $t = 0$ the agent knows μ_t and σ_t for $t \in \{0, ..., T-1\}$.

The agent's objective is to maximize the full-period Sharpe ratio of a managed portfolio. The agent manages the portfolio by placing, at beginning of each period, a fraction w_t of the vaule of the managed portfolio in the risky asset and a fraction $1 - w_t$ in the risk-free asset. The time t expected excess return and variance of the managed portfolio in period $t+1$ is then given by

$$\tilde{r}_{p,t+1} = w_t \tilde{r}_{t+1} \sim N(w_t \mu_t, w_t^2 \sigma_t^2)$$

The Sharpe ratio over the T periods is

$$SR = \frac{E[\frac{1}{T}\sum_{t=1}^{T}\tilde{r}_{p,t}]}{\sqrt{E[\frac{1}{T}\sum_{t=1}^{T}(\tilde{r}_{p,t}-\tilde{r}_p)^2]}},$$

Where the $\tilde{r}_p$ in the denominator is the sample average per period excess return $(\frac{1}{T}\sum_{t=1}^{T}\tilde{r}_{p,t})$.

Given the information structure of this optimization problem, maximizing the Sharpe ratio is equivalent to solving the constrained maximization problem:

$$\max_{w_0,\ldots,w_{T-1}} E[\frac{1}{T}\sum_{t=1}^{T}\tilde{r}_{p,t}] \ subject\ to\ E[\frac{1}{T}\sum_{t=1}^{T}(\tilde{r}_p-\tilde{r})^2]=\sigma_p^2$$

If the period length is sufficiently short, then $E[(\tilde{r}_{p,t}-\tilde{r})^2] \approx \sigma_t^2 = E_t[(\tilde{r}_{t+1}-\mu_t)^2]$. With this approximation, substituting in the conditional expectations for the managed portfolio from first two equations gives the Lagrangian:

$$\max_{w_0,\ldots,w_{T-1}} L \equiv \max_{w_t}(\frac{1}{T}\sum_{t=0}^{T-1}w_t\mu_t)-\lambda(\frac{1}{T}\sum_{t=0}^{T-1}w_t^2\sigma_t^2=\sigma_p^2).$$

The T first order conditions for optmality are

$$\frac{\partial L}{\partial W_t}|_{w_t=w_t^*} = \frac{1}{T}(\mu_t - 2\lambda w_t^*\sigma_t^2) = 0 \ \ \forall t \in \{0,...,T-1\}$$

giving an optimal weight on the risky asset at time t of

$$w_t^* = (\frac{1}{\lambda})\frac{\mu}{\sigma_t^2}$$

That is, the weight placed on the risky asset at time t should be proportional to the expected excess return over the next period and inversely proportional to the conditional variance.

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Figure 3.1 – Cross-sectional sample size of currencies available. The sample period spans from Jan. 1997 to Mar. 2018

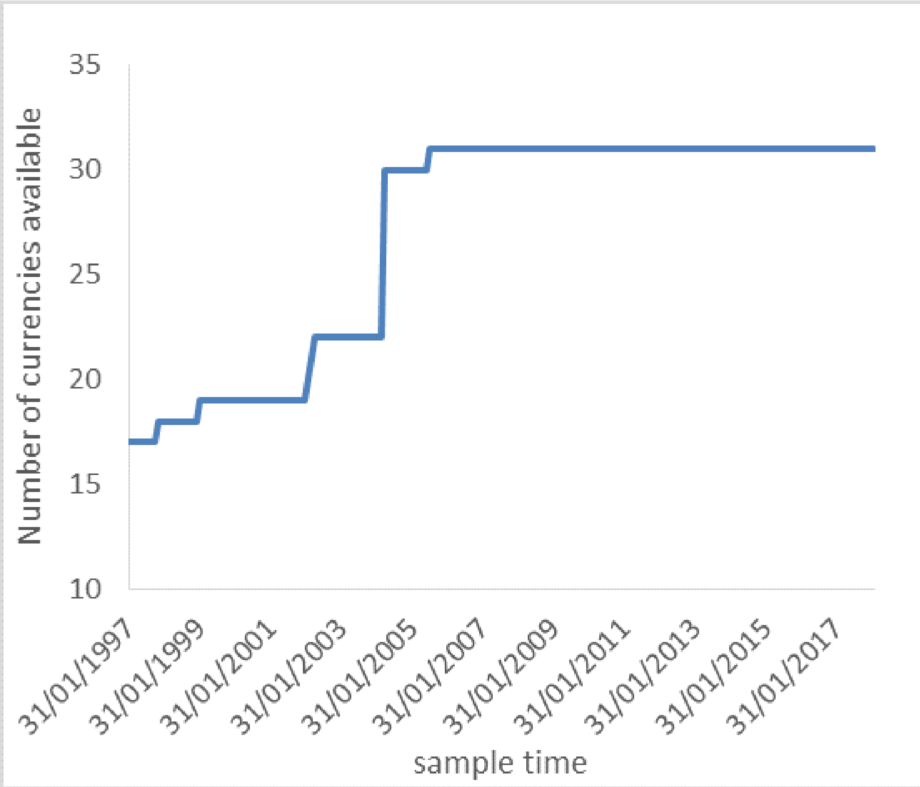

Table 3.1 – Currency Momentum Returns

		Currency momentum excess return						Spot rate changes				
				h						h		
	f	1	3	6	9	12	f	1	3	6	9	12
Mean		2.90	2.78	1.52	1.54	1.45		4.46	3.55	1.84	1.22	1.07
	1	(1.56)	(2.24)	(1.85)	(1.86)	(2.05)	1	(1.60)	(2.05)	(1.88)	(1.72)	(1.60)
Std. dev		10.25	6.52	4.67	3.54	3.15		11.98	6.87	4.40	3.30	3.08
Skewness		0.04	-0.15	0.35	-0.19	0.03		1.08	1.50	1.44	0.56	0.01
Sharpe ratio		0.28	0.43	0.32	0.43	0.46		0.37	0.52	0.42	0.37	0.35
Mean		4.36	2.26	2.03	2.41	1.55		4.99	2.10	1.37	1.10	0.39
	3	(2.16)	(1.41)	(1.51)	(1.81)	(1.30)	3	(1.92)	(1.30)	(1.23)	(1.15)	(0.42)
Std. dev		11.23	6.53	4.70	3.78	3.47		12.65	6.49	4.33	3.49	3.17
Skewness		0.10	-0.09	-0.33	-0.24	-0.02		1.11	0.36	-0.10	-0.28	-0.29
Sharpe ratio		0.39	0.35	0.43	0.64	0.45		0.39	0.32	0.32	0.32	0.12
Mean		5.15	4.47	3.99	3.09	1.93		3.50	2.59	1.68	0.60	-0.31
	6	(2.37)	(2.36)	(2.25)	(1.93)	(1.36)	6	(1.63)	(1.52)	(1.30)	(0.51)	(-0.26)
Std. dev		11.58	6.51	4.28	3.63	3.26		12.72	6.58	4.12	3.36	3.10
Skewness		0.08	-0.15	-0.58	-0.24	-0.15		0.97	0.32	0.06	0.01	-0.37
Sharpe ratio		0.44	0.69	0.93	0.85	0.59		0.28	0.39	0.41	0.18	-0.10
Mean		5.81	5.96	3.57	2.24	1.30		5.52	3.96	1.73	0.53	-0.58
	9	(2.25)	(2.68)	(1.82)	(1.36)	(0.90)	9	(2.20)	(2.04)	(1.08)	(0.39)	(-0.46)
Std. dev		12.19	6.82	4.50	3.57	3.12		13.55	6.76	4.20	3.19	2.94
Skewness		-0.29	-0.23	-0.25	-0.17	0.02		0.80	0.22	-0.25	-0.33	-0.73
Sharpe ratio		0.48	0.87	0.79	0.63	0.42		0.41	0.59	0.41	0.16	-0.20

Note: This table shows the portfolio statisitcs for currency momentum strategies. In the left panel, it reports the annulized 'winner minus loser' momentum excess return for different formation period and holding period in 1,3,6,9,12 months. Numbers in brackets are t-statistics based on Newey-West standard errors. The potfolio sample standard deviations, sharpe ratios and skewness are also reported as follow. In the right panel, it is the cooresponding statistics for changes of exchange rates.

Table 3.2 – Currency Momentum Returns with Transaction Costs

		Full quoted bid-ask spread						50% of quoted bid-ask spread				
		h						h				
	f	1	3	6	9	12	f	1	3	6	9	12
Mean		-0.58	-0.69	-1.95	-1.90	-1.96		1.16	1.05	-0.22	-0.18	-0.26
	1	(-0.32)	(-0.56)	(-2.25)	(-2.17)	(-2.60)	1	(0.63)	(0.85)	(-0.26)	(-0.21)	(-0.36)
Std. dev		10.23	6.54	4.68	3.60	3.21		10.23	6.52	4.67	3.57	3.17
Skewness		-0.10	-0.37	0.00	-0.47	-0.27		-0.03	-0.26	0.18	-0.33	-0.12
Sharpe ratio		-0.06	-0.11	-0.42	-0.53	-0.61		0.11	0.16	-0.05	-0.05	-0.08
Mean		0.88	-1.23	-1.46	-1.05	-1.88		2.62	0.52	0.29	0.68	-0.17
	3	(0.46)	(-0.79)	(-1.05)	(-0.76)	(-1.49)	3	(1.33)	(0.33)	(0.21)	(0.51)	(-0.14)
Std. dev		11.20	6.52	4.72	3.84	3.53		11.21	6.52	4.70	3.80	3.50
Skewness		-0.03	-0.30	-0.61	-0.50	-0.32		0.04	-0.20	-0.47	-0.37	-0.17
Sharpe ratio		0.08	-0.19	-0.31	-0.27	-0.53		0.23	0.08	0.06	0.18	-0.05
Mean		1.71	1.03	0.56	-0.28	-1.44		3.43	2.75	2.28	1.41	0.25
	6	(0.81)	(0.57)	(0.32)	(-0.17)	(-0.97)	6	(1.61)	(1.51)	(1.29)	(0.88)	(0.17)
Std. dev		11.58	6.52	4.33	3.69	3.33		11.58	6.51	4.30	3.65	3.29
Skewness		-0.02	-0.29	-0.71	-0.41	-0.37		0.03	-0.22	-0.64	-0.32	-0.26
Sharpe ratio		0.15	0.16	0.13	-0.08	-0.43		0.30	0.42	0.53	0.39	0.07
Mean		2.35	2.53	0.15	-1.18	-2.10		4.08	4.25	1.86	0.53	-0.40
	9	(0.91)	(1.14)	(0.07)	(-0.67)	(-1.33)	9	(1.58)	(1.92)	(0.94)	(0.31)	(-0.26)
Std. dev		12.23	6.85	4.60	3.68	3.24		12.21	6.83	4.54	3.62	3.17
Skewness		-0.38	-0.39	-0.39	-0.40	-0.28		-0.33	-0.31	-0.32	-0.28	-0.13
Sharpe ratio		0.19	0.37	0.03	-0.32	-0.65		0.33	0.62	0.41	0.15	-0.13

Note: This table shows the portfolio statisitcs for currency momentum strategies after taking consider of transaction costs. In the left panel, it reports the annulized 'winner minus loser' momentum excess return for different formation period and holding period in 1,3,6,9,12 months with full quoted bid-ask spread as transaction costs. In the left panel it reports the currency momentun excess return with 50% of full bid-ask spread as transaction costs. Numbers in brackets are t-statistics based on Newey-West standard errors. The potfolio sample standard deviations, sharpe ratios and skewness are also reported as follow. In the right panel, it is the cooresponding statistics for changes of exchange rates.

Figure 3.2 – Cumulative excess return of currency momentum strategies $Mom(6,1)$, $Mom(9,1)$, 'Dollar risk factor' DOL and US value-weighted equity portfolio. The shaded aeras indicate the recent financial crisis which are the burst of dot-com buble(from Jan. 2001 to Apr. 2002); the subprime debt crisis(from Jan. 2008 to May 2009); The European sovereign debt crisis(from Jun. 2011 to Dec. 2012). The sample period starts from Jan. 1997 to Mar. 2018.

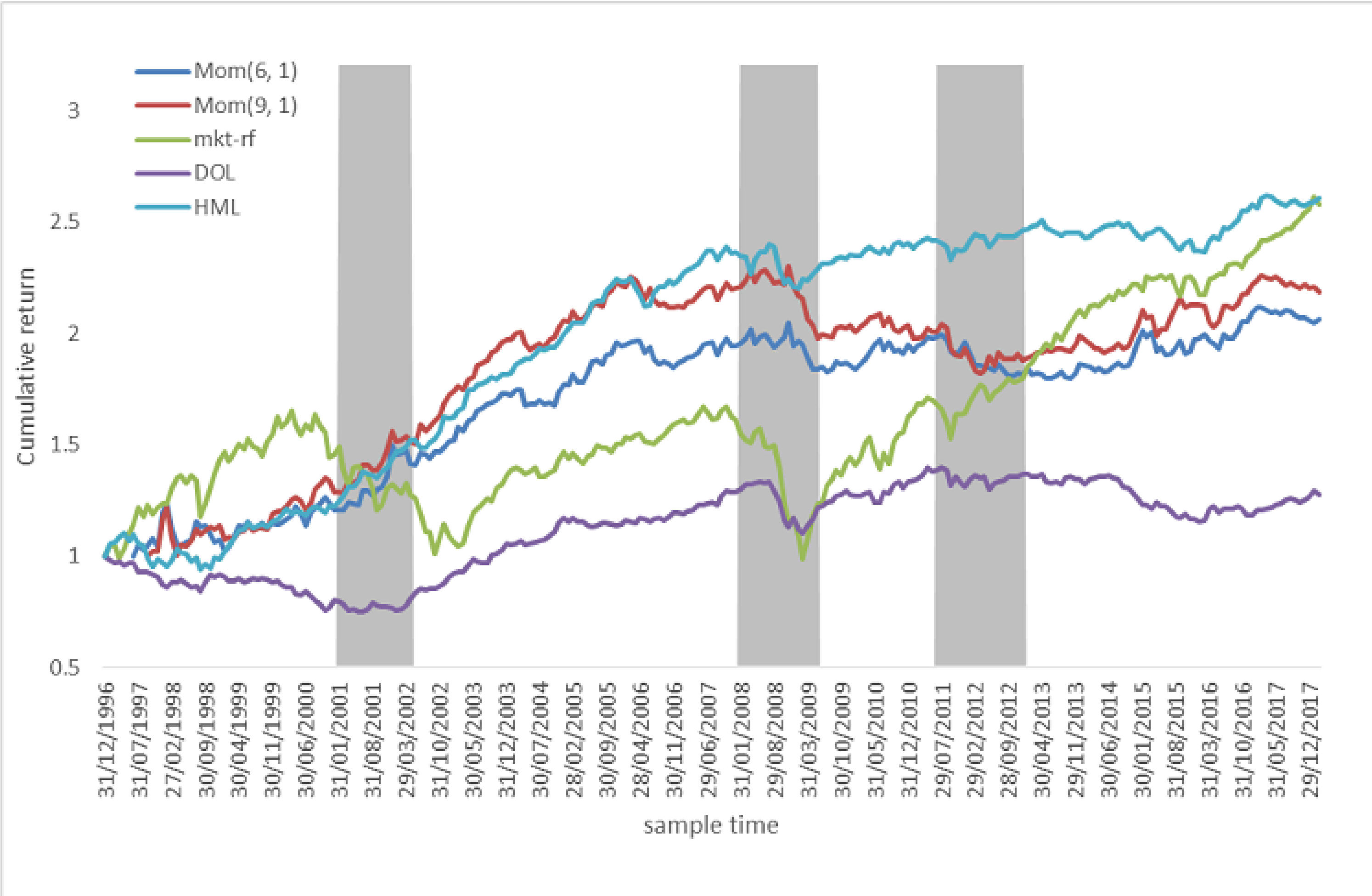

Table 3.3 – Dynamic Exposures to the Market Factor

Coefficient	1		2		3	
	Mom(6,1)	Mom(9,1)	Mom(6,1)	Mom(9,1)	Mom(6,1)	Mom(9,1)
α_0	0.47	0.51	0.58	0.71	0.58	0.71
	(2.22)	(2.25)	(2.26)	(2.56)	(2.27)	(2.57)
α_B			-0.60	-0.78	0.28	0.16
			(-1.33)	(-1.61)	(0.41)	(0.22)
β_0	-9.65	-5.69	5.06	3.38	5.06	3.38
	(-2.02)	(-1.12)	(0.71)	(0.44)	(0.71)	(0.44)
β_B			-26.89	-17.21	-10.95	-0.09
			(-2.84)	(-1.69)	(-0.83)	(-0.01)
$\beta_{B,U}$					-36.49	-39.19
					(-1.71)	(-1.71)
$adj.R^2$	0.01	0.00	0.05	0.02	0.05	0.02

Note: This table reports results of estimated coefficients, t-statistics in the brackets and adjust R^2 for three specifications of monthly times series regression.
(1) $R_t^{Mom} = \alpha_0 + \beta_0^m \times R_t^m + \varepsilon_t$;
(2) $R_t^{Mom} = \alpha_0 + \alpha_B^m \times I_{B,t-1}^m + (\beta_0^m + \beta_B^m \times I_{B,t-1}^m)R_t^m + \varepsilon_t$;
(3) $R_t^{Mom} = \alpha_0 + \alpha_B^m \times I_{B,t-1}^m + (\beta_0^m + I_{B,t-1}^m(\beta_B^m + I_{U,t}^m \times \beta_{B,U}^m))R_t^m + \varepsilon_t$.
The denpendent variables are monthly returns of momentum strategies Mom(6,1) and Mom(9,1), respectively. The independent variables are a constant intercept α_0; the *ex ante* down market indicator $I_{B,t-1}^m$; the contemporaneous market returnR_t^m; and the contemporaneous up-market indicator, $I_{U,t}^m$; and interaction terms. The sample runs from December 1997 to Feburary 2018.

Table 3.4 – Dynamic Exposures to DOL

Coefficient	1		2		3		4	
	Mom(6,1)	Mom(9,1)	Mom(6,1)	Mom(9,1)	Mom(6,1)	Mom(9,1)	Mom(6,1)	Mom(9,1)
α_0	0.47	0.53	0.63	0.65	0.38	0.40	0.38	0.40
	(2.45)	(2.40)	(2.49)	(2.38)	(1.61)	(1.70)	(1.61)	(1.70)
α_B^{DOL}			-0.40	-0.30	-0.24	-0.14	0.73	1.18
			(-0.92)	(-0.62)	(-0.58)	(-0.30)	(1.55)	(2.09)
β_0	-0.31	-0.31	-0.32	-0.31	0.41	0.43	0.41	0.43
	(-2.03)	(-1.70)	(-2.03)	(-1.69)	(2.70	(2.19)	(2.70)	(2.18)
β_B					-1.39	-1.42	-0.90	-0.76
					(-5.83)	(-4.56)	(-2.71)	(-1.64)
$\beta_{B,U}$							-1.09	-1.48
							(-2.41)	(-2.22)
$Adj.R^2$	0.03	0.03	0.03	0.02	0.20	0.18	0.22	0.22

Note: This table reports results of estimated coefficients, t-statistics in the brackets and adjust R^2 for three specifications of monthly times series regression.
(1) $R_t^{Mom} = \alpha_0 + \beta_0 \times R_t^{DOL} + \varepsilon_t$;
(2) $R_t^{Mom} = \alpha_0 + \alpha_B^{DOL} \times I_{B,t-1}^{DOL} + \beta_0 \times R_t^{DOL} + \varepsilon_t$;
(3) $R_t^{Mom} = \alpha_0 + \alpha_B^{DOL} \times I_{B,t-1}^{DOL} + (\beta_0 + \beta_B \times I_{B,t-1}^{DOL})R_t^{DOL} + \varepsilon_t$;
(4) $R_t^{Mom} = \alpha_0 + \alpha_B^{DOL} \times I_{B,t-1}^{DOL} + (\beta_0 + I_{B,t-1}^{DOL}(\beta_B + I_{U,t}^{DOL} \times \beta_{B,U}))R_t^{DOL} + \varepsilon_t$.
The denpendent variables are monthly returns of momentum strategies Mom(6,1) and Mom(9,1), respectively. The independent variables are an intercept α_0; the *ex ante* down-DOL indicator $I_{B,t-1}^{DOL}$; the contemporaneous DOL factor return R_t^{DOL}; the contemporaneous up-DOL indicator, $I_{U,t}^{DOL}$; and interaction terms. The sample runs from December 1997 to Feburary 2018.

Table 3.5 – Dynamic Exposures to HML

Coefficient	1		2		3		4	
	Mom(6,1)	Mom(9,1)	Mom(6,1)	Mom(9,1)	Mom(6,1)	Mom(9,1)	Mom(6,1)	Mom(9,1)
α_0	0.34	0.42	0.75	0.95	0.65	0.86	0.65	0.86
	(1.87)	(1.88)	(4.30)	(4.74)	(3.58)	(4.30)	(3.57)	(4.29)
α_B^{HML}			-1.39	-1.81	-1.04	-1.50	1.02	0.56
			(-3.21)	(-3.69)	(-2.06)	(-2.80)	(2.08)	(0.95)
γ_0	0.10	0.08	0.10	0.08	0.25	0.20	0.25	0.20
	(1.04)	(0.75)	(1.15)	(0.86)	(2.48)	(2.13)	(2.47)	(2.13)
γ_B					-0.43	-0.37	0.37	0.43
					(-1.79)	(-1.63)	(1.02)	(1.44)
$\gamma_{B,U}$							-1.53	-1.53
							(-3.73)	(-4.22)
$Adj.R^2$	0.01	0.00	0.04	0.05	0.07	0.07	0.14	0.13

Note: This table reports results of estimated coefficients, t-statistics in the brackets and adjust R^2 for three specifications of monthly times series regression.
(1) $R_t^{Mom} = \alpha_0 + \alpha_B^{DOL} \times I_{B,t-1}^{DOL} \gamma_0 \times R_t^{HML} + \varepsilon_t$;
(2) $R_t^{Mom} = \alpha_0 + \alpha_B^{HML} \times I_{B,t-1}^{HML} + \gamma_0 \times R_t^{HML} + \varepsilon_t$;
(3) $R_t^{Mom} = \alpha_0 + \alpha_B^{HML} \times I_{B,t-1}^{HML} + (\gamma_0 + \gamma_B \times I_{B,t-1}^{HML})R_t^{HML} + \varepsilon_t$;
(4) $R_t^{Mom} = \alpha_0 + \alpha_B^{DOL} \times I_{B,t-1}^{HML} + (\gamma_0 + I_{B,t-1}^{HML}(\gamma_B + I_{U,t}^{HML} \times \gamma_{B,U}))R_t^{HML} + \varepsilon_t$.
The denpendent variables are monthly returns of momentum strategies Mom(6,1) and Mom(9,1), respectively. The independent variables are: an intercept α_0; the *ex ante* down-HML indicator $I_{B,t-1}^{HML}$; the contemporaneous HML factor return R_t^{HML}; the contemporaneous up-HML indicator, $I_{U,t}^{HML}$; and interaction terms. The sample runs from December 1997 to Feburary 2018.

Table 3.6 – Collective Effects on Currency Market Pricing Factors

Coefficient	1		2		3		4	
	Mom(6,1)	Mom(9,1)	Mom(6,1)	Mom(9,1)	Mom(6,1)	Mom(9,1)	Mom(6,1)	Mom(9,1)
α_0	0.33	0.49	0.36	0.52	0.33	0.49	0.35	0.51
	(1.37)	(1.94)	(1.48)	(2.09)	(1.37)	(1.97)	(1.48)	(2.11)
α_B^{DOL}	0.03	0.18	0.01	0.16	0.52	1.02	0.38	0.88
	(0.09)	(0.47)	(0.04)	(0.43)	(1.23)	(1.87)	(0.91)	(1.68)
α_B^{HML}	-0.60	-1.09	0.76	0.27	-0.53	-0.98	0.76	0.27
	(-1.44)	(-2.32)	(1.76)	(0.46)	(-1.37)	(-2.30)	(1.79)	(0.50)
β_0	0.33	0.34	0.32	0.33	0.34	0.36	0.32	0.34
	(2.07)	(1.72)	(2.15)	(1.81)	(2.14)	(1.79)	(2.19)	(1.88)
β_B	-1.40	-1.40	-1.31	-1.31	-1.15	-0.97	-1.12	-0.94
	(-6.25)	(-4.89)	(-5.65)	(-4.51)	(-3.46)	(-2.12)	(-3.39)	(-2.08)
$\beta_{B,U}$					-0.57	-0.98	-0.43	-0.84
					(-1.18)	(-1.44)	(-0.92)	(-1.30)
γ_0	0.35	0.31	0.34	0.30	0.33	0.27	0.33	0.27
	(3.81)	(3.06)	(3.74)	(3.05)	(3.49)	(2.80)	(3.43)	(2.75)
γ_B	-0.54	-0.48	0.00	0.06	-0.52	-0.44	-0.01	0.06
	(-3.28)	(-2.80)	(-0.01)	(0.25)	(-3.05)	(-2.42)	(-0.02)	(0.23)
$\gamma_{B,U}$			-1.03	-1.03			-0.99	-0.96
			(-2.81)	(-2.98)			(-2.79)	(-2.85)
$Adj.R^2$	0.30	0.27	0.32	0.29	0.30	0.28	0.32	0.30

Note: This table reports results of estimated coefficients, t-statistics in the brackets and adjust R^2 for three specifications of monthly times series regression.
(1) $R_t^{Mom} = \alpha_0 + \alpha_B^{DOL} \times I_{B,t-1}^{DOL} + \alpha_B^{HML} \times I_{B,t-1}^{HML} + \gamma_0 \times R_t^{HML} + (\beta_0 + \beta_B \times I_{B,t-1}^{DOL})R_t^{DOL} + (\gamma_0 + \gamma_B \times I_{B,t-1}^{HML})R_t^{HML} + \varepsilon_t$;
(2) $R_t^{Mom} = \alpha_0 + \alpha_B^{DOL} \times I_{B,t-1}^{DOL} + \alpha_B^{HML} \times I_{B,t-1}^{HML} + \gamma_0 \times R_t^{HML} + (\beta_0 + \beta_B \times I_{B,t-1}^{DOL})R_t^{DOL} + (\gamma_0 + I_{B,t-1}^{HML}(\gamma_B + I_{U,t}^{HML} \times \gamma_{B,U}))R_t^{HML} + \varepsilon_t$;
(3) $R_t^{Mom} = \alpha_0 + \alpha_B^{DOL} \times I_{B,t-1}^{DOL} + \alpha_B^{HML} \times I_{B,t-1}^{HML} + \gamma_0 \times R_t^{HML} + (\beta_0 + I_{B,t-1}^{DOL}(\beta_B + I_{U,t}^{DOL} \times \beta_{B,U}))R_t^{DOL} + (\gamma_0 + \gamma_B \times I_{B,t-1}^{HML})R_t^{HML} + \varepsilon_t$;
(4) $R_t^{Mom} = \alpha_0 + \alpha_B^{DOL} \times I_{B,t-1}^{DOL} + \alpha_B^{HML} \times I_{B,t-1}^{HML} + \gamma_0 \times R_t^{HML} + (\beta_0 + I_{B,t-1}^{DOL}(\beta_B + I_{U,t}^{DOL} \times \beta_{B,U}))R_t^{DOL} + (\gamma_0 + I_{B,t-1}^{HML}(\gamma_B + I_{U,t}^{HML} \times \gamma_{B,U}))R_t^{HML} + \varepsilon_t$.
The denpendent variables are monthly returns of bottom ten percent losser portfolio for momentum strategies Mom(6,1) and Mom(9,1), respectively. The independent variables are: an intercept α_0; the *ex ante* down-DOL indicator $I_{B,t-1}^{DOL}$; the *ex ante* down-HML indicator $I_{B,t-1}^{HML}$; the contemporaneous DOL factor return R_t^{DOL}; the contemporaneous HML factor return R_t^{HML}; the contemporaneous up-DOL indicator, $I_{U,t}^{DOL}$; the contemporaneous up-HML indicator, $I_{U,t}^{HML}$; and interaction terms. The sample runs from December 1997 to Feburary 2018.

Table 3.7 – Dynamic Risk Hedged Portfolios

	ex ante estimation betas			
	5-month rolling		36-month rolling	
	Mom(6,1)	Mom(9,1)	Mom(6,1)	Mom(9,1)
Mean	0.00	-2.18	4.64	4.45
	(0.00)	(-0.69)	(1.81)	(1.46)
Std. dev	52.58	50.99	38.26	40.35
Skewness	-0.17	-0.22	-0.14	-0.00
Sharpe ratio	0.00	-0.04	0.12	0.11

	ex post estimation betas			
	5-month rolling		36-month rolling	
	Mom(6,1)	Mom(9,1)	Mom(6,1)	Mom(9,1)
Mean	-4.88	-2.72	0.32	-0.97
	(-2.37)	(-1.36)	(0.17)	(-0.49)
Std. dev	28.38	27.71	31.57	32.46
Skewness	0.08	-0.14	0.07	-0.34
Sharpe ratio	-0.17	-0.10	0.01	-0.03

Note: This table reports the annulized return, t-statistics based on Newey-West standard errors in brackets, annulized standard deviation, sample skewness and sharpe ratios of the risk adjusted portfolio based on Mom(6,1) and Mom(9,1). As a comparation the corresponding statistics for Mom(6,1) and Mom(9,1) are list in the first column. Note that annulized return and standard deviation are reported in percentage.

Table 3.8 – Dynamic Exposures to Losser Portfolios

Coefficient	1			2			3	
Losser Portfolio	Mom(6,1)	Mom(9,1)		Mom(6,1)	Mom(9,1)		Mom(6,1)	Mom(9,1)
α_0	-0.09	-0.12	α_0	-0.29	-0.44	α_0	-0.21	-0.33
	(-0.57)	(-0.77)		(-1.01)	(-1.58)		(-1.18)	(-1.80)
α_B^{DOL}	0.04	-0.36	α_B^{HML}	-1.02	-0.72	α_B^{DOL}	0.16	-0.30
	(0.12)	(-0.94)		(-1.93)	(-1.30)		(0.46)	(-0.73)
β_0	0.89	0.89	γ_0	0.21	0.26	α_B^{HML}	-0.30	0.01
	(9.12)	(6.91)		(1.47)	(2.05)		(-0.93)	(0.01)
β_B	0.66	0.49	γ_B	-0.54	-0.62	β_0	0.90	0.89
	(2.74)	(1.51)		(-1.12)	(-1.58)		(9.14)	(7.36)
$\beta_{B,U}$	0.24	0.60	$\gamma_{B,U}$	1.27	1.24	β_B	0.72	0.50
	(0.72)	(1.38)		(2.62)	(3.06)		(2.75)	(1.43)
						$\beta_{B,U}$	0.00	0.43
							(-0.01)	(0.89)
						γ_0	-0.06	0.01
							(-0.91)	(0.19)
						γ_B	-0.03	-0.12
							(-0.15)	(-0.69)
						$\gamma_{B,U}$	0.56	0.50
							(2.16)	(2.09)
$Adj.R^2$	0.63	0.61	$Adj.R^2$	0.10	0.11	$Adj.R^2$	0.65	0.63

Note: This table reports results of estimated coefficients, t-statistics in the brackets and adjust R^2 for three specifications of monthly times series regression.
(1) $R_t^{Losser} = \alpha_0 + \alpha_B^{DOL} \times I_{B,t-1}^{DOL} + (\beta_0 + I_{B,t-1}^{DOL}(\beta_B + I_{U,t}^{DOL} \times \beta_{B,U}))R_t^{DOL} + \varepsilon_t$;
(2) $R_t^{Losser} = \alpha_0 + \alpha_B^{DOL} \times I_{B,t-1}^{HML} + (\gamma_0 + I_{B,t-1}^{HML}(\gamma_B + I_{U,t}^{HML} \times \gamma_{B,U}))R_t^{HML} + \varepsilon_t$;
(3) $R_t^{Mom} = \alpha_0 + \alpha_B^{DOL} \times I_{B,t-1}^{DOL} + \alpha_B^{HML} \times I_{B,t-1}^{HML} + \gamma_0 \times R_t^{HML} + (\beta_0 + I_{B,t-1}^{DOL}(\beta_B + I_{U,t}^{DOL} \times \beta_{B,U}))R_t^{DOL} + (\gamma_0 + I_{B,t-1}^{HML}(\gamma_B + I_{U,t}^{HML} \times \gamma_{B,U}))R_t^{HML} + \varepsilon_t$.
The independent variables are the same as previous tables. The denpendent variables are monthly returns of bottom ten percent losser portfolio for momentum strategies Mom(6,1) and Mom(9,1), respectively.

Table 3.9 – Dynamic Exposures to Winner Portfolios

Coefficient	1			2			3	
Winner Portfolio	Mom(6,1)	Mom(9,1)		Mom(6,1)	Mom(9,1)		Mom(6,1)	Mom(9,1)
α_0	0.29	0.28	α_0	0.35	0.42	α_0	0.14	0.18
	(2.04)	(2.03)		(1.41)	(1.56)		(0.92)	(1.14)
α_B^{DOL}	0.77	0.82	α_B^{HML}	0.01	-0.16	α_B^{DOL}	0.53	0.58
	(2.79)	(2.41)		(0.02)	(-0.42)		(2.53)	(2.13)
β_0	1.30	1.32	γ_0	0.45	0.46	α_B^{HML}	0.46	0.28
	(16.47)	(12.81)		(4.39)	(4.17)		(1.77)	(0.92)
β_B	-0.24	-0.26	γ_B	-0.18	-0.19	β_0	1.22	1.23
	(-1.22)	(-1.08)		(-0.58)	(-0.61)		(15.56)	(11.65)
$\beta_{B,U}$	-0.85	-0.88	$\gamma_{B,U}$	-0.26	-0.29	β_B	-0.40	-0.44
	(-2.95)	(-2.22)		(-0.85)	(-0.95)		(-2.49)	(-2.36)
						$\beta_{B,U}$	-0.43	-0.41
							(-1.62)	(-1.23)
						γ_0	0.27	0.28
							(4.19)	(4.16)
						γ_B	-0.04	-0.06
							(-0.26)	(-0.42)
						$\gamma_{B,U}$	-0.43	-0.46
							(-2.40)	(-2.43)
$Adj.R^2$	0.61	0.58	$Adj.R^2$	0.20	0.21	$Adj.R^2$	0.67	0.66

Note: This table reports results of estimated coefficients, t-statistics in the brackets and adjust R^2 for three specifications of monthly times series regression.
(1) $R_t^{Winner} = \alpha_0 + \alpha_B^{DOL} \times I_{B,t-1}^{DOL} + (\beta_0 + I_{B,t-1}^{DOL}(\beta_B + I_{U,t}^{DOL} \times \beta_{B,U}))R_t^{DOL} + \varepsilon_t$;
(2) $R_t^{Winner} = \alpha_0 + \alpha_B^{DOL} \times I_{B,t-1}^{HML} + (\gamma_0 + I_{B,t-1}^{HML}(\gamma_B + I_{U,t}^{HML} \times \gamma_{B,U}))R_t^{HML} + \varepsilon_t$;
(3) $R_t^{Winner} = \alpha_0 + \alpha_B^{DOL} \times I_{B,t-1}^{DOL} + \alpha_B^{HML} \times I_{B,t-1}^{HML} + \gamma_0 \times R_t^{HML} + (\beta_0 + I_{B,t-1}^{DOL}(\beta_B + I_{U,t}^{DOL} \times \beta_{B,U}))R_t^{DOL} + (\gamma_0 + I_{B,t-1}^{HML}(\gamma_B + I_{U,t}^{HML} \times \gamma_{B,U}))R_t^{HML} + \varepsilon_t$.
The independent variables are the same as previous tables. The denpendent variables are monthly returns of top ten percent winner portfolio for momentum strategies Mom(6,1) and Mom(9,1), respectively.

Table 3.10 – ARMA(1,1)-GARCH(1,1) Model for Currency Factors

ARMA(1,1)-GARCH(1,1)					
DOL			HML		
Parameters	Coefficients	T-stats	Parameters	Coefficients	T-stats
C	0.10	(0.67)	C	0.10	(0.55)
AR1	0.52	(0.61)	AR1	0.88	(4.25)
MA1	-0.43	(-0.46)	MA1	-0.82	(-3.06)
K	0.01	(1.43)	K	0.02	(2.06)
ARCH1	0.15	(1.96)	ARCH1	0.12	(2.83)
GARCH1	0.57	(2.41)	GARCH1	0.69	(7.36)

Note: This table reports estimated coefficients, t-statistics in the brackets of ARMA(1,1)-GARCH(1,1) model for currency market prcing factors DOL and HML.

Table 3.11 – Currency Momentum Return and Factor Volatility

Coefficient	1		2		3	
	Mom(6,1)	Mom(9,1)	Mom(6,1)	Mom(9,1)	Mom(6,1)	Mom(9,1)
α_0	0.03	0.43	0.19	0.61	0.17	0.68
	(0.05)	(0.59)	(0.35)	(1.10)	(0.25)	(0.92)
κ_o	19.13	12.62			-1.11	-3.07
	(1.19)	(0.68)			(-0.06)	(-0.13)
κ_B	-32.61	-38.40			7.18	4.04
	(-3.16)	(-3.12)			(1.25)	(0.54)
λ_o			6.56	3.50	8.79	-1.71
			(1.24)	(0.62)	(0.42)	(-0.06)
λ_B			-13.84	-15.44	-17.09	-14.70
			(-3.75)	(-3.17)	(-2.26)	(-1.49)
$Adj.R^2$	0.03	0.05	0.04	0.06	0.04	0.05

Note: This table reports results of the estimated coefficients, t-statistics in the brackets and adjust R^2 for four specification of monthly times series regression.
(1) $R_t^{Mom} = \alpha_0 + (\kappa_o + \kappa_B \times I_{B,t-1}^{HML}) \times h_t^{DOL} + \varepsilon_t$
(2) $R_t^{Mom} = \alpha_0 + (\lambda_o + \lambda_B \times I_{B,t-1}^{HML}) \times h_t^{HML} + \varepsilon_t$
(3) $R_t^{Mom} = \alpha_0 + (\kappa_o + \kappa_B \times I_{B,t-1}^{HML}) \times h_t^{DOL} + (\lambda_o + \lambda_B \times I_{B,t-1}^{HML}) \times h_t^{HML} + \varepsilon_t$
The denpendent variables are monthly returns of momentum strategies Mom(6,1) and Mom(9,1), respectively. The independent variables are: an intercept α_0; the *ex ante* down-HML indicator $I_{B,t-1}^{HML}$; the contemporaneous conditional volatility of DOL h_t^{DOL}; the contemporaneous conditional volatility of HML h_t^{HML}. The sample runs from December 1997 to Feburary 2018.

Table 3.12 – Optimized Momentum Strategies

	Mom(6,1)	ACS(6,1)	DWSD(6,1)	DWSH(6,1)	Mom(9,1)	ACS(9,1)	DWSD(9,1)	DWSH(9,1)
	No transaction costs							
Mean	4.80	11.60	17.98	16.06	3.10	13.55	16.26	18.80
	(1.05)	(2.53)	(2.99)	(2.73)	(0.61)	(2.99)	(2.97)	(2.59)
Std.dev	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00
Skewness	-0.55	-0.06	5.44	4.99	-0.47	0.00	6.58	4.03
Sharpe ratio	0.25	0.61	0.95	0.85	0.16	0.71	0.86	0.99
	Transcation costs 50% of full quoted bid-ask spread							
Mean	2.01	9.04	17.73	15.52	0.51	11.12	16.09	17.94
	(0.44)	(2.00)	(2.94)	(2.64)	(0.10)	(2.48)	(2.91)	(2.50)
Std.dev	19.00	19.00	19.00	19.00	19.02	19.10	19.00	19.00
Skewness	-0.57	-0.13	5.35	4.92	-0.49	-0.07	6.44	4.14
Sharpe ratio	0.11	0.47	0.93	0.81	0.03	0.58	0.85	0.94
	Transcation cost full quoted bid-ask spread							
Mean	-0.78	6.37	17.46	14.95	-2.06	8.60	15.90	17.07
	(-0.17)	(1.44)	(2.89)	(2.55)	(-0.40)	(1.95)	(2.86)	(2.40)
Std.dev	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00
Skewness	-0.58	-0.20	5.25	4.86	-0.51	-0.13	6.28	4.25
Sharpe ratio	-0.04	0.33	0.92	0.79	-0.11	0.45	0.84	0.90

Note: This table reports results of the annualized average return, t-statistics based on Newey-West standard errors in brackets, annulized sample standard deviation, skewness and Sharpe ratio for plain currency momentum strategies Mom(6,1) and Mom(9,1), optimized momentum strategies 'ACS' and 'DWS' based on Mom(6,1) and Mom(9,1). The first panel shows the results without transaction costs. The second panel shows the results with 50% of full quoted bis-ask spread. The third panel shows the results with full bid-ask spread. Data sample starts from December, 2003 to Feb 2018.

Table 3.13 – Collective Effects of Interaction terms between HML and DOL (a)

Coefficient	1		2		3		4	
	Mom(6,1)	Mom(9,1)	Mom(6,1)	Mom(9,1)	Mom(6,1)	Mom(9,1)	Mom(6,1)	Mom(9,1)
α_0	0.35	0.42	0.26	0.30	0.25	0.27	0.25	0.27
	(1.93)	(1.87)	(1.24)	(1.34)	(1.23)	(1.17)	(1.23)	(1.17)
α_B^{DOL}			0.64	1.12	0.69	1.22	0.68	1.18
			(1.44)	(2.09)	(1.65)	(2.45)	(1.58)	(2.30)
β_0	-0.38	-0.37	0.35	0.39	0.35	0.37	0.35	0.37
	(-2.51)	(-2.08)	(2.30)	(1.95)	(2.16)	(1.84)	(2.15)	(1.84)
β_B			-0.97	-0.81	-0.95	-0.75	-0.96	-0.81
			(-3.03)	(-1.81)	(-2.83)	(-1.71)	(-2.63)	(-1.72)
$I_{U,t}^{DOL}$			-0.93	-1.36	-0.95	-1.42	-0.93	-1.30
			(-2.25)	(-2.18)	(-2.29)	(-2.33)	(-1.98)	(-1.85)
ϕ_0	0.17	0.14	0.14	0.10	0.15	0.14	0.15	0.14
	(1.69)	(1.36)	(1.54)	(1.12)	(1.20)	(1.06)	(1.20)	(1.05)
ϕ_B					-0.03	-0.08	-0.02	0.01
					(-0.19)	(-0.47)	(-0.10)	(0.04)
$\phi_{B,U}$							-0.03	-0.21
							(-0.13)	(-0.77)
$Adj.R^2$	0.05	0.04	0.23	0.22	0.23	0.22	0.23	0.22

Note: This table has similar structure as Table 3 except the 'carry trade risk factor' HML_t and interaction terms are also included in the regression. It reports results of the estimated coefficients, t-statistics in the brackets and adjust R^2 for four specification of monthly times series regression. The denpendent variables are monthly return of momentum strategies $Mom(6,1)$ and $Mom(9,1)$, respectively. The independent variables are a constant intercept; the ex ante bear market indicator $I_{B,t-1}$; the contemporaneous 'dollar risk factor' DOL_t; and the contemporaneous up-market indicator, IU_t; 'carry trade factor' HML_t; and interaction terms. Coefficients α_0 and α_B^{DOL} are multiplied by 100. The sample runs from December 1997 to Feburary 2018.

Table 3.14 – Collective Effects of Interaction terms between HML and DOL (b)

Coefficient	1		2		3	
	Mom(6,1)	Mom(9,1)	Mom(6,1)	Mom(9,1)	Mom(6,1)	Mom(9,1)
α_0	0.65	0.87	0.65	0.86	0.65	0.86
	(3.65)	(4.18)	(3.66)	(4.27)	(3.65)	(4.26)
α_B^{HML}	0.82	0.37	0.65	0.22	0.64	0.20
	(1.87)	(0.63)	(1.53)	(0.37)	(1.51)	(0.32)
γ_0	0.32	0.27	0.28	0.24	0.28	0.24
	(3.25)	(2.75)	(2.79)	(2.46)	(2.78)	(2.45)
γ_B	0.26	0.33	0.27	0.34	0.26	0.32
	(0.79)	(1.06)	(0.81)	(1.03)	(0.79)	(1.10)
$\gamma_{B,U}$	-1.38	-1.39	-1.25	-1.28	-1.20	-1.18
	(-3.57)	(-3.71)	(-2.97)	(-2.87)	(-2.97)	(-3.23)
φ_0	-0.36	-0.34	-0.18	-0.19	-0.18	-0.19
	(-2.31)	(-1.94)	(-1.26)	(-1.17)	(-1.26)	(-1.17)
φ_B			-0.49	-0.42	-0.20	0.09
			(-1.38)	(-0.98)	(-0.43)	(0.14)
$\varphi_{B,U}$					-0.52	-0.91
					(-0.86)	(-1.17)
$Adj.R^2$	0.18	0.17	0.20	0.18	0.20	0.20

Note: This table reports results of the estimated coefficients, t-statistics in the brackets and adjust R^2 for four specification of monthly times series regression. The denpendent variables are monthly return of momentum strategies $Mom(6,1)$ and $Mom(9,1)$, respectively. The independent variables are a constant intercept; the ex ante bear market indicator IB_{t-1}; the contemporaneous 'dollar risk factor' DOL_t; and the contemporaneous up-market indicator, IU_t; and interaction terms. Coefficients α_0 and α_B^{HML} are multiplied by 100. The sample runs from December 1997 to Feburary 2018.

Figure 3.3 – Dynamic risk exposures of two currency momentum strategies Mom(6,1) and Mom(9,1) which is estimated by using a rolling 48-month window. Three subplots present the dynamic betas to three pricing factors: US market portfolio; dollar risk factor DOL; carry trade high minus low factor HML, repectively. Note that dynamic exposures to two currency pricing factors are estimated jointly in a two-variable regression. The shaded aeras indicate recent market drawdowns of the burst of dot-com buble (from Jan. 2001 to Apr. 2002); the subprime debt crisis(from Jan. 2008 to May 2009); The European sovereign debt crisis(from Jun. 2011 to Dec. 2012).

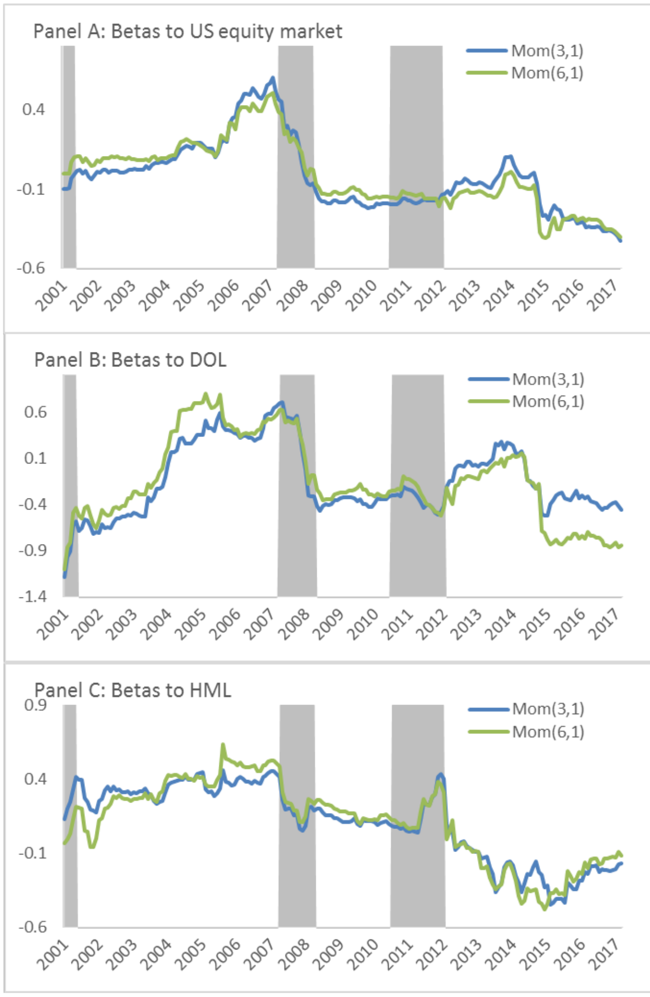

Figure 3.4 – This figure plots the cumulative return of avoid crash strategies(ACS), dynamic weighting strategies(DWS) and their base currency momentum strategies Mom(6,1) and Mom(9,1). The shaded aera correponds to US subprime debt crisis and European sovereign debt crisis. The sample period starts from Nov. 2003 to Feb. 2018.