THE PRICING OF RISK IN THE CARRY TRADE

by

Wenna Lu

A Thesis Submitted in Fulfilment of the Requirements for the Degree of Doctor of Philosophy of Cardiff University

Economics Section of Cardiff Business School, Cardiff University

March 2014

ABSTRACT

This thesis examines the relationship between foreign exchange (FX) volatility and excess returns from the currency market. We argue that FX volatility plays an important role in explaining the excess returns from the currency market so as in partially explaining the long stranding unsolved puzzles in FX market: the uncovered interest rate parity (UIP) puzzle and the purchasing power parity (PPP) puzzle.

There are two empirical parts in this thesis. In the first part, we take the FX volatility risk as risk factors to price the cross sectional excess returns from the carry trade in three different settings, the unconditional ICAPM model, the conditional ICAPM model and a model separating the volatility risk into a persistent volatility risk factor and a less persistent volatility risk factor. For all three models, we find that the excess returns from the carry trade are negatively correlated with the FX volatility risk factors. The volatility risk factors are negatively priced and can explain about 90% cross sectional excess returns from the carry trade. We argue that the excess returns from the carry trade are compensations for bearing volatility risks, especially during high volatility risk period and regardless whether the volatility risks are persistent or not.

In the second part, we investigate the puzzles in FX market under different FX volatility regimes. We find that the carry trade suffers from losses during high volatility period is because both the UIP and the PPP tends to reassert themselves under high volatility period, at least to some extent. Thus if we switch from the carry trade strategy to a PPP implied trading strategy during high volatility period, we could avoid the losses from the carry trade and have higher average excess returns. More importantly, we could make this “mixed” strategy tradable by using last period’s FX volatility state to forecast this period’s volatility state.

ACKNOWLEDGEMENTS

A PhD is a long and ambitious journey, which cannot be completed without support and encouragement. For me, words are never enough to express my gratitude towards those people who continuously contribute to the finishing of this thesis.

My first and greatest appreciation must go to my supervisor, Professor Laurence Copeland who has offered me tireless support throughout this journey. His advice, patience, generosity, and encouragement have been invaluable to me and I have benefited incredibly from those regular or irregular meetings I have had with him through the past 4 years. I owe a great debt of gratitude to him.

I would like to express my gratefulness to Professor Lucio Sarno for providing their sample data and to Professor Dr Lucas Menkhoff for comments on a working paper based on Chapter 7 of this thesis. I also would like to thank Dr Guangjie Jack Li and Dr Kevin Evans for helpful advice and stimulating discussions.

I must also thank Professor Patrick Minford and the Julian Hodge funding for the provision of studentship on my PhD studies. Without the opportunity and financial support, it would have been impossible to embark on this research.

My special thanks go to my parents and my boyfriend Yongdeng, for their great patience and unconditional care. I would not have made it this far without them.

Last but not least, my thanks also go to all staffs, especially, Elsie, Lainey and Wayne and all my friends at CARBS: Jingqi, Kailin, Anthonia and Maria who make this journey more enjoyable and colourful.

I dedicate this thesis to

my family, my boyfriend Yongdeng, and my cat

for their constant support and unconditional love.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1. INTRODUCTION

The carry trade refers to a trading strategy in foreign exchange (FX) market that borrows in currencies with low interest rates and lends in currencies with high interest rates. According to the uncovered interest rate parity (UIP), exchange rates are expected to move in the direction to offset the interest rate differentials. However, empirically, exchange rates are found to move in the opposite direction (Froot and Thaler (1990) and (Burnside, Eichenbaum et al. (2006))), i.e. high interest rate currencies tend to appreciate while low interest rate currencies tend to depreciate. The carry trade is a trading strategy by exploiting the failure of the UIP and this seemingly naive trading strategy has been profitable for decades and has been widely used by FX traders. (Lustig and Verdelhan (2008)) observe that a carry trade strategy levered up to match the volatility of stock returns would, over a period of 25 years, produce a return of $3.36 for every dollar invested compared to $ 2.71 for an investment in the stock market yielding a cumulative return difference of 65% (Abhyankar, Gonzalez et al. 2011). During the financial crisis in 2008, the carry trade has made substantial losses; however, its losses are relatively small when compared to the historic returns from the carry trade. The question is, given the very liquid foreign exchange market and the existence of international currency speculations, why the carry trade has been profitable for such a long time.

There has been an on-going debate about risk and non-risk based explanation in explaining the excess returns from the carry trade. Behind this debate is the debate about whether the underlying foreign exchange market is efficient or not. The risk-based explanation believes that by borrowing low interest rate currencies and investing in high interest rate currencies, investors load up on certain risks, the excess returns from the carry trade are simply compensations to investors for bearing those risks. While the non-risk based explanation argues that the excess returns arise because the FX market is not efficient.

In the first part of empirical work of this thesis, we argue that the excess returns from the carry trade can be explained by the FX volatility risk. To test this, based on the theoretical support of Chen (2002) version of Intertemporal Capital Asset Pricing Model (ICAPM), we provide three different settings: an unconditional ICAPM model, a conditional ICAPM model and a model with separated long- and short-run volatility risks obtained from a Component-GARCH model.

Chen (2002) argues that apart from changes in FX market return, risk-averse investors also want to directly hedge against changes in future market volatility. Therefore we would have a pricing kernel which contains two factors: the FX market return and the FX volatility to price the cross-sectional excess returns of the carry trade. We follow Menkhoff, Sarno et al. (2012) to aggregate average daily exchange rate changes into monthly observation as a proxy for FX volatility and this is equivalent to the measure of realized volatility. We find that the FX volatility factor is able to explain about 90% cross sectional excess returns from the carry trade for both 48-all-country sample and 29-OECD-country sample over a period of 334 months. The FX volatility risk is priced negatively which indicates that investors wish to buy insurance against changes in FX volatility. High interest rate currencies are negatively correlated with FX volatility risks and thus require higher return while low interest rate currencies are positively correlated with FX volatility risks and thus require lower returns. We name this model as unconditional ICAPM model as the loadings and price of FX volatility risk are not regime dependent.

Also we find that the volatility risk factor provides lesser pricing errors for the subsamples including the recent 2008 financial crisis period, which suggests that investors may care differently about the FX volatility risk during different volatility states. Therefore we propose a model with the same pricing kernel but both the loadings and the price of FX volatility risks are regime dependent on the FX volatility risk levels. We call this model the conditional ICAPM model, so as to distinguish from the unconditional ICAPM model. We find that the excess return from the carry trade is actually the compensation for bearing volatility risk during high volatility state, at least for the 29-OECD-country sample. Further, by pricing the volatility risk during different volatility states separately, we have a model which provides better fit than the unconditional ICAPM model. By explaining the excess return from the carry trade, we also partially explain the UIP puzzle.

We then start from a different angle by examining the relationship between the excess returns of the carry trade and the FX volatility risk at different frequencies: a persistent volatility risk component, the long-run volatility risk component, and a less persistent volatility risk, the short-run volatility risk. As argued by (Cochrane (2005)), that there should be a unique pricing kernel which is able to price all financial assets. Thus, as inspired by successful attempts in stock market, we follow Adrian and Rosenberg (2008) to decompose FX market volatility into short- and long-run components by using a Component-GARCH model. We then take the two volatility risk components as separated pricing factors to price the carry trade portfolios. We find that prices of both volatility risk components are negative which implies that investors pay insurances against changes in volatility, even if those changes have little persistence. Also we find that after we price the volatility risk components separately, the pricing errors are reduced, and this two components model provides better fit than the unconditional ICAPM model. Further, the volatility components we use are from a Component-GARCH model, which is a conditional measure of volatility and differs from the realized volatility measure as used in previous two settings, this proves that the FX volatility risk is able to explain the excess returns from the carry trade regardless the forms in which we proxy it.

To interpret the economics of long- and short-run volatility components, as inspired by Adrian and Rosenberg (2008) in stock market, we relate the long-run volatility component to the U.S. business cycle and the short-run volatility component to a measure of the tightness of financial constraints. However, we find the correlations for both of them are quite low. This is consistent with the literature that exchange rate is not correlated with traditional asset pricing variables (Burnside 2011, Burnside, Eichenbaum et al. 2011).

In the second part of our empirical work, we investigate the puzzles in FX market by examining the excess returns from different currency trading strategies under different FX volatility regimes.

We start from testing the Fama regression (Fama 1984) regime dependent on FX volatility and find that the negative beta estimates documented in most literature is only true for low FX volatility period. For high FX volatility period, estimates of beta tend to be positive or negative but small in absolute value. This finding explains the excess return pattern of the carry trade i.e. high and steady returns for a long period then followed by a crash during market turmoil.

Further, we test the relationship between the changes in exchange rate and real exchange rate deviations for individual currency regime dependent on FX volatility, and we find that for high volatility periods, there are strong connections between exchange rate changes and fundamentals, exchange rates revert back to their fundamentals more largely and quickly in high volatility periods than that in low volatility periods. Then we argue that crashes of the carry trade are caused by the quicker and larger exchange rates adjustments to their fundamental values. Suggested by these results, apart from the carry trade strategy, we set up another trading strategy, the fundamental strategy, by borrowing overvalued currencies and lending undervalued currencies. This fundamental strategy provides higher returns during high volatility periods when the carry trade strategy performs poorly. This is because those normal volatility periods are not only the periods in which the carry trade accumulates large returns but also the periods in which the exchange rates accumulate large deviations from their fundamentals, then in high volatility periods exchange rates adjust back largely and quickly towards their fundamentals and the carry trade strategy suffers losses. However, the fundamental strategy, which is borrowing most overvalued currencies and lending most undervalued currencies, captures the possible changes in exchange rates for both investment and funding currencies, and therefore provides large returns.

Therefore, it is natural to form a more profitable strategy by mixing the two strategies together, depending on volatility regimes. We define the high FX volatility regime as the times when the FX volatility falls in its fourth quartile, otherwise we are in the normal

FX volatility regime. We choose the carry trade strategy if we are in the normal volatility regime, and we switch to the fundamental strategy if we are in the high volatility regime. By doing this, we can form a much more profitable strategy with an annualized average return at about 10% without adjusting transaction costs. The average return after adjusting transaction costs is also as high as 8.6% p.a. Further, since we find that the FX volatility is auto-correlated at about 67%, we can use last period FX volatility regime as a forecast for current period volatility regime. By forecasting volatility regime, we can make the mixed strategy tradable. We find that although the average excess return of the tradable mixed strategy by using last period's volatility as regime is not as large as that of the non-tradable mixed strategy by using current period's volatility as regime (the average annual average return reduces by about 1%), it is still much larger than the excess return from either the carry trade strategy or the fundamental strategy, especially for the 2008 financial crisis periods. We find it is difficult to use either FX volatility risk factor or crash risk factor to explain the excess returns from the tradable strategy. If we suppose the pricing models are not miss-specified, then more complicated strategies provide higher returns, this indicates FX market inefficiency.

The outline of this thesis is as follow: in Chapter2, we provide a general review of literature related to this thesis (more detailed and specific reviews are provided in relative chapters), and in chapter 3 we report the main data set used in this thesis together with descriptive statistics for the main asset we study in this thesis: the interest rate sorted currency portfolios. In Chapter 4, Chapter 5 and Chapter 6, we use volatility risk factor to explain the cross sectional excess returns from the carry trade, unconditionally, conditionally and with different frequency volatility risk factors.

Chapter 7 examines the currency excess returns from other trading strategies rather than the carry trade regime dependent on the FX volatility. Chapter 8 concludes.

2. LITERATURE REVIEW

2.1. PUZZLES IN EXCHANGE RATE MARKET

There are a number of puzzles in exchange rate economics which economists struggle to explain either in economic theory or in empirical practice. Among these puzzles, we briefly review two of them: the forward premium puzzle and the purchasing power parity puzzle.

"Forward premium puzzle" refers to the puzzle that the forward premium tends to be inversely related to future exchange rate changes, in contrast to the Uncovered Interest Parity (UIP) hypothesis(Hansen and Hodrick 1980, Fama 1984).

If we assume that investors are risk neutral and have rational expectations, then the Uncovered Interest Parity (UIP) condition can be denoted by Eq. 2.1:

$$E_t(s_{t+1}) - s_t = i_t^* - i_t \qquad \text{Eq. 2.1}$$

where s_t is the logarithm of the spot price in foreign currency per unit of home currency at time t, i_t is the one-period risk-free interest rate at time t for home currency and i_t^* is the one-period risk-free interest rate at time t for foreign currency. It states that in an efficient speculative market, exchange rates should fully reflect information available to market participants and it should be impossible for a trader to earn excess returns by speculation because the expected change in exchange rate between two currencies will offset any interest rate differential.

In most literature, this relationship is analysed in the context of the relationship between spot and forward exchange rates under the assumption that covered interest rate parity (CIP) (Eq. 2.2) holds.

$$f_t - s_t = i_t^* - i_t \qquad \text{Eq. 2.2}$$

where f_t is the logarithm of the one-period forward price in foreign currency per unit of home currency at time t, CIP is a mild no arbitrage condition and there are extensive literature suggesting that CIP holds (Sarno and Taylor 2002). Note that unlike CIP, UIP is not a no-arbitrage condition because the expected exchange rate is unknown at time t due to risks of future exchange rate movements and therefore, deviations from the UIP do not imply arbitrage profits.

Using CIP to replace the interest rate differential $i_t^* - i_t$ with the forward premium/discount $f_t - s_t$, then to test UIP is equivalent to test Eq. 2.3 with the null hypothesis $\alpha = 0, \beta = 1$ and the regression error u_{t+1} must be uncorrelated with information available at time t (Fama 1984).

$$s_{t+1} - s_t = \alpha + \beta(f_t - s_t) + u_{t+1} \qquad \text{Eq. 2.3}$$

This regression appears frequently in the literature and much of literature refers this equation the Fama regression[1]. Under the null hypothesis, the log of the forward rate provides an unbiased forecast of the log of the future spot exchange rate.

Empirical studies based on the estimation of Fama Equation for a large variety of currencies and time periods, generally report results reject the UIP. It constitutes a stylized fact that estimates of beta using exchange rates against the US dollar are often statistically insignificantly different from zero and generally closer to minus unity than

[1] The possible effects of unit roots in spot rates changed the standard test equation. To achieve stationary, current spot rates were subtracted from both sides of the original test equation. See Lewis, K. K. (1994). Puzzles in international financial markets, National Bureau of Economic Research.

to plus unity. As reported by Froot and Thaler (1990) and confirmed by (Burnside, Eichenbaum et al. (2006)) the average estimate for beta is -0.85 across the countless studies that focus on this equation. This negative value of beta is the central feature of the forward bias puzzle. It means that instead of offsetting interest rate differential between two currencies, the future change in spot exchange rate is in the opposite direction of the UIP forecast, which will further enlarge the UIP deviation. In other words: high interest rate currencies tend to appreciate and low interest rate currencies tend to depreciate.

The purchasing power parity (PPP) hypothesis states that national price levels should be equal when expressed in a common currency. Although very few economists would believe that this simple proposition holds at each point in time, there is a large literature in international finance has examined empirically the validity of PPP in the long run. To investigate the validity of PPP in the long run, one can test if nominal exchange rates and relative prices are cointegrated or it is equivalent to test whether the real exchange rate is stationary over time. The logarithms of real exchange rate which is defined as the nominal exchange rate adjusted for relative price levels are shown in Eq. 2.4.

$$q_t = s_t + (p_t - p_t^*) \qquad \text{Eq. 2.4}$$

where q_t is denoted as logarithm of real exchange rate in foreign currency per unit of home currency at time *t.* The logarithm of consumer price index is denoted as p_t for home country and p_t^* for foreign countries at time *t*. The real exchange rate q_t may thus be interpreted as a measure of the deviation from PPP and must be stationary for long-run PPP to hold. (Rogoff 1996, Sarno 2005).

There is a large body of literature testing the long-run PPP since whether long-run PPP holds has important economic implications.

In the conventional test for PPP, the null hypothesis is that the process generating the real exchange rate series has a unit root, while the alternative hypothesis is that all of the roots of the process lie within the unit circle. The results are mixed: earlier studies generally reported the absence of significant mean reversion of the real exchange rate for the recent floating period (Mark 1990), but the results are different across different historical periods and across different nominal exchange rate regimes. There are debates on what sort of price index should be used implementing PPP: the consumer price index or the producer price index. Also, to increase the power of the test to reject the null hypothesis, researchers propose to use long span studies (Lothian and Taylor 1996) or panel unit root tests (Abuaf and Jorion 1990) in testing for mean reversion in the real exchange rate. Regardless of different price index used and test methods applied, whether long-run PPP is valid during the recent floating exchange rate regime is still one of the unsolved puzzles in this area.

Followed by the conventional test for long-run PPP, a number of authors argue that the presence of transactions costs may imply a nonlinear process in real exchange rate and they developed theoretical models of nonlinear real exchange rate adjustment arising from transactions costs in international arbitrage(Benninga and Protopapadakis 1988).

Based on the nonlinear real exchange rate literature, Taylor, Peel et al. (2001) suggests that the exchange rate will become increasingly mean reverting with the size of the deviation from the equilibrium level. Michael, Nobay et al. (1997) apply the exponential smooth transition autoregressive (ESTAR) model, which allows for smooth rather than discrete adjustment, to real exchange rate. Their results clearly reject the linear framework of real exchange rate in favour of an ESTAR process.

Taylor, Peel et al. (2001) provide strong confirmation that four major real bilateral dollar exchange rates are well characterized by nonlinearly mean reverting processes.

These models imply an equilibrium level of the real exchange rate in the neighbourhood, of which the behaviour of the real exchange rate is close to a random walk, becoming increasingly mean reverting with the absolute size of the deviation from equilibrium (Sarno, 2005). The systematic pattern in the estimates of the nonlinear models provides strong evidence of mean-reverting behaviour for PPP deviations. These results shed some light on the PPP puzzles and helps explain the mixed results of previous studies.

2.2. THE CURRENCY CARRY TRADE

The carry trade is a trading strategy in foreign exchange (FX) market that borrows in currencies with low interest rates and lends in currencies with high interest rates. It is a currency speculation strategy by exploiting the forward premium puzzle.

As mentioned in Section 2.1, the forward premium puzzle refers to the biasness of forward discounts in forecasting future exchange rate changes, and even in wrong directions. Given the covered interest rate parity holds, this is equivalent to the empirical failure of the uncovered interest rate parity which argues that the future changes in exchange rate should offset interest rate differential between two currencies, i.e. low interest rate currencies tend to appreciate and high interest rate currencies tend to depreciate. Fama (1984) and a lot of literature find that empirically the opposite is true that the UIP predicts future exchange rate changes in the opposite direction, i.e. high interest rate currencies appreciate a little on average although with a low predictive R^2.

In the financial markets, efforts to exploit the forward discount bias generally go under different names. Exploiting the bias means going long in the currency that sells at a forward discount, relative to others. By covered interest parity, this is the same thing as going long in the currency that pays a higher shout-term nominal interest rate, relative to others. In the early 1990s, among European currencies, the Italian interest rates are above the German interest rates and the strategy of borrowing in German Mark and investing in Italian lira was known as the convergence play.

In the mid-1990s, with Japanese interest rates very low, the strategy of borrowing in Japanese yen and going long in other currencies-especially dollar-linked currencies in Asia – was known as the yen carry trade.

During the years 2001-2006, with US interest rates very low, the strategy of borrowing in dollars and going long in euro or emerging market currencies has been known as the dollar carry trade.

Although under different names, these trading strategies are all currency trading strategies that exploit the forward premium puzzle, thus are generally named as the carry trade in the literature. "Carry" means interest rate differential, the carry trade is a trading strategy in foreign exchange market that borrows in low interesting currencies and lending high interest rate currencies.

The carry trade has attracted investors because it has been profitable for decades. As documented by many researchers, carry traders benefit from high Sharpe ratios compared with stock market (Burnside, Eichenbaum et al. 2006, Burnside, Eichenbaum et al. 2008). Lustig and Verdelhan (2008) observe that a carry trade strategy levered up to match the volatility of stock returns would, over a period of 25 years, produce a return of $3.36 for every dollar invested compared to $ 2.71 for an investment in the stock market yielding a cumulative return difference of 65% (Abhyankar, Gonzalez et al. 2011).

However it is a profitable and popular currency trading strategy, the excess return from the carry trade has exhibited one striking pattern: it has a high and stable return during a long period, but then suffers from a big loss during crisis period as high (low) interest rate currencies depreciate (appreciate) dramatically during crisis periods. As mentioned by Plantin and Shin (2006), high interest rate currencies has exhibited the classic price pattern of "going up by stairs, and coming down by elevator." Historically, there are long times during which one would have happily make money on average with the carry trade strategies, but then these times were dramatically punctuated (though not fully reversed) by crises, in 1992 in Western Europe, 1997-98 in East Asia, and 2008 in Central Europe, Iceland, and elsewhere.

Although the carry trade has made substantial losses during crisis periods, its losses are relatively small when compared to the historic returns from the carry trade. According to Menkhoff, Sarno et al. (2012), the carry trade portfolio of borrowing low interest rate currencies and lending high interest rate currencies from 48-country currencies has an average excess return of 7.2% annually after deducting transaction costs from 1983 to 2009, and that makes a cumulative excess return of about 190% over 26 years.

The question is how to explain the excess return from the carry trade given the very liquid foreign exchange market and the existence of international currency speculations. This question has received a great deal of attentions in the academic literature, and in next section, we review some of them.

2.3. RISK BASED EXPLANATIONS AND NON-RISK BASED EXPLANATIONS

In explaining the excess returns from the carry trade, generally speaking, there are two strands of literature: the risk-based explanation and the non-risk based explanation. The risk-based explanation argues that the excess returns from the carry trade are compensations for bearing certain risk while the non-risk based explanations argue that these excess returns reflect market inefficiencies.

The risk-based explanations understand the carry trade profits within a standard asset pricing framework based on systematic risk. Earlier contributions offer three types of fully-specified models. Verdelhan (2010) uses habit preferences in the vein of Campbell and Cochrane (1995), Bansal and Shaliastovich (2013) build on the long run risk model pioneered by Bansal and Yaron (2004), and Farhi and Gabaix (2008) argue the standard consumption-based model with disaster risk following Barro (2006). These three models have two elements in common: a persistent variable drives the volatility of the log stochastic discount factor and this variable commoves negatively with the country's risk-free interest rate. Backus, Foresi et al. (2001) show that the latter is a necessary condition for models with log-normal shocks to reproduce the forward premium puzzle.

Recently, literature explains stock market returns has shed light on currency market. The Fama and French (1993) portfolio sorting approach has a long tradition in the stock literature. The sorting procedure eliminates the diversifiable, stock-specific component of returns that is not of interest, thus producing much sharper estimates of the risk-return trade-off in stock markets. Lustig and Verdelhan (2007) bring this sorting approach to the literature on currency returns by sorting currencies into portfolios according to their sizes of forward discount. This is equivalent to sorting according to their interest rate differentials with certain currency providing covered interest rate parity hold. By sorting these currencies into portfolios, the currency-specific component of exchange rate changes that is not related to changes in the interest rate has been abstracted. This isolates the source of variation in excess returns that interests us, and it creates a large average spread between low and high interest rate portfolios. Recent literature which follows this sorting approach includes: (Lustig, Roussanov et al. (2011)), Burnside, Eichenbaum et al. (2011) and Menkhoff, Sarno et al. (2012).

Burnside (2011) explores traditional factor models, which have been used to explain the returns to stock market portfolios, e.g. the CAPM, the Fama-French three factor model and the consumption-CAPM. He finds that these traditional models fail to explain the returns to the carry trade. That is because those traditional factors are either uncorrelated with carry trade returns, i.e. they have zero betas, or the betas are much too small to rationalize the magnitude of the returns to the carry trade.

Burnside (2011) also examines less traditional factor models. These models adopt risk factors constructed specifically to price currency returns. Two successful examples are the *DOL* factor and *HML* factor constructed by Lustig, Roussanov et al. (2011) and the *VOL* factor by Menkhoff, Sarno et al. (2012).

Lustig, Roussanov et al. (2011) set up a framework assuming that the stochastic discount factor is linear in two pricing factors: (1) a FX market factor that measures the average excess return of all foreign currencies (the *DOL* factor) and (2) a carry-trade risk factor based on a zero-cost strategy that goes long in a portfolio of currencies of high interest rates countries and short in a portfolio of currencies of low interest rates countries (the *HML* factor). These factors work well in explaining the cross-sectional returns of the carry trade, but it is challenging to explain the economic interpretations of these factors.

Ang, Hodrick et al. (2006) use the Intertemporal-CAPM theory (Chen (2002)) and employ changes in the *VIX* index to proxy for volatility risk, considered as a non-traded risk factor. They find that market volatility is priced in the cross-section of US stock returns and that stocks with a higher sensitivity to volatility risk do earn lower returns.

Inspired by Ang, Hodrick *et al.* (2006) and Lustig, Roussanov et al. (2011), Menkhoff, Sarno et al. (2012) build up a stochastic discount factor which is linear in (1) the FX market return and (2) the innovation in FX market volatility. They adopt the *DOL* factor of Lustig, Roussanov et al. (2011) as a measure of the FX market return and create the *VOL* factor, which is similar to the measure of realized volatility, as a measure of the FX market volatility. Their model explains about 90% of the cross-sectional excess returns of the forward discount sorted currency portfolios and meanwhile has a strong theoretical support by the Intertemporal-CAPM model of Chen (2002), which argues that risk-averse investors also want to directly hedge against changes in future market volatility. Consistent with the results in stock market by Ang, Hodrick et al. (2006), Menkhoff, Sarno et al. (2012) find that FX volatility risk is negatively priced which indicates that investors would require a premium for bearing volatility risk. Currency portfolios have different loadings on volatility risk which provides a spread on loading of volatility risk between high interest rate currencies and low interest rate currencies and thus explains the cross-sectional returns.

Both Lustig, Roussanov et al. (2011) and Menkhoff, Sarno et al. (2012) models fall in the linear model unconditional category in the sense that neither prices nor loadings of risk factors are conditional on other factors. There are also nonlinear models which allow both the price and loadings of risk factors to change conditioning on other factors, such as the downside risk model of Ang, Chen et al. (2006).

Ang, Chen et al. (2006) study stock markets, by allowing both the market price of risk and the beta of currencies with the market to change conditional on the aggregate market return. Their conditional CAPM model fits better than the unconditional CAPM model in explaining the excess returns from stock market. The theory behind is that investors care differently about downside losses versus upside gains. Agents who place greater weight on downside risk demand additional compensation for holding stocks with high sensitivities to downside market movements. Lettau, Maggiori et al. (2013) examine the pricing ability of CAPM in currency market and find that the unconditional CAPM cannot explain the cross section of currency returns is because the spread in currency beta is not sufficiently large to match the cross sectional variation in expected returns. Therefore, inspired by Ang, Chen et al. (2006), they allow both price and loadings of market risk factor to vary conditioning on the level of FX market return and they find that the loadings of market risk between high and low interest currencies is highly conditional on bad market returns, and the market risk price is also higher than it is in the unconditional model.

Their model is consistent with the rare disaster explanation of the forward premium puzzle by Farhi and Gabaix (2008), which argues the standard consumption-based model with disaster risk following Barro (2006). They argue that the forward premium puzzle can be understood by the compensation of extreme events and the possibility of rare but extreme events is an important determinant of risk premiums in asset markets.

Apart from the FX market return which plays an role as a conditioning variable when explaining the excess return from the carry trade, literature are also emphasize the importance of FX volatility as a conditioning variable when examining the excess returns from the carry trade.

As reviewed in previous section, empirical studies generally report results reject the UIP as reported by Froot and Thaler (1990) and confirmed by (Burnside, Eichenbaum et al. (2006)). However, Clarida, Davis et al. (2009) find that the violation of the UIP is an artefact of the volatility regime and when volatility is in a high regime, the UIP predicts future exchange rate changes in the right direction. They take three different approaches to proxy the FX volatility: the realized volatility, the currency option implied volatility and the conditional volatility from a GARCH model. Their results are reported to be consistent among different methods to proxy FX volatility.

The findings of Clarida, Davis et al. (2009) are consistent with the historical performance of the carry trade that it has relative high and stable returns for a long period, but then suffers from big losses during crisis period. The big losses from the carry trade are actually results of UIP reasserting itself during high volatility period. The speed of exchange rate adjusts toward the UIP level is quicker than that it deviates away from the UIP equilibrium, as observed by Plantin and Shin (2006) that high interest rate currencies has exhibited the classic price pattern of "going up by stairs, and coming down by elevator."

These finds are consistent with the crash risk literature of (Brunnermeier, Nagel et al. (2008)), in which they argue that a possible explanation for the high Sharpe ratio of carry trades is that it represents the price of crash risk, i.e. a sudden adjustments in exchange rate. The existent of crash risk can be found from the negative skewed third moments of the carry trade returns.

Further, Nozaki (2010) argues that the crash risk inherent in carry trades is as a result of exchange rate adjustments toward their fundamental value. Therefore a trading strategy of taking long position in undervalued currencies and taking short position in overvalued currencies is less prone to crash risk and it outperforms the carry trade during the recent financial crisis as the return of this strategy characterized with a positive third moments. Jordà and Taylor (2012) argue that the deviation from the fundamental equilibrium exchange rate is an important predictor of exchange rate movements by using a vector error correction model. They find that fundamental-based strategies for currency speculation, especially those that incorporate the nonlinear adjustment of the exchange rate, outperform carry trades since they are crash-risk proofed. They show that by incorporating fundamental information in currency trading strategies, higher average returns would be obtained with no increase in the variance and even a decrease of the negative skewness in absolute value. They argue that a more complicated strategy provides higher return, suggesting FX market inefficiency.

Besides the risk based explanations, another strand of literature is the non-risk based explanations which argue that the excess returns reflect market inefficiencies. Recent successful attempts include: Lyons (2001) limits-to-speculation hypothesis; Gourinchas and Tornell (2004) investor-distorted-belief hypothesis; Bacchetta and Van Wincoop (2010) investor-rational-inattention mechanism;

The limits to speculation hypothesis of Lyons (2001) is based on the idea that financial institutions only take up a currency trading strategy if this strategy is expected to yield an excess return per unit of risk that is higher than the one implied by alternative trading strategies, such as, a simple buy and hold stock strategy. In the neighbourhood of UIP, expected excess returns and hence the forward bias are statistically significant and persistent but economically too small to attract speculative capital, while for expected excess returns which are large enough to attract speculative capital the spot forward relationship reverts rapidly towards the UIP condition.

Gourinchas and Tornell (2004) assume that the forward premium follows a persistent process but investors mistakenly perceive an additional transitory component in its dynamics. This distorted belief leads the nominal exchange rate to underreact to interest rate innovations.

Bacchetta and Van Wincoop (2010) develop a model where information is costly to acquire and process. Because of these costs, many investors optimally choose to assess available information, and revise their portfolios infrequently. This rational inattention mechanism produces a negative UIP coefficient along the lines suggested by Froot and Thaler (1990) and Lyons (2001): if investors are slow to respond to news of higher domestic interest rates, there will be a continued reallocation of portfolios towards domestic bonds and an appreciation of the currency subsequent to the shock.

3. Data and Stylized Facts

3.1. Introduction

In this chapter, we describe the main data set used in this thesis. These data are the main data set used in the four main empirical chapters. For those specific data used only in a certain chapter, we will only introduce them in the relative chapter.

The structure of this chapter is as follow: in Section 3.2, we introduce the currency exchange rate data used in this thesis and we also provide a measure of FX volatility. In Section 3.3, we explain the way we sort currency into portfolios with and without transaction costs deduction and we also provide the descriptive statistics of excess returns for associated portfolios. Section 3.4 concludes.

3.2.DATA

In this thesis, we use the data of spot exchange rates and 1-month forward exchange rates versus the US dollar to construct monthly excess returns for each currency in both two samples: 48-all country sample and 29-OECD country sample. To extract real exchange rates, we also use consumer price index data for 29-OECD countries. Moreover, bid and ask spot exchange rates and 1-month forward exchange rates versus the US dollar are used to deduct for transaction costs and to proxy for liquidity risk. Our data period spans from November 1983 to September 2011, and further extends to March 2013 for out of sample forecast.

The 48-all country sample contains the following countries: Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Croatia, Cyprus, Czech Republic, Denmark, Egypt, Euro area, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Kuwait, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Russia, Saudi Arabia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Ukraine, and the United kingdom. Menkhoff, Sarno et al. (2012) use the same sample but for a shorter period[2].

We also have another sample which contains 29-OECD countries[3]:Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Euro Area, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, South Korea, Mexico, Netherlands, New

[2] The sample of Menkhoff et al. (2012) covers from November 1983 to August 2009

[3] We exclude Chile, Estonia, Israel, Luxembourg and Turkey which are also OECD members due to data availability and stability.

Zealand, Norway, Poland, Portugal, Slovakia, Spain, Sweden, Switzerland and the United Kingdom.

The empirical tests are carried out mainly at the monthly frequency. However, we also use daily exchange rates of 48 countries to generate monthly realized FX market volatility.

3.2.1. Spot exchange rates and forward exchange rates

In this thesis, we use the data for spot exchange rates and 1-month exchange rates versus the US dollar to construct excess returns from the carry trade. Both the spot exchange rates and the forward exchange rates are the middle rates at the end of the day for each month. Data are obtained from BBI and Reuters (via DataStream)[4].

Following Menkhoff, Sarno et al. (2012) and the large literature since Fama (1984), we will work in logarithms of spot and forward rates for ease of exposition and notation. However, discrete returns rather than logarithm returns are used for asset pricing test to avoid having to assume joint log-normality of returns in the pricing kernel (Lustig, Roussanov et al. 2011).

We take US dollar as domestic currency and other currencies as foreign currencies. For each foreign currency the Log excess returns of borrowing the domestic US dollar and investing in each other foreign currency is calculated as interest rate differential minus the change in log exchange rate. (Eq. 3.1)

---

[4] Lustig, Roussanov et al. (2011), Menkhoff et al. (2012) and Burnside et al. (2008) also use these data but for different samples and shorter periods.

$$rx_{t+1} = (i_t^* - i_t) - (s_{t+1} - s_t) \qquad \text{Eq. 3.1}$$

where s_t is the log of the spot price in foreign currency per unit of domestic US dollar at time t, f_t is the log of the one-period forward exchange rate at time t, i_t is the one-period risk-free interest rate at time t for US dollar and i_t^* is the one-period risk-free interest rate at time t for foreign currency.

In normal conditions, forward rates satisfy the covered interest rate parity condition; the forward discount is equal to the interest rate differential (Eq. 3.2) Covered interest rate parity is a mild no arbitrage condition and has been proved to hold by extensive empirical evidence as shown in the survey of Sarno and Taylor (2002).

$$f_t - s_t = i_t^* - i_t \qquad \text{Eq. 3.2}$$

Using CIP and replacing the interest rate differential in Eq. 3.1, we can express the log excess return as in Eq. 3.3 and therefore we do not need to obtain interest rate data.

$$rx_{t+1} = (f_t - s_t) - (s_{t+1} - s_t) = f_t - s_{t+1} \qquad \text{Eq. 3.3}$$

Following Lustig, Roussanov et al. (2011) and Menkhoff, Sarno et al. (2012), we also provide discrete returns for asset pricing test and it is denoted in capital letters in Eq.3.4.

$$RX_{t+1} = \frac{F_t - S_{t+1}}{S_t} \qquad \text{Eq. 3.4}$$

We do not provide the descriptive statistics of excess return for each currency; instead, we will provide the descriptive statistics of excess return for portfolios, which are the main asset we study in this thesis, in Section 3.2.

3.2.2. THE FX MARKET VOLATILITY AND INNOVATIONS

To generate realized foreign exchange (FX) market volatility, we follow Menkhoff, Sarno et al. (2012) start from daily frequency to generate the volatility of monthly frequency. We take the daily middle rate of 48 currencies to proxy for the foreign exchange market volatility. All 48 currencies are incorporate here in order to get a closer proxy for the FX market volatility.

The volatility is denoted as VOL_t, and it is defined in Eq.3.5

$$VOL_t = \frac{1}{T_t}\sum_{T \in T_t}\left[\sum_{k \in K_\tau}\left(\frac{|\Delta s_\tau^k|}{K_\tau}\right)\right] \qquad \text{Eq. 3.5}$$

where $|\Delta s_\tau^k|$ is the absolute daily change in spot rates for each currency k on each day τ in the sample. We then average over all 48 currencies available on any given day and average daily values up to the monthly frequency. This proxy is similar to the measures of realized volatility (Andersen, Bollerslev, et. al, 2001). However, we follow Menkhoff, Sarno et al. (2012) here to use absolute returns and not squared returns in order to minimize the impact of outlier.

In Table 3.1 Panel A, we provide the quartiles, the mean and the coefficient of an AR (1) regression for VOL_t which indicates that VOL_t is auto-correlated with a significant coefficient about 0.67. In order to measure the innovation of VOL_t, we need a variable which is not auto-correlated and thus we examine both the first difference of VOL_t, denoted as $DVOL_t$ and the AR(1) residual of VOL_t, denoted as ΔVOL_t. As shown in Panel B of Table 3.1, the first difference $DVOL_t$ is significantly autocorrelated at about -28% and we reject the null of no-autocorrelation from the LM statistics while the AR (1) residual ΔVOL_t is not autocorrelated and we do not reject the null hypothesis of no-autocorrelation with 10% significant level. Therefore, we use the AR(1) residual ΔVOL_t to measure the innovation of FX volatility, which is also consistent with the measure in Menkhoff, Sarno et al. (2012). We also provide the quartiles and the mean for ΔVOL_t in Table 3.1 Panel A.

In Figure 3.1, both VOL_t and ΔVOL_t are plotted. Shaded areas in the figure correspond to U.S. NBER recessions[5]. Both volatility and volatility innovation increase dramatically during the most recent recession (December 2007 to June 2009). However, there are no significant increases during the previous two shaded recessions.

---

[5] The NBER recessions in our sample period include the following periods: July 1990 to March 1991, March 2001 to November 2001 and December 2007 to June 2009. The determinations of these periods are made by the NBER's Business Cycle Dating Committee and provided on the National Bureau of Economic Research website. The NBER defines a recession as a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales. (http://www.nber.org/cycles.html)

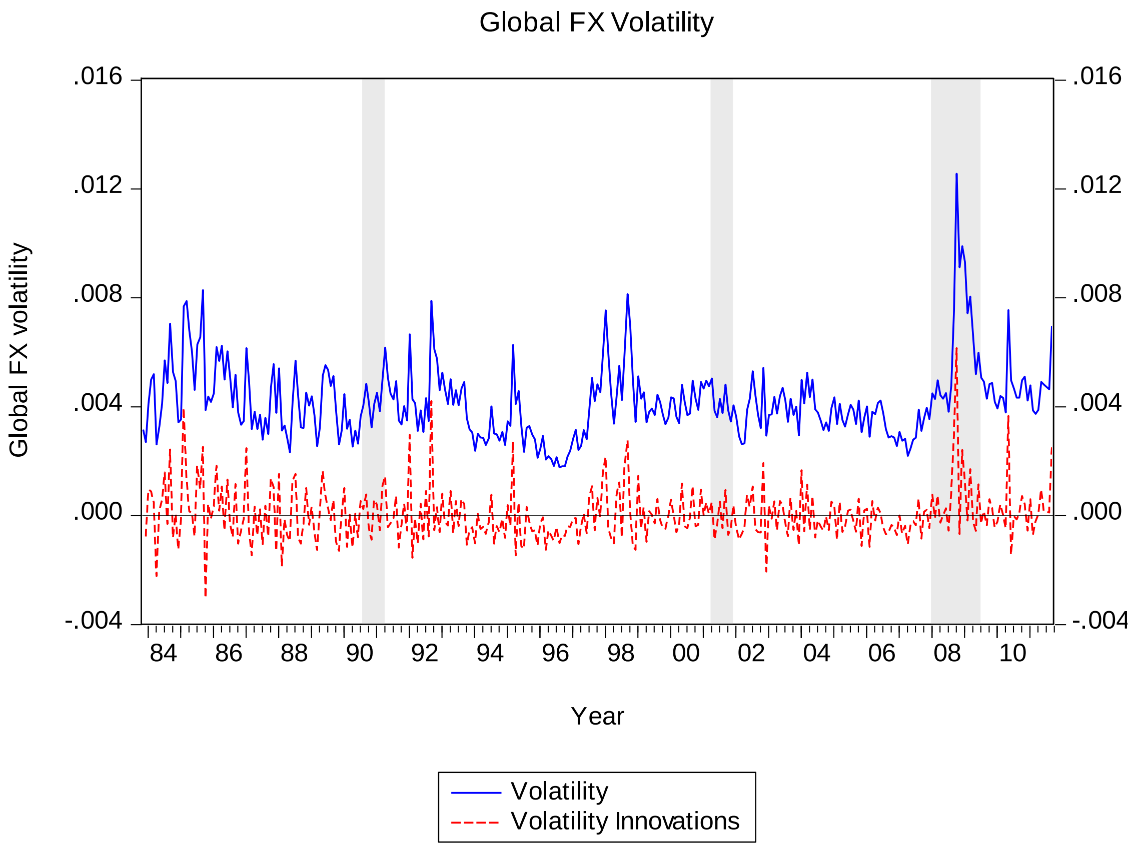
Table 3-1 Summary Statistics of Realized FX Volatility

Panel A. The Quartile of Realized FX Volatility							
	Minimum	1st Quartile	Medium	Mean	3rd Quartile	Maximum	AR(1)
VOL_t	0.0017	0.0033	0.0040	0.0042	0.0048	0.0125	0.6733 [0.0411]
ΔVOL_t	-0.0031	-0.0006	-0.0001	0.0000	0.0005	0.0061	-0.0895 [0.0552]

Panel B. Autoregressive estimation of realized FX volatility			
Realized FX volatility at 1st difference: $DVOL_{t+1} = \beta_1 + \beta_2 DVOL_t + \mu_t$			
	β_1	β_2	LM-stat (2-lag)
Coef.	0.0000	-0.2783***	18.8401
S.E.	[0.0000]	[0.0531]	(0.0001)
Realized FX volatility innovation: $\Delta VOL_{t+1} = \beta_1 + \beta_2 \Delta VOL_t + \mu_t$			
	β_1	β_2	LM-stat (2-lag)
Coef.	0.0000	0.0895	3.6989
S.E.	[0.0000]	[0.052]	(0.1000)

Note: Panel A of this table provides the quartiles and the mean for both FX volatility (VOL) and volatility innovations (the AR(1) residual of VOL). The AR(1) coefficients for both variables are also provided with the standard errors provided in the brackets. In Panel B, we conduct AR(1) estimations for both $DVOL$(the first difference of VOL) and ΔVOL. The standard errors are provided in the brackets while for the LM test with two-lags, the p-values are provided in the parentheses.

Figure 3-1 FX Volatility and Volatility Innovation



Note: this figure shows time series plots of FX volatility and volatility innovations with shaded areas correspond to NBER recessions. The sample period is 11/ 1983 to 09/2011.

3.2.3. *OTHER DATA*

We use the consumer price index (CPI) for 29 OECD countries in order to get real exchange rate for each currency. The CPI data are obtained from OECD StatExtracts[6] and are consumer prices of all items with the base year as 2005 at monthly frequency.

Other data used in this thesis includes: the bid and ask spot exchange rates and forward exchange rates[7] to deduct transaction cost and to generate bid-ask spread as a proxy for liquidity risk. We also use the other two proxies as liquidity risk which we will describe in the relative chapter.

Some macroeconomic variables are also applied to access the correlation study and robustness test, such as industrial production of the US as it is available at monthly observation. However, this data are not the main data set for this thesis thus we do not explain in detail here, descriptions will be provided in the relative chapters when necessary.

---

[6] Except CPI data for Australia, New Zealand, and Euro area, which we collect via DataStream.

[7] Data are obtained from BBI and Reuters (via DataStream).

3.3. PORTFOLIOS AND STYLIZED FACTS

In this section, we introduce the main asset we study in this thesis: the currency carry trade portfolios. We provide the portfolio sorting approach, the transaction costs deducting method and the descriptive statistics of the currency carry trade portfolios. We will price and examine the excess returns from these portfolios in the following chapters.

3.3.1. PORTFOLIO SORTING APPROACH

The portfolio sorting approach of Fama and French (1993) has a long tradition in the stock literature. The sorting procedure eliminates the diversifiable, equity-specific component of returns that is not of interest, thus producing much sharper estimates of the risk-return trade-off in stock markets. Lustig and Verdelhan (2007) bring this sorting approach to the literature on currency returns by sorting currencies into portfolios according to their sizes of forward discount. This is equivalent to sorting according to their interest rate differentials with certain currency providing the covered interest rate parity hold. By sorting these currencies into portfolios, the currency-specific component of exchange rate changes that is not related to changes in the interest rate has been abstracted. This isolates the source of variation in excess returns that interests us, and it creates a large average spread between low and high interest rate portfolios. Recent literature which follows this sorting approach includes: Lustig, Roussanov et al. (2011), Burnside, Eichenbaum et al. (2011) and Menkhoff, Sarno et al. (2012).

Following these literature, for both 48-all-country sample and 29-OECD-country sample, we sort currencies into 5 portfolios according to their risk-free interest rates differentials with US risk-free interest rate which are equivalent to 1-month forward discounts providing covered interest rate parity hold. Portfolios are rebalanced at the beginning of each month. After this sorting, we have two samples with 5 portfolios in each sample. Portfolio 1 contains currencies with the lowest interest rate differentials with the U.S. interest rate while Portfolio 5 contains currencies with the highest interest rate differentials with the U.S. interest rate. By sorting these currencies into 5 portfolios according to their interest rate differentials, we isolate the currency specific effects which cause the change in exchange rates but focus on the changes caused by interest rate differentials. For each portfolio, currencies are equally weighted; we deduct the transaction costs and provide the descriptive statistics for the excess returns of the currency carry trade portfolios in the following two sections.

3.3.2. TRANSACTION COSTS

According to the portfolio sorting approach introduced in previous section, since the portfolios are rebalanced monthly and according to Menkhoff, Sarno et al. (2012) the average turnovers of the portfolios are about 30% per month[8] and therefore, we expect that transaction costs play an important role in currency returns. Moreover, Eichenbaum, Burnside et al. (2007) argue that transaction costs for the carry trade can be quite high, therefore, in this section, we calculate the net returns.

We follow Menkhoff, Sarno et al. (2012) to deduct transaction costs and we deduct bid-ask spreads from returns whenever a currency enters and/or exits a portfolio. We assume that the investor has to establish a new position in each single currency in the first month and that he has to sell all positions in the last month. Returns for Portfolio 1 are adjusted for transaction costs in short positions whereas Portfolio 2 to Portfolio 5 are adjusted for transaction costs in long positions.

Table 3.2 provides the way we calculate excess returns for both long and short positions with transaction costs deducted. Returns in small case letters are

[8] Our 48-all-country sample contains the same currencies as Menkhoff *et al.* (2012) and therefore we expect the turnovers of our portfolios are similar to theirs.

logarithm returns while in capital letters are discrete returns. We use superscripts l and s to distinguish between long position and short position. S_t and F_t are the spot exchange rates and 1-month exchange rates versus the US dollar at time period t. Both the spot exchange rates and the forward exchange rates are the middle rates at the end of the day for each month. We also use the bid and ask price for both spot exchange rates and 1-month exchange rates, denoted with superscripts b for bid price and a for ask price. Small letters are the same variables in logarithm. To deduct transaction costs we consider three different situations. Under different situations, the net excess returns are calculated according to Table 3.2.[9]

[9] We follow Menkhoff *et al.* (2012) to deduct the transaction costs.

Table 3-2 Transaction Costs Adjustments

Situation	Net return for a long position	Net return for a short position
A currency enters a portfolio at time *t* and exits the portfolio at the end of month *t*	$rx^{l}_{t+1} = f_t^{b} - s^{a}_{t+1}$ $RX^{l}_{t+1} = \frac{F_t^{b} - S^{a}_{t+1}}{S_t}$	$rx^{s}_{t+1} = -f_t^{a} + s^{b}_{t+1}$ $RX^{s}_{t+1} = \frac{-F_t^{a} + S^{b}_{t+1}}{S_t}$
A currency that enters a portfolio at time *t* but stays in the portfolio at the end of month *t*	$rx^{l}_{t+1} = f_t^{b} - s_{t+1}$ $RX^{l}_{t+1} = \frac{F_t^{b} - S_{t+1}}{S_t}$	$rx^{s}_{t+1} = -f_t + s^{b}_{t+1}$ $RX^{s}_{t+1} = \frac{-F_t + S^{b}_{t+1}}{S_t}$
A currency exits the portfolio at the end of the month *t*, but already was in the portfolio the month before (*t-1*)	$rx^{l}_{t+1} = f_t - s^{a}_{t+1}$ $RX^{l}_{t+1} = \frac{F_t - S^{a}_{t+1}}{S_t}$	$rx^{l}_{t+1} = -f_t + s^{b}_{t+1}$ $RX^{s}_{t+1} = \frac{-F_t + S^{b}_{t+1}}{S_t}$

Note: this table provides the way we calculate excess returns under three different situations for both long (with superscripts *l*) and short (with superscripts *s*) positions with transaction costs deducted. Returns in small case letters are logarithm returns while in capital letters are discrete returns.

3.3.3. *DESCRIPTIVE STATISTICS FOR CURRENCY PORTFOLIOS*

In this section, we provide the descriptive statistics for the currency portfolios sorted according to interest rate differentials with and without transaction costs for both 48-all-country sample and 29-OECD-country sample.

From Eq. 3.1, we know that the excess returns have two components: the interest rate gap and the change in exchange rate.

$$rx_{t+1} = (i_t^* - i_t) - (s_{t+1} - s_t) \qquad \text{Eq. 3.1}$$

In Table 3.3, we provide these two components separately for 5 portfolios: the average forward discount (interest rate gap) (reported in the first row of each panel) and the average change in exchange rates (reported in the second row of each panel). The average risk premium, as shown in the third row, is equal to the difference between the first and the second row of each panel. Only when the first two rows are identical, there is no average risk premium. From Table 3.2, we can see that the average rates of depreciation/appreciation are not large enough to offset interest rate differentials, i.e. the UIP does not hold. Investors earn large negative excess returns on the first portfolio because the low interest rate currencies in the first portfolio do not appreciate enough to offset the forward discount: for example, they appreciate on average (take the 48-all-country sample as example, the OECD sample is the same) 1.21%, while the average forward discount, which equivalent to average interest rate differential is 2.77% lower than the US interest rate. On the other hand, the higher interest rate currencies in portfolio 5 do not depreciate enough to offset the forward premium, for example, they depreciate on average by 3.36%, but the average interest rate difference is on average 9.33%. These results suggest that investors can form a zero-cost trading strategy (the carry trade portfolio) by borrowing Portfolio 1 and investing in Portfolio 5, this strategy provide 7.53% annualized average excess return for the 48-all-country sample and 6.49% annualized average excess return for the 29-OECD-country sample. We stick to the notation of Menkhoff, Sarno et al. (2012) and denote the carry trade portfolio as *HML* (high-minus-low). Also, the *DOL* portfolio is the average excess return of all 5 portfolios. It is equivalent to borrowing U.S. dollar and lending in equally weighed all other currencies in the sample. As we can see here, the *DOL* has a positive average excess return for both samples, this indicates that investors require a positive return for borrowing dollar and lending in equally weighed all other currencies. This *DOL* factor is a measure of “dollar risk” and we take it as a proxy for FX market risk, we will illustrate more about this factor in the relative chapters.

Table 3-3 Forward Discounts and Log-returns

Portfolio	P1	P2	P3	P4	P5	*DOL*	*HML*
Panel A: 48-all-country sample							
Forward Discount	-2.77	-0.44	1.10	2.91	9.33	2.03	12.10
Depreciation	-1.21	-1.19	-1.9	-0.97	3.36	-0.38	4.57
Log-returns	-1.56	0.75	3.00	3.88	5.97	2.41	7.53
Panel B: 29-OECD-country sample							
Forward Discount	-2.02	-0.35	0.70	2.24	6.31	1.38	8.33
Depreciation	-1.40	-2.22	-1.71	-1.09	0.43	-1.20	1.83
Log-returns	-0.61	1.87	2.41	3.33	5.88	2.58	6.49

Note: this table reports the time-series average of the average forward discount (annualized and in percentage points), the average rate of depreciation (annualized and in percentage points) and the average log returns (annualized and in percentage points). Portfolio 1 contains currencies with the lowest forward discount. Portfolio 5 contains currencies with the highest interest rates. *DOL* is the equally-weighted average of all five portfolios and *HML* is the portfolio constructed by short portfolio1 and long portfolio 5.

Table 3.4 reports the descriptive statistics of portfolios for both the 48-all-country sample (Panel A) and the 29-OECD-country sample (Panel B). We provide both the log-returns and the discrete-returns with and without the transaction costs. The discrete-returns are used in asset pricing test to avoid having to assume joint log-normality of returns in the pricing kernel (Lustig, Roussanov et al. 2011). For each portfolio, we provide annualized mean, standard deviation, and skewness of excess returns for currency portfolios sorted monthly on time *t-1* forward discounts. Sharp Ratio which defined as average return per unit of standard deviation is also reported and denoted as SR in the table. The excess returns of Portfolio 1 are realized by borrowing in U.S. dollars and lending in the 20% of all currencies with the lowest forward discounts equally weighted, whereas Portfolio 5 are realized by borrowing in U.S. dollar and lending in the 20% of all currencies with highest forward discounts equally weighted. *DOL* denotes the average return of the five currency portfolios and *HML* denotes a long-short portfolio that is long in portfolio 5 and short in Portfolio 1.

For both samples when moving from portfolio 1 to portfolio 5 and the *HML* portfolio, the average returns monotonically increase and the skewness are almost monotonically increasing in absolute terms. This is consistent with Brunnermeier, Nagel et al. (2009), in which they argue that the returns from high interest rate currencies are negatively skewed which suggests that they are subject to crash risk. There is no clear pattern, however, for the standard deviation. After deducting the transaction costs from excess return, in both log and discrete terms, the excess returns adjusted for transaction costs to long a portfolio have decreased compare with the ones not adjusting for transaction costs. The carry trade portfolio provides an average annualized excess return of 7.53% for 48-all-country sample and 6.46% for 29-OECD-country sample before adjusting transaction costs and 6.83% and 5.70% respectively after adjusting transaction costs. The standard deviations for the 48-all-country sample are higher than that for the 29-OECD country sample, this explains that the average excess returns for the 48-all-country sample is higher than that for the 29-OECD-country sample. The skewness of the carry trade portfolio *HML* of borrowing Portfolio 1 and lending Portfolio 5 is highly negative, this explains, as argued by Brunnermeier, Nagel et al. (2009), why the carry trade is subject to crash risk.

In Figure 3.2, we plot the cumulative log returns for the carry trade portfolio (HML) for both samples. Shaded areas correspond to NBER recessions[10]. The cumulative excess returns over the 334 months period are 209% for 48-all-country sample and 180% for 29-OECD-country sample.

[10] The NBER recessions in Figure 3.2 are defined in the same way as in Figure 3.1.

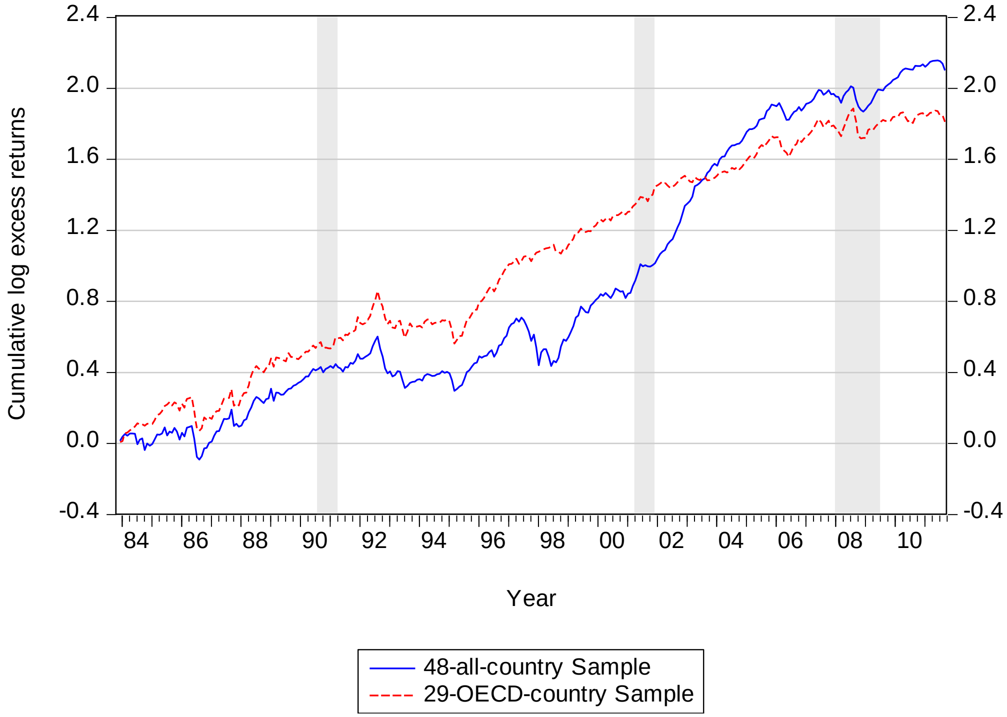
Interestingly, carry trades in the OECD countries were more profitable in the 80s and 90s; only in the last 10 years did the inclusion of emerging markets' currencies improve returns to the carry trade. Also, the two recessions in the early 1990s and 2000s did not have any significant influence on returns. It is only in the last recession – that also saw a massive financial crisis – that carry trade returns show some sensitivity to macroeconomic conditions. Most of the major spikes in carry trade returns seem rather unrelated to the U.S. business cycle. This coincides with Burnside (2011) which finds that most standard business cycle risk factors are unable to account for returns to carry trades.

Table 3-4 Descriptive Statistics

	Panel A. 48-all country sample							Panel B. 29-OECD Country Sample						
	Log return (without b-a)							Log return (without b-a)						
Portfolio	1	2	3	4	5	*DOL*	*HML*	1	2	3	4	5	*DOL*	*HML*
Mean(%)	-1.56	0.75	3.00	3.88	5.97	2.41	7.53	-0.613	1.87	2.41	3.33	5.88	2.58	6.49
Std. Dev.	8.43	8.54	8.40	8.44	10.39	7.76	9.07	9.80	10.39	9.67	9.92	9.99	9.09	8.41
Skewness	-0.09	-0.24	-0.19	-0.50	-0.76	-0.39	-1.15	0.04	-0.26	-0.20	-0.75	-0.61	-0.38	-0.93
SR	-0.19	0.09	0.35	0.46	0.57	0.31	0.83	-0.06	0.18	0.25	0.34	0.59	0.28	0.77
	Log return (with b-a)							Log return (with b-a)						
Portfolio	1	2	3	4	5	*DOL*	*HML*	1	2	3	4	5	*DOL*	*HML*
Mean(%)	-1.31	0.39	2.52	3.36	5.52	2.10	6.83	-0.29	1.50	2.16	3.06	5.41	2.37	5.70
Std. Dev.	8.42	8.54	8.40	8.47	10.45	7.78	9.11	9.77	10.28	9.65	9.80	9.98	9.05	8.38
Skewness	0.10	-0.25	-0.19	-0.53	-0.79	-0.41	-1.16	0.05	-0.26	-0.21	-0.57	-0.62	-0.34	-0.95
SR	-0.16	0.04	0.30	0.39	0.53	0.27	0.75	-0.03	0.15	0.22	0.31	0.54	0.26	0.68
	Discrete return (without b-a)							Discrete return (without b-a)						
Portfolio	1	2	3	4	5	*DOL*	*HML*	1	2	3	4	5	*DOL*	*HML*
Mean(%)	-2.04	0.26	2.46	3.32	4.89	1.79	6.93	-1.27	1.28	1.91	2.66	5.12	1.94	6.39
Std. Dev.	8.41	8.57	8.45	8.52	10.83	7.84	9.45	9.79	10.31	9.70	10.07	10.14	9.15	8.53
Skewness	-0.02	-0.37	-0.34	-0.64	-1.14	-0.52	-1.44	-0.05	-0.38	-0.32	-0.94	-0.81	-0.52	-0.98
SR	-0.24	0.03	0.29	0.39	0.45	0.23	0.73	-0.13	0.12	0.20	0.26	0.50	0.21	0.75
	Discrete return (with b-a)							Discrete return (with b-a)						
Portfolio	1	2	3	4	5	*DOL*	*HML*	1	2	3	4	5	*DOL*	*HML*
Mean(%)	-1.80	-0.10	1.98	2.81	4.43	1.46	6.23	-0.94	0.91	1.58	2.45	4.65	1.73	5.59
Std. Dev.	8.41	8.56	8.45	8.54	10.9	7.85	9.51	9.76	10.31	9.68	9.90	10.12	9.10	8.49
Skewness	-0.01	-0.38	-0.34	-0.67	-1.17	-0.53	-1.44	-0.05	-0.38	-0.32	-0.72	-0.80	-0.47	-1.00
SR	-0.22	-0.01	0.23	0.33	0.40	0.18	0.65	-0.10	0.09	0.16	0.25	0.46	0.19	0.66

Note: This table reports mean returns (annualized), standard deviations (annualized) and skewness of currency portfolios sorted monthly on time t-1 forward discounts. We also report Sharp Ratios (SR). *DOL* denotes the average return of the five currency portfolios and *HML* denotes a long-short portfolio that is long in portfolio5 and short in Portfolio 1. We report both log returns and excess returns for both samples: 48-all-country sample and 29-OECD-country sample. Returns are reported both without transaction costs adjustment (without b-a) and with transaction costs adjustment (with b-a). The transaction cost adjustments are computed according to Table 3.1. The time period spans from 11/1983 to 09/2011.

Figure 3-2 Cumulative Carry Trade Returns for Two Samples



Note: this figure plots cumulative log returns for the carry trade portfolio (*HML*) for both samples. Shaded areas correspond to NBER recessions. The time period spans from 11/1983 to 09/2011.

3.4. CONCLUSION

In this chapter, we introduce the main data set and construct the main asset studied in this thesis: the carry trade portfolios by sorting both the 48-all-country sample and the 29-OECD-country sample into 5 portfolios according to their interest rate differentials with the U.S interest rate.

We provide the descriptive statistics for the interest rate sorted portfolios and we generate the carry trade portfolio *HML* by taking a short position in Portfolio 1, currencies with the lowest interest rates, and taking a long position in Portfolio 5, currencies with the highest interest rates. We find that the sharp ratio of the carry trade portfolio is 0.75 for 48-all-country sample and 0.68 for 29-OECD-country sample after deducting transaction costs. The cumulative excess returns over the 334 months period are 209% for 48-all-country sample and 180% for 29-OECD-country sample.

The question is how to explain these excess returns from the carry trade. In the following chapters, we argue that the excess returns from the carry trade are compensations for bearing foreign exchange volatility risks.

4. Unconditional FX Volatility Risk Premium in the Carry Trade

4.1. Introduction

In this chapter, we provide a risk based explanation to the excess return from the carry trade by using Chen (2002) version of Intertemporal Capital Asset Pricing Model (ICAPM). We apply the same approach as used by Menkhoff, Sarno et al. (2012) and show that the excess returns can be explained by the foreign exchange (FX) market return and the FX market volatility risk. We call this model the unconditional ICAPM model as both the loadings and the price of FX volatility risks are not regime dependent on any other variables, so as to distinguish from the conditional ICAPM model in the next chapter.

We test the model with one new sample and longer time period and find that the results are consistent with the findings of Menkhoff, Sarno et al. (2012) that the FX volatility factor is able to explain about 90% of the cross sectional excess returns from the carry trade and moreover, we also find that liquidity risk plays an important part in explaining the excess returns from currency market, but to a lesser degree than the volatility risk.

The new finding of our study is that, by applying the model to a longer time period which covers the recent financial crisis period, we are able to compare the performance of this model with and without the recent crisis period, we find that the volatility risk factor provides lesser pricing errors for subsamples with crisis period. This indicates that a regime switching model with loadings of FX volatility risks varying depending on different regimes would work better.

The structure of this chapter is as follow: in Section 4.2, we review Chen (2002) version of Intertemporal Capital Asset Pricing Model (ICAPM) and show that departing from the ICAPM model, how to derive the Menkhoff, Sarno et al. (2012) model. In Section 4.3, we provide the method of asset pricing test, and two estimation methods. These standard methods are also used in the following chapters. Section 4.4 provides the main asset pricing results with FX volatility as a risk factor and Section 4.5 compares the performance of FX volatility risk and liquidity risk in pricing the excess returns from the carry trade. Section 4.6 analyses the performances of FX volatility risk with and without the recent crisis period and Section 4.7 concludes.

4.2. THE MODEL

Fama (1970) points out that the single-period CAPM does not apply in a multiperiod setting if investor preferences change across time or if the available investment opportunity set changes across time. Merton (1973) develops an intertemporal asset pricing model in which the changes in the investment opportunity set affect future asset returns. Hansen and Singleton (1983) show that we can use the consumption growth rates to price assets as a proxy of changes in opportunity set. But in reality, consumptions are difficult to measure, Campbell (1992) uses the aggregate budget constraint to substitute out the consumption growth rate with current and future market returns, but Campbell's model is a in a homoscedastic setting. Chen (2002) extends Campbell's model to a heteroskedastic environment which allows for both time-varying covariance and stochastic market volatility.

Suppose the pricing kernel can be modelled as:

$$m_{t+1} = \beta^{\theta_1} \left(\frac{C_{t+1}}{C_t}\right)^{\frac{-\theta_2}{\sigma}} (R_{W,t+1})^{\theta_3 - 1} \qquad \text{Eq. 4.1}$$

The pricing kernel described by Eq. 4.1 depends only on the consumption growth rate $\frac{C_{t+1}}{C_t}$ and the aggregate market return $R_{W,t+1}$. This specification includes Epstein and Zin (1989) recursive utility function representative agent as a special case.

The link between consumption and the changes in the investment opportunity set is provided by substituting out the consumption growth rate using the aggregate budget constraint. Following Campbell (1992), Chen (2002) shows that a log-linear approximation of the aggregate budget constraint gives three factors. The first factor is the market return; the second is the change in the forecasts of future market returns. The third factor is the change in the exponentially weighted forecasts of future market variances. The intuition behind this substitution is that an increased level of consumption today must be financed by a high current market return, an increased forecast of future market returns or a lower expectation of future market volatility.

Thus, Chen (2002) shows that risk-averse investors also want to directly hedge against changes in future market volatility. For an investor more risk averse than log utility, Chen shows that an asset that has a positive covariance between its return and a variable that positively forecasts future market volatilities causes that asset to have lower expected return. This effect arises because risk-averse investors reduce current consumption to increase precautionary savings in the presence of increased uncertainty about market returns.

In taking the ICAPM to the data, the recent literature in empirical asset pricing considers a two-factor stochastic discount factor with the market excess return and volatility innovations as risk factors:

$$m_{t+1} = 1 - b_1 rx_{t+1}^{m} - b_2 \Delta V_{t+1} \qquad \text{Eq. 4.2}$$

where rx_t^m is the log market excess return at time t and ΔV_t denotes volatility innovations at time t. Note that in the pricing kernel, we have the change in volatility rather than the level of volatility as a pricing factor and this is because as supported by the ICAPM theory of Chen (2005), apart from the market return, it is the change in future market volatility rather than the level of future market volatility that risk-averse investors want to directly hedge. The empirical applications of this model are consistent in this point for both stock and exchange rate market: Ang, Hodrick et al. (2006) employ changes in the VIX index rather than the level of the VIX to price the cross sectional excess return from the stock market and Menkhoff, Sarno et al. (2012) use the change of realized volatility to price the cross sectional excess return form the carry trade. As mentioned in the data section, Menkhoff, Sarno et al. (2012) use the AR(1) residual rather than the first difference of realized FX volatility to eliminate the existence of factor auto-correlation.

Ang, Hodrick et al. (2006) employ changes in the VIX index[11] to proxy for volatility risk, considered as a non-traded risk factor. They find that market volatility is priced in the cross-section of US stock returns and that shocks with a higher sensitivity to volatility risk do earn lower returns.

Menkhoff, Sarno et al. (2012) show that a similar approach is helpful to understand the cross-section of FX risk premium as well. They follow Lustig, Roussanov et al. (2011) and set up a framework assuming that the stochastic discount factor is linear in two pricing factors: (1) an FX market return, and (2) FX market volatility innovations. They use a straightforward measure to proxy

[11] VIX is a market volatility index provided by Chicago Board Options Exchange, and it is a measure of the implied volatility of S&P 500 index options.

for global FX volatility and their proxy has similarities to measures of realized volatility (Burnside, Eichenbaum et al. 2006). For the empirical analysis, they focus on volatility innovations as non-traded risk factor. And they find this factor captures the cross-sectional sensitivity among portfolios.

In this chapter, we follow the empirical frame work of Menkhoff, Sarno et al. (2012). The contribution of our study is that we extend our sample until September 2011 while for Menkhoff, Sarno et al. (2012), their sample finishes at August 2009. By adding another 25 months observation we have a more up to data sample and we are able to examine the performance of the model during and after the recent financial crisis. Apart from the 48-all-country sample, we also apply the model to a new sample: the 29-OECD-country sample as: (1) a robustness test and (2) a sample for further studies in the following chapters.

4.3. METHODOLOGY

This section summarizes the approach to cross-sectional asset pricing. The benchmark results rely on a standard stochastic discount factor approach (Cochrane 2005), which also used in Burnside (2010), Menkhoff, Sarno et al. (2012) and in Lustig, Roussanov et al. (2011).

Following Lustig, Roussanov et al. (2011) and Menkhoff, Sarno et al. (2012), this chapter uses discrete returns (not log returns) in all pricing exercise to satisfy the Euler equation. Discrete returns for currency k are defined as $RX_{t+1}^{k} = \frac{F_t^k - S_{t+1}^k}{S_t^k}$ where F_t^k and S_t^k are the level of the forward and spot exchange rate for currency k at time t respectively. The descriptive statistics of the discrete returns for portfolios are provided in Chapter 3, Table 3.4.

The carry trade is a zero-cost trading strategy and no-arbitrage relation applies so that risk-adjusted currency excess returns have a zero price and satisfy the basic Euler equation:

$$E_t[m_{t+1}RX_{t+1}^{k}] = 0 \qquad \text{Eq. 4.3}$$

Here, m_{t+1} denotes the SDF that prices returns denominated in dollars. The unconditional version of Eq. 4.3 is:

$$E(mRX) = 0 \qquad \text{Eq. 4.4}$$

This equation can be written as:

$$E(RX)E(m) + cov(RX, m) = 0 \qquad \text{Eq. 4.5}$$

In practice, the average unconditional returns to the strategies that we consider are positive. The most straightforward explanation of this finding is that $cov(RX, m) < 0$.

Our analysis uses Eq. 4.4 as our point of departure. We consider linear SDFs that takes the form

$$m_t = \xi[1 - (h_t - \mu)'b] \qquad \text{Eq. 4.6}$$

Here ξ is a scalar, h_t is a $k \times 1$ vector of risk factors, $\mu = E(h_t)$, and b is a $k \times 1$ vector of parameters. We set $\xi = 1$, because ξ is not identified by Eq.4.4. Given this assumption and the model for SDF given in Eq. 4.6, Eq. 4.5 can be rewritten as:

$$\mathrm{E(RX) = cov(RX, h)b = cov(RX, h)\Sigma_h^{-1}\Sigma_h b = \beta\lambda} \qquad \text{Eq. 4.7}$$

Where $\Sigma_h$is the covariance matrix of h_t. The betas in Eq. 4.7 are population coefficients in a regression of RX_t on h_t and measure the exposure of the payoff to aggregate risk. The $k \times 1$ vector λ measures the risk premiums associated with the risk factors (Cochrane, 2005).

We estimate parameters of Eq. 4.7 via both the Generalized Method of Moments (GMM) of Hansen (1982) and the FMB two-pass OLS methodology (Fama and MacBeth 1973).

To estimate the parameter of the SDF, b and μ, by using the GMM, and the moment restrictions Eq. 4.4 and $E(h) = \mu$. Eq. 4.4 can be rewritten as:

$$E\{RX[1 - (h - \mu)'b]\} = 0 \qquad \text{Eq. 4.8}$$

where RX is a $n \times 1$ vector of excess returns, the GMM estimators of μ and b are $\hat{\mu} = \bar{h}$ and

$$\hat{b} = (d_T' W_T d_T)^{-1} d_T' W_T \overline{RX} \qquad \text{Eq. 4.9}$$

where d_T is the sample covariance matrix of RX with h, and W_T is weighting matrix. Estimates of λ are obtained from $\hat{b}$ as $\hat{\lambda} = \hat{\Sigma}_h \hat{b}$, where $\hat{\Sigma}_h$ is the sample covariance matrix of h. The model's predicted mean returns, $\widehat{RX} = d_T \hat{b}$, are estimates of the right hand side of Eq. 4.8. The model R^2measures the fit between $\widehat{RX}$ and $\overline{RX}$. The pricing errors are the residuals, $\hat{\alpha} = \overline{RX} - \widehat{RX}$. Following (Burnside (2010)), we test that the pricing errors are zero using the statistic $J = T\hat{\alpha}' V_T^{-1} \hat{\alpha}$, where $V_T$is a consistent estimate of the asymptotic covariance matrix of $\sqrt{T}\hat{\alpha}$. The asymptotic distribution of J is χ^2 with $n - k$ degrees of freedom.

Besides the GMM tests, we also report results using traditional FMB two-pass OLS methodology (Fama and MacBeth 1973) to estimate portfolio betas and factor risk prices. There is an argument about whether including a constant or not in the second stage of the FMB regressions, i.e. whether or not allow a common over- or under-pricing in the cross-section of returns. Menkhoff, Sarno et al. (2012) point out that their results are virtually identical when they replace the DOL factor with a constant in the second stage regressions. Since DOL has basically no cross-sectional relation to the carry trade portfolio returns it seems to serve the same purpose as a constant that allows for a common mispricing. Therefore, we do not include a constant in the second stage of the FMB regressions. We report standard errors with Newey-West adjustments. The estimate of λ and the pricing errors are the same as the ones obtained from the first step of GMM, because the weighting matrix in GMM is equally weighted.

4.4. EMPIRICAL RESULTS

4.4.1. *PRELIMINARY RESULTS*

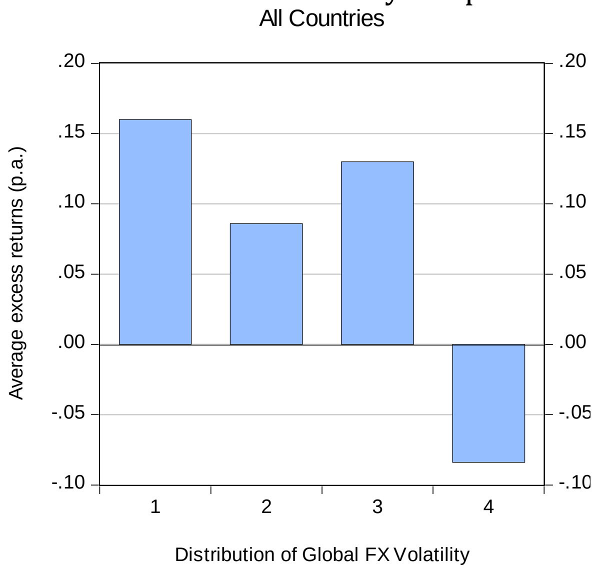
We first provide a simple graphical analysis to visualize the relationship between volatility innovations and currency excess returns. We divide the sample into four sub-samples depending on the value of volatility innovations. The first sub-sample contains the 25% months with the lowest realizations of the volatility innovations and the fourth sub-sample contains the 25% months with the highest realizations. We then calculate average excess returns of the carry trade portfolio for these four sub-samples and results are shown in Figure 4.1.

Figure 4.1 Panel (a) shows results for 48-all-country sample and Panel (b) shows results for 29-OECD-country sample. Bars show the annualized average excess returns of the carry trade portfolio, the HML portfolio as discussed in Chapter 3. As can be seen from the figure, average excess returns for the carry trade portfolio decrease almost monotonically when moving from the low to the high volatility innovation states for both 48-all-country sample and 29-OECD-country sample. The carry trade portfolio has positive average excess returns for the first three subsamples, when the volatility innovations are in the first three quartiles, and has negative excess returns for the last sub-sample, when the volatility innovations are in the top quartile.

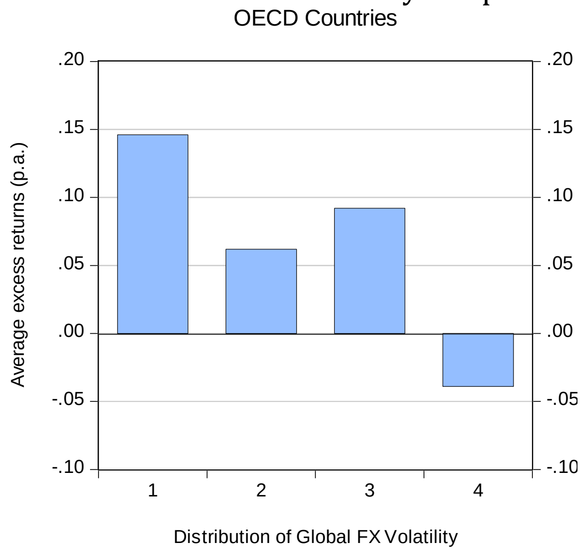
While this analysis is intentionally simple, it intuitively demonstrates the strong relationship between FX volatility innovations and excess returns to carry trade portfolios. The carry trade provides average excess returns when the FX volatility innovations are below 75% percentile, i.e. the carry trade performs well during normal periods, and it provides negative excess returns when the FX volatility innovations are above 25% percentile, i.e. the carry trade suffers losses during crisis period. Times of high volatility innovations are times when the low interest rate currencies perform well compared to high interest rate currencies i.e. low interest rate currencies provide a hedge in times of market turmoil. The following sections test this finding more closely.

Figure 4-1 Excess Returns and Volatility Risk

Panel A. 48-all-country sample



Panel B. 29-OECD-country sample



Note: figure 4.1 plots mean excess returns for carry trade portfolios conditional on FX volatility innovations being within the lowest to the highest quartile of its sample distribution (four categories from" lowest" to "highest" shown on the x-axis of each panel). The bars show mean excess returns for the carry trade portfolio (HML): average excess returns for being long in portfolio 5 (largest forward discounts) and short in portfolio 1 (lowest forward discounts).

4.4.2. Main results

This Section reports the main asset pricing tests results. Derived from the ICAPM model, the stochastic discount factor has two factors: the market excess return and the volatility innovations as shown in Eq. 4.2.

$$m_{t+1} = 1 - b_1 rx_{t+1}^{m} - b_2 \Delta V_{t+1} \qquad \text{Eq. 4.2}$$

where rx_t^m is the log market excess return at time t and ΔV_t denotes volatility innovations at time t.

The testing assets are the five forward discount sorted currency portfolios as described in Section 3.3. We use the DOL factor as a proxy of foreign exchange market return and ΔVOL factor as a proxy of foreign exchange market volatility innovations. Therefore, the stochastic discount factor is written in Eq. 4.10:

$$m_{t+1} = 1 - b_{DOL} DOL_{t+1} - b_{VOL} \Delta VOL_{t+1}^{FX} \qquad \text{Eq. 4.10}$$

We use the standard stochastic discount factor approach (Cochrane, 2005) as described in Section 4.2, and estimate parameters via both the Generalized Method of Moments (GMM) of Hansen (1982) and the traditional two-pass OLS method FMB (Fama and MacBeth 1973).

Panel A of Table 4.1 shows cross-sectional pricing results for the linear factor model based on the dollar risk factor DOL and FX volatility innovations ΔVOL. The test assets are excess returns to five carry trade portfolios based on currencies from two samples without adjusting the transaction costs as the results don't change much with transaction costs adjusted. However, the results with transaction costs adjusted are provided in Appendix A.1. In Table 4.1 Panel A, the estimate of λ_{VOL} , the risk price of volatility innovations, is estimated to be negative and significant for both two samples: 48-all-country sample (left part of the table) and 29-OECD-country sample (right part of the table). The estimated volatility risk price is about -0.07% for the two samples. This negative factor price is consistent with the ICAPM theory that investors demand a premium for bearing volatility risk: for portfolios whose returns co-move positively with volatility innovations, they are providing hedges to volatility risk and therefore investors demand a low return. On the other hand, for portfolios whose returns co-move negatively with volatility risk, they demand a risk premium. Moreover, there is about 0.7 basis point higher in volatility risk price (in absolute value) for the 48-all-country sample than that for the 29-OECD-country sample. This means that investors require higher premium for holding portfolios containing developing country currencies than with only OECD-country currencies. The ΔVOL actor yields a nice cross-sectional fit with R^2s of more than 90% for both two samples, and we cannot reject the null that the J-statistics is equal to zero (the pricing error is zero). The pricing errors are quite small in economic terms.

Panel B of Table 4.1 shows time-series beta estimates for the five forward discount-sorted portfolios based on all two samples. There are large and positive loadings on the ΔVOL factor, as shown by estimates of β_{VOL}, for portfolios have small size in forward discount (low interest rate currencies)and there are large and negative loadings on the ΔVOL factor for portfolios have large size in forward discount (high interest rate currencies) and those loadings are monotonically increasing as moving from portfolio 1 to portfolio 5 for both two samples. These loadings explain that the low returns of the carry trade during high volatility risk period.

Figure 4.2 plots the pricing errors of the above model. The fitted mean excess returns are plotted against the realized mean excess returns. The main finding is that the pricing errors are small in both two samples and volatility risk captures the return spreads across portfolios with different interest rate levels.

Table 4-1 Cross-sectional Asset Pricing Results: Volatility Risk

Panel A: Factor prices and loadings

48-all-country sample					29-OECD-country sample				
GMM	$DOL\%$	$\Delta VOL\ \%$	R^2	$J-stats$	GMM	$DOL\%$	$\Delta VOL\ \%$	R^2	$J-stats$
b	0.031	-7.134	0.927	1.084	b	-0.015	-5.227	0.902	2.112
S.E.	[0.052]	[2.951]		(0.781)	S.E.	[0.035]	[2.481]		(0.549)
λ	0.120	-0.072			λ	0.162	-0.065		
S.E.	[0.130]	[0.027]	MAE	5.0e-004	S.E.	[0.146]	[0.024]	MAE	5.3e-004
FMB	DOL%	ΔVOL %	$J-stats$		FMB	DOL%	ΔVOL %	$J-stats$	
λ	0.120	-0.072	0.938		λ	0.162	-0.065	1.990	
S.E.	[0.129]	[0.031]	(0.816)		S.E.	[0.149]	[0.026]	(0.574)	

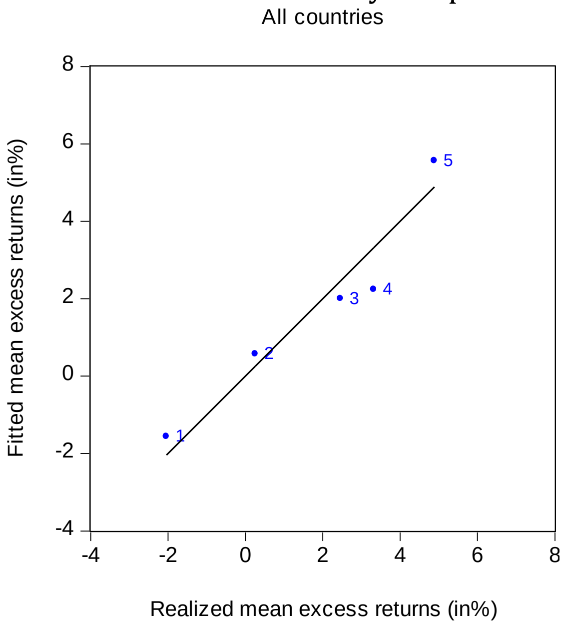
Panel B: Factor betas

48-all-country sample					29-OECD-country sample				
PF	α	DOL	ΔVOL	R^2	PF	α	DOL	ΔVOL	R^2
1	-0.003	0.972	3.442	0.775	1	-0.003	0.988	3.36	0.820
	[0.001]	[0.045]	[0.732]			[0.001]	[0.041]	[0.879]	
2	-0.001	1.006	1.021	0.818	2	-0.001	1.079	1.543	0.892
	[0.001]	[0.036]	[0.749]			[0.001]	[0.028]	[0.637]	
3	0.001	0.968	-0.697	0.800	3	-0.000	1.015	0.146	0.904
	[0.001]	[0.038]	[0.652]			[0.001]	[0.024]	[0.533]	
4	0.001	0.999	-0.916	0.841	4	0.001	1.006	-2.841	0.867
	[0.001]	[0.033]	[0.674]			[0.001]	[0.029]	[0.833]	
5	0.002	1.086	-4.637	0.677	5	0.001	0.930	-3.968	0.756
	[0.001]	[0.068]	[1.483]			[0.001]	[0.045]	[1.193]	

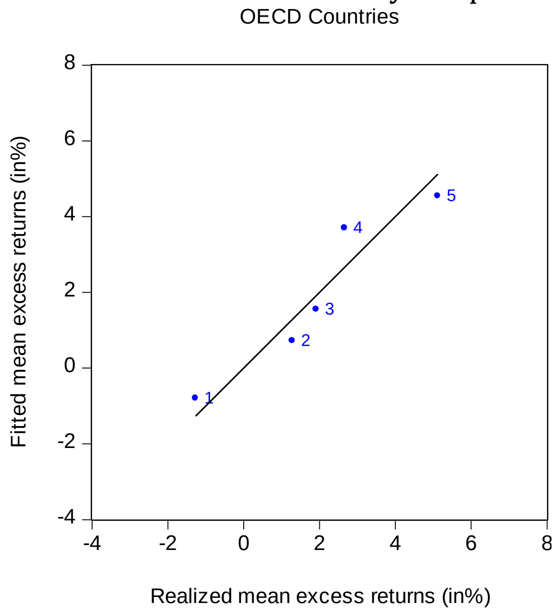
Note: Panel A shows coefficient estimates of SDF parameters b and factor risk prices λ obtained by GMM and FMB cross-sectional regression. The reported standard errors (S.E.) and J-statistics are based on the Newey-West approach. For J-statistics, p-value is provided in parentheses. MAE is the mean absolute error. Panel B reports results for the time-series regressions of excess returns on a constant, the dollar risk (DOL) factor, and FX volatility innovations (ΔVOL). Newey-West standard errors are reported in brackets. The period spans from 01/11/1983 to 30/09/2011.

Figure 4-2 Pricing Error Plots for Unconditional ICAPM Models

Panel A. 48-all-country sample



Panel B. 29-OECD-country sample



Note: the figure plots the fitted mean excess returns from 5 portfolios against the realized mean excess returns of the 5 portfolios. The distance from the points to the 45 degree line shows pricing errors of the model. The sample period is 12/1983 to 09/2011.

4.4.3. Robustness test

Following Ang, Hodrick et al. (2006) and Menkhoff, Sarno et al. (2012) we also build a factor-mimicking portfolio of volatility innovations. By converting the ΔVOL factor into return, we can examine the factor price of risk in a natural way: If the factor is a traded asset, then the risk price of this factor should be equal to the mean return of the traded portfolio.

To obtain the factor-mimicking portfolio, we regress volatility innovations on the five carry trade portfolio excess returns

$$\Delta VOL_{t+1} = a + b' rx_{t+1} + \mu_{t+1} \qquad \text{Eq. 4.11}$$

where rx_{t+1} is the vector of excess returns of the five carry trade portfolios. Then we calculate the factor-mimicking portfolio's excess return as: $rx_{t+1}^{FX} = \widehat{b'} rx_{t+1}$. The weights $\hat{b}$ of this portfolio for the 48-all-country sample is given by

$$rx_{t+1}^{FX} = 0.20 rx_{t+1}^{1} - 0.03 rx_{t+1}^{2} - 0.09 rx_{t+1}^{3} - 0.04 rx_{t+1}^{4} - 0.11 rx_{t+1}^{5} \qquad \text{Eq. 4.12}$$

Eq. 4.12 shows that the factor-mimicking portfolio for volatility innovations has positive loading on the return to Portfolio 1, and it has negative loadings on Portfolios 2-5.

Finally, we replace volatility innovations ΔVOL with $\Delta VOL_{FM} = \overline{rx}_{t+1}^{FM}$ in the pricing kernel to test the pricing ability of the factor-mimicking portfolio. Table 4.2 Panel A has shown a significantly negative price for the factor-mimicking portfolio of $\lambda_{VOL_{FM}} = -0.103\%$ which can be compared to the average monthly excess returns of the factor-mimicking portfolio of $\overline{rx}_{t+1}^{FM} = -0.107\%$. This makes sense economically as the factor prices itself.

The results are consistent for the 29-OECD-country sample. We follow the same procedural for 29-OECD-country sample to generate the factor-mimicking portfolio and as shown in Table 4.2 Panel A, the factor risk price is $\lambda_{VOL_{FM}} = -0.095\%$ which is close to the average excess return of $\overline{rx}_{t+1}^{FM} = -0.098\%$.

Table 4-2 Cross-Sectional Asset Pricing Results: Factor-mimicking Portfolio

Panel A: Factor Prices and Loadings

48-all-country sample					29-OECD-country sample				
GMM	$DOL\%$	$\Delta VOL_{FM}\%$	R^2	*J-stats*	GMM	$DOL\%$	$\Delta VOL_{FM}\%$	R^2	*J-stats*
b	-0.031	-0.595	0.926	2.077	b	0.017	0.499	0.890	3.755
S.E.	[0.032]	[0.207]		(0.557)	S.E.	[0.025]	[0.173]		(0.289)
λ	0.147	-0.103			λ	0.162	-0.095		
S.E.	[0.123]	[0.027]	MAE	5.4e-004	S.E.	[0.144]	[0.026]	MAE	5.6e-004
FMB	DOL%	ΔVOL_{FM}	*J-stats*		FMB	DOL%	ΔVOL_{FM}	*J-stats*	
λ	0.147	-0.103	2.057		λ	0.162	-0.095	3.510	
S.E.	[0.147]	[-0.103]	(0.557)		S.E.	[0.150]	[0.029]	(0.319)	

Panel B: Factor Betas

48-all-country sample					29-OECD-country sample				
PF	α	DOL	ΔVOL_{FM}	R^2	PF	α	DOL	ΔVOL_{FM}	R^2
1	-0.000	1.236	3.043	0.984	1	-0.001	1.175	2.706	0.951
	[0.000]	[0.012]	[0.080]			[0.000]	[0.015]	[0.096]	
2	-0.000	1.098	1.107	0.845	2	-0.000	1.175	1.406	0.925
	[0.001]	[0.037]	[0.167]			[0.000]	[0.024]	[0.133]	
3	0.000	0.936	-0.285	0.802	3	0.000	1.037	0.366	0.907
	[0.001]	[0.042]	[0.237]			[0.001]	[0.024]	[0.185]	
4	0.001	0.950	-0.458	0.845	4	0.001	0.875	-1.817	0.924
	[0.001]	[0.038]	[0.220]			[0.001]	[0.023]	[0.152]	
5	-0.001	0.779	-3.408	0.835	5	-0.001	0.739	-2.661	0.874
	[0.001]	[0.054]	[0.370]			[0.001]	[0.028]	[0.197]	

Note: The setup of this table is identical to Table 4.1 but we replace volatility innovations by the factor mimicking portfolio of volatility innovations ΔVOL_{FM}. Test assets are the five carry trade portfolios (excess returns) based on 48-all-country sample and 29-OECD country sample. The sample period is 12/1983 to 09/2011.

4.5. LIQUIDITY RISK

In this section, we test if liquidity risk can explain the excess returns from the carry trade. As augured by Brunnermeier and Pedersen (2009) that liquidity plays an important role in forward premium puzzle and also it is difficult to distinguish between FX volatility and liquidity risk. We follow Menkhoff, Sarno et al. (2012) to use three measures as liquidity proxies and investigate the liquidity pricing power. We then examine the relationship between liquidity risk and volatility risk and compare the pricing ability of the two risk factors.

The first measure we take is the global bid-ask spread (BAS), which is a classical measure from market microstructure. We use the same aggregating scheme as for FX volatility in Eq. 3.5 to obtain our global bid-ask spread measure ψ_t^{FX}

$$\psi_t^{FX} = \frac{1}{T_t} \sum_{T \in T_t} \left[\sum_{k \in K_\tau} \left(\frac{\psi_\tau^k}{K_\tau} \right) \right] \qquad \text{Eq. 4.13}$$

where ψ_τ^k is the percentage bid-ask spread of currency k on each day τ. Higher bid-ask spreads indicate lower liquidity, so that our aggregate measure ψ_t^{FX} can be seen as a global proxy for FX market illiquidity.

The next proxy of liquidity is the *TED* spread, which is defined as the interest rate difference between 3-month Eurodollar interbank deposits (LIBRO) and 3-month Treasury bills. Differences between these rates reflect among other things the willingness of banks to provide funding in the interbank market; a large spread should be related to lower liquidity. Hence, the *TED* spread serves as an illiquidity measure, as used e.g. by Brunnermeier and Pedersen (2009).

The final liquidity measure is by Pastor and Stambaugh (2001) , in which they construct a liquidity measure for the U.S. stock market based on price reversals. The general idea underlying their measure (denoted as PS here) is that stocks with low liquidity should be characterized by a larger price impact of order flow. Liquidity-induced movements of asset prices have to be reversed eventually such that stronger price reversals indicate lower liquidity. Their measure is a liquidity proxy, i.e. higher values of the PS measure mean higher liquidity. This contrasts with the other two liquidity measures which rather measure illiquidity.

Table 4.3 measures the correlation between ΔVOL and those three innovations of liquidity proxies, the correlations are more than 20% in absolute value for all three illiquidity or liquidity measures, which explains why it is difficult to separate liquidity risk and volatility risk.

Following Menkhoff, Sarno et al. (2012), to shed more light on the role of liquidity risk for currency returns, we run the same asset-pricing exercises as in Table 4.1, but replace volatility innovations with innovations of one of the three liquidity factors. Table 4.4 shows factor loadings and prices for these models[12]. All three models shown in Panels A to C perform quite well with R^2s ranging from 60% to 100% and are not rejected by the J-statistics. Moreover, factor prices λ have the expected sign – negative for illiquidity (BAS, TED) and positive for liquidity (PS) – and are significantly or marginally significant different from

[12] We only report GMM results in Table 4.4 to save space.

zero. However, none of these three models clearly outperforms the volatility risk factor in terms of R^2s and J-statistics for both samples.

To compare the pricing ability of volatility and liquidity as risk factors, we also evaluate specifications where we include volatility innovations and innovations of one of the liquidity factors jointly in the stochastic discount factor. We report results for the 48-all-country sample for the case where volatility innovations and one of the three liquidity factors are included. Results are shown in Table 4.5.

The central message of these results is that volatility innovations emerge as the dominant risk factor, consistent with evidence in Bandi, Moise et al. (2008) for the U.S. stock market. Panel A, for example, shows results when jointly including innovations to global FX volatility and global bid-ask spreads: both b_{VOL} and λ_{VOL} are significantly different from zero, whereas the bid-ask spread factor is found to be insignificant in this joint specification. The same result is found for the *TED* spread (Panel B) and the *PS* liquidity factor (Panel C). Volatility remains significantly priced, whereas liquidity factors always become insignificant when jointly included with volatility. We therefore conclude that volatility is more important than each of the three single liquidity factors. However, we cannot rule out and explanation based on volatility just being a summary measure of various dimensions of liquidity which are not captured by our three liquidity proxies.

Table 4-3 Correlation between ΔVOL factor and Liquidity Factors

BAS	*TED*	*PS*
0.209	0.263	-0.212

Note: this table provides the correlation between ΔVOL and innovations of three liquidity proxies: the bid-ask spread (BAS) (Panel A), the TED spread (TED), or the Pastor and Stambaugh (2003) liquidity measure (PS).

Table 4-4 Cross-sectional Asset Pricing Results: Liquidity Factors

48-all country sample (without b-a)					29-OECD-country sample (without b-a)				
Panel A. Bid-ask spread (*BAS*)									
GMM	*DOL*	*BAS*	R^2	*J-stats*	GMM	*DOL*	*BAS*	R^2	*J-stats*
b	-0.019	-67.416	0.713	4.144	*b*	0.012	-30.595	0.736	3.966
S.E.	[0.049]	[42.833]		(0.246)	S.E.	[0.027]	[19.430]		(0.312)
λ	0.150	-0.028			λ	0.160	-0.013		
S.E.	[0.180]	[0.025]	MAE:	0.0008	S.E.	[0.150]	[0.010]	MAE:	0.0013
Panel B. The *TED* spread (*TED*)									
GMM	*DOL*	*TED*	R^2	*J-stats*	GMM	*DOL*	*TED*	R^2	*J-stats*
b	-0.056	-4.369	0.723	6.386	*b*	-0.042	-4.047	0.806	2.362
S.E.	[0.078]	[2.972]		(0.094)	S.E.	[0.048	[3.421]		(0.501)
λ	0.150	-0.280			λ	0.160	-0.260		
S.E.	[0.120]	[0.160]	MAE:	0.0009	S.E.	[0.140	[0.130]	MAE:	7.1e-004
Panel C. The Pastor and Stambaugh (2003) liquidity measure (*PS*)									
GMM	*DOL*	*PS*	R^2	*J-stats*	GMM	*DOL*	*PS*	R^2	*J-stats*
b	0.037	0.136	0.664	6.111	*b*	0.030	0.128	0.852	3.461
S.E.	[0.039]	[0.084]		(0.106)	S.E.	[0.033	[0.068]		(0.326)
λ	0.150	5.220			λ	0.160	4.910		
S.E.	[0.130]	[2.830]	MAE:	0.0011	S.E.	[0.150	[2.170]	MAE:	5.6e-004

Note: this table shows factor prices and loadings for three different models. The results are based on GMM. The test assets are excess returns to the five carry trade portfolios based on both samples: 48-all-country sample and 29-OECD-country sample. Factors are the dollar risk (DOL) factor, and innovations of (1) average percentage bid-ask spreads denoted as *BAS* (Panel A), (2) the *TED* spread (Panel B), or (3) the Pastor and Stambaugh (2003) liquidity measure denoted as *PS* (Panel C). Newey-West standard errors are reported in brackets. MAE is the mean absolute error. For J-statistics, p-value is provided in parentheses. The sample period is spanned from 01/11/1983 to 30/09/2011.

Table 4-5 Cross-Sectional Asset Pricing Results: Volatility and Liquidity Risk

		Panel A: Volatility and *BAS* spreads			
GMM	*DOL*	*BAS*	ΔVOL	R^2	*J-stats*
b	-0.031	3.166	-7.388	0.927	1.030
S.E.	[0.053]	[36.530]	[3.605]		(0.598)
λ	0.150	-0.002	-0.074		
S.E.	[0.130]	[0.015]	[0.027]	MAE:	4.900e-004
		Panel B: Volatility and *TED* spread			
GMM	DOL	TED	ΔVOL	R^2	*J-stats*
b	-0.005	3.169	-11.387	0.964	0.512
S.E.	[0.077]	[5.020]	[6.563]		(0.774)
λ	0.150	0.130	-0.096		
S.E.	[0.160]	[0.290]	[0.039]	MAE:	3.360e-004
		Panel C: Volatility and *PS* liquidity measure			
GMM	*DOL*	*PS*	ΔVOL	R^2	*J-stats*
b	-0.081	-0.126	-12.262	0.931	0.142
S.E.	[0.097]	[0.174]	[6.737]		(0.931)
λ	0.150	-3.190	-0.110		
S.E.	[0.260]	[5.860]	[0.048]	MAE:	1.552e-004

Note: the setup is the same as in Table 4.4. The results are based on GMM. The test assets are excess returns to the five carry trade portfolios based on both samples: 48-all-country sample and 29-OECD-country sample. Factors are the dollar risk (DOL) factor, and innovations of (1) average percentage bid-ask spreads denoted as BAS (Panel A), (2) the TED spread (Panel B), or (3) the Pastor and Stambaugh (2003) liquidity measure denoted as PS (Panel C). Newey-West standard errors are reported in brackets. MAE is the mean absolute error. For J-statistics, p-value is provided in parentheses. The sample period is spanned from 01/11/1983 to 30/09/2011.

4.6. CRISIS RISK

Brunnermeier, Nagel et al. (2008) argue: crisis risk plays an important role in the carry trade pricing. As shown in Table 3.4, the carry trade portfolios are highly negatively skewed, and these negative skewness indicate that the carry trade is subject to crash risk.

In this section, we compare samples with and without the recent financial crisis period, since as shown in Figure 3.2, the carry trade has made great losses during the recent financial crisis period[13]. We construct two subsamples covering different data periods for both 48-all-country sample and 29-OECD-country sample: Subsample 1 spans from 12/1983 to 09/2007(as shown in Table 4.6 Panel A), and this is the subsample not including the recent crisis period, while Subsample 2 is from 12/1988-09/2011(as shown in Table 4.6 Panel B), and it is the subsample including the recent crisis period. We make Subsample 2 start 5 years later than Subsample 1 so that these two subsamples have the same number of observations and thus we can exclude the effects caused by the difference in the size of observations when comparing the asset pricing results from those subsamples. Panel C provides the full sample as a benchmark.

In Table 4.6, we report cross-sectional pricing results for the linear factor model based on the DOL factor and the ΔVOL factor. The test assets are excess returns to five carry trade portfolios based on currencies from 48-all-county sample (left) and 29-OECD-country sample (right). The estimation method here is GMM.

[13] It spans from December 2007 to June 2009 as defined by The NBER.

As shown in Table 4.6, the pricing errors (as shown by the MAE) are smaller for Subsample 2 which includes the crisis period (Panel B), compared with the pricing errors for Subsample 1 which does not include the crisis period (Panel A). This suggests that the ΔVOL factor works better during crisis period. However, it is difficult to compare the risk price of the ΔVOL factor for those two subsamples because the risk loadings for them are also changing. Therefore, we can only compare their combination effects which are indicated by the mean absolute pricing errors (MAE). For both sample, Subsample 2 has smaller pricing errors than Subsample 1.

Although this is just a simple preliminary study, an important message has been suggested: there might be a nonlinear risk-return trade-offs in the FX market, i.e. factor prices are depending on whether the current period is crisis period or not. This nonlinear relationship can be understood by changing in investors' sensitivities to forecasts of future volatility risks between crisis period and non-crisis period, which we will examine more closely in the next chapter.

Table 4-6 Crisis period and non-crisis period

Panel A: Subsample 1 (12/1983-09/2007)									
48-all-country sample (without b-a)					29-OECD-country sample (without b-a)				
GMM	*DOL*	ΔVOL	R^2	J-stats	GMM	*DOL*	ΔVOL	R^2	J-stats
b	0.013	-8.102	0.872	(0.602)	b	0.021	-10.236	0.821	(0.530)
S.E.	0.051	3.760			S.E.	0.048	4.508		
λ	0.146	-0.075			λ	0.180	-0.095		
S.E.	0.128	0.032	MAE:	0.672e-3	S.E.	0.146	0.037	MAE:	0.744e-3
Panel B: Subsample 2 (12/1988-09/2011)									
48-all-country sample (without b-a)					29-OECD-country sample (without b-a)				
GMM	*DOL*	ΔVOL	R^2	J-stats	GMM	*DOL*	ΔVOL	R^2	J-stats
b	-0.070	-7.364	0.874	(0.549)	b	-0.036	-5.449	0.870	(0.247)
S.E.	0.065	3.235			S.E.	0.038	2.743		
λ	0.099	-0.063			λ	0.096	-0.047		
S.E.	0.136	0.025	MAE:	0.466e-3	S.E.	0.159	0.018	MAE:	0.494e-3
Panel C: Full sample (12/1983-09/2011)									
48-all-country sample (without b-a)					29-OECD-country sample (without b-a)				
GMM	*DOL*	ΔVOL	R^2	J-stats	GMM	*DOL*	ΔVOL	R^2	J-stats
b	0.031	-7.134	0.927	(0.781)	b	-0.015	-5.227	0.902	(0.549)
S.E.	(0.052)	(2.951)			S.E.	(0.035)	(2.481)		
λ	0.147	-0.072			λ	0.162	-0.065		
S.E.	(0.126)	(0.027)	MAE	0.500e-3	S.E.	(0.146)	(0.024)	MAE	0.525e-3

Note: this table provides the cross sectional pricing results for three different time periods based on both 48-all-country sample and 29-OECD-country sample. The test assets are excess returns to the five carry trade portfolios. Factors are the dollar risk (DOL) factor, and the volatility risk (ΔVOL) factor. Panel A is from 12/1983-09/2007 (not including the recent financial crisis period), while Panel B is from 12/1988-09/2011 (including the recent financial crisis period). Panel C is from 12/1983-09/2011 (the full sample). MAE is the mean absolute error. For J-statistics, p-value is provided in parentheses.

4.7. CONCLUSION

In this chapter, we follow Menkhoff, Sarno et al. (2012) and conduct the standard asset pricing test for the excess return from 5 forward-discount sorted portfolios based on both 48-all-country sample and 29-OECD-country sample. We prove that the pricing kernel with 1) the FX market return and 2) the FX market volatility can be derived from Chen (2002) version of ICAPM model and therefore the pricing kernel has a strong theoretical support. We also introduce the standard stochastic discount factor approach (Cochrane, 2005) in detail in the methodology section. In the following two chapters of this thesis, we derive different settings form this model. For the asset pricing test, the same methodology is applied.

Different from Menkhoff, Sarno et al. (2012), we test the model with one new sample and longer time period and find that the results are consistent with the findings of that the FX volatility factor is able to explain about 90% of the cross sectional excess returns from the carry trade. Further, by applying the model to a longer time period which covers the recent financial crisis period, we are able to compare the performance of the this model with and without the recent crisis period, we find that the volatility risk factor provides lesser pricing errors for the subsamples with crisis period. This indicates that a regime switching model with loadings of FX volatility risks varying conditional on different regimes would work better, which we will investigate closely in the next chapter.

5. CONDITIONAL FX VOLATILITY RISK PREMIUMS IN THE CARRY TRADE

5.1. INTRODUCTION

In the previous chapter, based on Chen (2002) version of Intertemporal Capital Asset Pricing Model (ICAPM), and Menkhoff, Sarno et al. (2012), we show that the FX market volatility risk is able to explain about 90% cross sectional returns from the carry trade. The FX volatility risk is priced negatively which indicates that investors would like to buy insurance to hedge against FX volatility risk. More importantly, the unconditional ICAPM model performs better for the subsample that contains the recent financial crisis period and this may suggest a regime dependent model which separates the crisis periods from normal periods would work better.

In this chapter, we propose such a model: we argue that investors care differently about the FX volatility risk during different volatility states. The FX volatility risk can explain the cross sectional currency excess returns, especially during high volatility risk state. The excess returns from the carry trade are actually mainly the compensation for bearing volatility risk during high volatility state. Further, by pricing the volatility risk during different volatility states separately, we will have a model which provides better fit than the unconditional ICAPM model provided in the previous chapter. Since in this model, we price the FX volatility risk conditioning on volatility state, we call this model the conditional ICAPM model, to distinguish form the unconditional version in the previous chapter.

This chapter is inspired by the following literature: Ang, Chen et al. (2006) argue that investors care differently about downside losses versus upside gains. Agents who place greater weight on downside risk demand additional compensation for holding stocks with high sensitivities to downside market movements. Therefore they study stock markets, by allowing both the price and loading of market risk to change conditional on the aggregate market return. Their conditional CAPM model fits better than the unconditional CAPM model in explaining the excess returns from stock market. Following Ang, Chen et al. (2006), Lettau, Maggiori et al. (2013) apply this conditional CAPM model in currency market and they find that it can price the cross section of currency returns. Intuitively, the model captures the changes in correlation between the carry trade and the aggregate market returns: the carry trade is more correlated with the market during market downturns than it is during upturns.

In this chapter, we connect this idea with the unconditional ICAPM model we tested in previous chapter. The contribution of our study is that we let the price and loading of the FX volatility risk to change conditioning on the volatility states instead of allowing the price and loading of market risk to change as done by Lettau, Maggiori et al. (2013). We define the 'high' volatility state as that when the volatility innovations are in their top 25% quartile and the 'normal' volatility state as that when the volatility innovations are below the top 25% quartile boundary. We find that for both 48-all-country sample and 29-OECD-country sample, investors care differently about volatility risk during different period of volatility risk level. Moreover, for the 29-OECD-country sample, we find that the excess return from the carry trade is actually a compensation for bearing volatility risk during high volatility risk state only. This finding is consistent with the rare disaster explanation of the forward premium puzzle by Farhi and Gabaix (2008) and the crash risk literature by Brunnermeier, Nagel et al. (2009). Finally, we will also show that for both samples, this conditional-ICAPM model provides better fit and has less pricing error than the unconditional model.

The structure of this chapter is as follow: In Section 5.2, we explain the background and motivation of our study. In Section 5.3, we provide the model and apply it to price the currency portfolios in Section 5.4. Section 5.5 provides our main empirical results and Section 5.6 concludes.

5.2. BACKGROUND AND MOTIVATION

As early as Roy (1952), economists have recognized that investors care differently about downside losses than upside gains. If an asset tends to move downward in a declining market more than it moves upward in a rising market, it is an unattractive asset to hold because it tends to have very low payoffs when the wealth of investors is low. (Ang, Chen et al. (2006)) argue that investors place greater weight on downside risk, they demand additional compensation for holding stocks with high sensitivities to downside market movements. Therefore they study stock markets, by allowing both the market price of risk and the beta of currencies with the market to change conditional on the aggregate market return. Their conditional CAPM model fits better than the unconditional CAPM model in explaining the excess returns from stock market.

Lettau, Maggiori et al. (2013) find that the unconditional CAPM cannot explain the cross section of currency returns because the spread in currency beta is not sufficiently large to match the cross-sectional variation in expected returns. The downside risk CAPM explains currency returns because the difference in beta between high and low interest currencies is higher conditional on bad market returns, and the market price is also higher than it is unconditional. Intuitively, the model captures the changes in correlation between the carry trade and the aggregate market returns: the carry trade is more correlated with the market during market downturns than it is during upturns.

In the previous chapter, we following Chen (2002) theoretically and Menkhoff, Sarno et al. (2012) empirically to test the unconditional ICAPM model and find that the volatility risk factor is able to explain about 90% cross-sectional currency excess returns and volatility risk is priced negatively which indicates that investors would like to buy insurance to hedge against volatility risk. Therefore, they require a low return for holding assets which are positively correlated with volatility risk such as low interest rate currencies, and vice versa they require a high return for holding assets which are negatively correlated with volatility risk such as high interest rate currencies. The loadings of volatility risk are varying across currencies portfolios with different interest rate characteristics and that's why they can price the cross-sectional currency returns well. Moreover, when we compare the pricing errors of the unconditional ICAMP model between subsamples with and without the recent financial crisis, we find that the model provides better fit when during volatile period. This suggests that we might have a model with better fit if we test the high volatility period and normal volatility period separately.

As inspired by the better performance of conditional CAPM model in both stock and currency markets, in this chapter we improve the unconditional ICAPM model to a conditional version by allowing both the price of FX volatility risk and the loading of FX volatility risk to change conditioning on the FX volatility risk levels. We argue that investors care differently about volatility risk during different period of volatility risk level. The excess returns from the carry trade can be mainly explained by the volatility risk premium during high volatility risk state. We find that both price of volatility risk and the loading of FX volatility risk changes during high volatility states, and the differences are significant. Also, we find that this model provides a better fit in pricing the cross sectional return from the carry trade than the unconditional ICAPM model tested in previous chapter.

Our model is consistent with two strands of literature in FX market : the rare disaster explanation of the forward premium puzzle by Farhi and Gabaix (2008) and the crash risk literature by Brunnermeier, Nagel et al. (2009). The rare disaster literature argues that the forward premium puzzle can be understood by the compensation of extreme events. While the crash risk literature argues that the currency abnormal return is a compensation of crash risk i.e. a sudden adjustments in exchange rate. Because historically, the excess return from the carry trade has exhibited the following pattern: it has a high and stable return during a long period, but then suffers a big loss during crisis period. As mentioned by Plantin and Shin (2006), high interest rate currencies has exhibited the classic price pattern of "going up by stairs, and coming down by elevator." In Chapter 7, we will study this closely by showing that the adjustment speed of exchange rate depends on the FX volatility level: when the FX volatility is high, the adjustment is quicker and larger. This also explains that why investors demand higher compensation for bearing volatility risk when the FX volatility is in a high state.

Apart from the support of the literature, intuitively, the conditional ICAPM model captures the changes in correlation between excess returns of the carry trade and the FX market volatility. There is a negative correlation between the excess returns from the carry trade and the volatility risk. However, the correlations are changing with the different level of volatility risks.

Table 5.1 shows the correlations between excess returns and the volatility innovation factor conditioning on different levels of volatility innovations. The excess returns are from the 5 currency portfolios for both 48-all-country sample and 29-OECD-country sample as descripted in Chapter 3. P1 contains currencies with the lowest interest rates and P5 contains currencies with the highest interest rates. We also show the carry trade portfolio here, which is denoted as HML and it is formed by taking a short position in P1 and a long position in P5. The volatility innovation is denoted as ΔVOL and is defined in Chapter 3 as well, which is the residual from an AR(1) regression of monthly realized volatility. Here, we show the correlations between the excess returns and ΔVOL conditioning on different percentiles of ΔVOL, from the top 5% percentile to the full sample as indicated by the first column.

As shown in Table 5.1, for both samples, the excess returns and the ΔVOL factor are negatively correlated regardless of which percentiles the ΔVOL is in. However, the correlations change across portfolios and across percentiles. For the 29-OECD-Country-Sample, as shown in Table 5.1 Panel B, there is a clear monotonically decreasing (in absolute value) pattern when moving from P1 to P5 and HML for each row of quartile and a clear decreasing (in absolute value) pattern when moving from the top 5% volatility innovation percentile to the whole sample for each column of portfolio. This table generally indicates the following: (1) excess returns and volatility innovations are negatively correlated; (2) the negative correlation between excess returns and volatility innovations are smaller for portfolios contain low interest rate currency and larger for portfolios contain high interest rate currencies and the carry trade portfolio. This difference provides a spread in volatility risk loadings and explains why ΔVOL can price cross-sectional currency portfolios as tested empirically in the previous chapter; and (3) the negative correlation between excess returns and volatility innovations are larger when volatility risk is in its high percentiles.

As for the 48-All-Country-Sample (shown in Panel A of Table 5.1), the correlations follow the similar pattern as the 29-OECD-Sample, except for some of them which are underlined. The explanation about these exceptions is that there might be some outliers for Portfolio 4 and Portfolio 5 in the 48-All-Country sample, and these outliers behave differently when the volatility risk is high. These differences also affect the correlation between the carry trade portfolio and the volatility innovation when the volatility risk is high. However, apart from those outliers, for most of the correlations, they have the similar pattern as the 29-OECD-country sample.

In the previous chapter, we have tested empirically that ΔVOL can price the cross sectional excess returns among currency portfolios and as we mentioned that is because the negative correlation between excess returns and volatility innovations are smaller for portfolios contain low interest rate currency and larger for portfolios contain high interest rate currencies and the carry trade portfolio. Therefore, it would be interesting to estimate the factor risk price for different volatility states as the negative correlations between excess returns and volatility innovations are larger conditioning on high volatility percentiles.

In next section, we introduce a model which captures the different volatility risk loading and price during high volatility period. This model still has the same pricing kernel with two factors: the FX market return and the FX market volatility, so it is still in an ICAPM setting, however, by adding the volatility risk as a regime, the pricing kernel is conditioning on volatility risk states, thus we call this model conditional ICAPM so as to distinguish from the unconditional ICAPM in the previous chapter.

Table 5-1 Correlation of Excess Returns and Volatility Innovation (ΔVOL)

		Panel A. 48 all-country sample						Panel B. 29-OECD-country sample					
ΔVOL Percentiles	Obs.	P1	P2	P3	P4	P5	*HML*	P1	P2	P3	P4	P5	*HML*
0.05	17	-0.57	-0.61	-0.63	-0.59	-0.46	-0.06	-0.50	-0.59	-0.68	-0.68	-0.70	-0.58
0.15	50	-0.23	-0.25	-0.35	-0.31	-0.35	-0.23	-0.16	-0.27	-0.34	-0.44	-0.52	-0.52
0.25	84	-0.20	-0.26	-0.33	-0.35	-0.33	-0.24	-0.17	-0.29	-0.34	-0.41	-0.43	-0.39
0.35	117	-0.15	-0.22	-0.33	-0.32	-0.35	-0.31	-0.12	-0.23	-0.28	-0.41	-0.41	-0.39
0.45	150	-0.11	-0.21	-0.30	-0.29	-0.37	-0.36	-0.10	-0.20	-0.26	-0.36	-0.39	-0.38
0.55	184	-0.08	-0.17	-0.25	-0.25	-0.35	-0.35	-0.08	-0.16	-0.21	-0.32	-0.34	-0.34
0.65	217	-0.07	-0.15	-0.23	-0.24	-0.31	-0.30	-0.08	-0.15	-0.18	-0.30	-0.30	-0.27
0.75	250	-0.05	-0.12	-0.21	-0.21	-0.30	-0.31	-0.06	-0.11	-0.16	-0.28	-0.28	-0.28
0.85	284	-0.03	-0.11	-0.20	-0.20	-0.30	-0.31	-0.03	-0.10	-0.15	-0.27	-0.28	-0.30
0.95	317	-0.01	-0.11	-0.19	-0.20	-0.29	-0.32	-0.02	-0.09	-0.19	-0.25	-0.27	-0.30
All	334	-0.01	-0.11	-0.19	-0.18	-0.28	-0.32	-0.03	-0.10	-0.14	-0.24	-0.27	-0.29

Note: this table shows the correlations between excess returns and the volatility innovation factor conditioning on different levels of volatility innovations. The first column shows the percentiles of ΔVOL, changing form the top 5% percentile to the full sample. We show the correlations between the excess returns from the 5 currency portfolios for both 48-all-country sample (Panel A) and 29-OECD-country sample (Panel B) conditioning on ΔVOL levels. The underlined numbers in Panel A are numbers exhibited different pattern from others. The sample period is 12/1983 to 09/2011.

5.3. MODEL

In this section, we provide the conditional ICAPM model. This can be derived from the unconditional ICAPM model which, as explained in previous chapter, has been theoretically supported by Chen (2002) and empirically tested by Menkhoff, Sarno et al. (2012) in currency market. We derive our conditional ICAPM from the two factor model of Menkhoff, Sarno et al. (2012): the SDF is shown in Eq. 4.2, and it contains two risk factors: the FX market return and the FX volatility innovations.

$$m_{t+1} = 1 - b_1 rx_{t+1}^m - b_2 \Delta V_{t+1} \qquad \text{Eq. 4.2}$$

We improve this model one step further by allowing the loading of risks, b_1 and b_2 to vary according to a threshold of FX volatility innovations, the threshold we pick up is the 3rd quartile of the ΔVOL factor (the quartiles for ΔVOL are reported in Table 3.1), as shown in the following equation Eq. 5.1. The pricing kernel has the same two factors as the unconditional ICAPM, but we separate the pricing kernel for the high volatility state. The reason we pick up the 3rd quartile as the threshold is suggested by the bar plots of the excess returns of the carry trade portfolio in the previous chapter, the average excess return from the carry trade portfolio is positive when the volatility innovation is in its top quartile and negative when it is in the other three quartiles.

For all *t+1:*

$$m_{t+1} = 1 - b_1 rx_{t+1}^m - b_2 \Delta V_{t+1}$$

Eq. 5.1

For *t+1* when ΔV_{t+1}> the 3rd quartile :

$$m_{t+1} = 1 - b_1^- rx_{t+1}^m - b_2^- \Delta V_{t+1}$$

where b_1^- and b_2^- denote the loadings of risk factors when the volatility innovation is in its top quartile.

According to Cochrane (2005), the methodology explained in the previous chapter, the expected returns are thus modelled as in Eq. 5.2:

$$E[RX_i] = b_1\lambda_1 + (b_1^- - b_1)\lambda_1^- + b_2\lambda_2 + (b_2^- - b_2)\lambda_2^- \qquad \text{Eq. 5.2}$$

where bs are the loadings of risks and λs are the price of risks, and $i = 1, \dots, 5$ as for 5 portfolios. This empirical framework is flexible in allowing variations in both the loadings and the price of risks. Since the correlations between market return and excess returns do not vary much conditioning on volatility risk (the correlations are provided in Appendix A.2) so we assume $b_1^- = b_1$, then the expected returns are modelled as in Eq. 5.3:

$$E[RX_i] = b_1\lambda_1 + b_2\lambda_2 + (b_2^- - b_2)\lambda_2^- \qquad \text{Eq. 5.3}$$

Note that the model reduces to the unconditional ICAPM in the absence of differential pricing of extreme volatility risk from unconditional volatility risk $\lambda_2^- = 0$; or if the downside beta equals the unconditional ICAPM beta: $b_2^- = b_2$.

5.4. ASSET PRICING TEST

We estimate the model with the two-stage procedure of Fama and MacBeth (1973). In our model the first stage consists of two time-series regressions, one for the entire time series and one for the observations of high volatility risk periods. These two regressions produce point estimates for the unconditional and high volatility risk state betas, which are then used as explanatory variables in the second stage.

The first-stage regressions are:

$For\ t = 1, \dots, T\ and\ i = 1, \dots, 5$

$$rx_{it} = a_i + b_{1i} DOL_t + b_{2i} \Delta VOL_t + \epsilon_{it}$$

Eq. 5.4

$Whenever\ \Delta VOL_t > 0.000485\ \ and\ i = 1, \dots, 5$

$$rx_{it} = a_i^- + b_{1i}^- DOL_t + b_{2i}^- \Delta VOL_t + \epsilon_{it}$$

The second-stage regression is a cross-sectional regression of the average return of the assets on their unconditional and high state betas. The second-stage regression is:

$$\overline{rx}_i = \hat{b}_{1i} \widehat{\lambda_1} + \hat{b}_{2i} \lambda_2 + (\hat{b}_{2i}^- - \hat{b}_{2i}) \lambda_2^- + \epsilon_i \qquad \text{Eq. 5.5}$$

$i = 1, \dots, 5$ where $\overline{rx}_i$ is the time average return for portfolio i , $\hat{b}_{1i}$, $\hat{b}_{1i}^-$, $\hat{b}_{2i}$ and $\hat{b}_{2i}^-$ are the point estimates from the first stage estimations. In the estimation we restrict $\widehat{\lambda_1} = \overline{DOL}$, this is consistent with the theory that the market price of risk is equal to the sample average of the market excess return. This is hold because that the market has a unit loading of market risk and therefore the risk price is equal to the average of market return. From the second stage estimation, we can get the volatility risk price λ_2 and the additional volatility risk price λ_2^- during high volatility state.

5.5. Empirical results

Our data set are the 48-all-country sample and the 29-OECD-country sample as reported in the data chapter. There are 5 interest rate sorted portfolios for each sample, and the empirical test is carried out in monthly frequency, the data spans from 1983M11 until 2011M09. The estimation method is the Fama and MacBeth (1973) two-stage procedure.

Table 5.2 reports the estimation results from the 1st stage regression. For each sample, in Panel A we report the time series estimates for the entire sample, it is the same result as shown in the previous chapter that low interest rate portfolios have positive loading on volatility risk while high interest rate portfolios have negative loading. Panel B is the same time series regression for the state with high volatility risk, i.e. when the volatility innovation exceeds the 3rd quartile and thus the number of observation is 83 which is about a quarter of all 334 observations. As shown in Table 5.2, Panel B, for the 29-OECD-country sample, portfolios with lower interest rate currencies have higher loadings of volatility risk compared with that in Panel A for the whole sample, while portfolios with lower interest rate currencies have higher negative loadings of volatility risk compared with that in Panel A for the whole sample. Actually, all 5 portfolios have larger absolute loadings of volatility risk during high volatility risk period, and the loading spreads from portfolio1 to portfolio 5 is about 12.7 which is higher than the spread of the full sample, which is 7.9. This is implied by the negative correlations between portfolio excess returns and volatility risk as reported in Table 4.1 for the 29-OECD-country-sample, for each portfolio, the correlations are more negative when the volatility risk is higher.

However, for the 48-all-counaty sample as reported in Table 4.1, there are some exceptions in the correlation pattern between the excess returns and the volatility risk. These exceptions also affect the loading of volatility risk in the high volatility state. As shown in Table 4.2 Panel B, for the 48-all-country sample the spread of the loading for volatility risk between Portfolio 1 and Portfolio 5 does not change much compared with the regression contains the whole observation in Panel A. These exceptions also affect the 2nd stage regression.

For both samples, there is no significant change for the loading of FX market risk, the DOL factor, after we include an additional extra volatility risk factor in the time series regressions. Therefore it makes sense to ignore their difference in the second stage regression as this helps us to focus on the volatility risk factor.

Table 5.3 shows the results from the 2nd stage regression, which provides the risk price for each risk factor. We provide the results from unconditional-ICAPM model in Panel A as a benchmark (the same results as reported in Chapter 4, Table 4.3). Panel B shows the results for the conditional ICAPM model which includes the extra volatility risk. We define the extra volatility risk as the premium for bearing extra volatility risk during high volatility state (when ΔVOL_t exceeds the 3rd quartile). For 29-OECD-country sample, after we include the extra volatility risk factor in the cross sectional regression, the volatility risk price becomes insignificant while the extra volatility risk factor is highly significant. This suggests that excess return from the carry trade is actually a compensation for bearing the extra volatility risk during high volatility period. This is consistent with the rare disaster explanation of the forward premium puzzle by Farhi and Gabaix (2008) and the crash risk literature by Brunnermeier, Nagel et al. (2009).

Therefore, the excess return from the carry trade is actually the compensation for bearing volatility risk during high volatility state.

For the 48-all-country sample, as we mentioned before, since the exceptions in correlation affect the loading of volatility risk during high volatility state and the risk premium is determined by the product of the risk loading and the risk price, therefore, it affects the volatility risk price as well. Both the volatility risk and the extra volatility risk are priced significantly.

Moreover, the conditional ICAPM model provides better fit in pricing the cross-sectional currency returns. After we include the extra volatility risk factor, for the 29-OECD-country sample, the adjusted R^2 increases from 85% for the unconditional ICAPM model to 90% for the conditional ICAPM model. As for the 48-all-country sample, there is a 7% increase in the adjusted R^2, from 90% to 97%.

In Figure 5.1, for both samples, we plot the fitted mean excess returns against the realized mean excess returns for all five portfolios. The realized mean excess returns are shown as the 45 degree line while the distances between the dots to the line indicate the pricing errors. As we can see from the figure, the conditional ICAPM provides less pricing error than the unconditional ICAPM model in explaining the cross-sectional excess returns from the carry trade.

Table 5-2 The First Stage of FMB Regression

Panel A. For all observations (334-month)					Panel B. For observations when ΔVOL_t>0.00048 (83-month)				
48-all-country sample					48-all-country sample				
PF	α	DOL	ΔVOL	R^2	PF	α	DOL	ΔVOL	R^2
1	-0.003	0.962	3.771	0.774	1	-0.002	0.956	3.784	0.829
	[0.001]	[0.051]	[0.689]			[0.003]	[0.063]	[1.872]	
2	-0.001	0.998	1.372	0.818	2	-0.001	0.977	1.778	0.878
	[0.001]	[0.046]	[0.649]			[0.002]	[0.060]	[1.495]	
3	0.001	0.962	-0.353	0.800	3	0.003	0.941	-1.687	0.859
	[0.001]	[0.040]	[0.679]			[0.003]	[0.055]	[1.832]	
4	0.001	0.992	-0.567	0.841	4	0.002	0.980	-1.121	0.867
	[0.001]	[0.039]	[0.657]			[0.002]	[0.056]	[1.754]	
5	0.003	1.086	-4.222	0.675	5	-0.001	1.147	-2.754	0.716
	[0.001]	[0.068]	[1.294]			[0.004]	[0.110]	[2.827]	
29-OECD-country sample					29-OECD-country sample				
PF	Alpha	DOL	ΔVOL	R^2	PF	Alpha	DOL	ΔVOL	R^2
1	-0.003	0.988	3.36	0.820	1	-0.008	0.991	7.071	0.877
	[0.001]	[0.041]	[0.879]			[0.003]	[0.062]	[2.109]	
2	-0.001	1.079	1.543	0.892	2	-0.001	1.071	2.321	0.924
	[0.001]	[0.028]	[0.637]			[0.002]	[0.046]	[1.084]	
3	-0.000	1.015	0.146	0.904	3	0.001	0.972	0.246	0.923
	[0.001]	[0.024]	[0.533]			[0.002]	[0.046]	[1.161]	
4	0.001	1.006	-2.841	0.867	4	0.002	1.044	-3.916	0.905
	[0.001]	[0.029]	[0.833]			[0.002]	[0.045]	[1.948]	
5	0.001	0.930	-3.968	0.756	5	0.006	0.923	-5.723	0.811
	[0.001]	[0.045]	[1.193]			[0.003]	[0.061]	[2.451]	

Note: this table reports the results from the 1st stage time series FMB regression based on both 48-all-country sample and 29-OECD-country sample. The test assets are excess returns to the five carry trade portfolios. Factors are the dollar risk (DOL) factor, and the volatility risk (ΔVOL) factor. Panel A provides estimation for the full sample while Panel B provides estimation when the volatility innovations are in the top quartile. Newey-West standard errors are reported in the brackets.

Table 5-3 The Second Stage of FMB Regression

Panel A. Unconditional ICAPM model

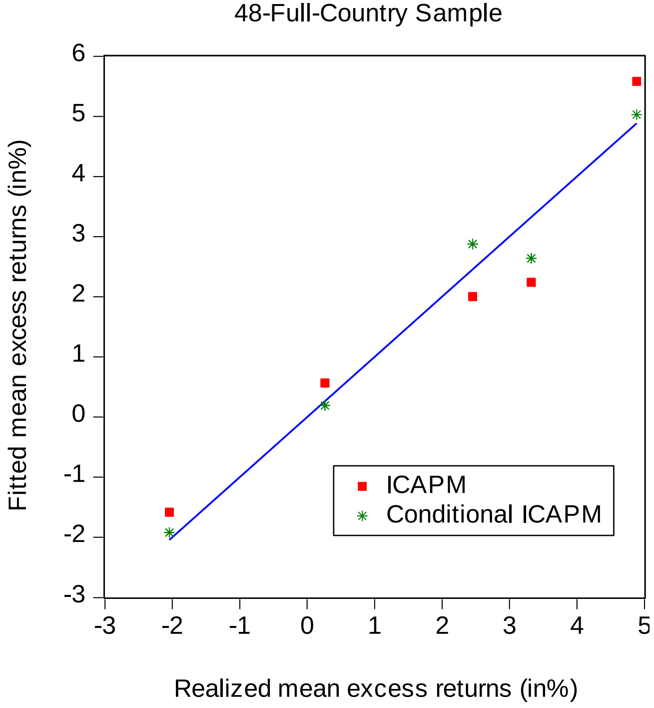
48-all-country sample				
	Market Return ($DOL\%$)	Market Volatility Risk ($VOL\%$)	R^2	MAE
λ	0.147***	-0.072***	0.902	5.012e-4
S.E.	[0.023]	[0.015]]		
29-OECD-country sample				
	Market Return ($DOL\%$)	Market Volatility risk ($VOL\%$)	R^2	MAE
λ	0.162***	-0.061***	0.853	5.363e-4
S.E.	[0.014]	[0.008]		

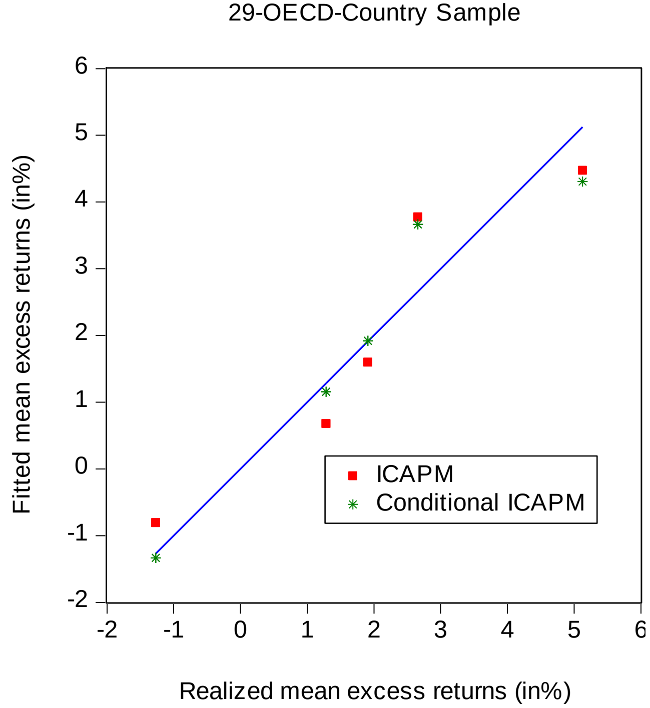
Panel B. Conditional I-CAPM model

48-all-country sample					
FMB	Market Return ($DOL\%$)	Market Volatility risk ($VOL\%$)	Extra Volatility Risk	R^2	MAE
λ	0.147	-0.080***	-0.053***	0.968	2.432e-4
S.E.		[0.002]	[0.013]		
29-OECD-country sample					
FMB	Market Return ($DOL\%$)	Market Volatility risk ($VOL\%$)	Extra Volatility Risk	R^2	MAE
λ	0.162	-0.031	-0.046***	0.898	3.411e-4
S.E.		[0.015]	[0.012]		

Note: this table reports the results from the 2nd stage time series FMB regression based on both 48-all-country sample and 29-OECD-country sample. The test assets are excess returns to the five carry trade portfolios. Factors are the dollar risk (DOL) factor, and the volatility risk (ΔVOL) factor. Panel A provides estimation for the full sample while Panel B provides estimation when the volatility innovations are in the top quartile. Newey-West standard errors are reported in the brackets.

Figure 5-1 Pricing Error Plots for Unconditional and Conditional ICAPM Models





Note: The figure plots the fitted mean excess returns from 5 portfolios against the realized mean excess returns of the 5 portfolios for both unconditional ICAPM model (squares) and conditional ICAPM model (stars). The distance from the points to the 45 degree line shows pricing errors of the model. The sample period is 12/1983 to 09/2011.

5.6. CONCLUSION

In this chapter, we improve the unconditional ICAPM model into a conditional version by allowing both the loading and price of volatility risk to vary according to volatility risk state. The conditional ICAPM model provides a better fit for both the two samples compared with the unconditional model. More importantly, for the 29-OECD-country sample, the excess return from the carry trade is actually a compensation for bearing volatility risk during high volatility risk period. The carry trade portfolio is more negatively correlated with volatility risk during high volatility and this explains the pattern of excess return from the carry trade: a consistent and stable return for a long period followed by a big loss during turbulent period. Our study is also consistent with the rare disaster explanation of the forward premium puzzle by Farhi and Gabaix (2008) and the crash risk literature by Brunnermeier, Nagel et al. (2009). These findings suggest that it would be interesting to examine the reason that the carry trade suffers from big losses during the turbulent period and if we can construct any other trading strategies to avoid the losses. We will provide an empirical study regarding to this in Chapter 7.

6. DECOMPOSED FX VOLATILITY RISK PREMIUMS IN THE CARRY TRADE

6.1. INTRODUCTION

In the previous chapters, we find that the cross sectional excess returns from the carry trade can be explained by the FX volatility risk, which indicates that investors want to directly hedge against changes in future market volatility and therefore market volatility risks are negatively priced. The excess returns from the carry trade therefore are compensations for bearing FX volatility risk, especially the volatility risk during the volatile periods, as indicated by the conditional ICAPM model. In this chapter, we start from a different angle by examining the relationship between the excess returns of the carry trade and the FX volatility risk at different frequencies: a persistent volatility risk component, the long-run volatility risk, and a less persistent volatility risk, the short-run volatility risk.

This chapter is inspired by literature in stock market. Based on the theoretical support of Chen (2002) version of ICAPM model, Ang, Hodrick et al. (2006) use the stock market return and market volatility to explain the cross-sectional excess return from the sorted portfolios in stock market. Inspired by this, Menkhoff, Sarno et al. (2012) apply the same pricing kernel in currency market and find it to be very successful as well. Based on Menkhoff, Sarno et al. (2012), we also test the robustness of the same pricing kernel in Chapter 4 by using a new sample and longer data period and find the results are consistent. These findings are consistent with the modern asset pricing theory that a unique pricing kernel is able to price all financial assets (Cochrane, 2005). As suggested by this theory, it would be very tempting and interesting to apply other successful models in stock market to currency market.

Volatility risk are subject to shocks at different frequencies as argued by Lee and Engle (1993) and investors make their decision heavily depend on whether the risk is permanent or transitory, thus by separating the source of volatility risk, we could examine how the permanent and transitory volatility risks are separately priced in the carry trade and the proportions of volatility risk premiums subject to different frequencies.

In this chapter, we decompose FX market volatility into short- and long-run components by using a Component-GARCH model as inspired by Adrian and Rosenberg (2008), and we take the two volatility risk components as separated pricing factors to price the carry trade portfolios.

We find that prices of both volatility risk components are negative which implies that investors pay for insurance against changes in volatility, even if those changes have little persistence. We take the unconditional-ICAPM model as the benchmark model, and we find that after we price the volatility risk components separately, the pricing errors are reduced, and this two components model provides better fit.

Moreover, we find that for different samples, the proportions of volatility risk premium are different. For the 48-all-country sample, investors require about equally proportion of compensation for bearing long- and short-run volatility risks, while for the 29-OECD-country sample, the risk premium are mainly from bearing the short-run volatility risk.

To interpret the economics of long- and short-run volatility components, as inspired by Adrian and Rosenberg (2008) in stock market, we relate the long-run volatility component, to the U.S. business cycle and the short-run volatility component to a measure of the tightness of financial constraints. However, we find the correlations for both of them are quite low. This is consistent with the literature that exchange rate is not correlated with traditional risk factors Burnside (2011).

The contribution of this chapter is that we are the first to decompose FX market volatility into long- and short-run components. As far as we know, there are literature decomposing the exchange rate volatility between currency pairs, however, there is no literature decomposing FX market volatility yet. This is because, compared with stock market return, it is relatively difficult to measure the FX market return as there are not as many cross-sectional observations as that in stock market. In this chapter, we take the average excess return of borrowing U.S. dollar and lending in equally weighted 48 other currencies as the FX market return. Moreover, we use the two FX volatility components to price the excess returns from the carry trade and we find that our model provides better fit than the single volatility factor model as proposed by Menkhoff, Sarno et al. (2012) and tested in Chapter 4 of this thesis. Further, in this Chapter, the volatility components we use are from the Component-GARCH model, which are the conditional measure of volatility and it is different from the implied volatility measure in Ang, Hodrick et al. (2006), in which they use the implied volatility-the VIX data as a proxy of stock market volatility, and different from the realized volatility measure as in in Chapter 4, in which we aggregate the average daily absolute changes in exchange rate across currencies into monthly observation. The conditional volatility measure also provides a good fit for pricing the carry trade which proves that the fact that FX volatility risk is able to explain the excess return from the carry trade is independent of the methods in which we proxy it.

The structure of this chapter is as follow: in Section 6.2, we introduce some background literature and motivation of our work; followed by Section 6.3 in which we model conditional volatility by using a component GARCH model; Section 6.4 contents the main asset pricing test results and Section 6.5 concludes.

6.2. BACKGROUND AND MOTIVATION

As argued by Cochrane (2005), the modern asset pricing theory believes that there should be a unique pricing kernel that is able to price all financial assets. Based on this theory, literature in FX market has been highly influenced by stock market literature, not only in sharing the same pricing kernel but also in some of the research methods. Taking the Fama and French (1993) portfolio sorting approach as an example, this portfolio sorting approach has a long tradition in the stock literature and has been brought to the currency literature by Lustig and Verdelhan (2007) in which they sort currencies into portfolios according to their interest rate differentials with certain currency. As mentioned in Chapter 3, by sorting these currencies into portfolios, we abstract the currency-specific component of exchange rate changes and focus on exchange rate changes caused by interest rate differentials. This portfolio sorting approach has been very popular in recent currency literature (Lustig, Roussanov et al. (2011), Burnside (2011)and Menkhoff, Sarno et al. (2012)) and enable us to apply some research methods from equity market literature into currency market literature.

Table 6.1 lists some of the successful attempts in currency market which are inspired by research methods in stock market. Ang, Hodrick et al. (2006) use a pricing kernel which contains two factors, the market return and market volatility, to explain the cross-sectional excess return from the sorted portfolios in the stock market. This pricing kernel can be derived from Chen (2002) version of ICAPM model. Menkhoff, Sarno et al. (2012) apply the same pricing kernel in currency market and find it is able to explain about 90% excess return from the carry trade. Rather than implied volatility as used by Ang, Hodrick et al. (2006), they use realized volatility formed by aggregate the average daily absolute changes in exchange rate across currencies into monthly observation. We test the same model in Chapter 4 by using a new sample and longer data period and find the results are robust. Given such a good performance of stock market model applying in currency market, it would be very tempting and interesting to apply other successful models in stock market to currency market.

One of them in this strand of literature is by Adrian and Rosenberg (2008). Started from Ang, Hodrick et al. (2006), they explore the cross-sectional pricing of volatility risk in one step deep by decomposing stock market volatility into long- and short-run components. They find that prices of risk are negative and significant for both volatility components which imply that investors pay for insurance against increases in volatility, even if those increases have little persistence. They also find that their asset pricing model with the market return and the two volatility components as cross-sectional pricing factor outperforms the model used by Ang, Hodrick et al. (2006). Furthermore, they relate the persistent component, the long-run volatility component, to the U.S. business cycle and the less persistent component, the short-run volatility component to a measure of the tightness of financial constraints, which interpret the economics of long-and short-run volatility.

Table 6-1 Currency Market Literature Influenced by Stock Market Literature

Stock Market	Currency Market
Fama and French (1993)	Lustig and Verdelhan (2007)
Ang, Hodrick et al. (2006)	Menkhoff, Sarno et al. (2012)/ Chapter 4
Adrian and Rosenberg (2008)	Chapter 6

The idea that market volatility is subject to shocks at different frequencies is from Lee and Engle (1993) and thus they develop the Component-GARCH (CGARCH) model which decomposes volatility into permanent and transitory components. The CGARCH model has been widely used recently in both economics and finance because separating the permanent and transitory risk premium could help us to understand the source of uncertainty, and investment decisions heavily depend on whether this uncertainty is permanent or transitory.

Apart from Adrian and Rosenberg (2008), there is a large body of literature providing evidence that the CGARCH model works better than the standard GARCH models in explaining stock market volatility. Apart from its success in equity market, literature has shown that the CGARCH model is also a superior volatility model for exchange rates, as it can distinguish the permanent and transitory volatility components to describe volatility dynamics better than other GARCH models.

Black and McMillan (2004) find evidence of short-run and long-run components in exchange rates, which exhibit different rates of volatility persistence and decay from a shock to volatility. They also find that the CGARCH specification provides a more adequate description of exchange rate volatility than a GARCH specification. (Byrne and Davis (2005)) find that for a pool-able subsample of

European countries, it is the transitory and not the permanent component of volatility which adversely affects investment. Pramor and Tamirisa (2006) analyse exchange rate volatility trends in Central and Eastern European currencies and the euro and find the long-run volatility is mainly driven by shocks to economic fundamentals rather than shifts in market sentiment. Simon and Amalia (2011) examine the relationship in the volatility of sovereign yields using a CGARCH model to decompose permanent and transitory volatility. The results suggest that transitory shifts in debt market sentiment tend to be less important determinants of bond yield volatility than shocks to the underlying fundamentals. Rangel (2011) uses a CGARCH model to obtain long-run and short-run volatility components for currencies pairs.

However, those studies are all applied for currency pairs. As far as we know, there is no literature that uses the CGARCH model to decompose foreign exchange market volatility into long-run and short-run components. Our Chapter contributes in this point that we decompose FX market volatility into long-run and short-run components and using those components as pricing factors for cross sectional currency portfolios.

6.3. MODELLING CONDITIONAL VOLATILITIES

In this section, we apply the component-GARCH model in FX market to obtain the conditional volatilities at different frequencies. For the specification of the component-GARCH model, we follow Adrian and Rosenberg (2008) to use the conditionally log-normal models of volatility as Nelson (1991) shows that conditionally log-normal models of volatility perform better than square-root or affine volatility specifications. In modelling FX market risk, we incorporate these features and specify the dynamics of the FX market return rx^M_{t+1} and its conditional volatility v_{t+1} as:

Market excess return: $$rx^M{}_{t+1} = \theta_1 + \theta_2 s_{t+1} + \theta_3 l_{t+1} + \sqrt{v_{t+1}}\varepsilon_{t+1} \quad \text{Eq. 6.1}$$

Market volatility: $$\ln\sqrt{v_{t+1}} = s_{t+1} + l_{t+1} \quad \text{Eq. 6.2}$$

Short-run component: $$s_{t+1} = \theta_4 s_t + \theta_5 \varepsilon_t + \theta_6 (|\varepsilon_t| - \sqrt{2/\pi}) \quad \text{Eq. 6.3}$$

Long-run component: $$l_{t+1} = \theta_7 + \theta_8 l_t + \theta_9 \varepsilon_t + \theta_{10} (|\varepsilon_t| - \sqrt{2/\pi}) \quad \text{Eq. 6.4}$$

where rx^M_{t+1} denotes the FX market return and we use the DOL factor, the DOL factor measures the monthly average return of borrowing U.S. dollar and lending the other 48 equally weighted currencies, to proxy it. v_{t+1} is the FX market volatility and the log-volatility $ln\sqrt{v_{t+1}}$ in Eq.5.2 is the sum of two components, the long-run component l_{t+1} and the short-run component s_{t+1}. Each component is a first order autoregressive process AR (1) with its own rate of mean reversion. Without loss of generality, let l be the slowly mean-reverting, long-run component and s be the quickly mean-reverting, short run component

($\theta_4 < \theta_8$). We normalize the unconditional mean of s to be zero as it is difficult to separate the unconditional mean of *s* from the unconditional mean of *l* as the log-volatility is equal to the sum of them.

ε_t is a normal i.i.d. error term with zero expectation and unit variance. The term $\left|\varepsilon_t\right| - \sqrt{2/\pi}$ in Eq.6.3 and Eq. 6.4 are the shocks to the volatility component. For these error terms, equal-sized positive or negative innovations result in the same volatility changes, although the magnitude can be different for the short and long run components. We also allow for an asymmetric effect of returns on short- and long-run volatilities by including the market innovation in Eq.6.3 and Eq. 6.4.

We estimate the volatility model from 12/1983 to 09/2011 by using the maximum likelihood estimation method. The monthly market excess returns are measured by the DOL factor from 48-all-country sample. To proxy the FX market returns, we include as many currencies as possible in our sample. As mentioned in previous chapters, the DOL factor measures the monthly average return of borrowing U.S. dollar and lending the other 48 equally weighted currencies and in Table 6.2 Panel A, we provide the summary statistics for the monthly market excess return, it has a mean of about 0.2%. This positive excess return suggests that investors demand a low but positive risk premium for borrowing in U.S. dollar and holding a portfolio of equally weighted other currencies.

Table 6.2 Panel B provides Maximum Likelihood estimation results for the volatility model. In the expected return equation, we find that short-run volatility has a significant negative coefficient (θ_2), while the long-run volatility has a significant positive coefficient (θ_3). The expected return thus depends positively on long-run volatility but negatively on short-run volatility. This is similar to the correlations in stock market. As mentioned by Adrian and Rosenberg (2008), this explains why there are contradictory findings in the sign of the correlation between stock market return and market volatility.

We can identify the short-and long-run components by their relative degrees of autocorrelation: the short-run volatility component has an autoregressive coefficient (θ_4) of 0.311, and the long-run component has an autoregressive coefficient of (θ_8) 0.976. While the long-run component is highly persistent, it is not permanent; we reject the hypothesis that $\theta_8 = 1$ at 1% level. Because the short-and long-run components determine log-volatility additively, we are not able to identify the means of the two components separately, and we estimate only the mean of the long-run component (θ_7).

We find negative returns increase short run volatility more than positive returns. The asymmetric effect for the short-run component is large and significant, while the asymmetric effect for the long-run component is not significant. Thus, we would expect short-run volatility to be linked to market skewness, since a negative return shock disproportionately increases short-run volatility, which further raises the likelihood of another large move.

We also test the auto-correlation in the error term by providing the Q-statistics with 10 and 20 lags, and the p-value suggest that we do not reject the null that there is no auto-correlation in the error term.

Table 6-2 Time-series Estimation of the Volatility Components

Panel A. Summary Statistics of Market Excess Return (334 months)				
Mean	Median	S.D.	Skewness	Kurtosis
0.0020	0.0030	0.0220	-0.3900	0.9300

Panel B. The Maximum Likelihood Estimation			
Market Excess Return: $rx_{t+1}^{M} = \theta_1 + \theta_2 s_{t+1} + \theta_3 l_{t+1} + \sqrt{v_{t+1}}\varepsilon_{t+1}$			
	θ_1	θ_2	θ_3
Coef.	0.0553***	-0.0349***	0.0139***
S.E.	0.0000	0.0042	0.0000
Short-Run Component: $s_{t+1} = \theta_4 s_t + \theta_5 \varepsilon_t + \theta_6(\lvert\varepsilon_t\rvert - \sqrt{2/\pi})$			
	θ_4	θ_5	θ_6
Coef.	0.3110***	-0.0648***	0.0527***
S.E.	0.0240	0.0004	0.0034

Long-Run Component: $l_{t+1} = \theta_7 + \theta_8 l_t + \theta_9 \varepsilon_t + \theta_{10}(\lvert\varepsilon_t\rvert - \sqrt{2/\pi})$				
	θ_7	θ_8	θ_9	θ_{10}
Coef.	-0.0886***	0.9761***	0.0015	0.0545***
S.E.	0.0001	0.0001	0.0012	0.0030
	p-value of $\theta_8 = 1$:		0.0000	

	10 lags	20 lags
Ljung-Box Q-statistic of ε_t	11.30	18.80
p-value	0.33	0.54

Note: this table reports the summary statistics of the monthly market excess return and the maximum likelihood estimates of the volatility components model. The market excess return is measured as the average monthly excess return of borrowing U.S. dollar and investing in 48 other currencies (for some months, we have less than 48 currencies, depends on currency data availability). The variance of the market excess return v is defined as $v = exp(2(s + l))$, where l denotes the long-run volatility component and s the short-run volatility component. The sample spans from 12/1983 to 09/2011.

In Figure 6.1, we plot the estimated volatility of the FX market return at a monthly frequency for 12/1983 to 09/2011 in the third figure, together with the other two measure of volatility: the option implied volatility by the VIX[14] index in the first figure and the realized volatility measure of Menkhoff, Sarno et al. (2012) in the second figure. As we can see from the figure, all three measures have a big increase in volatility in the recent financial crisis.

In Figure 6.2 and Figure 6.3, we plot the estimated long-run volatility component l and the short-run volatility component s separately. As we can see from the figures, the short-run component is clearly much less persistent than the long-run component.

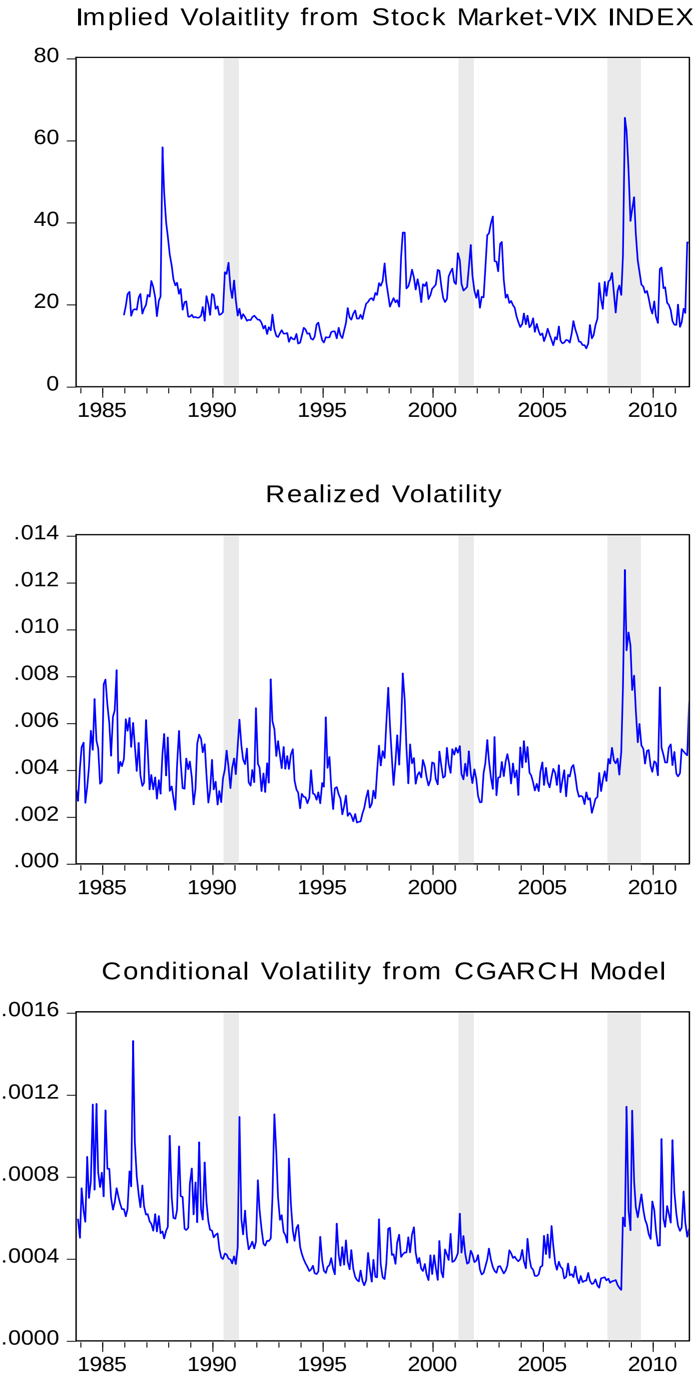
Table 6.3 provides the descriptive statistics of the factors we use in the asset pricing test in the next section. We have introduced DOL and ΔVOL factors in previous chapters. Factor V stands for the estimated conditional volatility for FX market and it is the exponential sum of the long- and short-run components from the C-GARCH model. In the empirical analysis, we focus on volatility innovations, to correct the problem of auto-correlation, we take the residuals of the AR(2) regression for V (as V is an AR(2) process), and denote it as VRES. Similarly, LRES stands for the long-run volatility innovation while SRES stands for the short-run.

---

[14] VIX is a market volatility index provided by Chicago Board Options Exchange, and it is a measure of the implied volatility of S&P 500 index options. The VIX data is obtained from Chicago Board Options Exchange website (https://www.cboe.com/micro/vix/historical.aspx,), and it is available from 01/01/1986.

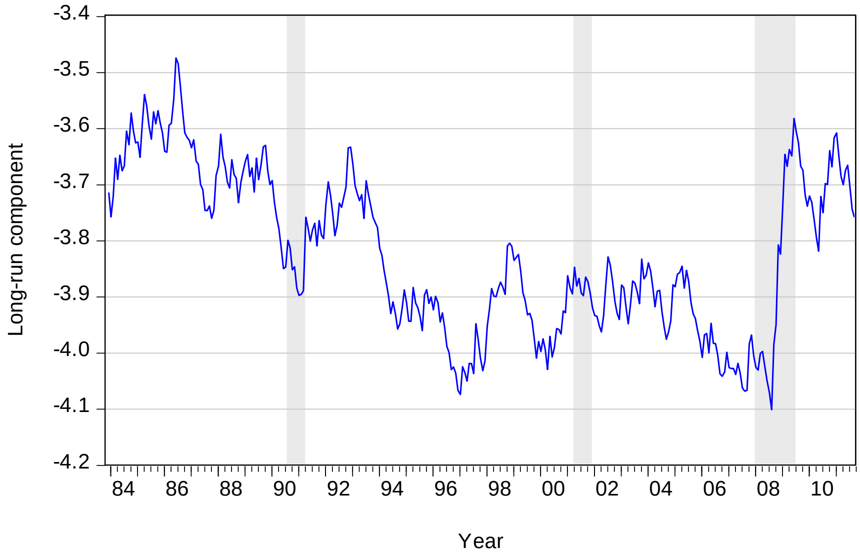
Both of them are the AR(1) residuals of long-run and short-run volatility components from the C-GARCH model (as both of them are AR (1) processes).

Figure 6-1 FX Market Volatility: Three Different Measures



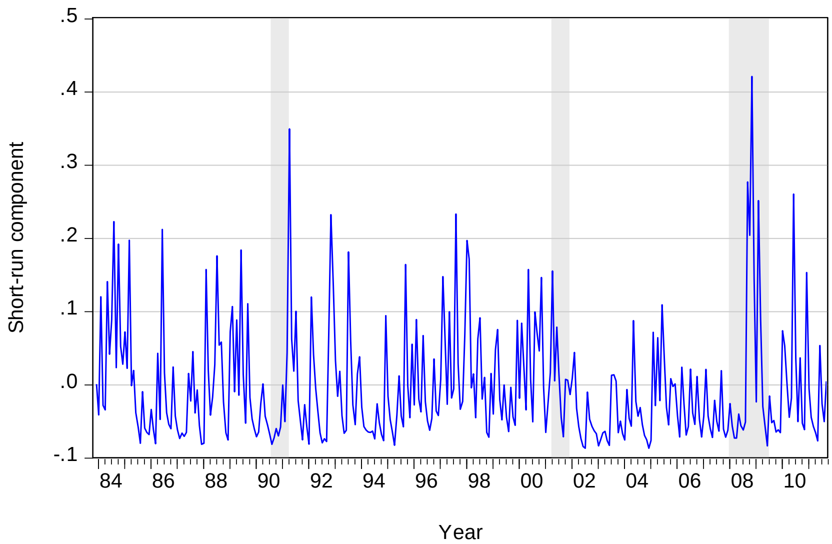
Note: this figure plots three measures of the annualized volatility at monthly frequency for 12/1983 to 09/2011. The first figure is the *VIX* index, the stock option implied stock market volatility; the second figure is the measure of realized volatility by Menkhoff, Sarno et al. (2012), the ΔVOL factor, and last figure plots the conditional volatility from the volatility components model. Shaded areas correspond to NBER recessions.

Figure 6-2 The Long-run Volatility Component



Note: this figure plots the estimated long-run volatility component (l) at a monthly frequency from 12/1983 to 09/2011. Shaded areas correspond to NBER recessions.

Figure 6-3 The Short-run Volatility Component



Note: this figure plots the estimated short-run volatility component (s) at a monthly frequency from 12/1983 to 09/2011. Shaded areas correspond to NBER recessions.

Table 6-3 Summary Statistics of Pricing Factors

Pricing Factor	Mean (%)	S.D. (%)	Skewness	Kurtosis
DOL	0.1480	2.262	-0.5175	1.1363
ΔVOL	0.0009	0.1018	1.4981	5.1793
V (V=EXP(l+s))	0.0500	0.0190	1.4310	2.7009
Market variance *(VRES) (AR(2) residual)*	-0.0000	0.0132	2.5315	8.1394
Short-run volatility *(SRES) (AR(1) residual)*	-0.0003	7.5356	1.9321	3.8489
Long-run volatility *(LRES) (AR(1) residual)*	-0.0139	3.4163	1.1414	0.9984

Note: this table reports mean, standard deviations (the mean and standard deviation are in percentage), skewness and kurtosis for 6 different factors. The *DOL* and *ΔVOL* factor are generated simply from the data and have been reported in the data chapter, while the other four factors are generated from the C-GARCH model. The *V* factor is the conditional market volatility measure, and the *VRES* is the market volatility innovation which is generated by the AR(2) residual of factor *V*. The *LRES* and *SRES* are long- and short-run volatility innovations. Both of them are the AR(1) residuals of long-run and short-run volatility components from the C-GARCH model. All variables are monthly observations and the time period is spanned from 11/1983 to 09/2011.

6.4. EMPIRICAL RESULTS

In Chapter 4, we consider a two-factor stochastic discount factor with the market excess return and volatility innovations as risk factors:

$$m_{t+1} = 1 - b_1 rx_{t+1}^m - b_2 \Delta V_{t+1} \qquad \text{Eq. 4.2}$$

We find that excess returns to the carry trade portfolios can be understood very well by their covariance exposure with FX market volatility risk. To study the pricing ability of volatility risk one step further, we decompose FX market volatility into long- and short-run components and examine the pricing ability of those components separately.

In our setting with a two-component volatility factors, the equilibrium pricing kernel thus depends on both the short- and long-run volatility components as well as the excess market return, thus it reads:

$$m_{t+1} = 1 - b_1 rx_{t+1}^m - b_2 \Delta l_{t+1} - b_3 \Delta s_{t+1} \qquad \text{Eq. 6.5}$$

where the pricing kernel depends on three factors: the FX market excess returnΔs_{t+1} , the long-run volatility component Δl_{t+1} and the short-sun volatility component Δs_{t+1}.

According to Cochrane (2005), the methodology explained in the Chapter 4, the expected returns are thus modelled as follow:

$$E[RX_i] = b_1\lambda_1 + b_2\lambda_2 + b_3\lambda_3 \qquad \text{Eq. 6.6}$$

Eq. 6.6 shows that expected returns depend on three risk premiums. The first risk premium arises from the loading of FX market risk b_1, times the market risk price λ_1. This is the risk-return trade-off in a static CAPM model. b_2 and b_3 are the loadings of the long- and short-run volatility risks, while λ_2 and λ_3 are the risk prices .

In taking the three factor models into the data, we use *DOL* factor as the proxy for FX market risk and *LRES* and *SRES* from the Component-GARCH model as proxies for long- and short-run volatility risks, so the pricing kernel in Eq. 6.7 writes:

$$m_{t+1} = 1 - b_{DOL}DOL_{t+1} - b_{LRES}LRES_{t+1} - b_{SRES}SRES_{t+1} \qquad \text{Eq. 6.7}$$

We estimate the risk loadings and risk prices of the three factor model by using only the Fama-Macbeth (FMB) method here, since as mentioned in Chapter 4 the first stage GMM will give the same estimates as FMB methods. This makes the presentation of the results more compact to compare with the pricing abilities of other factors in the existing literature.

We report the results from those two stages separately. In the first stage, we obtain loadings for each portfolio from time-series regressions. For 48-all-country sample (Table 6.4) and 29-OECD-country sample (Table 6.5), we provide the time series estimation of the excess return from 5 currency portfolios on (1) *DOL, SRES* and *LRES* (Panel A), (2) *DOL* and *LRES* (Panel B) and (3) *DOL* and *SRES* (Panel C).

In the second stage, we conduct cross-sectional regressions to estimate prices of risk and the results are shown in Table 6.6 for 48-all-country sample and Table

6.7 for 29-OECD-country sample. We also provide the cross-sectional results for other combination of factors as in the existing literature so as to compare with our model.

The test assets are the same as in previous two chapters: the five currencies portfolios sorted by interest rate differential/forward discount, based on both 48-all-country sample and for 29-OECD-country sample. Portfolio 1 contains currencies with the lowest interest rate differentials while Portfolio 5 contains currencies with the highest interest rate differentials. As shown in Table 6.4 and 6.5, for both samples, factor loadings on long- and short-run volatility exhibit significant variability across portfolio 1 to portfolio 5. We find that portfolios with low interest rate currencies have large positive loadings on both long- and short-run volatility innovations, while portfolios with high interest rate currencies have negative loadings on both two volatility innovations. The loadings for both volatility factors are approximately monotonically decreasing from portfolio 1 to 5.

This explains why carry trades perform especially poorly during times of market turmoil. During market turmoil, both short-run and long-run volatility are high, since high interest rate currencies are negatively related to innovations of both volatility components and thus deliver low returns in times of unexpected high volatility, when low interest rate currencies provide a hedge by yielding positive returns.

In Table 6.6, we analyse the pricing of volatility risk in the cross-section of the 5 portfolios for 48-all-country sample, while Table 6.7 is the same regressions for 29-OECD-country sample. The relative second stage time series regressions corresponding to the time series regressions reported in Table 6.4 and 6.5 are reported in Column (5), (6) and (7). In Column (1) to (4) we provide the risk prices and pricing abilities of other factors in existing literature so as to compare with our main model. The first stage time series regressions of these factors are not reported so as to save space and also as some results are reported in the previous chapters.

Table 6.6 column (1) use only the market excess return: *DOL* factor which is the average interest rate difference between the U.S. and foreign currencies, as the only pricing factor. We find that *DOL* factor is only significant in time-series regression (the first-stage regression), but not significant in cross-sectional pricing (the second-stage regression). This coincides with (Lustig, Roussanov et al. 2011)which argues that the *DOL* factor only explains the time-series variation. They also argue *HML* factor (the carry trade factor, which is calculated by the returns to portfolio 5 minus returns to portfolio 1) is the country-specific factor which explains most of the cross-sectional variation in average excess returns between high and low interest rate currencies. As shown in column (2). We find that the pricing kernel with both *DOL* and *HML* factors is able to explain about 75%

cross-sectional returns for both samples and this is consistent with the results of (Lustig, Roussanov et al. 2011).

Column (3) shows the same results as Table 4.1 Panel A, we use both DOL and ΔVOL as pricing factors. The ΔVOL factor is the innovation of realized FX volatility. The theoretical support of this application, as we reported in earlier chapters, is the Chen (2002) version of the ICAPM model. To test that this pricing kernel is robust among different measures of volatility, we use the conditional volatility measure from the component-GARCH model. In column (4) of Table 6.6, we use factor $VRES$, which is the AR(2) residual from factor V generated by the C-GARCH model. The $VRES$ factor is priced negatively and significantly in both samples: 48-all-country sample (Table 6.6, column (4)) and 29-OECD-country sample (Table 6.7, column (4)). The conditional volatility measure does a fairly good job in explaining the cross-sectional mean excess returns from all five portfolios in each sample. The $VRES$ factor yields a nice cross-sectional fit with R^2s slightly less than the VOL factor but still quite large at around 90% for both samples, and we cannot reject the null that the J-statistics is equal to zero. The pricing errors are quite small in economic terms.

We then go on to explore the pricing of each volatility component. In column (5) of Table 6.6 for 48-all-country sample, we see that both the long-run and short-run volatility components are significant pricing factors at the 5% level, and both components have negative prices of risk. These negative prices mean that for portfolios whose returns co-move positively with either components of volatility innovations, they are providing hedges to volatility risk and therefore investors demand a low return. On the other hand, for portfolios whose returns co-move negatively with either components of volatility risk, they demand a risk premium. Investors are willing to pay insurances for volatility risks and they even will pay more for volatility risks with smaller persistence (short-run volatility risk). The two components factor yields a nice cross-sectional fit with R^2s even slightly higher than the model with ΔVOL factor, and we cannot reject the null that the J-statistics is equal to zero. The pricing errors are quite small in economic terms. In column (5) and (6) of Table 6.6, we test the two volatility components separately, both of them are negatively and significantly priced, the significance of each component even improves to 1% significant level from 5% significant level when using two components together. This may be because the long-run and short-run components are correlated at about 50%, when applying them in the same regression, the multi-collinearity problem raises, which will reduce the significant level of the regressors correlated. This problem is more critical in the case of 29-OECD-country sample in Table 6.7. In Table 6.7, although the two volatility components are negatively and significantly priced when testing them separately in column (6) and (7), they become insignificant when both components are included in the same regression. The correlation between those two components reduces the significance of both components.

Table 6-4 Factor Loadings for 48-all-country Sample

Panel A. 1st stage of Regression (5)						Panel B. 1st stage of Regression (6)					Panel C. 1st stage of Regression (7)				
PF	α	*DOL*	*LRES*	*SRES*	R^2	PF	α	*DOL*	*LRES*	R^2	PF	α	*DOL*	*SRES*	R^2
1	-0.003	0.939	0.045	0.013	0.759	1	-0.004	0.949	0.056	0.766	1	-0.004	0.954	0.022	0.765
	0.001	[0.049]	[0.022]	[0.011]			0.001	[0.048]	[0.020]			0.001	[0.047]	[0.010]	
2	-0.001	0.998	0.008	0.025	0.822	2	-0.002	1.001	0.031	0.820	2	-0.002	1.008	0.025	0.824
	0.001	[0.040]	[0.020]	[0.010]			0.001	[0.035]	[0.019]			0.001	[0.040]	[0.009]	
3	0.001	0.963	-0.038	0.004	0.802	3	0.000	0.97	-0.038	0.801	3	0.000	0.971	-0.007	0.799
	0.001	[0.036]	[0.033]	[0.013]			0.001	[0.036]	[0.025]			0.001	[0.037]	[0.009]	
4	0.001	0.996	-0.014	0.000	0.842	4	0.001	1.005	-0.019	0.843	4	0.001	1.005	-0.005	0.842
	0.001	[0.034]	[0.020]	[0.009]			0.001	[0.033]	[0.017]			0.001	[0.034]	[0.008]	
5	0.002	1.104	0.000	-0.042	0.669	5	0.002	1.118	-0.053	0.619	5	0.002	1.104	-0.044	0.658
	0.001	[0.076]	[0.035]	[0.018]			0.001	[0.080]	[0.035]			0.001	[0.076]	[0.017]	

Note: this table reports the results of 1st stage of FMB (Fama and MacBeth (1973)) regressions. The test assets are excess returns of 5 portfolios for 48-all-country sample. Panel A, the risk factors are the *DOL* factor, long-run volatility innovations (*LRES*), and short-run volatility innovations (*SRES*); Panel B has only *DOL* and *LRES* and Panel C consists of *DOL* and *SRES*. Newey-West standard errors are provided in brackets. The sample period is spanned from 01/11/1983 to 30/09/2011.

Table 6-5 Factor Loadings for 29-OECD-country Sample

Panel A 1st stage of Regression (5)					
PF	α	*DOL*	*LRES*	*SRES*	R^2
1	0.003	0.963	0.022	0.016	0.805
	0.001	[0.049]	[0.023]	[0.011]	
2	-0.001	1.065	0.032	0.004	0.890
	0.001	[0.026]	[0.018]	[0.009]	
3	0.000	1.008	-0.003	0.002	0.904
	0.000	[0.024]	[0.018]	[0.009]	
4	0.001	1.017	-0.015	-0.006	0.860
	0.001	[0.033]	[0.022]	[0.009]	
5	0.003	0.946	-0.036	-0.016	0.743
	0.001	[0.051]	[0.030]	[0.014]	

Panel A 1st stage of Regression (6)				
PF	α	*DOL*	*LRES*	R^2
1	-0.003	0.969	0.038	0.810
	0.001	[0.048]	[0.021]	
2	-0.001	1.071	0.034	0.891
	0.001	[0.027]	[0.018]	
3	-0.001	1.014	-0.004	0.905
	0.000	[0.024]	[0.016]	
4	0.000	1.022	-0.025	0.855
	0.001	[0.035]	[0.018]	
5	0.002	0.952	-0.056	0.737
	0.001	[0.055]	[0.033]	

Panel A 1st stage of Regression (7)				
PF	α	*DOL*	*SRES*	R^2
1	-0.003	0.973	0.020	0.810
	0.001	[0.046]	[0.010]	
2	-0.001	1.072	0.011	0.890
	0.001	[0.027]	[0.009]	
3	-0.001	1.015	0.000	0.905
	0.000	[0.024]	[0.007]	
4	0.000	1.02	-0.01	0.855
	0.001	[0.035]	[0.008]	
5	0.002	0.948	-0.025	0.736
	0.001	[0.054]	[0.015]	

Note: this table reports the results of 1st stage of FMB (Fama and MacBeth (1973)) regressions. The test assets are excess returns of 5 portfolios for 29-OECD-country sample. Panel A, the risk factors are the DOL factor, long-run volatility innovations (*LRES*), and short-run volatility innovations (*SRES*); Panel B has only *DOL* and *LRES* and Panel C consists of *DOL* and *SRES*. Newey-West standard errors are provided in brackets. The sample period is spanned from 01/11/1983 to 30/09/2011.

Table 6-6 Factor Prices of Different Factors for 48-all-country Sample

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Excess market return	Coef.	0.0016	0.0014	0.0015	0.0016	0.0015	0.0015	0.0015
(DOL)	S.E.	[0.0012]	[0.0012]	[0.0012]	[0.0012]	[0.0012]	[0.0012]	[0.0012]
Long-run volatility	Coef.					-0.0411**	-0.0451***	
risk *(LRES)*	S.E.					[0.0181]	[0.0170]	
Short-run volatility	Coef.					-0.0564**		-0.0700***
(SRES)	S.E.					[0.0340]		[0.0270]
Market variance	Coef.				-0.0148***			
(VERS)	S.E.				[0.0056]			
HML	Coef.		0.0051***					
	S.E.		[0.0015]					
ΔVOL *(%)*	Coef.			-0.0721***				
	S.E.			[0.0220]				
R^2		0.0770	0.7762	0.9272	0.9068	0.9280	0.9231	0.8119
MAE		0.0017	8.9584e-004	5.0019e-004	5.6578e-004	4.8238e-004	5.0522e-004	7.7085e-004
J-statistics		(0.000)	(0.091)	(0.559)	(0.462)	(0.424)	(0.671)	(0.136)

Note: this table reports the results of 2nd stage of FMB (Fama and MacBeth (1973)) regressions for the forward discount sorted portfolios of the 48-all-country sample. In the 1st stage of FMB, portfolio returns are regressed on the risk factors to obtain factor loadings (reported in Table 6.4). In the 2nd stage of FMB, the average returns of portfolios are regressed on the loadings, giving an estimate of the price of risk for each factor. Newey-West standard errors are provided in brackets. (Significance at the 1% level is denoted by ***, at the 5% level by **, and at the 10% level by *). MAE is the mean absolute error. For J-statistics, p-value is provided in parentheses.

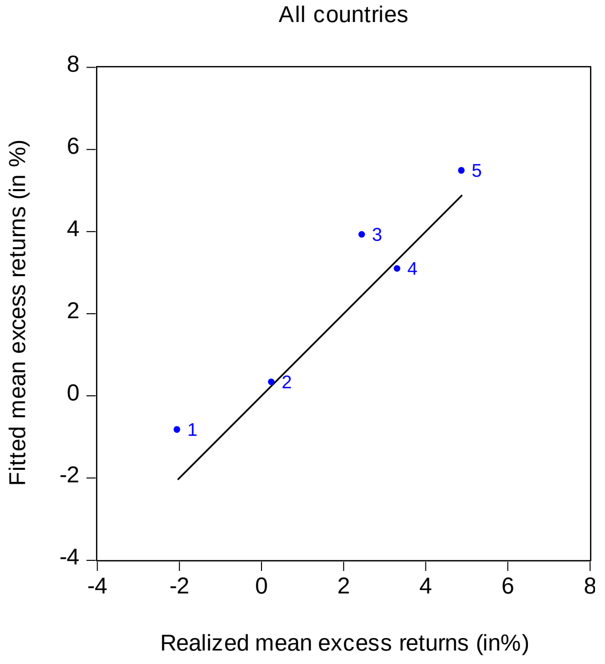
Table 6-7 Factor Prices of Different Factors for 29-OECD-country Sample

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Excess market return	Coef.	0.0016	0.0014	0.0016	0.0018	0.0017	0.0017	0.0017
(DOL)	S.E.	[0.0014]	[0.0014]	[0.0014]	[0.0014]	[0.0014]	[0.0014]	[0.0014]
Long-run volatility	Coef.					-0.0011	-0.0459**	
risk *(LRES)*	S.E.					[0.0006]	[0.0210]	
Short-run volatility	Coef.					-0.1672		-0.1077**
(SRES)	S.E.					[0.1490]		[0.0510]
Market variance	Coef.				-0.0175**			
(VERS)	S.E.				[0.0078]			
HML	Coef.		0.0064***					
	S.E.		[0.0020]					
ΔVOL *(%)*	Coef.			-0.0653***				
	S.E.			[0.0197]				
R^2			0.7845	0.902	0.8956	0.9817	0.8686	0.9488
MAE		5.0019e-004	8.0264e-004	4.9305e-004	1.8034e-004	5.3625e-004	3.2910e-004	5.0019e-004
J-statistics		(0.559)	(0.011)	(0.568)	(0.955)	(0.492)	(0.831)	(0.559)

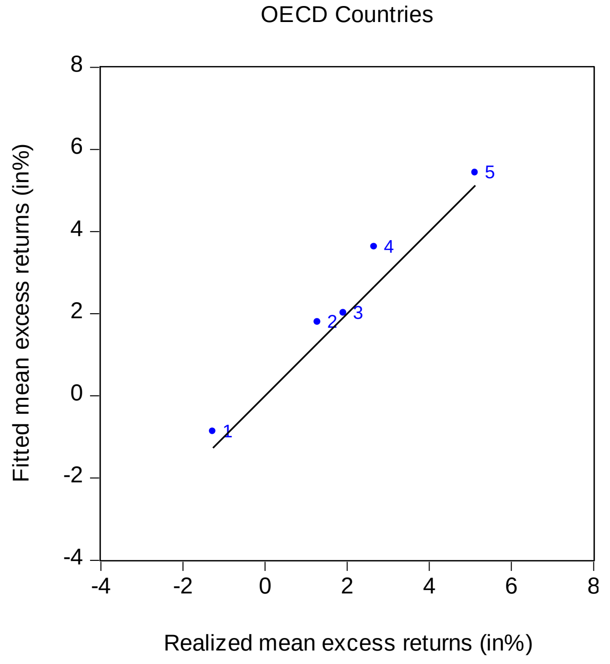
Note: this table reports the results of 2nd stage of FMB (Fama and MacBeth (1973)) regressions for the forward discount sorted portfolios of the 29-OECD-country sample. In the 1st stage of FMB, portfolio returns are regressed on the risk factors to obtain factor loadings (reported in Table 6.4). In the 2nd stage of FMB, the average returns of portfolios are regressed on the loadings, giving an estimate of the price of risk for each factor. Newey-West standard errors are provided in brackets. (Significance at the 1% level is denoted by ***, at the 5% level by **, and at the 10% level by *). MAE is the mean absolute error. For J-statistics, p-value is provided in parentheses.

Figure 6-4 Pricing Error Plots for Long- and Short-Run Volatility Components Model

Panel A. 48-all-country sample



Panel B. 29-OECD-country sample



Note: this figure shows the average excess returns for the forward discount sorted portfolios against the predicted returns from the models reported in column (5) of Table 6.6 and Table 6.7 for both samples.

In Figure 6 we plot the actual returns of 5 portfolios and the predicted returns from our long- and short-run volatility components model (column (5)) for both samples. Each dot stands for the predicted return of one portfolio from the component model. The 45-degree line shows the actual returns so that the distance from each dot to the 45-degree line will show us the mean pricing error for each portfolio. As we can see from the figure, the deviations for each portfolio from the 45-degree line are quite small, which indicates a small pricing error so the component model works well in explaining the spreads of mean excess return for all 5 portfolios. The pricing error of our long- and short-run volatility components model is the smallest for regression 5 among all regressions for the 48-all-country sample.

However, the asset pricing test results of the two components volatility model are not very consistent through two samples. This is due to the difficulty in measuring the FX market return so as to model the volatility of the market return. As far as we know, although there is literature using Component-GARCH model to decompose volatility of returns for a single currency, we are the first to decompose FX market volatility. Different from stock market, it is difficult to provide a unique measure for the FX market return since the return from currency market has to be a return from a certain trading strategy. For different trading strategies the average returns are different. In this thesis, without loss of general measure, we use DOL factor of the 48-all-country sample as a measure of market volatility, this measure is not perfect, because, it only takes (1) 48 currencies and not all the currencies in the market, (2) currencies are equally weighted (3) no specific trading strategies have been taking into consideration.

Therefore, this can somehow explain why the decomposed factors from the DOL measure works quite well for the 48-all-country sample but not very well for the 29-OECD sample as the proxy is still not general enough to measure the FX market return.

One concern of taking decomposed FX volatility as pricing factors is that, compared with stock market, we have limited number of currencies, after we sort them into portfolios, we have only 5 portfolios, this reduces the number of observation in the second stage of FMB estimation, especially in this chapter, after decomposition, we increase the number of pricing factors from two to three, this further reduces the degree of freedom and makes the estimation results highly variable according to sample specific characteristics.

Another difference between FX market and stock market lies in the economic interpretations of the long- and short-run volatility components. As mentioned in Section 6.2, one of the motivations for decomposing FX volatility into long- and short-run components is that we may examine the correlation of these components with macroeconomics variables and market sentiments as inspired by what Adrian and Rosenberg (2008) have done for the stock market. They find that their long-run volatility component is highly correlated with business cycle risk while the short-run volatility component is correlated with market sentiments.

To interpret the economics of long- and short-run volatility components, as inspired by Adrian and Rosenberg (2008) in stock market, we relate the long-run volatility component, to the U.S. business cycle[15] and the short-run volatility component to a measure of the tightness of financial constraints[16]. However, we find the correlations for both of them are quite low. This is consistent with Burnside (2011), in which he tests all traditional factors used in stock market pricing to explain the excess returns from the carry trade and finds that none of them work. That is because those traditional factors are either uncorrelated with carry trade returns, i.e. they have zero betas, or the betas are much too small to rationalize the magnitude of the returns to the carry trade.

[15] We follow Adrian and Rosenberg (2008) and use the innovations of U.S. industrial production growth as a proxy of the U.S. business cycle since it is available at monthly observation.

[16] To measure the tightness of financial constraints, we use market skewness. Following Adrian and Rosenberg (2008), we estimate market skewness form daily average change in spot rates and calculate the sample skewness within each month.

6.5. CONCLUSION

This chapter is inspired by the successful attempt of Component-GARCH model in cross-sectional pricing of stock market (Adrian and Rosenberg (2008)). We use the average return of equally weighted 48-currency portfolio as market excess return, and decompose the market excess return into long- and short-run volatility components according to the same volatility dynamic specification of Adrian and Rosenberg (2008). Our main conclusion is consistent with the findings in stock market that that prices of risk are negative and significant (at least for 48-all-country sample) for both volatility components which implies that investors pay for insurance against increases in volatility, even if those increases have little persistence.

The contribution of this chapter is the following: (1) the model with decomposed volatility risk factors provides better fit than the benchmark model provided in Chapter 4 and (2) as far as we know, we are the first to decompose FX market volatility into long- and short-run factors as in previous literature they only do it for currency pairs.

7. THE CARRY TRADE VERSUS FUNDAMENTAL

7.1. INTRODUCTION

In the first part of empirical work of this thesis, we argue that the excess returns from the carry trade can be explained by the FX volatility risk. In this chapter, we investigate the puzzles in FX market by examining the excess returns from different currency trading strategies under different FX volatility regimes. We argue that both the forward premium puzzle and the purchasing power parity puzzle can be partially explained by taking the FX volatility regimes into consideration.

The idea that FX volatility regimes are important for examining the excess return from the carry trade is motivated by the pattern of excess return from the carry trade: stable and consistent returns for a long period followed by big losses during market turmoil. Also, it is supported by the finding in Chapter 5 that the excess returns from the carry trade is actually a compensation for bearing extra volatility risk during high volatility risk period which suggests a nonlinear relationship between excess return from the carry trade and the FX market volatility.

In this chapter, we find that the violation of UIP is an artefact that only happens when the FX volatility is in normal period. Further, we find that during high volatility periods, there are strong connections between exchange rate changes and fundamentals, exchange rates revert back to their fundamentals largely and quickly in high volatility periods. Thus we argue that the big losses of the carry trade during high volatility period are caused by the quick and large exchange rates adjustments to their fundamental values. Both the UIP and the PPP tend to reassert itself during high volatility period.

Suggested by these results, apart from the carry trade strategy, we set up another trading strategy, the fundamental strategy, by borrowing overvalued currencies and lending undervalued currencies. This fundamental strategy provides higher returns during high volatility period when the carry trade strategy performs poorly. Therefore, we show that by switching between the carry trade strategy and the fundamental strategy according to the FX volatility regime, we would have a trading strategy providing higher ex-post returns than either single strategy. Moreover, we show that by forecasting next period FX volatility regime, we can make this mixed strategy tradable, and it is still providing much larger excess returns than that from either the carry trade strategy or the fundamental strategy, especially for the crisis periods.

More complicated strategies provide higher returns. There are two possible explanations 1) this may indicate that the FX market is inefficient. Since rational investors would diversify the crash risk from the carry trade strategy during high volatility period by conducting the fundamental strategy instead. 2) Although we cannot use either the FX volatility risk or crash risk to price the excess returns from the fundamental strategy, there may be other risks in conducting the fundamental strategy during high volatility risk period. Further study is required.

The structure of this chapter is that Section 7.2 provides background and motivation of our study and Section 7.3 provides preliminary results of the regime-dependent regressions which suggest us to form two different strategies: the carry trade and the fundamental strategy in Section 7.4. We then mix the two strategies according to different volatility regimes in Section 7.5. In section 7.6, we provide out of sample forecast for different time periods to make the mixed strategy tradable. Section 7.7 concludes.

7.2. Background and motivation

In the previous chapters, we argue that the excess return from the carry trade is a compensation for bearing FX volatility risk, especially during high volatility period. This is consistent with Brunnermeier, Nagel et al. (2008) in which they argue that a possible explanation for the high Sharpe ratio of carry trades is that it represents the price of crash risk, i.e. sudden adjustments in exchange rate. Because historically, the excess return from the carry trade has exhibited the following pattern: it has a high and stable return during a long period, but then suffers a big loss during crisis period. As mentioned by Plantin and Shin (2006), high interest rate currencies has exhibited the classic price pattern of "going up by stairs, and coming down by elevator." This is consistent with the idea of nonlinear adjustment in the exchange rate: the larger the divergence from the equilibrium exchange rate is, the faster the exchange rate adjusts. (Taylor, Peel et al. 2001)

The uncovered interest rate parity (UIP) argues that the future changes in exchange rate will offset interest rate differential between two currencies, i.e. low interest rate currencies tend to appreciate and high interest rate currencies tend to depreciate. However, empirically, the opposite is true, high interest rate currencies appreciate a little on average although with a low predictive R^2, (Fama 1984), i.e. the UIP predicts future exchange rate changes in the opposite direction. This violation of the uncovered interest rate parity (UIP), often referred to as the forward premium puzzle, is precisely what makes the carry trade profitable on average.

Empirical studies generally report results reject the UIP as reported by Froot and Thaler (1990) and confirmed by Burnside, Eichenbaum et al. (2006). However, Clarida, Davis et al. (2009) find that the violation of the UIP is an artificial fact of the volatility regime:

when volatility is in the top quartile, the UIP predicts future exchange rate changes in the right direction. In other words, the UIP will reassert itself, at least to some extent, during high volatility period. In this chapter, we test the UIP for 8 individual currencies regime dependent on FX volatility level. To proxy the FX volatility, we stick to the realized volatility measure as used by Menkhoff, Sarno et al. (2012)[17]. The results are consistent with Clarida, Davis et al. (2009).

Further, Nozaki (2010) argues that the crash risk inherent in carry trades is as a result of exchange rate adjustments toward their fundamental value. Therefore a trading strategy of taking a long position in undervalued currencies and taking a short position in overvalued currencies is less prone to crash risk and it outperforms the carry trade during the recent financial crisis as the return of this strategy characterized with positive third moments.

In this chapter, we start from testing the Fama regression (Fama 1984) regime dependent on FX volatility and find that the negative beta estimates documented in most literature is only true for the "normal period" (the lowest 75% FX volatility periods), for the "crisis period" (the top 25% high FX volatility periods), estimates of beta tend to be positive or negative but small in absolute value. This finding explains the excess return pattern of the carry trade i.e. high and steady returns for a long period then followed by big losses during market turmoil.

Further, we test the relationship between the changes in exchange rate and real exchange rate deviations for individual currency regimes dependent on FX volatility,

---

[17] As shown in the Chapter 3.2.2

and we find that for high volatility periods, there are strong connections between exchange rate changes and fundamentals, exchange rates revert back to their fundamentals largely and quickly in high volatility periods. Thus we argue that the big losses of the carry trade are caused by the quick and large exchange rates adjustments to their fundamental values. That is equivalent of arguing both the UIP and the PPP tend to reassert itself during high volatility period.

Suggested by these results, we set up two trading strategies: the carry trade strategy and the fundamental strategy. We take the 29-OECD country sample and following Lustig, Roussanov et al. (2011), for the carry trade strategy, we sort 29 currencies into 5 portfolios according to their interest rates, as mentioned in previous chapters. The carry trade portfolio is formed by taking short position in portfolio 1 (portfolio contains the smallest interest rate currencies) and taking long position in portfolio 5 (portfolio contains the highest interest rate currencies), while the fundamental strategy is formed by sorting 29 currencies into 5 portfolios according to their size of real exchange rate deviations from the sample averages. The fundamental portfolio is formed by taking short position in portfolio 1 (those most overvalued currencies) and taking long position in portfolio 5 (those most undervalued currencies).

Then we show that the excess returns from these two strategies are FX volatility regime dependent. We divide volatility into 4 regimes according to its quartiles. The 1st quartile contains the lowest volatility periods, while the 4th quartile contains the highest volatility periods. We find that the carry trade portfolio has higher average returns during the first three quartiles and have large negative average return during the 4th quartile. On the other hand, the fundamental portfolio has lower average returns during the first three quartiles, but have large positive average return during the 4th quartile.

These returns coincide with the regime dependent regressions results. The "normal" period in which carry trade accumulates large returns is also the period that the spot rates accumulate large deviations from their fundamentals. Followed by high volatility periods in which spot rates adjust back largely and quickly towards their fundamentals and the carry trade strategy suffers losses. But the fundamental strategy which is borrowing most overvalued currencies and lending most undervalued currencies well captures the possible changes in spot rates for both investment and funding currencies, and therefore provide large excess returns.

Our results are counterintuitive to the view of slow adjustments of exchange rates toward their fundamental value. As observed by Rogoff (1996), the half-life of a deviation from the PPP can be as three to five years. With slow adjustments, exchange rates overvaluation or undervaluation should not matter for investors who change their positions frequently on a monthly basis. However, we find that the fundamental value of a currency carries valuable information for currency speculators, because it signals a possibility of a large and quick adjustment of the exchange rate (i.e. crash risk) and our results are in line with Jordà and Taylor (2012), in which they argue that the deviation from the fundamental equilibrium exchange rate is an important predictor of exchange rate movements by using a vector error correction model. They find that fundamental-based strategies for currency speculation, especially those that incorporate the nonlinear adjustment of the exchange rate, outperform carry trades since they are crash-risk proofed.

Our findings are consistent with theirs in the sense of the third moments, the skewness of the excess returns. We find that the skewness for the carry trade portfolio is highly negative which indicates crash risk, but for the fundamental strategy, the skewness is almost zero, which indicates that the fundamental strategy is crash risk proofed.

Therefore, it is natural to form a more profitable strategy by switching between the two strategies depending on volatility regimes. If volatility is in its first three quartile regimes we choose the carry trade strategy, and if volatility is in its last quartile regime we choose the fundamental strategy. By doing this, we form a much more profitable strategy with an annual average return about 10% without transaction cost. The return with transaction cost is also provided and large (8.6% p.a) as well.

More importantly, we show that by forecasting next period's volatility, we can make the mixed strategy tradable. To forecast nest period's volatility, we make use of the diagnostic that the realized FX volatility is auto-correlated (0.67), so we use last period's volatility as an indicator of current period volatility regime. By using all the data available at the end of last period, we can form a tradable mixed strategy for current period. Although the excess return by using last period's volatility as regime is not as large as that by using this period's volatility as regime (the annual average return reduces by about 1%), it is still much larger than the excess return from the carry trade strategy or the fundamental strategy, especially for the crisis periods.

More complicated strategies provide higher returns. There are two possible explanations: (1) this may indicate that the FX market is inefficient. Since rational investors would diversify the crash risk from the carry trade strategy during high volatility period by conducting the fundamental strategy instead; (2) although we cannot use the FX volatility risk to price the excess returns from the fundamental strategy, there may be other risks in conducting the fundamental strategy during high volatility risk period. Further study is required.

7.3. THE REVISED FAMA REGRESSION

As documented in Chapter 2, the Uncovered Interest Parity (UIP) states that in an efficient speculative market, prices should fully reflect information available to market participants and it should be impossible for a trader to earn excess returns to speculation (Sarno 2005). Empirically, to test the UIP is equivalent to test Eq. 2.3 with the null hypothesis $\alpha = 0, \beta = 1$ and u_{t+1} has a conditional mean of zero (Fama 1984).

$$s_{t+1} - s_t = \alpha + \beta(f_t - s_t) + u_{t+1} \qquad \text{Eq. 2.3}$$

where s_t is the log of the spot price in foreign currency per unit of home currency at time t, f_t is the log of the one-period forward exchange rate, and u_t is the regression error. This regression appears frequently in the literature and much of literature refers this equation the Fama regression. Under the null hypothesis, the log of the forward rate provides an unbiased forecast of the log of the future spot exchange rate.

Empirical studies based on the estimation of Fama Equation for a large variety of currencies and time periods, generally report results reject the UIP. It constitutes a stylized fact that estimates of beta using exchange rates against the US dollar are often statistically insignificantly different from zero and generally closer to minus unity than to plus unity. As reported by Froot and Thaler (1990) and confirmed by Burnside, Eichenbaum et al. (2006) the average estimate for beta is -0.85 across the countless studies that focus on this equation. This negative value of beta is the central feature of the forward bias puzzle. It means that instead of offset interest rate differential between two currencies, the future change in spot exchange rate will enlarge this differential, i.e. high interest rate currencies tend to appreciate and low interest rate currencies tend to depreciate. The carry trade is a trading strategy by exploiting the future of the UIP.

However, Clarida, Davis et al. (2009) argue that the well documented negative beta estimates in Fama regressions are an artificial fact depending on volatility regime. They document significant volatility regime sensitivity for Fama regressions estimated over low and high volatility periods. They find that when volatility is in the top quartile, the Fama regression produces a positive coefficient that is greater than unity. They use both realized and option implied measures as volatility proxies and find they results are consistent.

In this section, we test the regime dependent Fama regression by using 8-country[18] spot and 1-month forward rates set against the U.S. over our data period, from November 1983 to September 2011, at monthly frequency. For the measure of FX volatility, we use the same realized volatility measure as used in previous chapter and the descriptive statistics are provided in Table 3.1. We split the sample into two regimes according to the FX volatility level: a 'high' volatility and 'normal' volatility regime. These are defined in terms of the quartiles of the empirical distribution of FX realized volatility over the sample period. If realized volatility at time t is above the 75th percentile of the volatility distribution of the full sample period, then period t is in a high volatility regime; while if realized volatility is below the 75th percentile of the volatility distribution for the full sample, then period t is in a normal volatility regime. Table 7.1 provides the quartiles for the FX volatility, as we can see that the 75% cut-off point of the realized volatility is

---

[18] The same 8 countries as in Clarida, R., et al. (2009). "Currency carry trade regimes: Beyond the Fama regression." Journal of International Money and Finance **28**(8): 1375-1389.

.

0.0048 and therefore the two regimes can be split as following: for time t, if the volatility exceeds 0.0048, the 3rd quartile, then time t is in high volatility regime, otherwise, it is in normal volatility regime. In this way we get about one quarter of the observations in the sample for the high volatility regime and about three quarters of the observations for the low volatility regime. Those two regimes are defined as $Volalitity_H$ and $Volalitity_N$ in Table 7.1.

Some literature argue that there is a relationship between the level of volatility and the excess returns, such as Clarida, Davis et al. (2009) while some literature emphasis the relationship between the innovation of volatility and excess returns such as Menkhoff, Sarno et al. (2012) and our asset pricing tests in the previous chapters. In this chapter we stick to the level of FX volatility to split the sample into two regimes. We find that the results are also robust if we use the innovation of FX volatility. The reason we stick to the level of volatility here is that the FX volatility level is significantly autocorrelation with a coefficient of 0.67 while the FX volatility innovation is not significantly autocorrelated (As shown in Table 3.1), the property of autocorrelation makes it possible to forecast next period volatility regime conditioning on this period volatility regime and we will show this in later section of this chapter.

TABLE 7-1 HIGH VOLATILITY AND NORMAL VOLATILITY REGIMES

	Min	The 1st quartile	Medium	Mean	The 3rd quartile	Max
Volatility	0.0017	0.0033	0.0040	0.0042	0.0048	0.0125

$$\begin{Bmatrix} V_t > 0.0048 & \text{time } t \text{ is in high volatility regime} \\ V_t \leq 0.0048 & \text{time } t \text{ is in normal volatility regime} \end{Bmatrix}$$

Note: this table provides the mean and quartiles of FX volatility, VOL. The 3rd quartile is applied as the boundary between high/normal volatility regimes.

As shown in Table 7.2, we estimate the change in exchange rates on the forward premium/discount individually for each currency for the whole sample period (Panel A), the high volatility period (Panel B) and the normal volatility period (Panel C). Our findings are consistent with Clarida, Davis et al. (2009) that the estimates of beta are negative is only true for the normal volatility period, while for the high volatility period, the estimates tend to be positive or negative but insignificant, i.e. the UIP is reasserting itself to some extent.

For the whole sample period in Panel A, most of the estimated beta (6 out of 8) are negative, although only for GBP that the beta is significant at 5% level. Generally speaking, these results coincide with the literature on the test of Fama regression. This explains that why the carry trade is profitable during the whole period.

While for normal volatility periods, as shown in Table 7.2 Panel C, beta tend to be negative and big in absolute value, while in high volatility periods, as shown in Panel B, beta tend to be positive or negative but insignificant. The estimate of beta is negative means that exchange rate is changing in the opposite direction from UIP prediction, i.e. high interest rate currencies tend to appreciate while low interest rate currencies tend to depreciate, therefore carry trades are profitable; while on the other hand, when the estimate of beta is positive, it means exchange rate is reverting back to UIP prediction. i.e. high interest rate currencies tend to depreciate while low interest rate currencies tend to appreciate, carry trades suffer losses. This coincides with the fact of carry trades that they gain large profits during a long calm time period, but then suffer large losses during crisis period.

Table 7-2 Fama Regression: For 8 Individual Currencies[19]

$$s_{t+1} - s_t = \alpha + \beta(f_t - s_t) + u_{t+1}$$

Name	Panel A. Full Sample			Panel B. $Volalitity_H$			Panel C. $Volalitity_L$		
	$\hat{\alpha}$	$\hat{\beta}$	T	$\hat{\alpha}$	$\hat{\beta}$	T	$\hat{\alpha}$	$\hat{\beta}$	T
AUD	0.001	-0.581	321	0.010	-0.108	78	0.000	-1.341*	243
	(0.003)	(0.769)		(0.009)	(1.912)		(0.003)	(0.765)	
CAD	0.000	-0.842	321	0.007*	-2.931	78	-0.002*	-0.308	243
	(0.001)	(0.756)		(0.004)	(1.970)		(0.001)	(0.745)	
CHF	-0.004	-0.705	334	-0.001	2.299	85	-0.006**	-2.419***	249
	(0.002)	(0.820)		(0.006)	(1.817)		(0.002)	(0.867)	
DEM	-0.002	0.564	182	0.002	3.989**	54	-0.003	-1.500	128
	(0.003)	(0.894)		(0.006)	(1.860)		(0.003)	(0.951)	
GBP	0.003	-1.740**	334	0.003	-0.058	85	0.003	-2.577***	249
	(0.002)	(0.864)		(0.007)	(2.278)		(0.002)	(0.838)	
JPY	-0.005*	-0.529	334	-0.011*	0.129	85	-0.002	-0.637	249
	(0.002)	(0.681)		(0.005)	(1.511)		(0.003)	(0.742)	
NOK	-0.003	1.002*	321	-0.002	2.447**	78	-0.002	-0.517	243
	(0.002)	(0.543)		(0.005)	(1.021)		(0.002)	(0.655)	
NZD	0.002	-0.951*	321	0.011	-1.485	78	-0.001	-0.641	243
	(0.003)	(0.496)		(0.007)	(0.942)		(0.003)	(0.607)	

Note: this table provides the estimated coefficients by using ordinary least square methods. Panel A. the full sample contains all time period observations, while Panel B contains 25% of the observations when the FX volatility is in its top quartile ($Volalitity_H$) and Panel C contains 75% of the observations when the FX volatility is in its first three quartiles ($Volalitity_N$). Standard deviations are reported in the parenthesis, and *** denotes 1% significant, ** denotes 5% significant and * 10% denotes significant. The time period spans from 11/1983 to 09/2011.

[19] The 8 countries are: Australia (AUD), Canada (CAD), Switzerland (CHF), Germany (DEM), the UK (GBP), Japan (JPY), Norway (NOK) and New Zealand (NZD).

One possible explanation of the large losses on carry trades during high volatility periods is the crash risk (Brunnermeier, Nagel et al. 2008) as indicated by the negative skewness of the carry trade. However, consistent with Nozaki (2010), we argue that the process that the carry trade crashes or the process the UIP reassert itself is also the process that exchange rates largely adjust towards fundamentals. Therefore, it would be interesting to test the relationship between the changes in exchange rate and deviation from the fundamental equilibrium exchange rate. We use the deviation of real exchange rate from its sample mean to generate the latter.

To generate real exchange rate, we collect the consumer price index (CPI) for 29-OECD countries in order to get real exchange rate for each currency. The CPI data are from OECD StatExtracts[20] and are consumer prices of all items with the base year as 2005 at monthly frequency. The data spans from November 1983 to September 2011, and further extends to March 2013 for out of sample forecast. We only carry out this empirical study on the 29-OECD-country sample as quality of the CPI data for the 48-all-country sample is not as high as that for the 29-OECD-country sample[21].

The logarithm of consumer price index is denoted as p_t for the U.S. and p_t^* for other countries. The real exchange rate is calculated as

$$q_t = s_t + (p_t - p_t^*) \qquad \text{Eq. 7.1}$$

[20] This is except CPI data for Australia, New Zealand, and Euro area, which we collect from DataStream.

[21] The CPI data could become quite messy given providing by different statistics bureau, therefore in this chapter, we study the 29-OECD-Country only as the CPI data for these countries are provided with the same standard of measurements and thus comparable.

where q_t is denoted as real exchange rate for each of the 29 currencies against U.S. dollar. Following Jordà and Taylor (2012), we assume weak purchasing power parity that q_t is a stationary variable and it converges to an equilibrium $\bar{q}$ in the long run. Further, we assume this real exchange rate equilibrium $\bar{q}$ can be calculated by the average of the real exchange rate across the sample period for each currency. Therefore, the deviation of real exchange rate from its mean for period t is calculated as $q_t - \bar{q}$. If we assume that equilibrium real exchange rate $\bar{q}$ is a reflection of currency fundamentals, then this deviation can be taken as the real exchange rate deviation from its fundamental value. If the deviation at period t for certain currency is positive, then it means this currency is undervalued according to its fundamentals, if it is negative, then it is overvalued according to its fundamentals.

In a more general setting, the real exchange rate equilibrium $\bar{q}$ could be time varying, for example, Nozaki (2010) estimates it from a cross-country panel regression for the real effective exchange rate (REER), but in this chapter, we will stick to the assumption of weak purchasing power parity, although the natural thing to do here is to determine the stationary properties of real exchange rate, such steps are common when the objective of the analysis is to directly examine whether purchasing power parity holds in the data; when one is interested in determining the speed of adjustment to long-run equilibrium. However interesting it is to investigate these issues, they are of second order importance for our analysis given our stated focus on deviation of profitable investment strategies. For this reason, we provide a far less extensive analysis of these issues.

To test the relationship between the changes in exchange rate and deviation from the fundamental equilibrium exchange rate. We conduct a simple OLS estimation in the same format as the Fama regression in Table 7.2.

As shown in Table 7.3, we test currencies individually for the whole sample (Panel A), the high volatility sample (Panel B) and the normal volatility sample (Panel C). We regress the change in exchange rate on a constant and last period's real exchange rate deviation from its sample mean for all 8 currencies separately. As mentioned before, we assume the sample mean of real exchange rate gives its equilibrium value. If the real exchange rate deviation from its sample mean $q_t - \bar{q}$ is positive, then it means this currency is undervalued from its fundamental value at period *t*. On the other hand, if the deviation is negative, then it means this currency is overvalued.

From Table 7.3 Panel A, all the estimates of coefficient for the real exchange rate deviation δ are negative and significant for 6/8 currencies, this indicates that currencies in period *t+1* will adjust to their fundamental values, although this adjustment is small, i.e. currencies undervalued from their fundamentals in period t will appreciate in period *t+1*, while currencies overvalued from their fundamentals in period *t+1* will depreciate in period *t+1*. More interestingly, if we regress the same regression on different sample separated by volatility regimes, we can find that the estimated δ are more negative and large in absolute value in high volatility period (as shown in Table 7.3 Panel B), while for normal volatility period in Panel C, δ are much smaller in absolute value and even positive for CAD, CHF and GBP.

This is a very interesting preliminary finding as it can partially explain the PPP puzzle. Our finding implies that there is connection between exchange rate changes and the PPP fundamental exchange rate. Exchange rates do revert back towards fundamentals, but since this connection is also regime dependent on FX volatility, it is difficult to observe. As we can see from Table 7.3 Panel C, in normal volatility period, exchange rate changes little or even the opposite direction towards its fundamental level, which makes overvalued currencies stay overvalued or even appreciated and undervalued currencies stay undervalued or even depreciated; while in high volatility period (Panel B), exchange rate adjusts towards its fundamentals more quickly and largely. However, because high volatility periods only make up 25% of the overall sample, the effect that exchange rate adjust towards their fundamentals is difficult to observe.

In this section, we test the Fama regression regime dependent on the volatility level the negative estimate coefficients during normal volatility period explain the excess return of carry trades while the positive estimate coefficients during high volatility period explain the losses of carry trades during crisis period. Furthermore, we argue the loss of carry trades during crisis time is due to exchange rates correcting back to their fundamentals. So we test the relationship between changes in exchange rate and real exchange rate deviations from sample means, we find that during high volatility period, the speed of exchange rate adjusting towards fundamental level is higher than that during normal volatility period. In the following section, based on the results of this section, we will set up two trading strategies: the carry trade strategy and the fundamental strategy, and we will analyse the excess returns of these two strategies during different volatility regimes.

Table 7-3 Real Exchange Rate Regression: For 8 Individual Currencies

$$s_{t+1} - s_t = \gamma + \delta(q_t - \bar{q}) + u_{t+1}$$

Name	Panel (a) Full Sample			Panel (b) $Volalitity_H$			Panel (c) $Volalitity_N$		
	$\hat{\gamma}$	$\hat{\delta}$	T	$\hat{\gamma}$	$\hat{\delta}$	T	$\hat{\gamma}$	$\hat{\delta}$	T
AUD	-0.001	-0.011	321	0.009	-0.033	78	-0.004**	-0.001	243
	(0.002)	(0.011)		(0.006)	(0.032)		(0.002)	(0.011)	
CAD	-0.001	-0.010	321	0.003	-0.033	78	-0.002**	0.000	243
	(0.001)	(0.009)		(0.003)	(0.026)		(0.001)	(0.008)	
CHF	-0.003	-0.022*	334	-0.004	-0.044*	85	-0.002	0.002	249
	(0.002)	(0.012)		(0.005)	(0.024)		(0.002)	(0.013)	
DEM	-0.002	-0.028**	128	0.002	-0.056*	54	-0.003	-0.011	128
	(0.002)	(0.014)		(0.007)	(0.029)		(0.003)	(0.018)	
GBP	-0.000	-0.036***	334	0.008*	-0.116***	85	-0.001	0.009	249
	(0.002)	(0.015)		(0.005)	(0.000)		(0.002)	(0.016)	
JPY	-0.003*	-0.023**	334	-0.010***	-0.030	85	-0.001	-0.013	249
	(0.002)	(0.011)		(0.004)	(0.023)		(0.002)	(0.012)	
NOK	-0.001	-0.035***	321	0.006	-0.109***	78	-0.003*	-0.003	243
	(0.002)	(0.013)		(0.005)	(0.030)		(0.002)	(0.014)	
NZD	-0.001	-0.019*	321	0.003	-0.030	78	-0.003	-0.013	243
	(0.002)	(0.010)		(0.005)	(0.027)		(0.002)	(0.011)	

Note: this table provides the estimated coefficients by using ordinary least square methods. Panel A. the full sample contains all time period observations, while Panel B contains 25% of the observations when the FX volatility is in its top quartile ($Volalitity_H$) and Panel C contains 75% of the observations when the FX volatility is in its first three quartiles ($Volalitity_N$). Standard deviations are reported in the parenthesis, and *** denotes 1% significant, ** denotes 5% significant and * 10% denotes significant. The time period spans from Nov 1983 to Sep 2011.

7.4. THE CARRY TRADE STRATEGY AND THE FUNDAMENTAL STRATEGY

The approach of sorting currencies into portfolios is first mentioned by Lustig and Verdelhan (2007), as inspired by the portfolio sorting approach in equity market. By sorting currencies into portfolios according to their interest rate differentials, we can, to some extent, exclude the currency specific effects that cause the changes in exchange rate, but focus on the changes that caused by interest rate differentials (Lustig and Verdelhan 2007).

In order to study the changes in exchange rate caused by interest rate differentials and fundamentals separately, we sort currencies into portfolios according to the level of interest rate differentials and fundamentals separately, which will give us two different trading strategies: the carry trade strategy and the fundamental strategy.

The first strategy the carry trade strategy is formed by sorting 29 currencies into 5 portfolios according to the size of its forward discount, which is also equal to its interest rate differential with the US (providing the covered interest rate parity hold). Portfolio 1 contains currencies with the lowest interest rate while portfolio 5 contains currencies with the highest interest rate among 29 currencies. The carry trade portfolio is formed by taking a long position in portfolio 5 and taking a short position in portfolio 1.

The second strategy is the fundamental strategy: 29 currencies are sorted into 5 portfolios according to the size of its real exchange rate deviation from the sample mean which, as mentioned before, is calculated by $q_{t+1} - \bar{q}$, where $\bar{q}$ is the average real exchange rate for each currency across the sample period. Portfolio 1 contains currencies with the most negative deviation (the most overvalued currencies) while portfolio 5 contains currencies with the most positive deviation (the most undervalued currencies) among 29 currencies. The fundamental portfolio is formed by taking long position in portfolio 5 and taking short position in portfolio 1.

In Table 7.4, we provide the descriptive statistics for the carry trade strategy in Panel A and the fundamental strategy in Panel B.

As we can see from Table 7.4, Panel A, the interest rate differentials sorted portfolios have the usual pattern as in previous chapters. We are interested in Panel B, portfolios sorted by their real exchange rate deviation. From porfolio1 to portfolio 5 and HML_{FM} portfolio (formed by borrowing portfolio 1 and lending portfolio 5), there is also a monotonically increasing pattern in the average returns with or without transaction costs. Portfolio 1 contains those most overvalued currencies and thus has negative average return while portfolio 5 contains those most undervalued currencies and thus has the largest positive returns. By taking a short position in portfolio 1 and a long position in portfolio 5, we form the fundamental trading strategy (HML_{FM}). This strategy provides slightly higher average return and Sharp Ratio compared with the carry trade strategy (HML_{CT}). However, the advantage of this strategy lies in the skewness. The realized skewness of return for this strategy is almost positive while for the carry trade strategy, the realized skewness of return is highly negative. According to Brunnermeier, Nagel et al. (2008), negative skewness indicates crash risk of the carry trade. Therefore, apart from giving a similar average return and Sharp Ratio, the fundamental strategy outperforms the carry trade strategy by having a less negative skewness and thus to some extent, being crash risk protected.

For both the carry trade and the fundamentals strategies, as in previous chapters, portfolios are re-balanced at the end of each month. So we also report the excess returns after transaction cost adjusted. Since as argued by Burnside, Eichenbaum et al.

(2006), transaction costs are available and can be quite high for some currencies. The way that transaction costs are adjusted is reported in Chapter 3.3.2. As we can see, after adjusting transaction costs, there are about 1% reduction in the average returns for both HML_{CT} and HML_{FM}, other patterns do not change much.

In the next section, we show by switching between the carry trade strategy and the fundamental strategy according to the FX volatility regime, higher excess return can be obtained.

Table 7-4 Descriptive Statistics

	Panel A: The Carry Trade Strategy							Panel B: The Fundamental Strategy						
	29-OECD Country Sample- Log return (without b-a)							29-OECD Country Sample- Log return (without b-a)						
Portfolio	1	2	3	4	5	DOL_{CT}	HML_{CT}	1	2	3	4	5	DOL_{FM}	HML_{FM}
Mean(%)	-0.61	1.87	2.41	3.33	5.88	2.58	6.49	-0.63	1.84	2.34	3.35	5.95	2.57	6.58
Std. Dev.	9.80	10.39	9.67	9.92	9.99	9.09	8.41	10.10	10.13	10.28	10.10	9.16	9.13	8.04
Skewness	0.04	-0.26	-0.20	-0.75	-0.61	-0.38	-0.93	-0.70	-0.13	-0.35	-0.26	-0.21	-0.37	**-0.07**
SR	-0.06	0.18	0.25	0.34	0.59	0.28	0.77	-0.06	0.18	0.23	0.33	0.65	0.28	**0.82**
	29-OECD Country Sample- Log return (with b-a)							29-OECD Country Sample- Log return (with b-a)						
Portfolio	1	2	3	4	5	DOL_{CT}	HML_{CT}	1	2	3	4	5	DOL_{FM}	HML_{FM}
Mean(%)	-0.29	1.50	2.16	3.06	5.41	2.37	5.70	-0.46	1.46	2.15	3.08	5.52	2.35	5.98
Std. Dev.	9.77	10.28	9.65	9.80	9.98	9.05	8.38	10.09	10.15	10.20	10.05	9.21	9.11	8.03
Skewness	0.05	-0.26	-0.21	-0.57	-0.62	-0.34	-0.95	-0.70	-0.14	-0.33	-0.28	-0.28	-0.37	-0.07
SR	-0.03	0.15	0.22	0.31	0.54	0.26	0.68	-0.05	0.14	0.21	0.31	0.60	0.26	0.74

Note: this table reports mean returns (annualized), standard deviations (annualized) and skewness of currency portfolios sorted by forward discounts (Panel A) and by real exchange rate deviation (Panel B) with and without transaction cost adjusted for the 29-OECD country sample. Sharp Ratios (SR) are also reported. The time period is spanned from 11/1983 to 09/2011.

7.5. FX VOLATILITY AND CURRENCY EXCESS RETURNS

To illustrate the relationship between the two strategies and FX volatility, in this section we first plot the excess returns from the carry trade portfolio and the fundamental portfolio under 4 different FX volatility states, from low to high.

Figure 7.1 Panel A shows mean excess returns for the carry trade portfolio (the darker bars) and for the fundamental portfolio (the lighter bars) with/without transaction cost adjusted conditional on the current period of FX volatility being within the lowest to highest quartile of its sample distribution (four categories from "lowest" to "highest" shown on the x-axis of each panel). The quartile boundaries of the FX volatility are shown in Table 7.1.

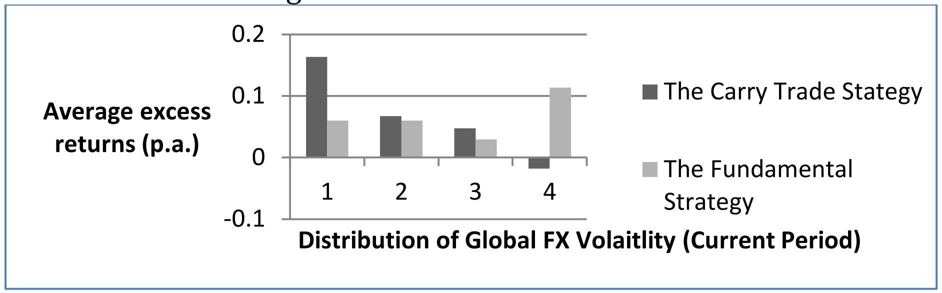
From the bar plots, we can see that except for the last bar that when the FX volatility is in its 4^{th} quartile, the carry trade portfolio has higher average excess returns than the fundamental portfolio. However, for the 4^{th} volatility quartile, the carry trade portfolio has negative average return because of crash risk: a quick exchange rate adjustment towards its fundamentals, while the fundamental portfolio which is formed by borrowing the most overvalued currencies and lending the most undervalued currencies, has forecasted this quick exchange rate adjustment and therefore provides with a large positive average return.

In Panel B, we plot the same graph of the log excess returns against the last period volatility instead the current period volatility. From the graph, we can see that if the last period volatility is in the top 25% regime, the fundamental strategy performs better than the carry trade strategy. So that's why in Section 7.6, we can use last period's volatility to forecast this period's FX volatility regime in order to make a tradable strategy.

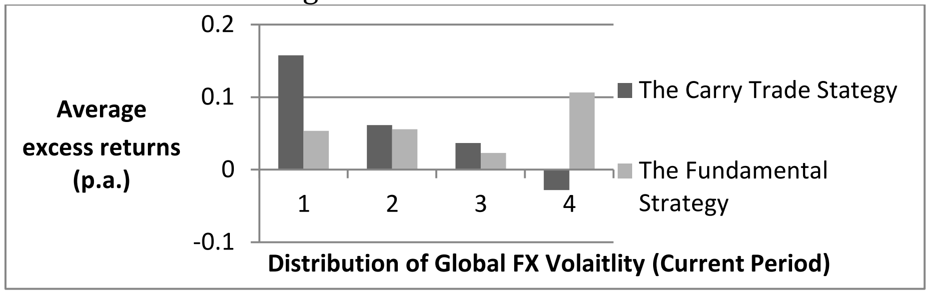
Figure 7-1 Excess Returns and FX Volatility

Panel A: Log excess return and volatility of current period

Log Excess Returns without b-a

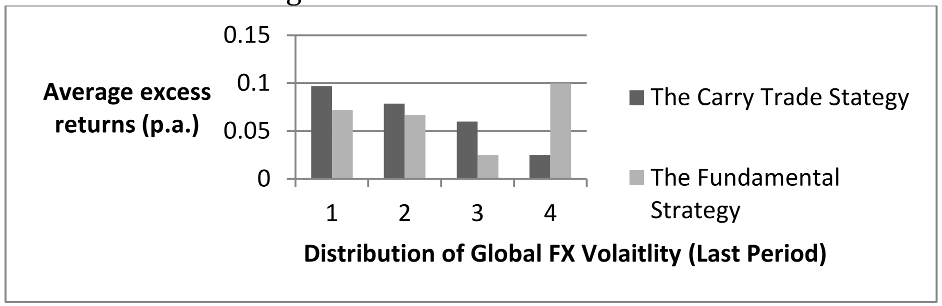


Log Excess Returns with b-a

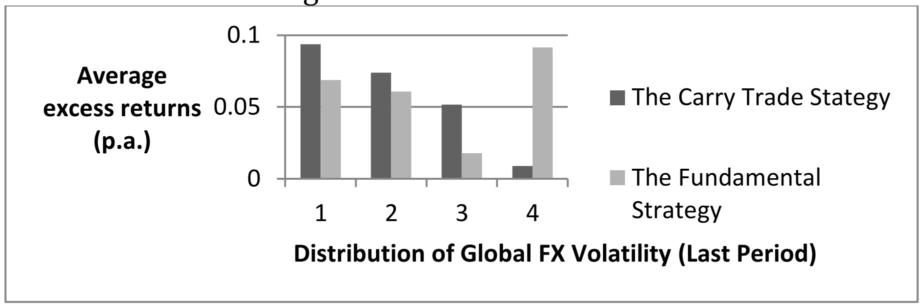


Panel B. Log excess return and volatility of last period

Log Excess Returns without b-a



Log Excess Returns with b-a



Note: this figure plots mean excess returns for the carry trade portfolio and the fundamental portfolio against the current period (Panel A)/the last period(Panel B) FX volatility being within the lowest to highest quartile of its sample distribution (four categories from "lowest" to "highest" shown on the x-axis of each panel). The mean excess returns are plotted both with and without transaction cost adjusted.

As shown by Figure 7.1, the average excess return from the carry trade portfolio outperforms that from the fundamental portfolio when the FX volatility is in its first 3 quartiles, while the opposite is true when the volatility is in its top quartile, and these results are also consistent with the regression results in Section 7.3.

Therefore, we can set up a mixed trading strategy, which switches between the carry trade strategy and the fundamental strategy depending on either the current or last period FX volatility regimes.

If the *current* period's volatility exceeds 0.0048 (the 3rd quartile of FX volatility), we take the fundamental strategy, otherwise we stick to the carry trade strategy. From Table 7.5, we can see that this mixed strategy provides an average annually excess return as large as 9.70% without adjusting transaction cost and 8.65% with adjusting transaction costs, the Sharp Ratio is larger than 1 even after adjusting the transaction costs. Compared with the fundamental strategy, the skewness of this mixed strategy is more negative; however, it is much smaller in absolute value than that of the carry trade strategy.

If we take last period FX volatility as the regime, then the mixed strategy is made by the fundamental strategy if the *last* period's volatility exceeds 0.0048 (the 3rd quartile of FX volatility), otherwise we stick to the carry trade strategy. The descriptive statistics of this mixed strategy is provided by Table 7.6. Compared with Table 7.5, the mixed strategy provides a lower average annualized excess return of 8.46% without adjusting transaction cost and 7.56% after adjusting transaction cost. However, this average excess return is still larger than that of either the carry trade strategy or the fundamental strategy. The Sharp Ratio of this mixed strategy is still larger than 1 without transaction cost adjusting and 0.91 after transaction cost adjusting and the negative skewness is smaller in absolute value than the carry trade strategy. More importantly, this mixed strategy is tradable since investors can make their decision on whether to follow the carry trade strategy or the fundamental strategy based on last period's FX volatility level, if it exceeds the 3rd quartile, investors invest in the fundamental strategy otherwise, they invest in the carry trade strategy.

The reason we can use last period's volatility to forecast this period's volatility is that FX volatility is auto-correlated with a coefficient 0.67. During our sample period, we calculated the realized probability of FX volatility at t falls in the high volatility regime conditioning on volatility at $t-1$ is in the high volatility regime, it is 51%, and the realized probability of FX volatility at time t falls in the normal volatility regime conditioning on volatility at time $t-1$ is in the normal volatility regime is 84%. If FX volatility is a random walk, then the former number should be around 25% and the later should be around 75%.

Table 7-5 The Descriptive Statistics for the Mixed Strategy

With current period volatility: $volatility_t$=0.0048							
29-OECD Country Sample- Log return (without b-a)							
Portfolio	1	2	3	4	5	DOL_{mix}	HML_{mix}
Mean (%)	-2.76	1.93	2.44	4.50	6.94	2.61	9.70
Std. Dev.	10.37	10.18	10.24	9.89	9.29	9.14	8.60
Skewness	-0.59	-0.07	-0.40	-0.30	-0.14	-0.36	-0.32
S.R.	-0.27	0.19	0.24	0.45	0.75	0.29	1.13
29-OECD Country Sample- Log return (with b-a)							
Portfolio	1	2	3	4	5	DOL_{mix}	HML_{mix}
Mean (%)	-2.34	1.44	2.18	4.09	6.31	2.34	8.65
Std. Dev.	10.30	10.19	10.16	9.84	9.29	9.09	8.55
Skewness	-0.60	-0.07	-0.37	-0.32	-0.22	-0.38	-0.31
S.R.	-0.23	0.14	0.21	0.42	0.68	0.26	1.01

Note: this table has the same setting as Table 7.4 and it provides the descriptive statistics for the mixed strategy that is constructed depending on the current period FX volatility regime.

Table 7-6 The Descriptive Statistics for the Mixed Strategy

With current period volatility: $volatility_{t-1}$=0.0048							
29-OECD Country Sample- Log return (without b-a)							
Portfolio	1	2	3	4	5	DOL_{mix}	HML_{mix}
Mean (%)	-1.75	1.62	2.63	3.68	6.71	2.58	8.46
Std. Dev.	10.09	10.24	10.02	9.81	9.72	9.12	8.40
Skewness	-0.34	-0.19	-0.31	-0.50	-0.33	-0.38	-0.39
S.R.	-0.17	0.16	0.26	0.38	0.69	0.28	1.01
29-OECD Country Sample- Log return (with b-a)							
Portfolio	1	2	3	4	5	DOL_{mix}	HML_{mix}
Mean (%)	-1.41	1.11	2.28	3.32	6.15	2.29	7.56
Std. Dev.	10.06	10.24	10.00	9.80	9.63	9.09	8.34
Skewness	-0.33	-0.19	-0.31	-0.52	-0.32	-0.38	-0.31
S.R.	-0.14	0.11	0.23	0.34	0.64	0.25	0.91

Note: this table has the same setting as Table 7.4 and it provides the descriptive statistics for the mixed strategy that is constructed depending on the last period FX volatility regime.

7.6. OUT OF SAMPLE FORECAST

In this section, we conduct out of sample test for the mixed strategy constructed by using last period volatility regime. To make a tradable strategy, we can only use information available at the time point of investment decision making. We test the performance of the tradable mixed strategy for two different sample periods: from 2011M10 to 2013M03 and from 2007M12 to 2013M03.

We have provided the descriptive statistics for the tradable mixed strategy in Table 7.6 for the sample period from 1983M11 to 2011M09. In this section, we test if this strategy is profitable for the following sample period.

We extend our sample from 2011M09 to 2013M03, first we set up the carry trade strategy and the fundamental strategy at the beginning of each month. For the carry trade, we sort currencies into portfolios according their forward discount/premium; while for the fundamental strategy, we sort currencies by their real exchange rate deviation from the equilibrium, where we assume that the sample averages of real exchange rate for each currency from 1983M11 to 2011M09 will give the equilibrium real exchange rates. Table 7.7 provides the descriptive statistics for sample from 1983M11 to 2013M3, including 18 months forecast period from 2011M10 to 2013M3. The average excess returns for the carry trade portfolio and fundamental portfolio are provided by HML_{CT} and HML_{FM} respectively and they are slightly higher than that for sample 1983M11 to 2011M09 (As shown in Table 7.6).

Figure 7.2 Panel A plots the realized volatility from 1983M11 to 2013M03. The shaded area is the forecast period from 2011M10 to 2013M03. The horizontal solid line is the 3rd quartile of volatility from 1983M11 to 2011M09, and it is equal to 0.00479.

Therefore, according to the strategy, if last period volatility falls below this value, we will go for the carry trade strategy, and if last period volatility falls above this value, we will go for the fundamental strategy.

From Figure 7.2 Panel A, we find that for the forecast period starts from 2011M10 to 2013M3, there are only 3 months that the volatility of last period falls above the 0.00479 boundary (2011M10, 2011M11 and 2011M12). Therefore, the mixed strategy for the forecast period is a combination of only 3 months going for the fundamental strategy and the rest 15 months all going for the carry trade strategy. Thus, we expect that the average return for the mixed strategy would not be so different from the average return of the carry trade strategy. Table 7.8 provides the descriptive statistics for the forecasted 18-month period only. Panel A provides the excess return from the mixed strategy while Panel B and Panel C provide the excess return from the carry trade strategy and the fundamental strategy respectively. The average excess return from the mixed strategy $HML_{mix}$is actually lower than the excess return from the carry trade strategy HML_{CT} due to the bad performance of the fundamental strategy with an average excess return HML_{FM} equal to 4.16 without adjusting transaction costs.

However, the mixed strategy works well during crisis period, so it would be interesting to see if we can provide an ex ante trading strategy which covers the recent global financial crisis period started from 2007M12 and provides a better performance than the other two strategies. So we assume the equilibrium real exchange rate for each currency is provided by the average exchange rate from 1983M11 to2007M11, and the FX volatility boundary is 0.00458, the 3rd quartile of FX volatility from 1983M11 to 2007M11. As we can see from Figure 7.2 Panel B, we find that for the forecast period

2007M12 to 2013M03, there are more periods of the realized volatility fall above the boundary.

Table 7.9 provides the descriptive statistics for both the sample and forecast period. Table 7.9 Panel B and C are identical to Table 7.7 Panel B and C. The difference between Table 7.7 and Table 7.9 lies in Panel A for the mixed strategy. The volatility boundary is different because as the sample changes the 3rd quartile point of volatility also changes.

Table 7.10 provides the descriptive statistics for only the forecasted 63 months from 2007M12 to 2013M3. The average excess return from the mixed strategy outperforms both the other strategies. This becomes clearer as we focus on the subsample from 2007M12 to 2011M09, the NBER announced recent recession period, as shown by Table 7.11. The differences among the three strategies during the crisis period are very large.

In Figure 7.3, we plot the cumulative log excess return for different time periods: panel A includes both sample period and forecast period, while other panels includes different forecast period only. Panel B includes 18-month forecast period time, since the FX volatility is not high during this period, the cumulative excess returns generated by the mixed strategy is not very different from the returns generated by the carry trade, and even 1% smaller. However, when the forecast period includes the high volatility period (Panel C and Panel D), the mixed strategy works much better than the other two strategies.

Table 7-7 Descriptive Statistics for Returns from 1983M11 to 2013M3

Panel A. The Mixed Strategy with $volatility_{t-1}$=0.00479

Log return (without transaction cost)

Portfolio	1	2	3	4	5	DOL_{mix}	HML_{mix}
Mean(%)	-1.71	1.27	2.28	3.63	6.75	2.44	8.46
Std. Dev.	10.01	10.19	9.96	9.79	9.79	9.11	8.35
Skewness	-0.34	-0.20	-0.31	-0.50	-0.35	-0.40	-0.37
SR	-0.17	0.12	0.23	0.37	0.69	0.27	1.01

Log return (with transaction cost)

Portfolio	1	2	3	4	5	DOL_{mix}	HML_{mix}
Mean(%)	-1.42	0.81	1.87	3.20	6.28	2.15	7.70
Std. Dev.	10.00	10.20	9.96	9.81	9.80	9.11	8.36
Skewness	-0.33	-0.20	-0.32	-0.53	-0.36	-0.38	-0.31
SR	-0.14	0.08	0.19	0.33	0.64	0.24	0.92

Panel B. The Carry trade Strategy

Log return (without transaction cost)

Portfolio	1	2	3	4	5	DOL_{CT}	HML_{CT}
Mean(%)	-0.71	1.55	2.08	3.42	5.90	2.45	6.61
Std. Dev.	9.70	10.26	9.61	9.92	10.07	9.08	8.36
Skewness	0.03	-0.27	-0.21	-0.74	-0.61	-0.40	-0.89
SR	-0.07	0.15	0.22	0.34	0.59	0.27	0.79

Log return (with transaction cost)

Portfolio	1	2	3	4	5	DOL_{CT}	HML_{CT}
Mean(%)	-0.53	1.20	1.76	3.03	5.66	2.22	6.19
Std. Dev.	9.70	10.26	9.61	9.94	10.09	9.09	8.38
Skewness	0.04	-0.27	-0.22	-0.75	-0.62	-0.41	-0.90
SR	-0.05	0.12	0.18	0.30	0.56	0.24	0.74

Panel C. The Fundamental Strategy

Log return (without transaction cost)

Portfolio	1	2	3	4	5	DOL_{FM}	HML_{FM}
Mean(%)	-0.61	1.57	2.39	3.03	5.89	2.45	6.50
Std. Dev.	10.13	10.03	10.25	10.08	9.16	9.13	7.86
Skewness	-0.72	-0.15	-0.37	-0.26	-0.22	-0.38	0.00
SR	-0.06	0.16	0.23	0.30	0.64	0.27	0.83

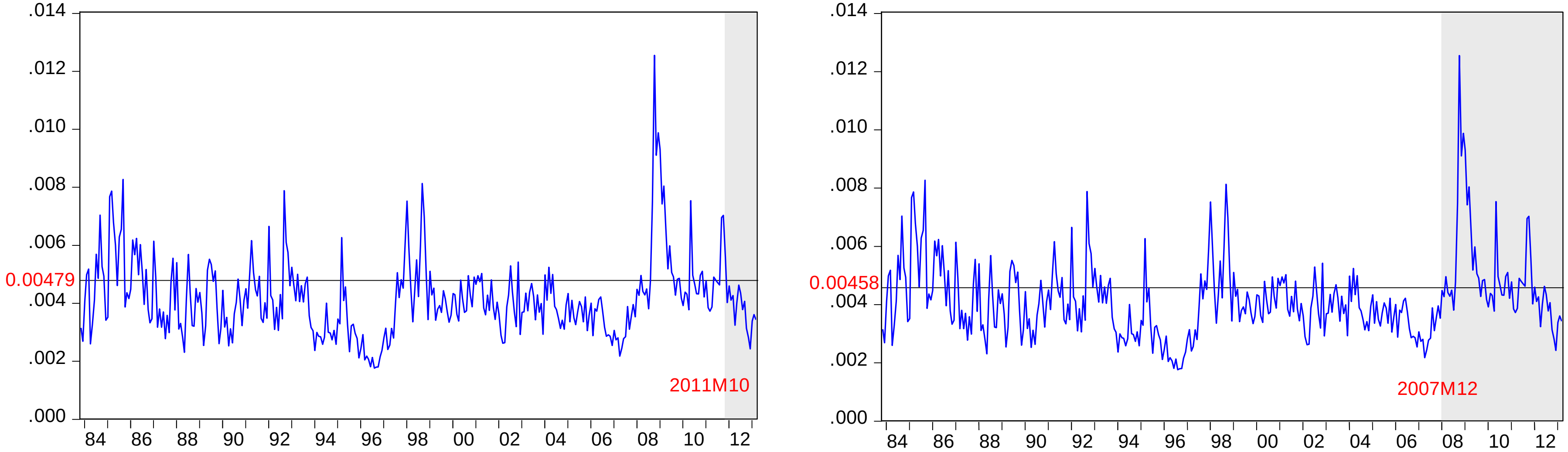
Log return (with transaction cost)

Portfolio	1	2	3	4	5	DOL_{FM}	HML_{FM}
Mean(%)	-0.45	1.17	2.00	2.65	5.72	2.22	6.17
Std. Dev.	10.12	10.03	10.24	10.06	9.15	9.12	7.84
Skewness	-0.72	-0.15	-0.38	-0.28	-0.22	-0.39	0.00
SR	-0.04	0.12	0.20	0.26	0.62	0.24	0.79

Note: this table reports mean returns (annualized), standard deviations (annualized) and skewness of currency portfolios sorted by forward discounts (Panel A) and by real exchange rate deviation (Panel B) with and without transaction cost adjusted for the 29-OECD country sample. Sharp Ratios (SR) are also reported. The time period is spanned from 11/1983 to 03/2013, and the forecast period is spanned from 10/2011 to 03/2013.

Figure 7-2 Realized Volatility from 1983M11 to 2013M3

Panel A. with forecast period from 2011M10 to 2013M3 Panel B. with forecast period from 2007M12 to 2013M3



Note: This figure plots the realized volatility from 11/1983 to 03/2013. In Panel A, the shaded area is from 10/2011 to 03/2013 and the horizontal line with value 0.00479 is provided by the 3rd quartile of realized volatility from 11/1983 to 09/2011. In Panel B, the shaded area is from 12/2007 to 03/2013 and the horizontal line with value 0.00458 is provided by the 3rd quartile of realized volatility from 11/1983 to 11/2007.

Table 7-8 Descriptive Statistics for Returns of the Forecasted Period from 2011M10 to 2013M3

Panel A. The Mixed Strategy with $volatility_{t-1}$=0.00479														
	Log return (without transaction cost)							Log return (with transaction cost)						
Portfolio	1	2	3	4	5	DOL_{mix}	HML_{mix}	1	2	3	4	5	DOL_{mix}	HML_{mix}
Mean(%)	-1.04	-5.19	-4.36	4.01	6.83	0.05	7.87	-0.81	-5.42	-4.56	3.79	6.65	-0.07	7.46
Std. Dev.	8.76	9.42	8.77	10.13	11.34	9.16	7.31	8.76	9.40	8.76	10.12	11.32	9.15	7.30
Skewness	-0.15	-0.67	-0.57	-0.60	-0.56	-0.69	0.32	-0.15	-0.67	-0.57	-0.6	-0.57	-0.69	0.33
SR	-0.12	-0.55	-0.50	0.40	0.60	0.01	1.08	-0.09	-0.58	-0.52	0.37	0.59	-0.01	1.02
Panel B. The Carry trade Strategy														
	Log return (without transaction cost)							Log return (with transaction cost)						
Portfolio	1	2	3	4	5	DOL_{CT}	HML_{CT}	1	2	3	4	5	DOL_{CT}	HML_{CT}
Mean(%)	-2.60	-4.45	-4.04	5.17	6.25	0.07	8.85	-2.37	-4.65	-4.23	5.07	6.14	-0.01	8.51
Std. Dev.	7.79	9.94	8.43	10.28	11.74	9.14	7.57	7.79	9.94	8.43	10.28	11.74	9.14	7.57
Skewness	-0.52	-0.51	-0.70	-0.51	-0.52	-0.70	0.20	-0.53	-0.51	-0.70	-0.50	-0.51	-0.69	0.21
SR	-0.33	-0.45	-0.48	0.50	0.53	0.01	1.17	-0.30	-0.47	-0.50	0.49	0.52	0.00	1.12
Panel C. The Fundamental Strategy														
	Log return (without transaction cost)							Log return (with transaction cost)						
Portfolio	1	2	3	4	5	DOL_{FM}	HML_{FM}	1	2	3	4	5	DOL_{FM}	HML_{FM}
Mean(%)	-0.35	-2.92	0.50	0.19	3.81	0.25	4.16	-0.25	-3.20	0.28	-0.04	3.68	0.09	3.93
Std. Dev.	10.89	8.16	10.14	9.45	9.16	9.21	4.28	10.88	8.13	10.15	9.45	9.15	9.21	4.26
Skewness	-0.88	-0.88	-0.55	-0.39	-0.25	-0.69	-0.02	-0.88	-0.89	-0.54	-0.39	-0.24	-0.69	-0.03
SR	-0.03	-0.36	0.05	0.02	0.42	0.03	0.97	-0.02	-0.39	0.03	0.00	0.40	0.01	0.92

Note: this table reports mean returns (annualized), standard deviations (annualized) and skewness of currency portfolios sorted by forward discounts (Panel A) and by real exchange rate deviation (Panel B) with and without transaction cost adjusted for the 29-OECD country sample. Sharp Ratios (SR) are also reported. The time period is spanned from 10/2011 to 03/2013. There are 18-month observations.

Table 7-9 Descriptive Statistics for Returns From 1983M11 to 2013M3

Panel A. The Mixed Strategy with $volatility_{t-1}$=0.00458														
	Log return (without transaction cost)							Log return (with transaction cost)						
Portfolio	1	2	3	4	5	DOL_{mix}	HML_{mix}	1	2	3	4	5	DOL_{mix}	HML_{mix}
Mean(%)	-2.37	1.74	2.15	4.29	6.64	2.49	9.01	-2.01	1.31	1.66	3.78	6.22	2.19	8.23
Std. Dev.	9.94	10.39	9.94	9.94	9.47	9.13	8.30	9.94	10.40	9.93	9.95	9.48	9.13	8.31
Skewness	-0.45	-0.24	-0.32	-0.44	-0.27	-0.39	-0.28	-0.45	-0.24	-0.33	-0.46	-0.27	-0.39	-0.29
SR	-0.24	0.17	0.22	0.43	0.70	0.27	1.09	-0.20	0.13	0.17	0.38	0.66	0.24	0.99
Panel B. The Carry trade Strategy														
	Log return (without transaction cost)							Log return (with transaction cost)						
Portfolio	1	2	3	4	5	DOL_{CT}	HML_{CT}	1	2	3	4	5	DOL_{CT}	HML_{CT}
Mean(%)	-0.71	1.55	2.08	3.42	5.90	2.45	6.61	-0.53	1.20	1.76	3.03	5.66	2.22	6.19
Std. Dev.	9.70	10.26	9.61	9.92	10.07	9.08	8.36	9.70	10.26	9.61	9.94	10.09	9.09	8.38
Skewness	0.03	-0.27	-0.21	-0.74	-0.61	-0.40	-0.89	0.04	-0.27	-0.22	-0.75	-0.62	-0.41	-0.90
SR	-0.07	0.15	0.22	0.34	0.59	0.27	0.79	-0.05	0.12	0.18	0.30	0.56	0.24	0.74
Panel C. The Fundamental Strategy														
	Log return (without transaction cost)							Log return (with transaction cost)						
Portfolio	1	2	3	4	5	DOL_{FM}	HML_{FM}	1	2	3	4	5	DOL_{FM}	HML_{FM}
Mean(%)	-0.36	1.35	2.38	3.84	5.19	2.48	5.55	-0.19	0.96	1.87	3.54	5.04	2.24	5.23
Std. Dev.	10.23	9.96	10.28	10.05	8.95	9.13	7.99	10.22	9.96	10.29	10.05	8.95	9.12	7.97
Skewness	-0.58	-0.19	-0.20	-0.41	-0.29	-0.38	0.00	-0.58	-0.19	-0.21	-0.43	-0.29	-0.38	-0.01
SR	-0.04	0.14	0.23	0.38	0.58	0.27	0.69	-0.02	0.10	0.18	0.35	0.56	0.25	0.66

Note: this table reports mean returns (annualized), standard deviations (annualized) and skewness of currency portfolios sorted by forward discounts (Panel A) and by real exchange rate deviation (Panel B) with and without transaction cost adjusted for the 29-OECD country sample. Sharp Ratios (SR) are also reported. The time period is spanned from 12/2007 to 03/2013.

Table 7-10 Descriptive Statistics for Returns of the Forecasted Period from 2007M12 to 2013M03

Panel A. The Mixed Strategy with $volatility_{t-1}$=0.00458														
	Log return (without transaction cost)							Log return (with transaction cost)						
Portfolio	1	2	3	4	5	DOL_{mix}	HML_{mix}	1	2	3	4	5	DOL_{mix}	HML_{mix}
Mean(%)	-3.09	-1.17	-2.74	2.76	1.58	-0.53	4.67	-2.74	-1.40	-3.09	2.31	1.26	-0.73	4.00
Std. Dev.	13.24	13.02	12.50	12.86	11.97	12.11	8.21	13.24	13.02	12.50	12.86	11.97	12.11	8.21
Skewness	-0.76	-0.58	-0.60	-0.85	-0.54	-0.65	0.59	-0.77	-0.58	-0.60	-0.85	-0.54	-0.65	0.61
SR	-0.23	-0.09	-0.22	0.21	0.13	-0.04	0.57	-0.21	-0.11	-0.25	0.18	0.11	-0.06	0.49
Panel B. The Carry trade Strategy														
	Log return (without transaction cost)							Log return (with transaction cost)						
Portfolio	1	2	3	4	5	DOL_{CT}	HML_{CT}	1	2	3	4	5	DOL_{CT}	HML_{CT}
Mean(%)	-1.17	-2.14	-2.54	1.48	1.76	-0.52	2.93	-0.99	-2.34	-2.82	1.21	1.61	-0.67	2.60
Std. Dev.	10.14	12.88	12.21	14.32	13.90	12.10	8.50	10.13	12.87	12.23	14.33	13.90	12.11	8.50
Skewness	-0.18	-0.42	-0.35	-0.92	-1.05	-0.64	-0.87	-0.18	-0.42	-0.35	-0.93	-1.05	-0.64	-0.87
SR	-0.12	-0.17	-0.21	0.10	0.13	-0.04	0.34	-0.10	-0.18	-0.23	0.08	0.12	-0.05	0.31
Panel C. The Fundamental Strategy														
	Log return (without transaction cost)							Log return (with transaction cost)						
Portfolio	1	2	3	4	5	DOL_{FM}	HML_{FM}	1	2	3	4	5	DOL_{FM}	HML_{FM}
Mean(%)	-0.09	-1.65	-2.81	1.52	0.30	-0.55	0.39	-0.03	-1.78	-3.04	1.33	0.24	-0.66	0.27
Std. Dev.	15.06	12.40	13.07	12.07	10.64	12.14	8.68	15.07	12.39	13.07	12.09	10.64	12.15	8.68
Skewness	-0.73	-0.71	-0.52	-0.82	-0.61	-0.64	0.42	-0.73	-0.72	-0.52	-0.83	-0.61	-0.64	0.42
SR	-0.01	-0.13	-0.21	0.13	0.03	-0.04	0.04	0.00	-0.14	-0.23	0.11	0.02	-0.05	0.03

Note: this table reports mean returns (annualized), standard deviations (annualized) and skewness of currency portfolios sorted by forward discounts (Panel A) and by real exchange rate deviation (Panel B) with and without transaction cost adjusted for the 29-OECD country sample. Sharp Ratios (SR) are also reported. The time period is spanned from 12/2007 to 03/2013. There are 63-month observations.

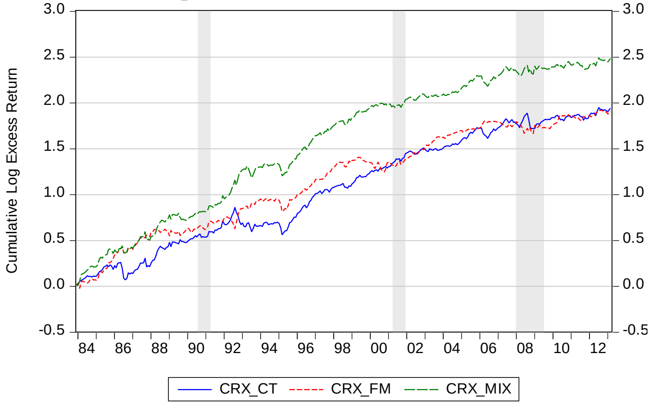
Table 7-11 Descriptive Statistics for Returns of the Forecasted Period from 2007M12 to 2011M09

Panel A. The Mixed Strategy with $volatility_{t-1}$=0.00458														
	Log return (without transaction cost)							Log return (with transaction cost)						
Portfolio	1	2	3	4	5	DOL_{mix}	HML_{mix}	1	2	3	4	5	DOL_{mix}	HML_{mix}
Mean(%)	-3.99	-0.75	-1.36	3.01	-0.57	-0.73	3.42	-3.64	-0.97	-1.76	2.48	-0.94	-0.97	2.70
Std. Dev.	14.78	14.30	13.75	13.96	12.30	13.21	8.74	14.78	14.30	13.76	13.97	12.31	13.21	8.75
Skewness	-0.70	-0.55	-0.63	-0.86	-0.49	-0.60	0.69	-0.71	-0.55	-0.62	-0.86	-0.49	-0.60	0.72
SR	-0.27	-0.05	-0.10	0.22	-0.05	-0.06	0.39	-0.25	-0.07	-0.13	0.18	-0.08	-0.07	0.31
Panel B. The Carry trade Strategy														
	Log return (without transaction cost)							Log return (with transaction cost)						
Portfolio	1	2	3	4	5	DOL_{CT}	HML_{CT}	1	2	3	4	5	DOL_{CT}	HML_{CT}
Mean(%)	-0.59	-1.22	-1.94	0.00	-0.04	-0.76	0.55	-0.43	-1.42	-2.26	-0.33	-0.20	-0.93	0.23
Std. Dev.	11.02	13.97	13.52	15.74	14.76	13.20	8.83	11.01	13.96	13.53	15.75	14.76	13.20	8.84
Skewness	-0.14	-0.42	-0.32	-0.87	-1.08	-0.59	-1.07	-0.14	-0.42	-0.32	-0.88	-1.08	-0.59	-1.08
SR	-0.05	-0.09	-0.14	0.00	0.00	-0.06	0.06	-0.04	-0.10	-0.17	-0.02	-0.01	-0.07	0.03
Panel C. The Fundamental Strategy														
	Log return (without transaction cost)							Log return (with transaction cost)						
Portfolio	1	2	3	4	5	DOL_{FM}	HML_{FM}	1	2	3	4	5	DOL_{FM}	HML_{FM}
Mean(%)	-0.28	-2.40	-1.84	1.39	-0.71	-0.77	-0.43	-0.25	-2.53	-2.09	1.19	-0.79	-0.89	-0.54
Std. Dev.	16.41	13.69	14.34	13.09	11.42	13.23	9.89	16.42	13.68	14.35	13.12	11.42	13.24	9.89
Skewness	-0.69	-0.64	-0.52	-0.83	-0.58	-0.60	0.45	-0.68	-0.64	-0.52	-0.84	-0.58	-0.60	0.45
SR	-0.02	-0.18	-0.13	0.11	-0.06	-0.06	-0.04	-0.02	-0.18	-0.15	0.09	-0.07	-0.07	-0.05

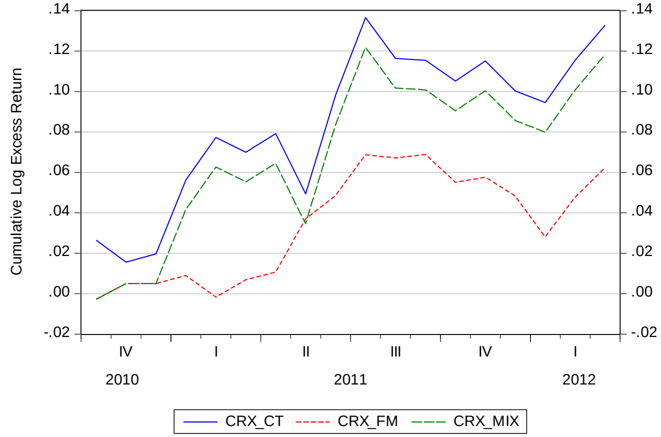
Note: this table reports mean returns (annualized), standard deviations (annualized) and skewness of currency portfolios sorted by forward discounts (Panel A) and by real exchange rate deviation (Panel B) with and without transaction cost adjusted for the 29-OECD country sample. Sharp Ratios (SR) are also reported. The time period is spanned from 12/2007 to 09/2011. There are 45-month observations.

Figure 7-3 Cumulative Log Excess Returns for 3 Strategies

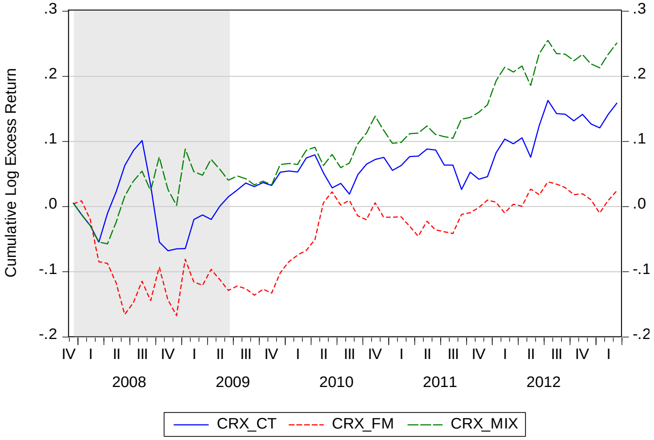
Panel A: For period from1983M12 to 2013M03



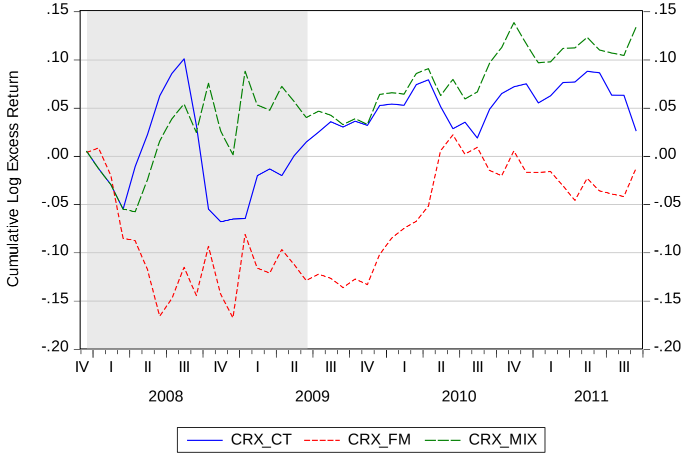
Panel B: For period from 2010M10 to 2013M03



Panel C: For period from2007M12 to 2013M03



Panel D: For period from2007M12 to 2010M09



Note: This figure plots the cumulative returns of three different strategies over different time periods.

7.7. CONCLUSION

The forward premium puzzle and purchasing power parity puzzle are two long standing and unsolved puzzles in foreign exchange market. In this chapter, we argue that these two puzzles can be partially explained by taking the FX volatility into consideration. We estimate simple regressions of changes in exchange rate with forward discount and real exchange rate deviations regime depended on FX volatility. The results suggest that, when FX volatility is high, changes in exchange rate follow the prediction of UIP and these changes are a process of exchange rates reverting back to fundamentals.

Following by these results, we set up two different trading strategies: the carry trade strategy and the fundamental strategy. We argue that higher average returns can be achieved by switching between these two strategies depending on volatility level. The mixed strategy provides higher average return than the carry trade strategies because it is, to some extent, crash risk protected. We can even make this mixed strategy tradable by using previous period volatility to forecast this period's volatility regime.

More complicated strategies provide higher returns. Jordà and Taylor (2012) argue that this indicates FX market is inefficient, since rational investors would diversify the crash risk from the carry trade strategy during high volatility period by conducting the fundamental strategy instead. However, although we cannot use either the FX volatility risk or crash risk to price the excess returns from the fundamental strategy, there may be other risks in conducting the fundamental strategy during high volatility risk period. Further study is required.

8. GENERAL CONCLUSION

There are many long-standing and unsolved puzzles in foreign exchange (FX) market. This thesis partially explains two of them: the uncovered interest rate parity (UIP) puzzle and the purchasing power parity (PPP) puzzle, by examine the relationship between foreign exchange (FX) volatility and excess returns from the currency market.

The main assets we study in this thesis are currency portfolios sorted by their interest rate differentials, which are often referred to as the carry trade in the literature. In the first part of empirical work, we explain the cross sectional excess returns of the carry trade portfolios in a standard risk-return profile. We start from taking FX volatility risk as a risk factor which is theoretically supported by Chen (2002) and empirically tested by Menkhoff, Sarno et al. (2012). We name this model as unconditional ICAPM model and test it with different sample and data period from Menkhoff, Sarno et al. (2012), and the results are found to be consistent. Moreover, we improve the unconditional ICAPM model in two dimensions: (1) we allow both loadings and price of volatility risk factor to vary conditioning on FX volatility level and we call this model the conditional ICAPM model, so as to distinguish with the unconditional ICAPM model; (2) We decompose foreign exchange volatility into two components: a persistent volatility risk component, the long-run volatility risk, and a less persistent volatility risk, the short-run volatility risk. We use both long- and short-run volatility risk factors to price the cross-sectional excess return from the carry trade.

The contribution of the above empirical studies are the following: first we confirm the argument of Ang, Hodrick et al. (2006) and Menkhoff, Sarno et al. (2012) that the excess returns from the carry trade are compensations for bearing FX volatility risk and volatility risk factors are negatively priced which indicates that investors wish to buy insurance against changes in FX volatility. High interest rate currencies are negatively correlated with FX volatility risks and thus require higher return while low interest rate currencies are positively correlated with FX volatility risks and thus require lower returns.

More importantly, we find that the conditional ICAPM model is able to provide even lower pricing error for explaining the excess return from the carry trade by pricing the volatility risk during different volatility state separately. This suggests that the excess return from the carry trade is actually the compensation for bearing extra volatility risk during high volatility state, at least for the 29-OECD-country sample. This finding is consistent with the rare disaster explanation of the forward premium puzzle by Farhi and Gabaix (2008) and the crash risk literature by Brunnermeier, Nagel et al. (2009).

Further, we decompose FX market volatility into long- and short-run components by using a Component-GARCH model and we find that prices of both volatility risk components are negative which implies that investors pay for insurance against changes in volatility, even if those changes have little persistence. Also we find that after we price the volatility risk components separately, the pricing errors are reduced, the two components model provides better fit than the unconditional ICAPM model. By using a conditional measure of volatility, we also prove that the FX volatility risk is able to explain the excess returns from the carry trade regardless the method in which we proxy it.

Therefore, by using three different settings of empirical study to explain the excess return from the carry trade, we also partially explain the UIP puzzle as the carry trade is a trading strategy exploiting the failure of the UIP.

In the second part of empirical work, we examine the excess returns from different currency trading strategies under different FX volatility regimes. We find both the violations of UIP and PPP are artefact and are only true when FX volatility at normal level. During high volatility period, both UIP and PPP tend to reassert themselves to some extent. Thus if we switch from the carry trade strategy to a PPP implied trading strategy during high volatility period, we could avoid the losses from the carry trade and have higher average excess returns. More importantly, we could make this "mixed" strategy tradable by using last period's FX volatility state to forecast this period's volatility state.

The contributions of this study are the following: by taking volatility regimes into account, we can partially explain the UIP and the PPP puzzles. Our findings are consistent with the non-linear adjustment literature for exchange rates. Moreover, the tradable "mixed" strategy we create provides higher return than the carry trade, which means that we create an even bigger puzzle than the UIP puzzle because we can neither use FX volatility risk nor the crash risk to explain the excess returns from the mixed strategy. There are two possible ways to explain this: First, by taking the mixed trading strategy, investors are bearing other risks rather than FX volatility risk or crash risk. By using only the FX volatility risk factor or the crash risk factor to explain it would lead to a model misspecification. Alternatively, one could argue that the FX market is inefficient since the more complicated strategy can provide higher return. Therefore, this is not the end of the story and further studies are required.

REFERENCE

Andersen, T. G., et al. (2001). "The distribution of realized exchange rate voaltility." Journal of the American Statistical Association **96**: 42-55.

Abhyankar, A., et al. (2011). "Salvaging the C-CAPM: Currency carry trade risk premia and conditioning information." Available at SSRN.

Abuaf, N. and P. Jorion (1990). "Purchasing power parity in the long run." The Journal of Finance **45**(1): 157-174.

Adrian, T. and J. Rosenberg (2008). "Stock returns and volatility: Pricing the short-run and long-run components of market risk." The Journal of Finance **63**(6): 2997-3030.

Ang, A., et al. (2006). "Downside risk." Review of Financial Studies **19**(4): 1191-1239.

Ang, A., et al. (2006). "The cross - section of volatility and expected returns." The Journal of Finance **61**(1): 259-299.

Bacchetta, P. and E. Van Wincoop (2010). "Infrequent portfolio decisions: A solution to the forward discount puzzle." The American Economics Review **100**(3): 870-904.

Backus, D. K., et al. (2001). "Affine Term Structure Models and the Forward Premium Anomaly." The Journal of Finance **56**(1): 279-304.

Bandi, F. M., et al. (2008). "The joint pricing of volatility and liquidity." Manuscript, University of Chicago.

Bansal, R. and I. Shaliastovich (2013). "A long-run risks explanation of predictability puzzles in bond and currency markets." Review of Financial Studies **26**(1): 1-33.

Bansal, R. and A. Yaron (2004). "Risks for the long run: A potential resolution of asset pricing puzzles." The Journal of Finance **59**(4): 1481-1509.

Barro, R. J. (2006). "Rare disasters and asset markets in the twentieth century." The Quarterly Journal of Economics **121**(3): 823-866.

Benninga, S. and A. Protopapadakis (1988). "The equilibrium pricing of exchange rates and assets when trade takes time." Journal of International Money and Finance **7**(2): 129-149.

Black, A. L. and D. G. McMillan (2004). "Long-run trends and volatility spillovers in daily exchange rates." Applied Financial Economics **14**: 895-907.

Brunnermeier, M. K., et al. (2008). Carry trades and currency crashes, National Bureau of Economic Research.

Brunnermeier, M. K., et al. (2009). Carry trades and currency crashes, University of Chicago Press.

Brunnermeier, M. K. and L. H. Pedersen (2009). "Market liquidity and funding liquidity." Review of Financial Studies **22**(6): 2201-2238.

Burnside, C. (2010). Identification and inference in linear stochastic discount factor models, National Bureau of Economic Research.

Burnside, C. (2011). Carry trades and risk, National Bureau of Economic Research.

Burnside, C., et al. (2006). The returns to currency speculation, National Bureau of Economic Research.

Burnside, C., et al. (2008). "Carry trade: The gains of diversification." Journal of the European Economic Association **6**(2 - 3): 581-588.

Burnside, C., et al. (2011). Carry trade and momentum in currency markets, National Bureau of Economic Research.

Byrne, J. P. and E. P. Davis (2005). "The impact of short-and long-run exchange rate uncertainty on investment: A panel study of industrial countries." Oxford Bulletin of Economics and Statistics **67**: 307-329.

Campbell, J. Y. (1992). Intertemporal asset pricing without consumption data, National Bureau of Economic Research.

Campbell, J. Y. and J. H. Cochrane (1995). By force of habit: A consumption-based explanation of aggregate stock market behavior, National Bureau of Economic Research.

Chen, J. (2002). Intertemporal CAPM and the cross-section of stock returns. EFA 2002 Berlin Meetings Discussion Paper.

Clarida, R., et al. (2009). "Currency carry trade regimes: Beyond the Fama regression." Journal of International Money & Finance **28**(8): 1375-1389.

Clarida, R., et al. (2009). "Currency carry trade regimes: Beyond the Fama regression." Journal of International Money and Finance **28**(8): 1375-1389.

Cochrane, J. H. (2005). Asset pricing, Princeton University Press Princeton.

Eichenbaum, M., et al. (2007). "The returns to currency speculation in emerging markets." American Economic Review **97**(2): 333-338.

Epstein, L. G. and S. E. Zin (1989). "Substitution, risk aversion, and the temporal behavior of consumption and asset returns: A theoretical framework." Econometrica: Journal of the Econometric Society: 937-969.

Fama, E. and K. R. French (1993). "Common Risk Factors in the Returns on Stocks and Bonds." Journal of Financial Economics **33**(3): 56.

Fama, E. F. (1970). "Multiperiod consumption-investment decisions." American Economic Review **60**(1): 163-174.

Fama, E. F. (1984). "Forward and spot exchange rates." Journal of Monetary Economics **14**(3): 319-338.

Fama, E. F. and J. D. MacBeth (1973). "Risk, return, and equilibrium: Empirical tests." The Journal of Political Economy: 607-636.

Farhi, E. and X. Gabaix (2008). Rare disasters and exchange rates, National Bureau of Economic Research.

Froot, K. A. and R. H. Thaler (1990). "Anomalies: foreign exchange." The Journal of Economic Perspectives **4**(3): 179-192.

Gourinchas, P.-O. and A. Tornell (2004). "Exchange rate puzzles and distorted beliefs." Journal of International Economics **64**(2): 303-333.

Hansen, L. P. (1982). "Large sample properties of generalized method of moments estimators." Econometrica: Journal of the Econometric Society: 1029-1054.

Hansen, L. P. and R. J. Hodrick (1980). "Forward exchange rates as optimal predictors of future spot rates: an econometric analysis." The Journal of Political Economy: 829-853.

Hansen, L. P. and K. J. Singleton (1983). "Stochastic consumption, risk aversion, and the temporal behavior of asset returns." The Journal of Political Economy **91**(2): 249.

Jordà, Ò. and A. M. Taylor (2012). "The carry trade and fundamentals: nothing to fear but FEER itself." Journal of International Economics **88**(1): 74-90.

Lee, G. G. and R. F. Engle (1993). "A Permanent and Transitory Component Model of Stock Return Volatility." Available at SSRN 5848.

Lettau, M., et al. (2013). Conditional Risk Premia in Currency Markets and Other Asset Classes, National Bureau of Economic Research.

Lewis, K. K. (1994). Puzzles in international financial markets, National Bureau of Economic Research.

Lothian, J. R. and M. P. Taylor (1996). "Real exchange rate behavior: the recent float from the perspective of the past two centuries." Journal of Political Economy **104**(3): 488.

Lustig, H., et al. (2011). "Common Risk Factors in Currency Markets." Review of Financial Studies **24**(11): 3731-3777.

Lustig, H. and A. Verdelhan (2007). "The Cross-Section of Foreign Currency Risk Premia and Consumption Growth Risk." American Economic Review **97**: 89-117.

Lustig, H. and A. Verdelhan (2007). "The cross section of foreign currency risk premia and consumption growth risk." THE AMERICAN ECONOMIC REVIEW.

Lustig, H. and A. Verdelhan (2008). The cross-section of foreign currency risk premia and consumption growth risk: A reply, National Bureau of Economic Research.

Lyons, R. K. (2001). The microstructure approach to exchange rates, Citeseer.

Mark, N. C. (1990). "Real and nominal exchange rates in the long run: An empirical investigation." Journal of International Economics **28**(1): 115-136.

Menkhoff, L., et al. (2012). "Carry trades and global foreign exchange volatility." The Journal of Finance **67**(2): 681-718.

Menkhoff, L., et al. (2012). "CarryTrades and Global Foreign Exchange Volatility." The Journal of Finance **67**(2): 681-718.

Merton, R. C. (1973). "An intertemporal capital asset pricing model." Econometrica: Journal of the Econometric Society: 867-887.

Michael, P., et al. (1997). "Transactions costs and nonlinear adjustment in real exchange rates; An empirical investigation." Journal of Political Economy **105**(4): 862-879.

Nozaki, M. (2010). Do Currency Fundamentals Matter for Currency Speculators?, International Monetary Fund.

Pastor, L. and R. F. Stambaugh (2001). Liquidity risk and expected stock returns, National Bureau of Economic Research.

Plantin, G. and H. Shin (2006). "Carry trades and speculative dynamics." Available at SSRN 898412.

Plantin, G. and H. S. Shin (2006). "Carry trades and speculative dynamics." as yet unpublished, March, available at SSRN: http://ssrn. com/abstract **898412**.

Pramor, M. and N. T. Tamirisa (2006). "Common voatility trends in the central and Eastern European currencies and the euro." IMF working paper no. 206.

Rangel, J. G. (2011). "FX co-movements: Disentangling the role of global market factors, carry-trades and idiosyncratic components." Working Papers -- Bank of Mexico.

Rogoff, K. (1996). "The purchasing power parity puzzle." Journal of Economic literature: 647-668.

Rogoff, K. (1996). "The purchasing power parity puzzle." Journal of Economic literature **34**(2): 647-668.

Roy, A. D. (1952). "Safety first and the holding of assets." Econometrica: Journal of the Econometric Society: 431-449.

Sarno, L. (2005). "Viewpoint: Towards a solution to the puzzles in exchange rate economics: where do we stand?" Canadian Journal of Economics/Revue canadienne d'économique **38**(3): 673-708.

Sarno, L. and M. P. Taylor (2002). The economics of exchange rates, Cambridge University Press.

Simon, S. R. and M. Z. Amalia (2011). "Volatility in EMU sovereign bond yields: Permanent and transitory components." ICEI working paper.

Taylor, M. P., et al. (2001). "Nonlinear Mean - Reversion in Real Exchange Rates: Toward a Solution To the Purchasing Power Parity Puzzles." International Economic Review **42**(4): 1015-1042.

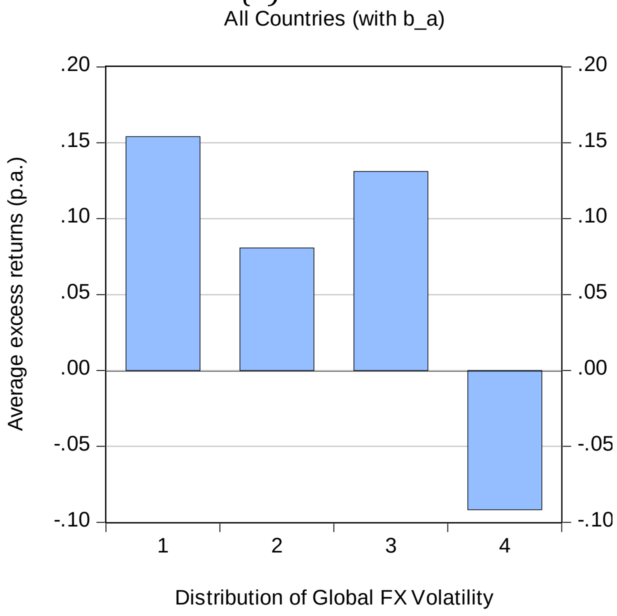
Verdelhan, A. (2010). "A Habit - Based Explanation of the Exchange Rate Risk Premium." The Journal of Finance **65**(1): 123-146.

APPENDIX

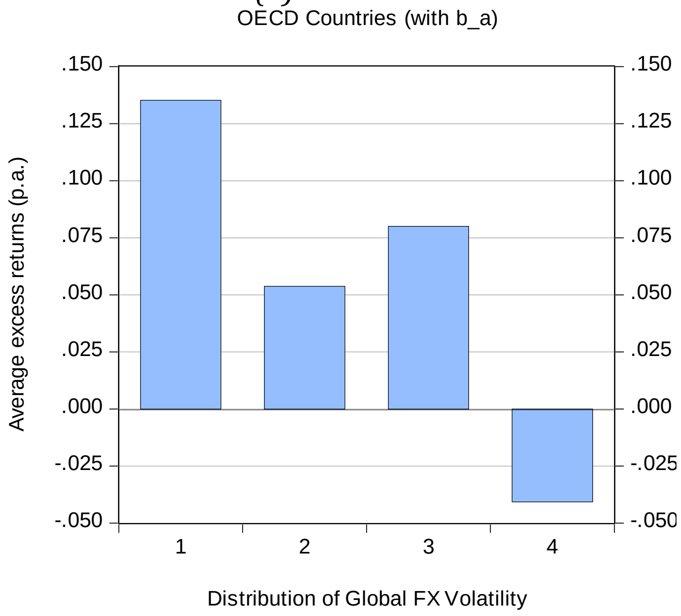
A.1. ASSET PRICING RESULTS WITH TRANSACTION COSTS

Figure A.1.1 (Corresponds to Figure 4.1 with Transaction Costs Deducted)

Panel (a) All countries



Panel (b) OECD countries



Note: This Figure has the same setup as Figure 4.1.

Table A.1.1 (Corresponds to Table 4.1 with Transaction Costs Deducted)

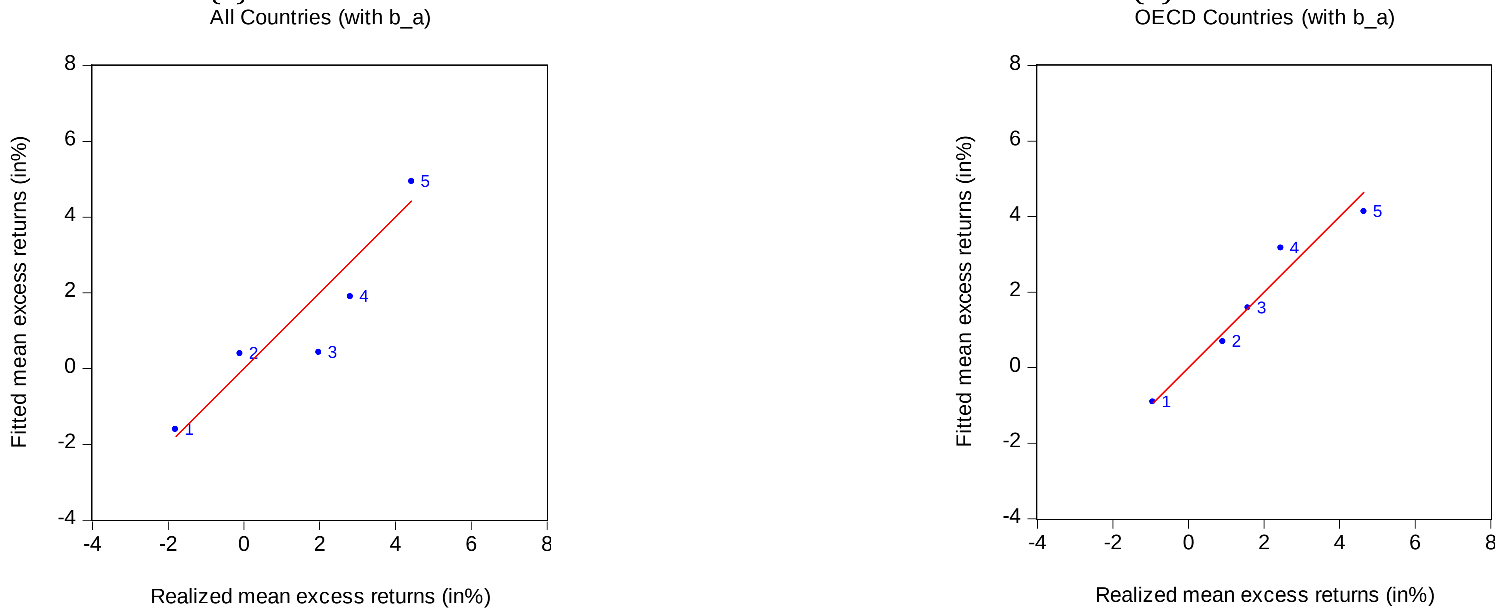
Panel A: Factor prices and loadings									
48-all-country sample					29-OECD-country sample				
GMM	$DOL\%$	$\Delta VOL\ \%$	R^2	$J-stats$	GMM	$DOL\%$	ΔVOL %	R^2	J − stats
b	-0.030	-6.386	0.938	0.950	b	-0.017	-5.916	0.951	0.587
S.E.	[0.049]	[2.772]		(0.813)	S.E.	[0.035]	[2.804]		(0.899)
λ	0.121	-0.065			λ	0.144	-0.060		
S.E.	[0.130]	[0.026]	MAE	4.075e-004	S.E.	[0. 145]	[0.023]	MAE	2.5e-004
FMB	DOL%	ΔVOL %	$J-stats$		FMB	DOL%	ΔVOL %	J − stats	
λ	0.121	-0.065	0.938		λ	0.144	-0.060	1.121	
S.E.	[0.863]	[0.044]	(0.816)		S.E.	[0.015]	[0.033]	(0.772)	
Panel B: Factor betas									
48-all-country sample					29-OECD-country sample				
PF	α	DOL	ΔVOL	R^2	PF	α	DOL	ΔVOL	R^2
1	-0.003	0.959	3.848	0.772	1	-0.003	0.985	3.631	0.822
	[0.001]	[0.047]	[0.739]			[0.001]	[0.042]	[0.856]	
2	-0.001	0.996	1.348	0.818	2	-0.001	1.077	1.636	0.890
	[0.001]	[0.036]	[0.745]			[0.001]	[0.028]	[0.646]	
3	0.001	-0.027	-0.600	0.800	3	-0.000	1.013	0.236	0.904
	[0.001]	[0.037]	[0.678]			[0.001]	[0.025]	[0.543]	
4	0.001	0.993	-0.580	0.841	4	0.001	0.996	-1.999	0.865
	[0.001]	[0.034]	[0.689]			[0.001]	[0.028]	[0.737]	
5	0.002	1.093	-4.291	0.679	5	0.001	0.929	-3.504	0.747
	[0.001]	[0.069]	[1.409]			[0.001]	[0.049]	[1.200]	

Note: this table has the same setup as Table 4.1.

Figure A.1.2 Pricing Error Plots (Corresponds to Figure 4.2 with transaction costs deducted)

Panel (a) All countries

Panel (b) OECD countries



Note: this figure has the same setup as Figure 4.2.

A.2. CORRELATION OF EXCESS RETURNS AND FX MARKET RETURNS

Table A.2.1 Correlation of Excess Returns and FX Market Returns (*DOL*)

		Panel A. 48 all-country sample	Panel B. 29-OECD-Country Sample
ΔVOL Percentile	Obs.	HML	HML
0.05	17	<u>0.03</u>	0.15
0.15	50	0.16	0.13
0.25	84	0.16	0.15
0.35	117	0.16	0.14
0.45	150	0.17	0.10
0.55	184	0.14	0.10
0.65	217	0.18	0.10
0.75	250	0.19	0.10
0.85	284	0.17	0.12
0.95	317	0.18	0.19
All	334	0.17	0.14

Note: this table shows the correlations between excess returns of the carry trade portfolio *HML* and the FX market returns conditioning on different levels of volatility innovations for both 48-all-country sample (Panel A) and 29-OECD-country sample (Panel B). The first column shows the percentiles of ΔVOL, changing form the top 5% percentile to the full sample The underlined numbers in Panel A are numbers exhibited different pattern from others.